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CHARACTERISING THE FINANCIAL CYCLE IN LUXEMBOURG

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CHARACTERISING THE FINANCIAL CYCLE IN LUXEMBOURG*

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Abstract

This paper characterises the financial cycle in Luxembourg using both the *growth* and *classical* cycle definitions. We implement both a frequency-based approach –using band-pass filters– to measure the *growth* cycle and a turning-point approach to capture the *classical* cycle.

The financial cycle is characterized using varibales related to domestic credit and asset prices. We identify the dates of peaks/troughs for *growth* and *classical* cycles, describe the characteristics of cycle phases and analyze the synchronisation between cycles for each macro-financial variable considered and the real activity. Additionally, we evaluate the synchronisation of credit and house prices across the neighbouring countries, based on the medium-term *classical* cycle.

Finally, we introduce two novel tools to monitor the evolution of the financial cycle which are intended to contribute to informing macroprudential policy. The first tool is an optimal decision rule in the form of two warning thresholds signalling *growth* cycle phases related to a possible *classical* turning-point. The second tool is a measure of the probability of a turning-point in the *classical* cycle in each quarter after a peak in the *growth* cycle. The tools are built on the lead/lag relationships between peaks and troughs of *growth* and *classical* cycles. A composite index of the *growth* cycle is proposed as well.

Keywords : financial cycles, turning-points, synchronisation, band-pass filter, survival data, Area Under the Receiver Operating Characteristic Curve, Luxembourg.

JEL classification : E32, G01, G18.

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RESUMÉ NON-TECHNIQUE

La crise dite des «*sub-primes*» de 2007-2008 a démontré combien une bonne compréhension du cycle financier est importante afin de garantir la stabilité financière. En raison de l'interaction entre les sphères réelle et financière, les récessions économiques apparaissent plus longues et violentes lorsqu'elles s'accompagnent d'une « crise » bancaire systémique ; l'activité dans le secteur bancaire étant de nature pro-cyclique. Aussi, des changements dans la régulation et la supervision du système financier sont apparus de manière régulière en réponse aux turbulences financières et les banques centrales se sont vues dotées d'instruments macro-prudentiels pour prévenir et/ou atténuer les conséquences des crises systémiques.

Le cycle financier résulte de l'interaction entre le crédit disponible dans une économie et l'évolution du prix des actifs. Cette interaction est au cœur de la pro-cyclicité qui caractérise une grande partie de l'activité dans le secteur bancaire. Ainsi, une mesure correcte de la notion de cycle financier est un pré-requis pour la mise en œuvre des instruments de la politique macro-prudentielle s'attaquant au risque induit par la pro-cyclicité. Néanmoins, les nombreuses analyses théoriques et empiriques ont montré une grande difficulté à appréhender dans la pratique la notion de cycle financier de manière universelle.

Par conséquent, dans ce cahier, à l'instar de la littérature sur le cycle des affaires (ou cycle réel), deux définitions des cycles déduits des séries temporelles sont étudiées, à savoir, le cycle *classique* et le cycle de *croissance*. Tandis que le premier se réfère à l'évolution de la donnée en niveau, le second prend compte le taux de croissance de la série. Ainsi, les cycles *classique* et de *croissance* diffèrent par construction. Logiquement, une contraction du cycle *classique* (i.e. dans le niveau de la série temporelle) n'est apparente que si la croissance de la série est négative. Ceci suggère une relation entre les dates des points de retournement des cycles calculés selon les définitions précitées. Effectivement, les pics et creux du cycle de *croissance* précèdent ceux du cycle *classique*.

Ce cahier d'études s'attache à rechercher des outils pertinents et efficaces spécifiques au Luxembourg pour la datation des cycles financiers puis à prévoir leurs phases d'expansion et de récession. Ainsi, afin de fournir un examen approfondi du cycle financier, dans un premier temps, une étude individuelle sur les cycles des différentes formes de crédits (crédits domestiques, crédits des sociétés non financières, crédits des ménages, les crédits octroyés au secteur privé), du PIB et des actifs financiers, tels que le prix de l'immobilier et les prix des actions est effectuée.

A partir des variables citées plus haut, une datation et une description des cycles sont fournies à l'aide de deux méthodes empiriques souvent usitées en théorie des cycles réels. A l'issue de ces exercices de datation des phases des cycles financiers, des travaux en termes de concordances entre les cycles nationaux mais aussi vis-à-vis d'une sélection des pays européens (Belgique, France et Luxembourg) sont présentés. Selon notre étude, les cycles du prix immobiliers ne sont pas clairement synchrones avec ceux des crédits, ce qui renforce l'idée selon laquelle l'évolution des prix immobiliers au Luxembourg serait plutôt liée à des facteurs structurels. Au niveau européen, d'après nos estimations des

indices de concordance, les cycles immobiliers belges et luxembourgeois serait relativement synchronisés.
Afin de détecter de manière précoce des points de retournement du cycle *classique* des variables étudiées, deux outils novateurs sont développés dans ce cahier d'études. Le premier outil met en lumière des seuils d'alertes permettant de prédire les retournements de cycle déduits des variables en niveau. Le second, quant à lui, propose une mesure de probabilité des phases de retournement du cycle à partir d'un modèle pour l'analyse des données de survie. Ces deux instruments fournissent quelques prévisions en termes d'occurrences des prochains points de retournement. Selon le modèle de survie estimé en regroupant les variables de crédit et du prix des actifs, la probabilité d'un futur point de retournement pour les prix immobilier au Luxembourg serait au plus haut vers le deuxième trimestre de 2018 sous la condition qu'aucun point de retournement n'ait été observé d'ici là. Il est néanmoins prudent de souligner que les conclusions obtenues se basent sur des analyses purement statistiques qui, par définition, peuvent s'avérer sensibles aux données utilisées et requièrent donc des actualisations régulières. De surcroit, le modèle pour l'analyse de survie tel qu'il est définit dans ce cahier d'études s'applique uniformément à l'ensemble des cycles sans une réelle prise en compte de la spécificité des composantes cycliques (des séries individuelles). Enfin, nos analyses ne permettent pas d'identifier une quelconque relation de causalité entre les variables étudiées.
Dans un deuxième temps, une analyse s'inscrivant davantage dans une optique multivariée, est exposée. Il s'agit de la construction d'un agrégat synthétique visant à reproduire les phases du cycle financier à partir des actifs financiers et du crédit domestique. Des conclusions robustes émergent. En effet, la durée moyenne du cycle financier est de 10 ans. En outre, une comparaison avec le cycle réel montre que l'amplitude des phases décroissantes du cycle réel est plus importante lorsque ces phases sont concomitantes avec les phases décroissantes de l'indicateur agrégé du cycle financier.
En définitive, ce travail a permis de dégager un certain nombre de conclusions pertinentes pour une bonne compréhension de la formation du cycle financier. A terme, ces informations pourraient servir à définir des indicateurs avancés de crise plus fiables, lesquels s'avèrent nécessaires aux autorités macro-prudentielles dans leurs fonctions d'identification, d'évaluation et du suivi des risques pour la stabilité financière et économique.

1 INTRODUCTION

The last global financial crisis revealed several dysfunctions within financial systems across the world. One of the main lessons highlights how the pro-cyclical behaviour of banks can extend negative shocks across the financial system to the real economy, and lead to deeper recessions. As a result, a new international framework for banking regulation has been developed aiming to, among other things, counter the procyclicality of banks' activity (BCBS, 2011). Since then national policy-makers are advancing in the development of their respective macro-prudential toolkits. The Countercyclical Capital Buffer (CCB) is among the macro-prudential policy instruments expected to mitigate the procyclicality of bank balance sheets. Such an instrument aims to enhance the resilience of banks when facing crises linked to excessive domestic credit growth. The implementation of macro-prudential policy instruments (e.g. CCBs) requires a clear understanding of the domestic financial cycle specifics, including the determinants. The aim of our study is to improve the understanding of the financial cycle in Luxembourg and, by that means, to contribute to the analysis underlying the calibration of Countercyclical Capital Buffer (CCB) for the banking system.

The empirical literature on financial cycles is rather recent but growing rapidly on the basis of developments in the measurement of real business cycles. Indeed, most of the tools employed to characterise business cycles have been extended to financial cycle studies. A fundamental distinction in the analysis of cycles is that between the *classical* and *growth* cycle. While the former refers to the evolution of the absolute levels of the series, the latter takes into consideration the gap between the series growth rate and its long-term trend (Pagan, 1997). Therefore, the *classical* and *growth* cycles differ by construction, given the fact that a contraction in the *classical* cycle would occur only if growth is negative. This suggests a lag-lead relationship between the dates of turning-points resulting from these approaches. Accordingly, turning-points in the *growth* cycle should precede the turning-points in the *classical* cycle. Besides, turning-points in the *growth* cycle tend to be more numerous than in the *classical* cycle. In fact, growth contractions do not always imply *classical* cycles because a growth rate below the long-term trend rate does not necessarily imply negative growth (Boehm and Moore, 1984). Therefore, a relationship could be established between the characteristics of *growth* cycles (e.g. amplitude) and the likelihood of turning-points in the *classical* cycles.

The studies of Claessens et al. (2011) and Drehmann et al. (2012) provide insights on how to define and characterise financial cycles. These studies follow the *classical* cycle definition and propose to measure financial cycles using a methodology similar to the one implemented by the National Bureau of Economic Research (NBER) with the purpose of identifying turning-points in the United States business cycle. This methodology was initially developped by Burns and Mitchell (1946) (i.e. turning-point approach). Then, Claessens et al. (2011) characterize financial cycles in terms of the duration, amplitude and slope of their phases (i.e. expansion, up-turn, downturn). An additional feature studied by Claessens et al. (2011) is the synchronisation of financial cycles on the basis of the *Concordance index* (Harding and Pagan, 2002). They provide evidence on the amplification role as characterised by the pro-cyclical behaviour of banks and suggest that a high synchronisation of financial cycles tends to be linked to more intense stress events.

The work of Drehmann et al. (2012) partially utilizes the complementarity between the *classical* and *growth* cycles. Their study suggests that the medium-term horizon is the most relevant timeframe to consider in order to make a valid financial cycle analysis. Therefore, they propose to make use of the turning-point approach with a specific calibration aimed at capturing longer financial cycles. Additionally, building up on the results of Claessens et al. (2011) and following Burns and Mitchell (1946), Drehmann et al. (2012) suggest that in the case of high concordance of financial cycles the relevant turning-points are those of the common cycle (or “reference cycle” in the terminology of real business cycle). With the purpose of identifying a common cycle, the Harding and Pagan’s (2006) algorithm is used. Finally, adopting the *growth* cycle tradition, Drehmann et al. (2012) propose a composite index combining the filtered series that have exhibited clear similarities. It is shown that the composite measure identifies most turning-points in the reference cycle.

A common criticism of these studies would be the weakness of the analysis of the synchronisation of cycles which rely on the *Concordance index* for identifying synchronized cycles. In fact, Harding and Pagan (2006) demonstrate that such an index can suggest synchronisation when there is none, which can consequentially lead to inaccurate conclusions. In order to enhance the robustness of the analysis, Harding and Pagan (2006) propose conducting several statistical tests.

In the present study we implement the same methodology as in Claessens et al. (2011) and Drehmann et al. (2012) for the measurement and characterisation of the financial cycles in Luxembourg. Similarly to the business cycle literature, there is no general consensus on the method of measurement of financial cycles (Canova, 1998). Consequently, we implement both, a frequency-based approach –on the basis of band-pass filters– to measure the *growth* cycle and a turning-point approach –as implemented by Harding and Pagan (2002)– to capture the *classical* cycle.

We introduce two innovations with respect to previous empirical studies on the measurement of the financial cycle. Firstly, even if we rely on the *Concordance index* for the synchronisation analysis, we strengthen the robustness of the exercise by implementing complementary tests of multivariate non-synchronisation before the search for a potential common cycle or construction of a composite index. Secondly, we utilize the complementarity between the *growth* and the *classical* cycle and propose two interrelated approaches to detect the *classical* peaks early in the financial cycle. On the one hand, we identify an optimal decision rule in the form of warning thresholds signalling the *growth* cycle phases presumably related with a *classical* turning-point. On the other hand, we measure, on the basis of survival data models, the probability (unconditional and conditional) of a turning-point in the *classical* cycle in each quarter after a peak in the *growth* cycle has been reached.

The paper is organized as follows. Section 2 explains the analytical framework and the methodology, and describes the data used in the study. In particular, sub-sections 2.1 and 2.2 describe the turning-point and frequency-based approaches for the measurement of the *classical* and *growth* cycles, respectively. Section 3 presents the basic features of financial cycles in Luxembourg (i.e. dating of peaks/trough, duration and amplitude of cycles phases phases) as well as the analysis of synchronisation; several robustness checks are also presented in this section. Section 4 extends the synchronisation analysis of *classical* cycles to neighbouring countries. In section 5 the results of the two approaches for early detection of *classical* turning-points given the developments in the *growth* cycle are described. Building on the results of the synchronisation analysis and in line with Drehmann et al. (2012), in section 6 we introduce a composite indicator of the financial cycle on the basis of the *growth* cycle definition. Finally, section 7 provides a conclusion.

Our study covers the period spanning 1980q1-2015q3. The results provide evidence of weak synchronisation between medium-term *classical* cycles of house prices, aggregate domestic credit and GDP. We also weakly identify a peak of the common medium-term cycle in 2008q3 and a trough in 2009q2. Likewise, a weak degree of synchronisation is also found across *growth* cycles of house prices, aggregate domestic credit and GDP. Additionally, while the *classical* cycles phases of credit variables and the equity price index are not synchronized at all, the *growth* cycles phases show some degree of synchronisation. This highlights the importance to distinguish between the two definitions of the cycle in empirical studies for policy analysis. The study of the international synchronisation of Luxembourg's financial cycles (*classical* definition) focuses on neighbouring countries (Belgium, France and Luxembourg).[1] Notably, we found that the cycles of Luxembourg's house prices and Belgian bank credit cycles tend to be synchronised. Conversely, French *classical* cycles are not synchronized with those of Luxembourg. Finally, the results of the exercise of early detection of turning-points in the *classical* cycle indicate probable turning-points in future quarters for the index of residential property prices. Based on past correlations between four credit variables and two asset prices, the estimated probability of a turning point in house prices appears to peak in 2018q2 (conditional on no turning-point observed before that date). Conversely, as all credit variables are still in their expansion phases, no signals have been issued in 2015q3 about a future *classical* turning-point and no probability assessment can be provided. These observations are supported by the evolution of the proposed composite index of the financial cycle.

It is worth to mention that the study of the synchronisation of cycles and the exercice of early detection of *classical* turning-points do not allow to conclude on any kind of causal relationship between the analyzed variables. Such statistical analyses identify links between the variables which could be related with divers direct and/or indirect channels. However, these analyses do not allow to single out these channels. Our results should be read with this caveat in mind.

[1] We deliberately leave Germany out of this analysis because of the acyclical evolution of the German credit and house price variables.

2 THE MEASUREMENT AND CHARACTERISATION OF THE FINANCIAL CYCLE

The literature on the financial cycle is continuously evolving though some commonality appears in the underlying theories.[2] Hence, variables related to the development of credit to the real economy and the evolution of asset prices appear as some of the most essential inputs to conduct the measurement of the financial cycle (Borio, Furfine and Lowe, 2001). In addition, empirical evidence supports the medium-term as the appropriate measurement horizon. However, similarly to the real business cycle literature, there is no agreement on the method of measurement. Consequently, rather than constrain ourselves by a particular method we adopt, in line with Drehmann et al. (2012), two alternative approaches: turning-points approach and frequency-based approach for capturing the *classical* and *growth* cycles, respectively.

2.1 THE TURNING-POINT APPROACH

Following the empirical literature on the financial cycle we consider the turning-point analysis as an alternative measurement approach (Claessens et al., 2011; Drehmann et al., 2012). This approach is similar to the one followed by the National Bureau of Economic Research (NBER) for dating the business cycle in the United States. While the approach was originally developed by Burns and Mitchell (1946), the computer programs for monthly series are attributed to Bry and Boschan (1971). For the purpose of this study we make use of Harding and Pagan's (2002) adaptation of the algorithm for quarterly series.

The algorithm identifies peaks and troughs in the log-level of time series that can be considered as turning-points (TPs) of the cycle. Then, censoring rules are applied to the full set of peaks/troughs for selecting the TPs of the cycle. Indeed, alternative calibrations of the algorithm allow extracting TPs which correspond to medium-term cycles. The censoring rules are applied iteratively in a specific order. Our implementation of Harding and Pagan's (2002) algorithm is fully automatised and thereby avoids any *hand-waving* adjustment of the final output, which ensures full reproducibility of our results.[3]

The duration of a complete cycle is measured from peak to peak. Then, it includes a downturn phase (from peak to trough) and an expansion phase (from trough to peak). Following Claessens et al. (2011) we also analyse the upturn phase which consists of the number of quarters it takes for a series to reach its previous peak after the trough. In line with Drehmann et al. (2012) we study medium-term cycles which are constrained to last at least 20 quarters.

[2] See for example, Aikman et al. (2014), Geanakoplos (2010), Fostel and Geanakoplos (2008), Bernanke et al. (1999) Bernanke and Gertler (1989).
[3] A detailed explanation of the implementation and calibration of the algorithm is available in appendix D.

2.2 THE FREQUENCY-BASED APPROACH

This approach allows us to estimate the cyclical component of a series by focusing on the frequency domain. Several *growth* cycle extraction models have been proposed in the statistical literature, the most popular being the filtering techniques proposed by Baxter and King (1999) and Christiano and Fitzgerald (2003). Alternatively, the Hodrick-Prescott filter is a widely used technique based on the time domain. It is not possible to unequivocally identify the most efficient technique in current circumstances. As a consequence, practitioners are bounded to select the method depending on the specificities of the empirical task at hand. In this paper, we make use of frequency-based techniques.

We make use of the Christiano and Fitzgerald (2003) filter (CF) on our set of macro-financial variables. This method is considered as an efficient way to approximate the ideal band-pass filter and it meets an entire set of "good" method criteria (Medhioub and Eleuch, 2013). The CF random walk filter is a band pass filter built on the Baxter and King (1999) filter (BK) principles. This kind of filters formulate the de-trending and smoothing problem in the framework of frequency. The CF filters approximate the ideal infinite band pass filter. The CF random walk filter uses the whole series for the calculation of each filtered data point. The advantage of the CF filter is that it is supposed to provide good results for a large class of time series compared to BK filter for example. The main limit of this tool is the importance given to the last observations, which are generally subject to ex-post corrections.

Different bands can be defined depending on the targeted length or duration of the cycle. Given our interest on medium-term cycles, the bands are set between 32 and 60 quarters.

The peaks (troughs) of *growth* cycles are defined as local maxima (minima) of the filtered series when it takes values above (below) the threshold, which is set to zero.[4] However, as highlighted by Boehm and Moore (1984), "*not all growth slowdowns lead to or include a classical downturn*". Hence, a zero threshold might overestate the number of peaks related with a turning-point in a *classical* cycle. In order to facilitate the comparison with the turning-point approach, Drehmann et al. (2012) suggest to take the cumulative sum (from zero) of the filtered series. Following this approach, the dates of peaks in the *growth* and *classical* cycles would tend to coincide. Our strategy differs radically as it refrains from disposing of the differences in the dating of peaks/troughs between the *growth* and *classical* cycles. Instead, we implement a procedure for optimally selecting decision rules that would detect the peaks/troughs in the *growth* cycle which are consistent with the *classical* cycle. The procedure we apply is widely used in the literature on Early Warning Systems (Kaminsky et al., 1998; Drehmann and Juselius, 2014; Detken et al., 2014).[5]

[4] Indeed, the focus is on the cyclical component, the starting observation has a weak importance in this precise case.

[5] A more detailed presentation of the procedure is given in appendix G (page 44).

Second, given the lead-lag linkages between the *growth* and *classical* cycles, we build a leading indicator of *classical* peaks taking into account the state in the *growth* cycle. Then, we apply statistical models for the analysis of survival data in order to calculate unconditional and conditional probabilities of a turning-point in the *classical* cycle given the number of quarters that passed-off after the peak in the *growth* cycle.

2.3 CHARACTERISATION OF THE FINANCIAL CYCLE

In addition to the duration, we characterize the financial cycle in terms of several features of the cyclical phases of the considered macro-financial variables. The characterisation depends on the adopted approach for the identification of cycles. In line with Claessens et al. (2011) we distinguish between the contraction and expansion phases for the analysis of cycles resulting from the turning-points approach (*classical* cycle). As regards contraction phases we analyse duration, amplitude and slope. Conversely, as expansion phases are generally much longer and subject to changes in structural factors, we focus mainly on the early part of expansion phases known as the “upturn” phase (Claessens et al., 2011). A detailed set of definitions of these characteristics is available in appendix D (page 44). As regards the frequency-based approach (*growth* cycle), we measure the duration and amplitude of contraction and expansion phases.

In addition, we assess the degree of synchronisation of the financial and the real cycles in Luxembourg. Moreover, we evaluate the synchronisation of bank credit and residential property price cycles (*classical* definition) across neighbouring countries. For such analyses, we make use of the *Concordance index*, originally proposed by Harding and Pagan (2002). This index measures the fraction of time the cycles of two series are in the same phase. In case of perfect (non-) synchronisation, the index equals (zero) one. Unlike Claessens et al. (2011) and Drehmann et al. (2012) and as suggested by Harding and Pagan (2006), we also study the components of the *Concordance index* to enhance the robustness of our evaluation. In particular, we implement tests of both bivariate and multivariate strong non-synchronisation (SMNS test) which are based on the correlation coefficient between the phases (Harding and Pagan, 2006).[6] Indeed, the possibility of a high *Concordance index* concomitant with a zero correlation between the state of the cycles (i.e. downturn or upturn) cannot be excluded.[7] Although, we could have used a mean corrected *Concordance index* to overcome this flaw, we stick to the to *Concordance index* because of its appealing interpretation and subsequently implement statistical tests to ensure robust conclusions.

The international study of Claessens et al. (2011) highlights the consequences of the synchronisation of financial cycles in terms of the intensity of their phases. More precisely, they show that when cycles are synchronised, downturns tend to be deeper and longer.

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[6] The correlation coefficients can be estimated one by one from a bivariate regression given in equation (24) in Harding and Pagan (2006). Alternatively, all the correlation coefficients can be simultaneously estimated following the procedure of section 5.1.2 in Harding and Pagan (2006).

[7] Such a situation may arise as a consequence of particularly long expansion phases. See footnote 4 on page 65 of Harding and Pagan (2006).

Conversely, given that our focus is on one specific country, i.e. Luxembourg, we do not investigate the implications of the synchronisation of cycles on the characteristics of these cycles. We are not interested, for instance, in measuring the impact of synchronisation on the amplitude of downturn phases. In fact, the analysis of financial cycles synchronisation across neighbouring countries merely aims to provide an additional characterisation of Luxembourg's cycles. However, if a sufficiently high degree of synchronisation is measured between Luxembourg's cycles we implement the algorithm proposed by Harding and Pagan (2006) for the identification of turning-points in the common or reference cycle. In addition, we combine the synchronised series into an aggregate indicator from which we extract its cyclical component using the CF filter.

2.4 THE DATA

In general, the study of economic cycles requires long time series. Consequently, the data selection is largely determined by its availability. We analyse several variables on a quarterly basis related to domestic credit and asset prices as well as the GDP.[8,9] The latter aims to represent the real business cycle.

Recently, European countries have adopted a new national accounts nomenclature (i.e. ESA2010). However, the length of the series diverges across countries. For instance, Luxembourg's ESA2010 GDP in quarterly frequency goes back only to 2000q1. In order to extend the series further back to at least 1980q1, one needs annual GDP series going back to 1980 based on the same nomenclature. Unfortunately, such a time series is still not available. Nevertheless, long GDP series can be constructed using ESA1995 nomenclature. The Luxembourg ESA1995 GDP quarterly series is available only from 1995, whereas the annual frequency data extend further back. Thus, for the purpose of this study, the annual ESA1995 GDP series was interpolated by a quadratic procedure in order to extend it back to 1980q1. Given that the interpolated portion of the GDP series represents an important share of the covered time span, we performed a robustness exercise aimed at evaluating the impact of interpolation on our results (see sub-section 3.3).

We consider four credit variables. Three of them focus on bank credit to the domestic non-financial private sector: loans to households (CRHH), loans to non-financial

[8] Appendix B provides data sources and describes the construction of the variables.

[9] Drehmann et al. (2012) also consider a particular specification of the credit-to-GDP. This variable is taken as a benchmark for the calibration of the Countercyclical Capital Buffer (CCB) in both Basel III and European law. Alternative definitions of such an indicator can be calculated. Among the criteria for selecting the preferred definition, one finds the evaluation of the capacity to predict crisis episodes. However, there have not been sufficient systemic crisis events in Luxembourg to run such an analysis. Alternatively, one can evaluate the capacity of alternative credit-to-GDP gap definitions to forecast the turning-points of a "common" cycle. Indeed, literature does specify that when real and financial cycles turn simultaneously, systemic crises tend to occur. Thus, the present study will serve the preparatory analyses aimed at identifying relevant indicators for the calibration of the CCB in Luxembourg by allowing to determine an adapted specification of the credit-to-GDP gap. Consequently, including a definition of the credit-to-GDP gap in our characterization of financial cycles would have implied endogeneity in the subsequent analysis. In such a case, we would have tried to predict the turning-points with a variable similar to the one underlying the cycle. Thus, with the aim of avoiding any endogeneity issues the credit-to-GDP gap is not analysed in the present study.

corporations (CRNFC) and the sum of the two (CRNFS). These variables are only available from 1999q1. However, quarterly series of total bank loans (to all institutional sectors) is available from 1980. The sectoral bank loans variables have been extended back to 1980 on the basis of fixed shares.[10] As a consequence, the three series present exactly the same evolution in the period before 1999 and differ only in their levels. While this represents a drawback for the analysis of the financial cycle, namely when using the frequency-based approach, the divergence in their behaviour beyond 1999 fully justifies the inclusion of both variables in the study. It is worth to mention that observations in the far past do not tend to affect the dating of turning-points in the *classical* cycle.

The fourth credit variable is an aggregate of credit to the domestic non-financial private sector compiled by the IMF. Even if it is intended to measure credit available from all possible sources to the non-financial sector, it is still safe to assume that some residual intra-financial credit is included by construction. Consequently, the results should be interpreted with this caveat in mind.

Two variables are being considered for the purpose of determining the asset prices: an index of house prices (HP) and the Eurostoxx50 index of equity prices (EQ). We preferred the European equity index to the Luxembourguish index LuxX mainly because of the length of the available series. While long quarterly series of EQ are available in public data sources, the LuxX series goes back to 1999 only, what is not sufficiently long for the purpose of our study. Moreover, these indexes are highly correlated, which is consistent with the openness that characterizes Luxembourg's economy. The index of residential house prices has been constructed by the BCL[11]. For the sake of the robustness checks, we have also studied the cycles of housing prices on the basis of a smoothed index, built using real estate transactions data excluding the outliers (see sub-section 3.3).

The analysis of the synchronisation of financial cycles across neighbouring countries focuses on bank credit to the domestic private non-financial sector and on house prices. In order to minimize the eventuality of a definition bias we have harmonized the variables as far as possible. Bank credit indicators for France and Belgium come from the Bank for International Settlements (BIS) data set on long series of credit to the private non-financial sector (BIS, 2013). This indicator combines all instruments of credit from banks to the private non-financial sector. The Luxembourg bank credit series employed in this study covers only banks loans to the domestic non-financial private sector; banks' holdings of securities issued by non-financial firms are deliberately left aside because they mainly fund international corporations with limited real domestic activity.

A common data source for the index of residential property prices is also used for the purpose of the international synchronisation analysis. Given that the long series of residential property price index produced by the Federal Reserve Bank of Dallas include Luxembourg (Mack and Martínez-García, 2011), we are able to control for a potential definition bias in this variable.

[10] See appendix B for details.
[11] Details are provided in Di Filippo and Kaempff (2014).

In line with previous international studies, all series are seasonally adjusted, in real terms (prices of 1999q1) and set to a homogeneous scale. The variables were therefore deflated by the CPI, transformed in logs and normalised by their respective values in 1999q1.

For the purpose of the frequency-based analysis, we assume that the transformed series are integrated of order one. Therefore, we take first differences of the transformed series.[12] In addition, we choose to remove the drift using the adjustment suggested by Christiano and Fitzgerald (2003).

In the following sections we present the results obtained from both, the turning-points and frequency-based approaches.

3 THE FINANCIAL CYCLE IN LUXEMBOURG

At first, the characterisation of the financial cycle in Luxembourg obtained from the turning-points approach is presented, followed by the results of the frequency-based approach. In both approaches, we first discuss the attributes of cycles of each individual variable considered in the analyses. Then, the synchronisation of cycle states is studied. Finally, we present a set of robustness exercises.

3.1 TURNING-POINTS ANALYSIS

The attributes of the financial cycle (*classical* definition) are presented in Figure 1 (page 15), and in Table 1.

Figure 1 shows that, depending on the variable, between one and three full medium-term cycles have been identified. Further, Table 1 contains the characteristics of each cycle's phases as well as the averages. In line with international evidence, the expansion phases tend to be longer and also have higher amplitudes than the downturns. The mean duration of full cycles ranges from 35 to 54 quarters. The mean amplitude and duration of the expansion (downturn) phases range, respectively, from 4.32% and 23 quarters (-8.72% and 8 quarters) to 20.15% and 45 quarters (-1.89% and 14.5 quarters), respectively. On the other hand, the mean amplitude and duration with regard to the upturn phases range from 0.73% and 9 quarters to 2.45% and 26 quarters, respectively.

Some specific features require a more detailed explanation. The starting period of the global financial crisis, the last quarter of 2007, is not identified as a peak of medium-term cycles of the credit variables, which have continued their expansion for more than one year

[12] We have also performed the analysis using annual growth rates. However, the quarterly growth rates have shown a higher capacity to detect turning-points in the *classical* cycle. This exercise is not presented in the paper.

beyond that date. Conversely, turning-points around that date have been identified for asset price variables as well as for the GDP. This stands against a domestic credit boom as being the cause for an excessive growth of asset prices that would have weakened Luxembourg's banking sector.

By construction, the cycles of the three bank credit variables (i.e. CRNFS, CRHH, CRNFC) have the same cycle time frame prior to 1999q1. Nevertheless, the characteristics of their phases could differ (essentially due to differences in the levels of these variables) as it can be seen from Table 1. However, more interesting insights would be learnt from the comparison of cycles after 1999q1 and from the comparison between disaggregated bank loans (i.e. CRHH, CRNFC) and aggregated domestic credit (i.e. DOMCRED). The latter three variables have cycles that share some characteristics before the start of the global financial crisis. Notwithstanding, the bank credit to households portrays a less cyclical behaviour, and the bank credit to non-financial corporations appears to have undergone an additional full cycle before the onset of the global financial crisis.

Noteworthy, the cycles preceding the global financial crisis show the most violent upturns, pointing to the business mood that prevailed during the period. This is particularly the case of bank credit to non-financial corporations, the aggregated domestic credit and the equity price index. The downturn of the last cycle undergone by credit variables, with the exception of bank credit to households, coincides with the global financial crisis event. This is when the bank credit to non-financial corporations presents the longest declining episode with an amplitude of -3.07% and a slope of -0.34%.

Table 1: Basic features the financial cycle in Luxembourg: turning-point analysis of credit and assets price related variables

Cycle			Expansion		Upturn			Downturn		
Peak	Trough	Duration	Amplitude	Duration	Amplitude	Duration	Slope	Amplitude	Duration	Slope
Bank credit to private non-financial sector (CRNFS)										
1982q1	1987q3	45	4.05	23	1.23	14	0.09	-3.05	22	-0.14
1993q2	1995q1	62	13.16	55	0.69	12	0.06	-2.03	7	-0.29
2008q4	2010q3	-	-	-	0.28	10	0.03	-0.58	7	-0.08
Mean		53.5	8.61	39	0.73	12	0.06	-1.89	12	-0.17
Bank credit to households (CRHH)										
1982q1	1987q3	45	4.32	23	1.31	14	0.09	-3.25	22	-0.15
1993q2	1995q1	-	-	-	0.73	12	0.06	-2.18	7	-0.31
Mean		45	4.32	23	1.02	13	0.08	-2.72	14.5	-0.23
Bank credit to non-financial corporations (CRNFC)										
1982q1	1987q3	45	4.48	23	1.36	14	0.10	-3.37	22	-0.15
1993q2	1995q1	36	8.94	29	0.78	12	0.07	-2.23	7	-0.32
2002q2	2004q4	26	9.37	16	1.00	9	0.11	-2.71	10	-0.27
2008q4	2011q1	-	-	-	0.04	18	0.00	-3.07	9	-0.34
Mean		36	7.60	23	0.80	13	0.07	-2.85	12	-0.27

Aggregated domestic credit to private non-financial sector (DOMCRED)										
1982q2	1985q3	42	10.02	29	0.60	9	0.07	-2.60	13	-0.20
1992q4	1994q2	63	18.51	57	1.68	17	0.10	-3.65	6	-0.61
2008q3	2009q4	-	-	-	1.89	2	0.95	-1.00	5	-0.20
Mean		52.5	14.27	43	1.39	9	0.37	-2.42	8	-0.34
House price index (HP)										
1980q3	1983q4	48	19.20	35	0.94	14	0.07	-4.54	13	-0.35
1992q3	1994q1	60	21.11	54	0.17	13	0.01	-1.24	6	-0.21
2007q3	2009q2	-	-	-	1.18	17	0.07	-2.42	7	-0.35
Mean		54	20.15	45	0.76	15	0.05	-2.73	9	-0.30
European equity price index (EQ)										
1989q4	1990q4	41	23.06	37	1.74	11	0.16	-3.89	4	-0.97
2000q1	2003q1	29	9.68	17	4.16	50	0.08	-12.10	12	-1.01
2007q2	2011q3	-	-	-	1.45	16	0.09	-10.18	17	-0.60
Mean		35	16.37	27	2.45	26	0.11	-8.72	11	-0.86
Real cycle (GDP)										
1980q3	1981q3	110	18.39	106	0.94	3	0.31	-0.97	4	-0.24
2008q1	2009q2	-	-	-	1.03	4	0.26	-0.92	5	-0.18
Mean		110	18.39	106	0.98	4	0.28	-0.94	5	-0.21

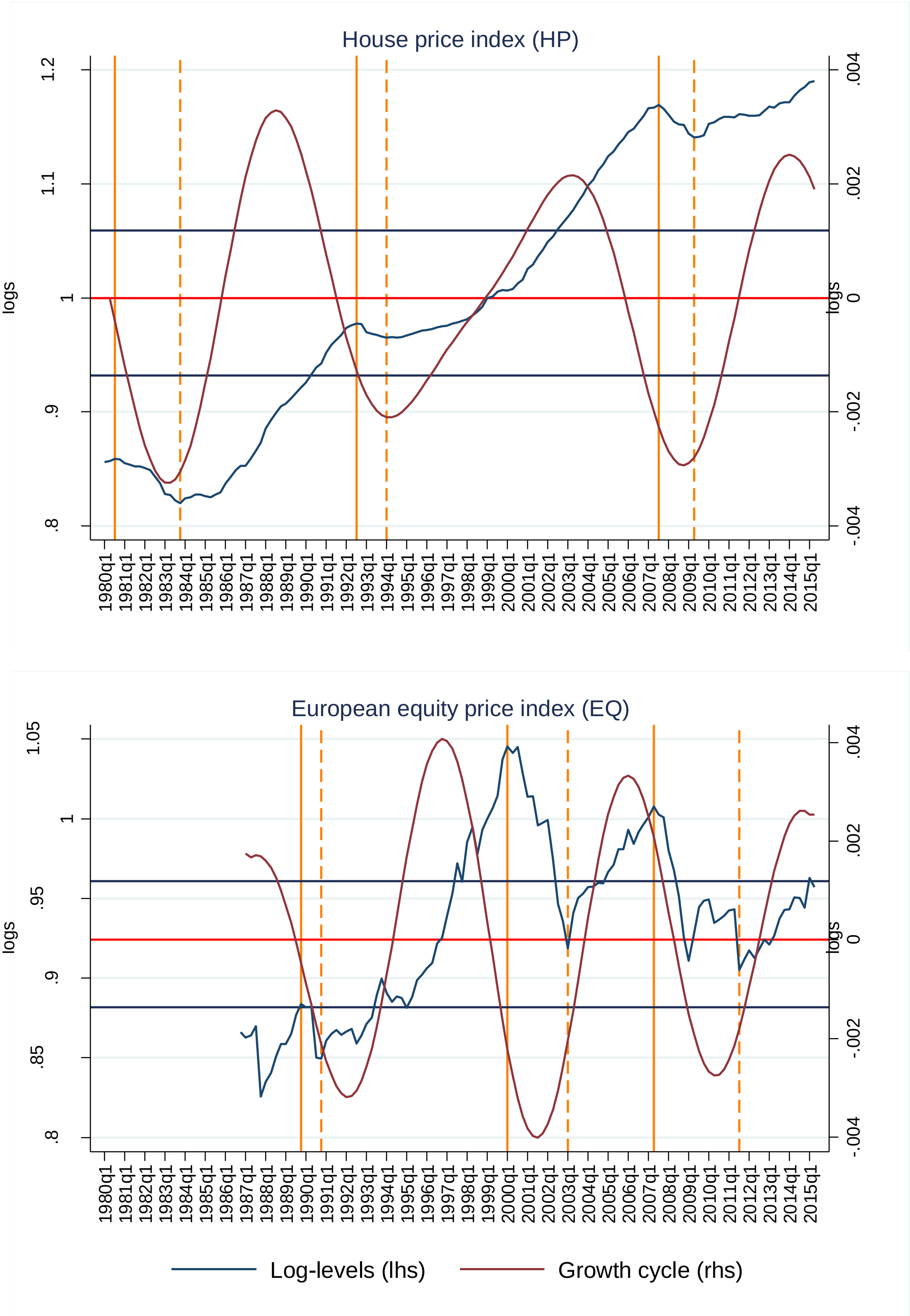
The *Concordance indexes* (Table 2) and correlation coefficient of cycle states (expansion or downturn) with the HACC standard errors (Table 3) are presented below.

Table 2 shows that the cycles' phases tend to coincide more than half of the time. The phases of the house price index cycles tend to be highly concordant with the GDP, CRHH, CRNFS and DOMCRED. The equity prices index tends to have rather low *Concordance indexes* with the other indicators except for GDP. As expected, *a priori* credit variables are highly concordant between themselves.

Table 2: Concordance index: turning-point analysis

Variables	GDP	HP	EQ	CRNFS	CRHH	CRNFC
HP	0.8803	-	-	-	-	-
EQ	0.7746	0.6831	-	-	-	-
CRNFS	0.7113	0.7324	0.6127	-	-	-
CRHH	0.7324	0.7535	0.5634	0.9507	-	-
CRNFC	0.6268	0.6479	0.5986	0.9155	0.8662	-
DOMCRED	0.8099	0.8451	0.6690	0.8732	0.8662	0.7887

Figure 1: The financial cycle in Luxembourg: *classical* and *growth* cycles of credit and asset prices related variables



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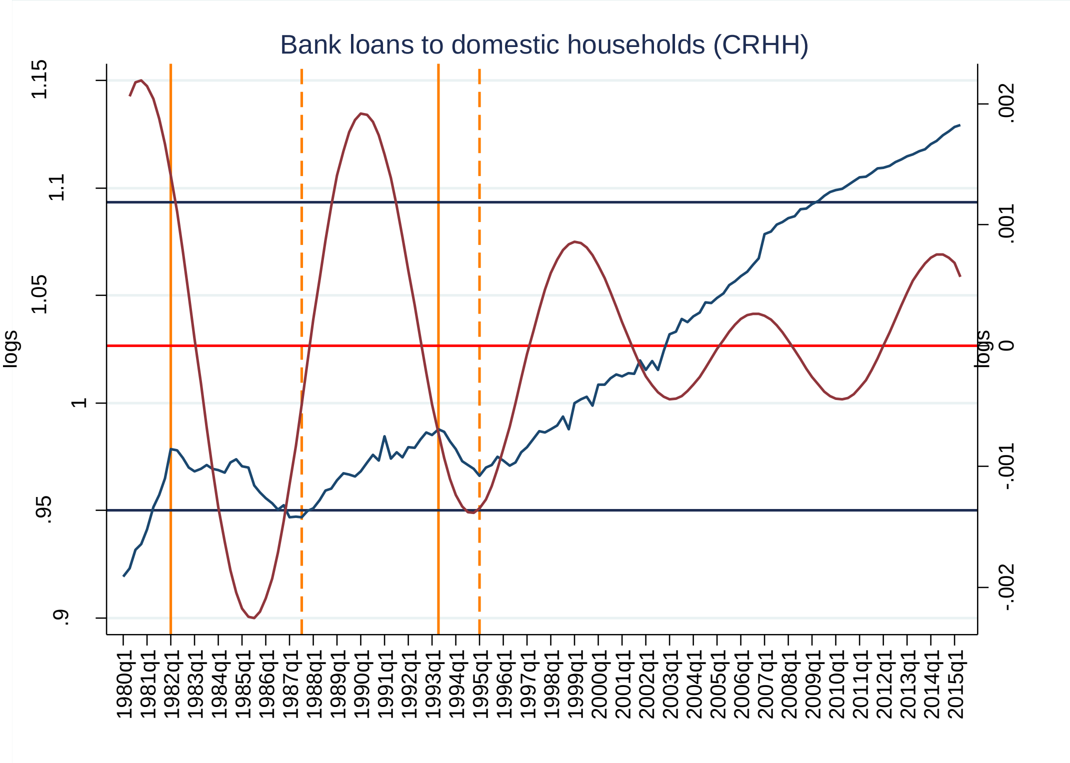

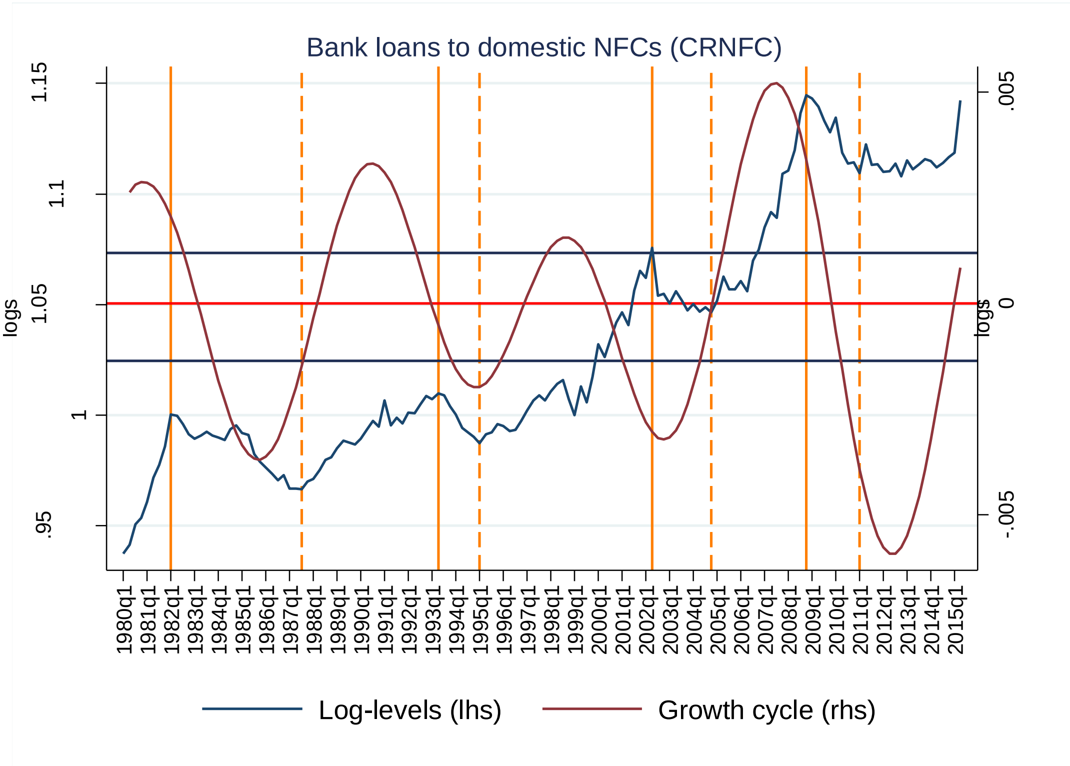

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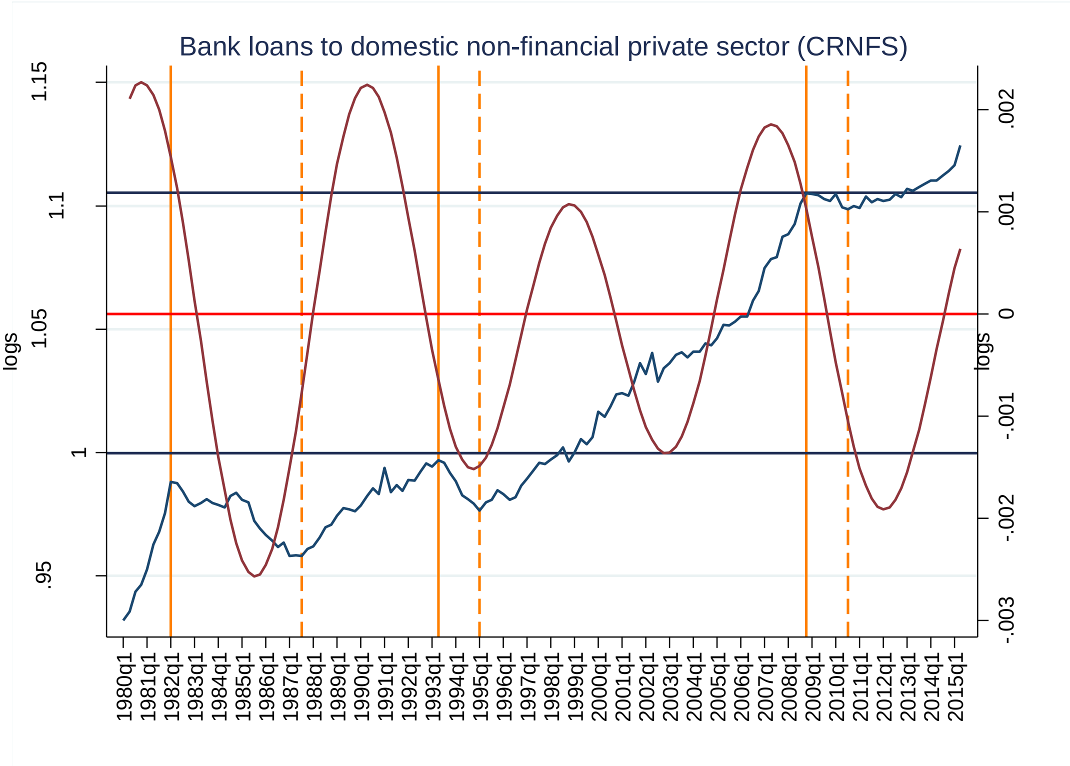

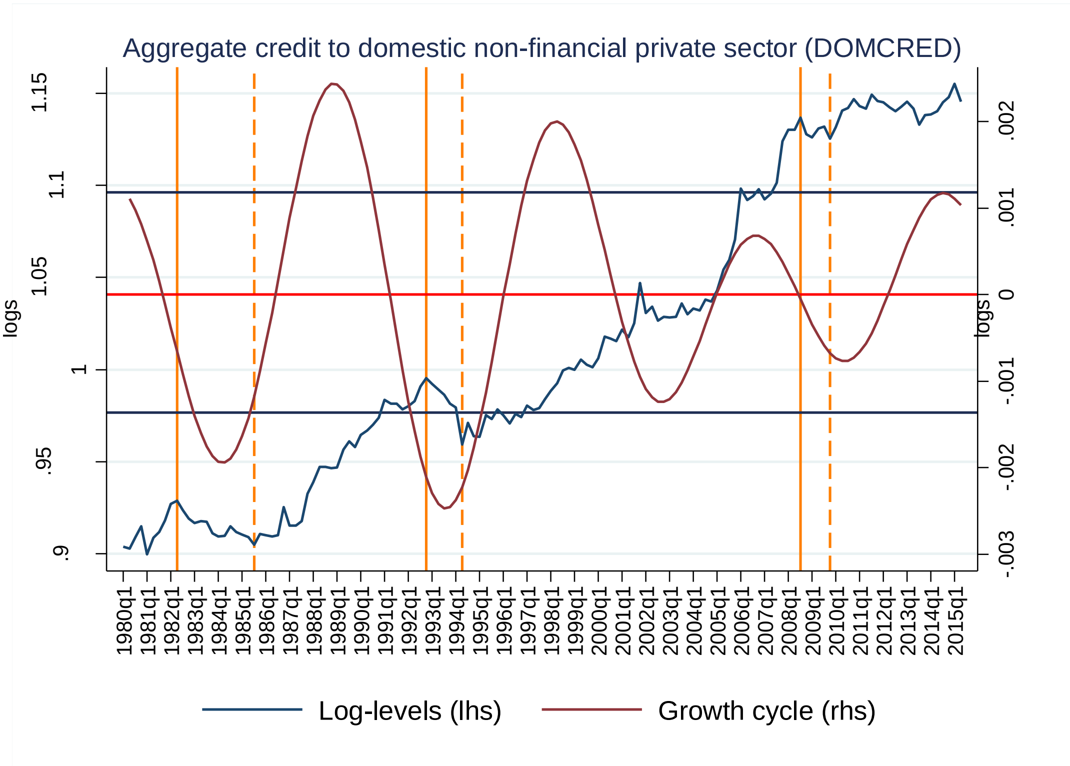

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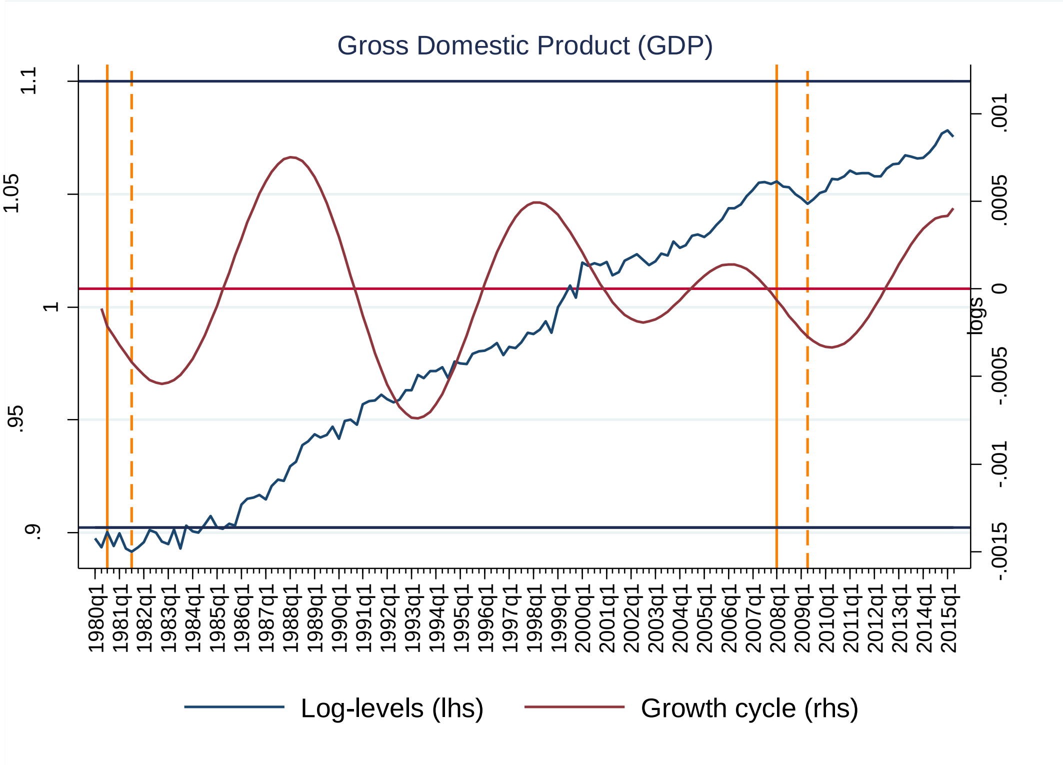

The solid (dashed) vertical lines represent peaks (troughs) obtained using BCL's implementation of Harding and Pagan (2002) algorithm. No discretionary censoring is applied. The window for identification of local extremes equals 10 data points around the targeted observation (i.e. 11 observations in total). The minimum length of phases and cycles are set, respectively, to 2 and 20 quarters.

The horizontal dark blue lines are warning thresholds for the growth cycle. If the growth cycle breaches them, there is an indication of probable turning-point of the log-levels series in future periods. The warning thresholds concern the credit and assets prices variables. They are plotted in the GDP chart for an illustrative purpose only.

Source: BCL, Statec, ECB; BCL calculations

The *Concordance index* might suggest a synchronisation of cycles when there is none. Therefore, we analyse the pairwise correlation coefficient of the cycles states (see Table 3). Each coefficient in Table 3 has been estimated from a regression specified with the variable in the corresponding row as the dependent variable and the variable in the corresponding column as the regressor.[13] The bottom row in Table 3 shows the results of multivariate tests where the null hypothesis means that all coefficients in the column are zero. The synchronisation of house prices with GDP and the aggregate domestic credit is confirmed. Conversely, house prices synchronisation with bank loans to households and to the private non-financial sector is not significant. The synchronisation across credit variables also holds, as the phases of aggregate domestic credit cycles are highly correlated with bank credit. However, the synchronisation between GDP and credit variables suggested by the *Concordance index* does not hold; the pairwise correlation

[13] Additionally, we perform a strong multivariate non-synchronisation (SMNS) test (Harding and Pagan, 2006). However, the weighting matrix of the SMNS test with all variables included, is almost singular and therefore it produces unreliable results.

coefficients depicted in Table 3 are negative for bank credit variables (and even statistically significant for bank loans to households). Likewise, the correlation coefficients between house prices and bank credit variables are non-significantly different from zero, the former being only synchronized with GDP and aggregate domestic credit. Accordingly, the correlation coefficients underlying the SMNS test, which have been simultaneously estimated using the Method of Moments (MMs), have higher variances and are not statistically significant.

Table 3: Correlation coefficients of cycles' phases: turning-point analysis

Dep. vars.(p-value)*	Independent variables GDP	HP	EQ	CRNFS	CRHH	CRNFC	DOMCRED
GDP	.	0.3462	0.1148	-0.0105	-0.0796	-0.0328	0.0742
	.	(0.0152)	(0.2512)	(0.8511)	(0.0447)	(0.5117)	(0.4499)
HP	0.8722	.	0.0378	0.2013	0.2032	0.1011	0.4816
	(0.0000)	.	(0.7663)	(0.1053)	(0.1570)	(0.3365)	(0.0013)
EQ	0.3450	0.0451	.	-0.0508	-0.2920	0.0266	-0.0290
	(0.1870)	(0.7671)	.	(0.6801)	(0.0001)	(0.8188)	(0.8387)
CRNFS	-0.0334	0.2546	-0.0539	.	0.9381	0.7500	0.7479
	(0.8506)	(0.0914)	(0.6821)	.	(0.0000)	(0.0000)	(0.0000)
CRHH	-0.2180	0.2208	-0.2661	0.8056	.	0.6042	0.6066
	(0.0004)	(0.1484)	(0.0002)	(0.0000)	.	(0.0000)	(0.0000)
CRNFC	-0.1236	0.1512	0.0334	0.8868	0.8319	.	0.6462
	(0.4910)	(0.3267)	(0.8182)	(0.0000)	(0.0000)	.	(0.0000)
DOMCRED	0.1754	0.4523	-0.0228	0.5550	0.5243	0.4056	.
	(0.4169)	(0.0022)	(0.8395)	(0.0000)	(0.0003)	(0.0003)	.
Chi2(6)**	1222.2	74.2	52.65	1242.97	2447.01	162.31	171.48
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

* HACC standard errors calculated using Newey-West procedure.

In order to substantiate our results, we run a SMNS test of house prices (HP) together with GDP and aggregate credit to the domestic non-financial private sector (DOMCRED). The test's null hypothesis is rejected[14] though the correlation coefficients simultaneously estimated by a MMs procedure are all statistically not different from zero with the exception of the one between HP and DOMCRED. This provides weak support for the existence of a common cycle across HP, GDP and DOMCRED. Nevertheless, we search for turning-points of a potential common cycle of these three variables by implementing the Harding and Pagan's (2006) algorithm which enables us to weakly identify one common peak and one trough in 2008q3 and 2009q2, respectively.

The results of the synchronisation analysis of *classical* cycles shed some light on the relationship between house prices and credit and thereby, contribute to the analysis of macro-prudential policy. It comes out clear from our analyses that, among the fundamental determinants of house prices, the bank credit does not seem to have been playing a decisive role. Nevertheless, as it was previously highlighted, the study of the synchronisation of cycles does not allow to conclude on any causal relationship. It rather identifies statistical linkages that characterize the behavior of the financial variables and

[14] The test results in a *Chi*2:517.51, *P*[*Chi*2(*df*=3)>*x*]=0.000.

might help monitoring their future behavior (under the assumption that these linkages would still be valid for future observations). The interpretation of our results should be done with this caveat in mind.

3.2 FREQUENCY-BASED FILTER ANALYSIS

Figure 1 provides a graphical representation of medium-term *growth* cycles while Table 4 presents the basic features. The dates of peaks/troughs and the duration of medium-term financial cycles are shown in this table. Additionally, the duration and amplitude of expansion and downturn phases are depicted. The last two columns in Table 4 indicate if turning-points in the *classical* cycle have occurred within a specific window around peaks/troughs in the growth cycle.[15] This additional information will be analyzed in section 5.

As it can be observed from Table 4, whether the *growth* cycle is measured from peak-to-peak or from trough-to-trough, credit variables (CRNFS, CRHH, CRNFC, DOMCRED) appear to have three complete cycles while asset prices variables (HP, EQ) have only two. As regards GDP, three complete *growth* cycles are measured from trough-to-trough while only two are measured from peak-to-peak. The duration of *growth* cycles is around nine years for credit variables on average. While *growth* cycles of asset price variables tend to be longer, the GDP appears to have cycles with similar duration. The *growth* cycle of the house price index tends to be the longest, lasting for more than twelve years. As expected, the duration of expansion and downturn phases of growth cycles tend to be balanced. The exception is the index of house prices which shows an expansion phase lasting for nine years (from 1994q2 to 2003q2) though with an amplitude below the mean.

Table 4: Basic features of the financial cycle in Luxembourg: frequency-based analysis of credit and asset prices related variables

Cycle				Expansion		Downturn		*Classical* TPs[a]	
Peak	Trough	Duration Tr.-to-Tr.	P.-to-P.	Ampl.	Dur.	Ampl.	Dur.	P.	Tr.
Bank credit to private non-financial sector (CRNFS)									
1980q4	1985q3	-	38	0.0048	19	-0.0048	19	Y	Y
1990q2	1994q4	34	34	0.0026	16	-0.0038	18	Y	Y
1998q4	2002q4	32	34	0.0032	18	-0.0024	16	N	N**
2007q2	2012q1	37	-	-	-	-0.0038	19	Y	Y
Mean		34.33	35.33	0.0035	17.66	-0.0037	18	-	-
Bank credit to households (CRHH)									
1980q4	1985q3	-	37	0.0042	18	-0.0044	19	Y	Y
1990q1	1994q4	37	36	0.0022	17	-0.0033	19	Y	Y
1999q1	2003q1	33	30	0.0007	14	-0.0013	16	N	N
2006q3	2010q2	25	-	-	-	-0.0007	15	N	N
Mean		31.66	34.33	0.0024	16.33	-0.0024	17.25	-	-

[15] The window has 29 quarters ; fourteen quarters before and after the peak/trough in the growth cycle.

				Bank credit to non-financial corporations (CRNFC)					
1980q4	1985q4	-	39	0.0070	19	-0.0066	20	Y	Y
1990q3	1994q4	36	33	0.0035	16	-0.0053	17	Y	Y
1998q4	2002q4	32	35	0.0084	19	-0.0048	16	Y	Y
2007q3	2012q2	38	-	-	-	-0.0111	19	Y	Y
Mean		35.33	35.66	0.0063	18	-0.0069	18	-	-
				Aggregated domestic credit to private non-financial sector (DOMCRED)					
-	1984q2	37	-	0.0046	18	-	-	Y*(1982q2)	Y
1988q4	1993q3	37	38	0.0045	19	-0.0049	19	Y	Y
1998q2	2002q4	30	34	0.0019	16	-0.0032	18	N**	N
2006q4	2010q2	-	34	0.0019	16	-0.0014	14	Y*	Y*
2014q3	-	-	-	0.0019	16	-0.0014	14	N	-
Mean		34.66	35.33	0.0029	17	-0.0027	16.25	-	-
				House price index (HP)					
-	1983q2	44	-	0.0063	21	-		Y*(1980q3)	Y
1988q3	1994q2	58	59	0.0042	36	-0.0054	23	Y	Y
2003q2	2008q4	-	43	0.0055	21	-0.0051	22	Y	Y
2014q1	-	-	-	-	-	-	-	-	-
Mean		51	51	0.0048	26	-0.0052	22.5	-	-
				European equity price index (EQ)					
-	1992q1	38	-	0.0074	19	-	-	Y*(1989q4)	Y
1996q4	2001q3	35	37	0.0073	18	-0.0081	19	Y	Y
2006q1	2010q2	-	37	0.0073	18	-0.0061	17	Y	Y
2014q4	-	-	-	-	-	-	-	-	-
Mean		36.5	37	0.0073	18.33	-0.0071	18	-	-
				Real cycle (GDP)					
-	1982q2	44	-	0.0013	23	-	-	-	-
1988q1	1993q2	37	41	0.0012	20	-0.0015	21	-	-
1998q2	2002q3	31	31	0.0003	14	-0.0007	17	-	-
2006q1	2010q2	-	-	-	-	-0.0005	17	-	-
Mean		34	36	0.0009	19	-0.0009	18	-	-

[a] TPs in the growth cycle within 14 quarters preceding or following TPs in the classical cycle ; Y :yes, N :no.

* False negative : the decision rule missed to associate the TP in the growth cycle with a TP in the classical cycle.

** False positive : the decision rule wrongly associated the TP in the growth cycle with a TP in the classical cycle.
The absence of stars means that the decision rule has correctly discriminated the TPs.

It is worth noting that the growth rate of bank loans to households (CRHH) has remained close to its medium-term trend. This can be clearly observed from Figure 1 and is also reflected in the decreasing amplitudes of expansion and downturn phases of the corresponding *growth* cycles depicted in Table 4. In contrast, the growth cycles of other credit variables show much more hilly developments.

As above, we have also run the analysis of the synchronisation of cycles on the basis of the *Concordance index* (see Table 5) and the correlation coefficient of cycle states (see Table 6).

As expected, the *Concordance index* indicates a high degree of synchronisation between the bank credit cycles. The degree of synchronisation is quite strong between bank credit cycles and the broad credit measure (DOMCRED). In contrast with the analysis of classical cycles, the synchronisation is rather strong between the credit cycles and GDP.

Moreover, DOMCRED is synchronized with equity prices as measured by the *Concordance index*. The house price cycle tends to be synchronized with GDP, DOMCRED and bank loans to households as phases coincide more than half of the time, but it is poorly synchronized with the remaining variables. In addition, the *Concordance index* between GDP and EQ is quite elevated. Finally, equity prices show a weak synchronisation of cycles phases with the other variables, namely, with house prices.

Table 5: *Concordance index*: frequency-based approach

Variables	GDP	HP	EQ	CRNFS	CRHH	CRNFC
HP	0.6522	-	-			
EQ	0.7304	0.4870	-			
CRNFS	0.7391	0.5304	0.6261			
CRHH	0.8174	0.6261	0.6870	0.8870		
CRNFC	0.7130	0.5043	0.6174	0.9739	0.8609	
DOMCRED	0.9304	0.6348	0.7130	0.8087	0.8696	0.7826

The correlation coefficients depicted in Table 6 confirm the synchronisation analysis based on the *Concordance index*. In effect, the cycle phases of credit variables show strong correlation with each other and GDP but are not strongly related to asset price variables. Noteworthy, the cycle phases of the index of house prices is only weakly correlated with GDP and aggregate domestic credit. Besides, the correlation coefficients of the cycle phases of bank credit variables with house prices are not statistically significant. The cycle of equity prices shows a rather strong correlation with GDP, aggregated domestic credit and, to a less extent, with bank loans to households.

Table 6: Correlation coefficient of cycles' phases: frequency-based approach

	Independent variables						
Dep. vars.(p-value)*	CRHH	CRNFC	CRNFS	DOMCRED	EQ	GDP	HP
CRHH	.	0.7158	0.7684	0.7338	0.3780	0.6303	0.2349
	.	(0.0000)	(0.0000)	(0.0000)	(0.0115)	(0.0000)	(0.1179)
CRNFC	0.7215	.	0.9461	0.5616	0.2314	0.4227	-0.0127
	(0.0000)	.	(0.0000)	(0.0000)	(0.1381)	(0.0015)	(0.9337)
CRNFS	0.7769	0.9490	.	0.6164	0.2591	0.4758	0.0460
	(0.0000)	(0.0000)	.	(0.0000)	(0.0930)	(0.0002)	(0.7638)
DOMCRED	0.7369	0.5595	0.6123	.	0.4462	0.8576	0.2571
	(0.0000)	(0.0000)	(0.0000)	.	(0.0017)	(0.0000)	(0.0834)
EQ	0.3308	0.2009	0.2243	0.3888	.	0.4455	-0.1127
	(0.0167)	(0.1453)	(0.1009)	(0.0039)	.	(0.0006)	(0.4226)
GDP	0.6400	0.4258	0.4778	0.8670	0.5169	.	0.3095
	(0.0000)	(0.0015)	(0.0002)	(0.0000)	(0.0001)	.	(0.0338)
HP	0.2277	-0.0122	0.0441	0.2482	-0.1248	0.2955	.
	(0.1188)	(0.9337)	(0.7638)	(0.0866)	(0.4216)	(0.0359)	.
Chi2(6)**	300.51	1088.63	1181.57	516.67	63.69	387.55	38.37
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

* HACC standard errors calculated using Newey-West procedure.

As expected, the dates of turning-points in the *growth* and *classical* cycles differs substantially. Conversely, the analyses of *growth* and *classical* cycles phases synchronisation throw out coincident conclusions which are that bank loans cycles tend to be unrelated with assets price indicators and, that house prices cycles tend to be concordant with the cycles of the aggregated economic activity and credit.

3.3 ROBUSTNESS

Several robustness exercises are implemented to check the stability of *classical* cycles' dating by taking into consideration various alternative data treatments. First, we examine for changes in the dating of house price cycles when the index is constructed on the basis of transactions data, excluding outliers. Second, we check the robustness of the dating for data updates. In particular, we implement a pseudo-real time analysis by iteratively extending the data series by adding new observations. For tractability reasons, we focus on the GDP and bank loans to the domestic non-financial private sector. Finally, we implement a simulation procedure to evaluate the effect of the interpolation of GDP series on the cycles identified through the frequency-based approach (the details of this exercise are presented in appendix E, page 45).

In the following paragraphs we present the results of the robustness exercises performed on the turning-points approach. The robustness of the frequency-based approach is discussed in appendix E.

We compare the cycles of the house price index presented in section 3 to an index built using real estate transactions data that excludes the outliers. As it can be observed in Figure 2 (page 36), the series follow a similar evolution but they show different short-term volatility, namely after 2007. As expected, the correlation coefficient is very high (99.9%). The non-parametric algorithm identifies the same number of medium-term *classical* cycles for both indices. The identified cycles appear to have similar characteristics. For two out of three cycles of the series excluding outliers, the peaks are reached one quarter before, compared to the raw house price index cycles. Troughs and durations remain unchanged. This supports the robustness of the non-parametric algorithm used for the identification of turning-points.

Figure 3 (page 37) shows the results of the pseudo real-time analysis of the identification of turning-points of GDP medium-term *classical* cycle. In order to evaluate the lag with which the turning-points are identified, we implement the non-parametric algorithm on six windows starting in 1980q1, and which go to, respectively, -1999q4,, 2008q2, 2008q3, 2010q2, 2011q2 and 2015q2. The first window help us to evaluate if the algorithm "wrongly" identifies a turning-point after the stagnation of GDP observed by the end of the nineties. The second and third windows allow us to verify the lag with which the peak of 2008q1 is identified (see Table 1 and/or the last chart in Figure 1). Likewise, the fourth and fifth windows allow us to perform a similar corroboration but for the 2009q2 trough. As it can be observed, the 2008q1 peak in the *classical* cycle of GDP is robust to data updates and identified with a lag of two quarters. In contrast, the trough in 2009q2 requires more than six additional quarters to be consistently identified.[16] For the illustrative purpose, we

[16] The identification lag is directly related with the parametrisation of the algorithm (see appendix D). Indeed, the minimum length of cycles' phases and the search window have been set to, respectively, two and eleven

deliberately left in the charts the troughs located in the last observation of the series (see the third and fourth charts of Figure 3); these troughs would have been censored otherwise.

The outcome of the pseudo real time analysis implemented on bank loans to the domestic non-financial private sector also brings us to similar conclusions. On the one hand, the peaks in the classical cycle are consistently identified with a two quarters lag (see the second and fifth charts of Figure 4 on page 40). On the other hand, the troughs require substantially longer lags to be consistently identified.

We conclude from the pseudo-real time analyses that the turning-points of the *classical* cycle identified non-parametrically are robust to extensions of the time window. Nevertheless, the identification is done with a lag that could be overly long, notably for the troughs. The information conveyed by the *growth* cycle could therefore be particurly useful for an early identification of turning-points in the *classical* cycle.

As previously mentioned, the GDP variable is available on a quarterly basis only from 1995q1 onwards. To get a quarterly GDP variable from 1980q1 to 1994q4, a quadratic algorithm is employed on annual GDP data. In order to evaluate the robustness of our frequency-based results, a parametric Bootstrap approach is used. According to this approach, the change of frequency for the GDP has no impact on the Christiano-Fitzgerald filter estimations for the cycle extractions (see Figure E.1, Annex E on page).

4 INTERNATIONAL SYNCHRONISATION OF LUXEMBOURG CLASSICAL CYCLES: A COMPARISON WITH BELGIUM AND FRANCE

In this section, we evaluate the synchronisation of the credit and house prices medium-term *classical* cycles across neighbouring countries (Luxembourg, Belgium and France).[17] In implementing this analysis we follow the turning-points approach and are especially attentive to avoid any definition bias. Consequently, we compiled a dataset of harmonized variables. Long series of harmonized indices of house prices are supplied by the Federal Reserve Bank of Dallas (Mack and Martínez-García, 2011). The dating of Luxembourg's house price cycles obtained from the Dallas's index slightly differs from the dating exposed in Table 1. Thus, in order to have an appraisal of the implied definition bias, we ran the analysis twice, alternatively including the Dallas and the BCL house price indexes. Given the fact that the conclusion of the synchronisation analysis remained unchanged, we present the results obtained using the BCL house price index below.

In order to assess the synchronisation of medium-term cycles of credit we make use of a broad measure of bank credit to the domestic non-financial private sector in Belgium and France. Such a measure includes banks holdings of securities issued by domestic non-

quarters.

[17] Germany is excluded from the analysis because a first examination indicated a markedly acyclical behavior of German house prices and credit series.

financial corporations. As regards Luxembourg, we deliberately consider a different bank credit variable for Luxembourg focused on bank loans. In fact, the experts' judgements indicate that the Luxembourg domestic real activity is essentially funded through bank loans while securities are essentially issued by multinational corporations, which then distribute the resulting funds across their affiliates abroad.

Table 7 presents the pairwise correlation coefficients of cycle phases obtained from the bivariate regressions of state variables for the cycles of house price indices and credit to the domestic private non-financial sector. As observed in Table 7, the cycle phases of Luxembourg house prices are synchronised with those of Belgium and to a lesser extent with those of France. The house price cycles of Belgium and France are not synchronised. Rather, their phases tend to be negatively correlated. Likewise, the credit cycle of Luxembourg is synchronised with the Belgian credit cycle, but unrelated to the French one.

Table 7: Correlation coefficient of domestic credit and house prices medium-term cycle phases: Belgium, France and Luxembourg

		Independent variables					
		Domestic credit			House prices		
Dep. vars. (p-value)*		BE	FR	LU	BE	FR	LU
	BE	.	-0.1158	0.5042	0.2189	0.2311	0.5444
Domestic		.	(0.4881)	(0.0002)	(0.2161)	(0.1876)	(0.0000)
	FR	-0.0654	.	0.0435	-0.1949	0.6844	0.0842
credit		(0.4914)	.	(0.7129)	(0.0020)	(0.0000)	(0.5485)
	LU	0.3971	0.0607	.	0.0459	0.2287	0.2546
		(0.0009)	(0.7105)	.	(0.7749)	(0.1707)	(0.0914)
Chi2(2)		33.87	13.16	37.87	32.00	99.51	62.08
p-value		(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
	BE	0.1280	-0.2017	0.0341	.	-0.1967	0.4052
House		(0.2409)	(0.0013)	(0.7752)	.	(0.0013)	(0.0160)
	FR	0.1164	0.6102	0.1462	-0.1695	.	0.3455
prices		(0.2208)	(0.0001)	(0.2082)	(0.0034)	.	(0.0273)
	LU	0.3389	0.0928	0.2013	0.4315	0.4270	.
		(0.0014)	(0.5428)	(0.1053)	(0.0119)	(0.0138)	.
Chi2(2)		-	-	-	48.80	51.24	141.26
p-value		-	-	-	(0.000)	(0.000)	(0.000)
Chi2(5)		59.61	84.27	40.04	69.84	208.27	166.92
p-value		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

*HACC standard errors calculated using Newey-West procedure.

In line with the evidence presented in section 3.1 (see Table 3 in page 19), it is interesting to see from Table 7 that the cycles of Luxembourg's house prices and banks loans to the domestic non-financial private sector tend to be unrelated. Rather, the estimated correlations suggest that the cycle of Luxembourg's house prices is more strongly synchronised with Belgium's bank credit. As highlighted in previous sections, it is worth to mention that the synchronisation of cycles does not imply a causality relationship. In fact, our result signalises the existence of direct and/or indirect channels linking both cycles, though we neither identify these channels nor we distinguish them. For instance, one can argue that the strengh of the Luxembourguish housing market pushes households to the Belgian border and thereby, drives a higher credit demand and stronger house prices in Belgium. However, we do not provide any analysis to support the validity of such a channel.

5 EARLY DETECTION OF TURNING-POINTS: LINKING GROWTH AND CLASSICAL CYCLES

As discussed in section 2.2, the *growth* and *classical* cycles of a variable are mathematically related. In fact, the growth rate of the variable should be sufficiently below the long-run trend for inducing a turning-point in the level. Hence, we expect the *growth* cycles to be more numerous than *classical* cycles and that only some of the peaks/troughs in the former precede turning-points in the latter. Indeed, only the *growth* cycle downturn phases which have enough amplitude to induce negative rates of growth are followed by a turning-point in the log-level of the series.

In this section we exploit the lead/lag relationship between the *growth* and *classical* cycles with the purpose of detecting forthcoming tuning-points early. We follow two different approaches.

Firstly, in order to distinguish those *growth* cycles with the possibility to trigger or announce a classical turning-point in the following quarters, we exploit the link between the amplitude of expansion and downturn phases of stationary series. More specifically, departures from the long-run trend of stationary series tend to be followed by an adjustment of a similar magnitude but in the opposite direction aimed at rejoining the trend. Therefore, one can expect that steeper expansion phases in *growth* cycles announce sufficiently marked downturn phases. Accordingly, we identify, using the methodology of signals extraction, optimal decision rules in the form of warning thresholds signalling those *growth* cycle phases presumably related with a classical turning-point.[18] Therefore, a *growth* cycle breaching the upper (bottom) threshold signals a probable peak (trough) in the *classical* cycle in future quarters. Such a decision rule applies to the individual variable, informing about the evolution of the financial cycle. Hence, it is a useful tool for real time monitoring of the cycle.

Secondly, we calculate the probability of a turning-point in each quarter following a peak and trough of the *growth* cycle. This calculation is performed by implementing simple survival data models on a data pool composed by the variables related to the financial cycle (i.e. credit- and assets price- related variables). Statistical models for survival data allow measuring the unconditional probability of occurrence of a turning-point in the *classical* cycle in each quarter following a peak in the *growth* cycle (i.e. failure function which equals one minus the survival function).[19] Moreover, it is also possible to assess the probability of a turning-point in the *classical* cycle in each quarter *t* after the peak in the

[18] See appendix G (page 44) for a presentation of the signals extraction method and for details on the application done in this paper.
[19] A more detailed explanation of the survival data models implemented is provided in appendix G.2 (page 46).

growth cycle, conditional upon the fact that no turning-point has been observed until *t* (i.e. hazard function).

5.1 SIGNALS EXTRACTION APPROACH

On the basis of the signals extraction method we identify common upper and bottom thresholds for the *growth* cycles for various financial indicators (see Appendix G.1 (page 48) for a presentation of the calculations). The thresholds are displayed in Figure 1 (page 15) by dark blue lines. Additionally, the last two columns in Table 4 (page 20) present the state of the *classical* cycle with which the *growth* cycle is associated (the number of stars indicates the type of detection error while their absence implies correct detection).

As can be observed in Figure 1 the peaks and troughs in the *growth* cycles of bank credit variables precede the turning-points in *classical* ones. Conversely, there is no peak in the *growth* cycles of asset prices variables and of the aggregated domestic credit that precedes the first peaks observed in the *classical* cycles; in Table 4 we attached a star for that matter and we indicate between brackets the date of the "missed" peak in the *classical* cycle.

It can be observed in Table 4 that every peak in the *growth* cycle that breaches the warning threshold is associated with peaks in the *classical* cycle, except for the aggregate credit to the domestic non-financial private sector (DOMCRED). Although, looking at Figure 1, it appears that the peak in 2006q4 in the *growth* cycle of DOMCRED is not signalling a tuning-point in the *classical* cycle because it is below the upper threshold (i.e. false negative); in Table 4 we attached a star for that matter. We attach two stars when the decision rule falsely associates the turning-point in the *growth* cycle to a turning-point in the *classical* cycle (i.e. false positive). For instance, the peak in 1998q2 in the *growth* cycle of DOMCRED results in false positive.

From the analysis of Table 4, the decision rule correctly identifies those peaks/troughs of the *growth* cycle associated with turning-points in the *classical* cycle in almost every case. The only exception is the DOMCRED: four out of nine turning-points in the *growth* cycle provide wrong signals. Therefore, such a decision rule could be a useful statistical tool for real time monitoring of the financial cycle. Based on cyclical patterns observed in our four credit variables and two asset prices, our estimated decision rule suggests that the *classical* cycles in asset prices may be approaching a peak. Instead, all bank credit variables are still in expansion and have not yet breached the upper warning thresholds.

5.2 SURVIVAL DATA APPROACH

In what follows, we present the estimated probabilities of a turning-point in the *classical* cycle taking into account the number of quarters after the peak in the *growth* cycle was reached.

Table 8 depicts the estimated probabilities for medium-term cycles. Each row of the table presents the results for different time intervals after the peak in the *growth* cycle was reached. The number of turning-points in the *classical* cycle which followed a peak in the *growth* cycle are specified in column (2); the third column indicates the number of peaks which were not followed by a turning-point (dubbed "censored observations" in survival data jargon). The columns (4) to (6) display the unconditional probability, the standard error as well as the 95% confidence interval. Likewise, columns (7) to (9) present the conditional probabilities. As it can be observed from Table 8, turning-points in the *classical* cycle are essentially observed between thirteen and seventeen quarters after a peak in the *growth* cycle was reached. In effect, the conditional probability is well above 10% in each of these intervals (see rows six to nine in column (8) in Table 8). Moreover, the interval covering thirteen to fourteen quarters appears to be the modal one as the unconditional probability reaches 69% (from 47% in the previous interval) and the conditional probability shows one of its highest values at 41.7%.

In order to employ this tool for assessing the probability of a future turning-point in the *classical* cycle of the individual variables, a previously observed peak in the *growth* cycle is needed. Therefore, given the current state of *growth* cycles of the credit variables analyzed in this study, it is not possible to implement this analysis on those indicators. However, as it can be observed from the first chart of Figure 1 (page 15), the *growth* cycle of house prices has just reached a peak. Therefore, the survival model estimated on the four credit variables and the two asset prices suggests that the probability of a turning point in house prices could be 41.7% in 2017q2 and 66.7% in 2018q2. These estimates are subject to significant uncertainty linked to the estimation of both growth and classical cycles in each of the individual variables.

Table 8: Conditional and unconditional probability of a turning-point given a peak in the growth cycle

Interval (quarter)		Peaks Growth	Classical Yes	Classical No	Probability of peak in classical cycle: Unconditional Prob.	S.Error	[95% Conf. Interval]		Conditional on survival (Hazard) Prob.	S.Error	[95% Conf. Interval]	
		(1)	(2)	(3)	(4)	(5)	(6)		(7)	(8)	(9)	
5	6	23	6	0	0.2609	0.0916	0.1266	0.4908	0.2609	0.1065	0.0957	0.5073
6	7	17	1	0	0.3043	0.0959	0.1583	0.5343	0.0588	0.0588	0.0015	0.2167
7	8	16	2	0	0.3913	0.1018	0.2263	0.6173	0.125	0.0884	0.0151	0.3482
11	12	14	1	0	0.4348	0.1034	0.2624	0.6568	0.0714	0.0714	0.0018	0.2635
12	13	13	1	0	0.4783	0.1042	0.2999	0.6949	0.0769	0.0769	0.0019	0.2838
13	14	12	5	0	0.6957	0.0959	0.5072	0.8646	0.4167	0.1863	0.1353	0.8535
14	15	7	1	0	0.7391	0.0916	0.5531	0.8938	0.1429	0.1429	0.0036	0.527
16	17	6	2	1	0.8261	0.0790	0.6505	0.9456	0.3333	0.2357	0.0404	0.9286
17	18	3	2	0	0.9420	0.0542	0.7762	0.9956	0.6667	0.4714	0.0807	1.8572
18	19	1	0	1	0.9420	0.0542	0.7762	0.9956	0.0000	-	-	-

Note: These statistics have been calculated by pooling together all analysed variables: house price index, equity price index, bank loans to domestic households, bank loans to domestic NFCs, bank loans to private non-financial domestic sector and aggregated credit to the private non-financial domestic sector.

6 PROPOSAL OF A COMPOSITE MEASURE OF THE FINANCIAL CYCLE IN LUXEMBOURG

The composite financial index is the key element within the analytic system designed to signal peaks and troughs in the financial cycle. The leading, coincident, and lagging financial indexes are essentially composite averages of several individual leading, coincident, or lagging indicators. They are constructed to summarize and reveal common turning-point patterns in financial data in a clearer and more convincing manner than any individual component primarily because they smooth out some of the volatility of individual components.

The aim of this section is to present the results of a simple aggregation approach, in order to calculate a composite index for Luxembourg's financial cycle. The estimation of the financial cycle, which is based on a Chritiano-Fitzgerald filter, is then compared to the business cycle. Regarding the choice of the varable used to proxy the business cycle, we rely on GDP since this variable offers a satisfactory track record of economic activity. In addition, the link between the financial and real spheres seems to be essential to capture the systemic risk occurence.

For the financial cycle, three distinct but independent market segments are selected: (i) banking credit for households, (ii) banking credit for non-financial corporations, (iii) housing and equity markets. It is natural to take into consideration also banking credits since they constitute the best link between savings and investments. This measure is often used in earlier studies related to both national and cross section analysis on credit dynamics. The two other variables are financial assets such as house prices and equity prices. Indeed, housing is an essential sector of the economy but also one that has been the source of vulnerabilities and crises in many countries. Despite its importance in financial imbalances, the housing sector has not received adequate attention from macroeconomists. According to IMF research, more than two thirds of systemic banking crises were preceded by boom-bust patterns in house prices[20]. The real estate bubbles are seen as a key trigger of the recent crisis in the US and in some European countries, such as Spain or Ireland, which have also spread to other countries. It is clear that house prices have to be a component of the financial cycle for Luxembourg, where a large share of mortgage loans is concentrated within a few systemic banks. Even if some studies argue against the inclusion of equity prices in a composite index of the financial cycle[21], this variable may be informative for the case of Luxembourg. The concordance indices of equities for Luxembourg is sligthly above 0.5, which may indicate the cycle synchonisation with other cycles (i.e. credits cycles and house prices cycles)[22]. Additionally, most of the studies on the financial cycle incorporate this asset, which frequently is at the origin of financial crises.

[20] For more details, see http://www.imf.org/external/Pubs/FT/irb/2014/03/index.pdf

[21] See Borio and al. (2012)

[22] The results are extracted from a preliminary approach where all the first points estimated by Chirstiano-Fitzgerald filters have been removed for precautionnary reasons. Indeed, Christiano and Fitzgerald (1999) precise that apart from data at the beginning and end of the data set, there is little gain from using the true time series. From this recommendation, concordance indexes have been calculated then estimated. They are all significant and high except for the equities index

A number of methodologies have been developed over the years to characterize cycles (business or financial cycle). This study is based on the "growth cycle approach". It first characterises how economic activity fluctuates around a trend, and then identifies a "growth cycle" as a deviation from this trend (Backus and Kehoe (1992); Stock and Watson (1998)). To detrend variables, a Christiano-Fitzgerald filter is used for the variables composing the financial index. For the financial cycle, the length is between 32 to 60 quarters, whereas the business cycle length is shorter : between 6 to 32 quarters. These cycle lengths are in accordance with the theoretical framework (Drehmann et al.(2012)).

The choice of how to combine the variables (the weighting method) is perhaps the most difficult aspect of constructing a financial composite index. "The difficulty in choosing weights lies in the lack of a reference series upon which different, meaningful weights can be derived and tested" (Illing and Liu (2003)). Various weighting technical methods are considered, including: variance equal weights (also called standard index), transformations of the variables using their sample Cumulative Distribution Functions and factor analysis[23]. In this section, only the variance equal weights results are discussed and compared to the real cycle, due to the fact that other approaches provide similar conclusions. Furthermore, the correlation analysis among cycles of various macro-financial variables reveals a high correlation between the cycle based on a standard approach and the cycles based on the Cumulative Distribution Functions method (see figure F.1, Annex F; see also table F.1).

For this analysis, the study period spans from 1986q4 to 2014q3. From the composite index, we calculate a Christiano-Fitzgerald filter to approximate the financial cycle.

As expected, the financial cycle has a longer duration than the business cycle. The standard business cycle duration lasts approximately two years whereas the financial cycle lasts about 10 years.

The financial cycle swings are also sharper than those of the business cycle. On average, the standard deviation of the frequency-based financial cycle is more than 12.6 times larger than the standard deviation of the business cycle.

Finally, the contraction phases of the financial cycle are much more pronounced than those of the business cycle except for the period 2008q4, which coincides with the recession caused by the subprime financial crisis.

We note that the weighting approaches mentioned above are too general to capture the specificity of Luxembourg. Nevertheless, we also do recognize the usefulness of the approaches in this first attempt to define the financial cycle. The next step in this area is to suggest a new national weighting procedure.

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cycles. For the equities binary upturn phases, the concordance index is on average about 0.55, which may be inconclusive to reject or accept the introduction of equities in the financial composite index. The preliminary studies on concordance index approach for the selection of the data to include in the financial index are available upon request.

[23] See Annex F for a detailled presentation of the methodology and the main results. Only the standard approach results are reported.

7 CONCLUSION

The characterisation of the financial cycle is an essential input for designing macro-prudential policy instruments, which target pro-cyclical developments in the financial sector. Our study contributes to the macro-prudential policy design by proposing a characterisation of the financial cycle in Luxembourg and novel tools for monitoring their developments. In particular, this work represents an important input for the analyses underlying the calibration of a Countercyclical Capital Buffer adapted to the Luxembourg case. Nevertheless, we recall that our results do not allow to determine any causal relationship between the analyzed variables. Statistical analyses identify links between the variables which could be related to various direct and/or indirect channels. However, these analyses do not identify these channels individually. Moreover, one cannot exclude that the established statistical relationships might be pinpointing some uncontrolled construction bias. Our results should be interpreted with this caveat in mind.

We implement both, a frequency-based approach –which make use of band-pass filters– and a fully non-parametric turning-points approach –using Harding and Pagan's (2002) algorithm– for measuring, respectively, the *growth* and *classical* cycles. While conceptually different, the *growth* and *classical* approaches to measure cycles can be complementary. This speaks in favor of studying both types of cycles for policy-oriented analyses.

Using a dataset that spans from 1980q1 to 2015q3, we identified the dates of peaks/troughs for both types of cycles and studied the amplitude and duration of their phases. In addition, we analyzed the synchronisation between cycles of macro-financial variables and the real activity. In addition, we evaluated the synchronisation of the credit and house prices medium-term *classical* cycles across the neighbouring countries: Luxembourg, Belgium and France. We deliberately take Germany out of the analysis because of the acyclical evolution of German credit and house price variables. Finally, we proposed two novel tools to monitor the evolution of the financial cycle. The first tool consists in an optimal decision rule in the form of warning thresholds signalling the *growth* cycle phases presumably related with a *classical* turning-point. The second tool is the measure of the probability of a turning-point in the *classical* cycle in each quarter that follows a peak in the *growth* cycle. A composite index of the *growth* cycle is proposed as well.

The results of the study of cycles synchronisation obtained for the case of Luxembourg are the following: (i) absence of synchronisation between the *classical* cycles of asset prices, namely house prices, and bank credit variables; (ii) weak synchronisation between the *classical* cycles of house prices, aggregate domestic credit and GDP (this result also holds for *growth* cycles); (iii) some degree of synchronisation measured across *growth* cycles of equity prices and credit variables.

When analysing the synchronisation across neighbouring countries we found that: (i) *classical* cycles of Luxembourg's house prices and Belgian bank credit to the domestic non-financial private sector tend to be synchronised. Conversely, (ii) French *classical* cycles are not synchronized with those of Luxembourg.

Finally, we perform an statistical analysis of the credit and asset prices variables and find evidence suggesting that residential property prices may be approaching a peak. According to the survival model, the estimated probability of a *classical* turning point is the highest in 2018q2 (conditional on no turning-point observed before that date). However, as the *growth* cycle of all credit variables are still in expansion, no signals have been issued in 2015q3 (our last observation) about a potential turning-point in the *classical* cycle of these variables. These results are consistent with the evolution of the composite index of the financial cycle which shows that the cycle is close to a peak.

To conclude, three limitations of the early detection exercise must be noted. First, to obtain a sufficiently large number of observations to estimate warning thresholds and probabilities of turning-points, all the macro-financial variables considered were pooled together. Therefore, the thresholds and probabilities are common to all variables. While the theoretical linkages between variables may support this procedure, the commonality of the outcomes might limit the confidence attached to the conclusions regarding individual variables. Second, conclusions are likely to be sensitive to data revisions and release of additional observations, and therefore require regular updates. Finally, the out-of-sample robusteness of the proposed tools was not evaluated because time series are not sufficiently long. As regards the last two limitations, the extension of the time series with forecasted observations could enhance the robustness of the exercise. This is left for future research. Our results should be read with these caveats in mind.

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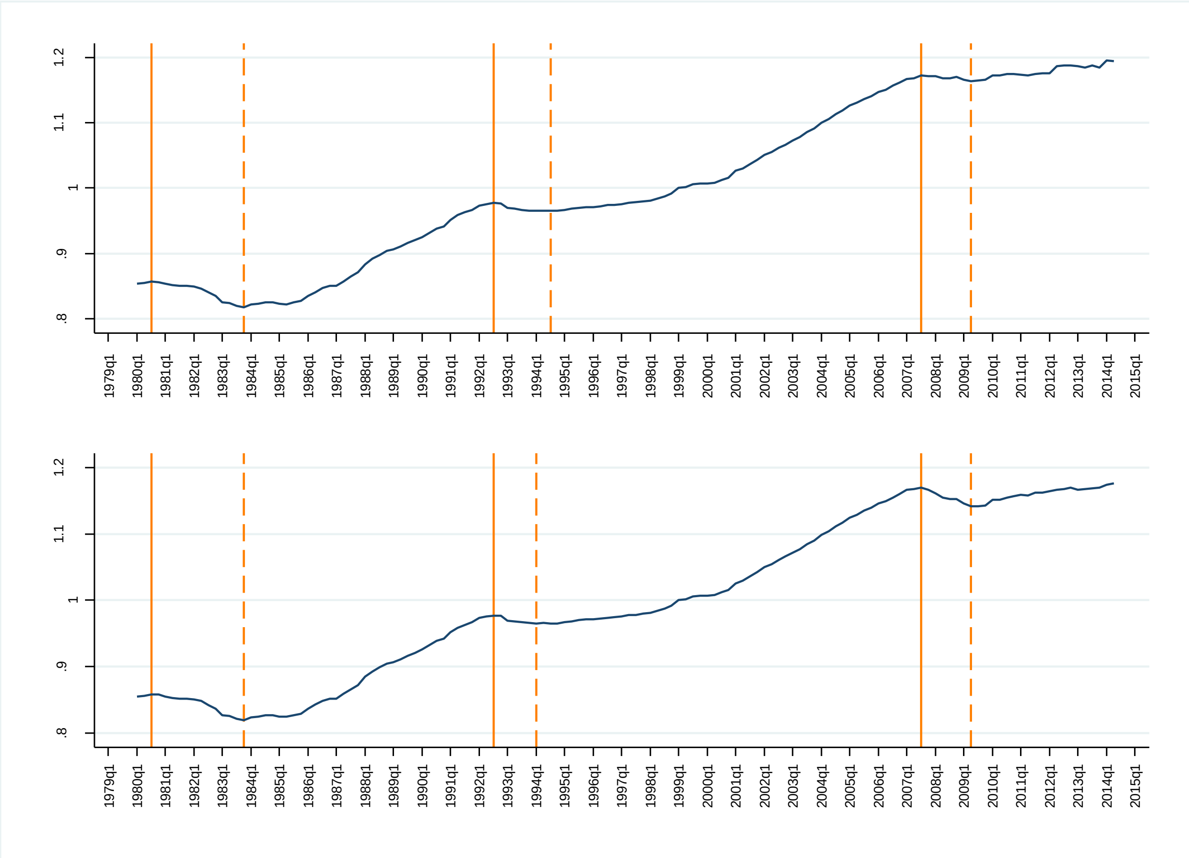
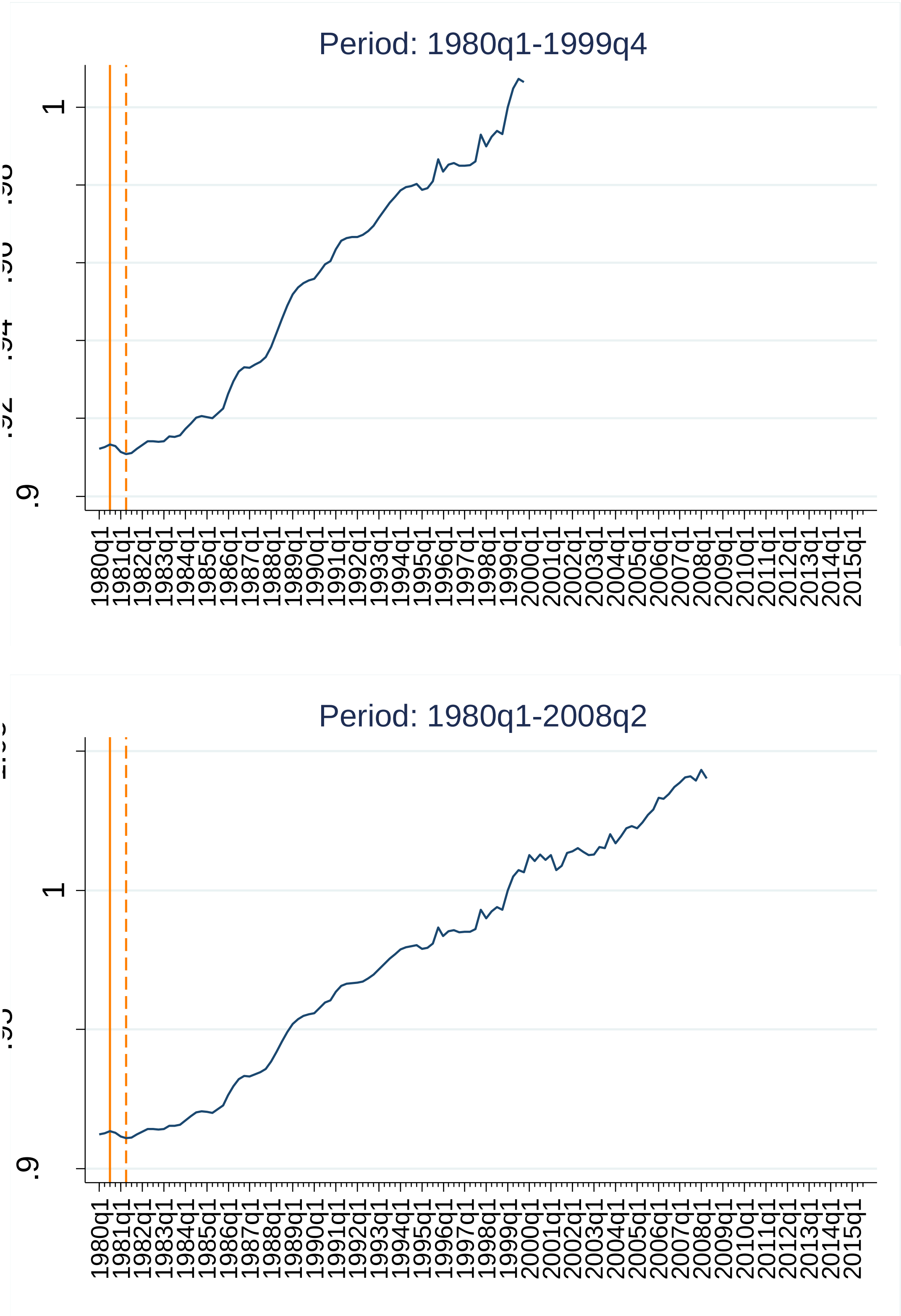
A APPENDIX OF FIGURES

Figure 2: Peaks and troughs of house price indexes: outliers-free index versus seasonally adjusted index



Source: BCL, Statec; BCL calculations

Figure 3: Peaks and troughs of Gross Domestic Product (seasonally adjusted) medium-term cycles: pseudo real time analysis



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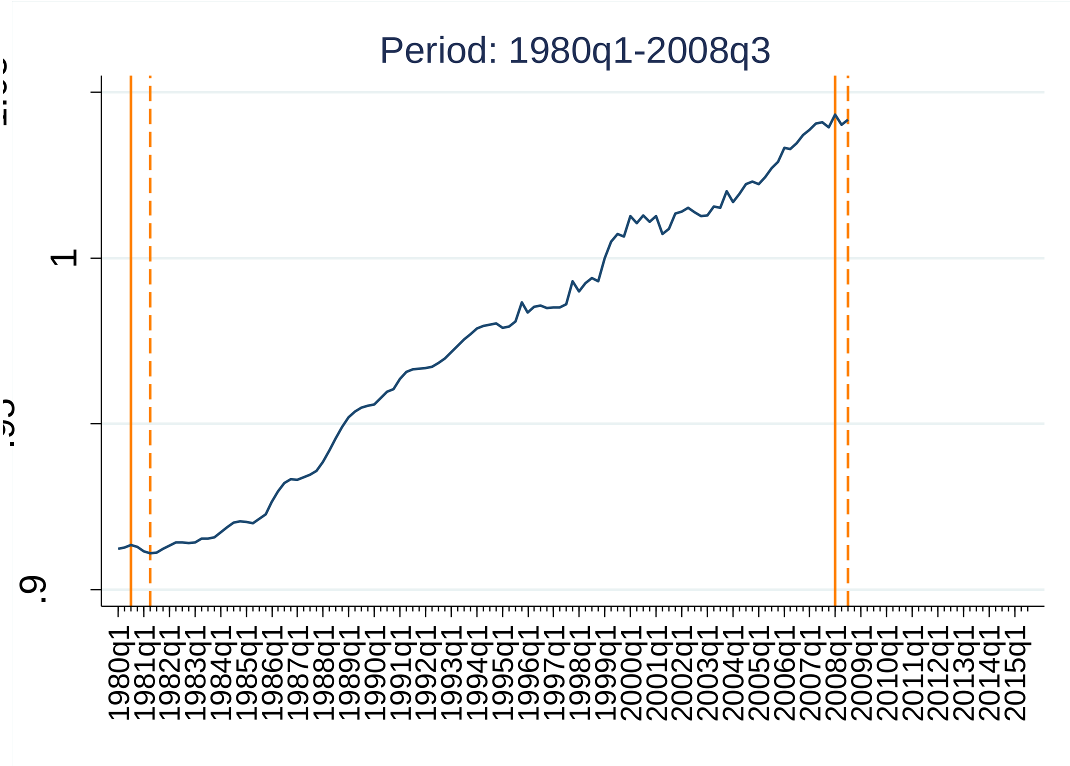

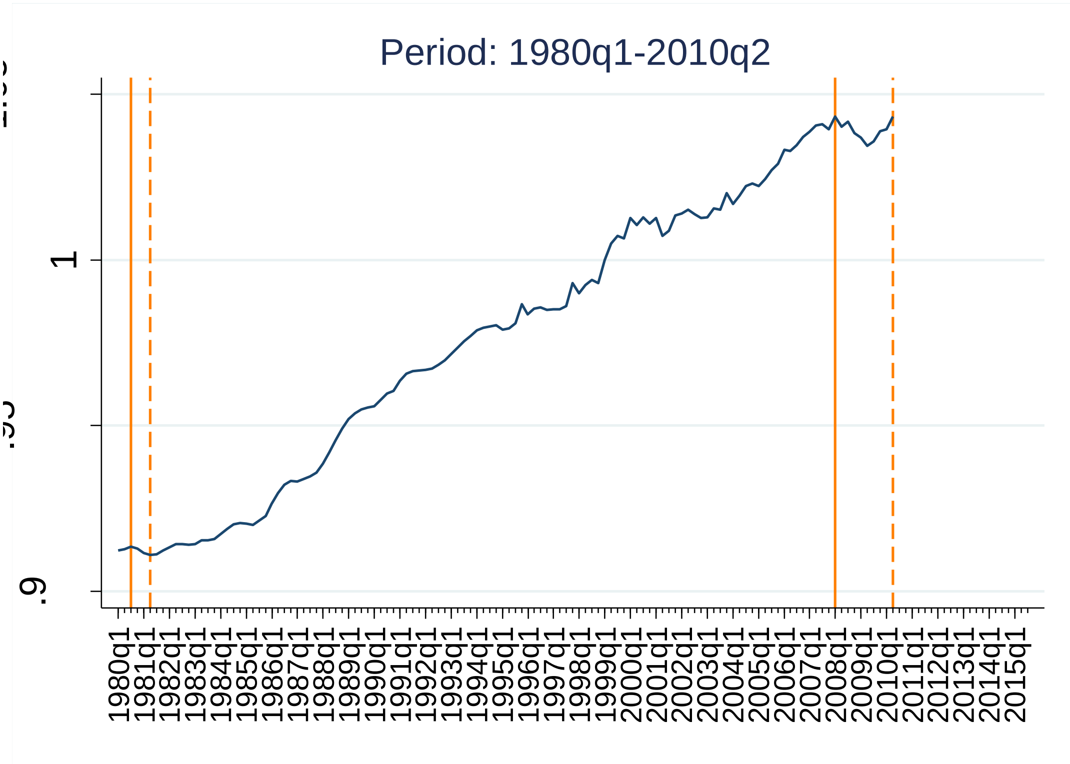

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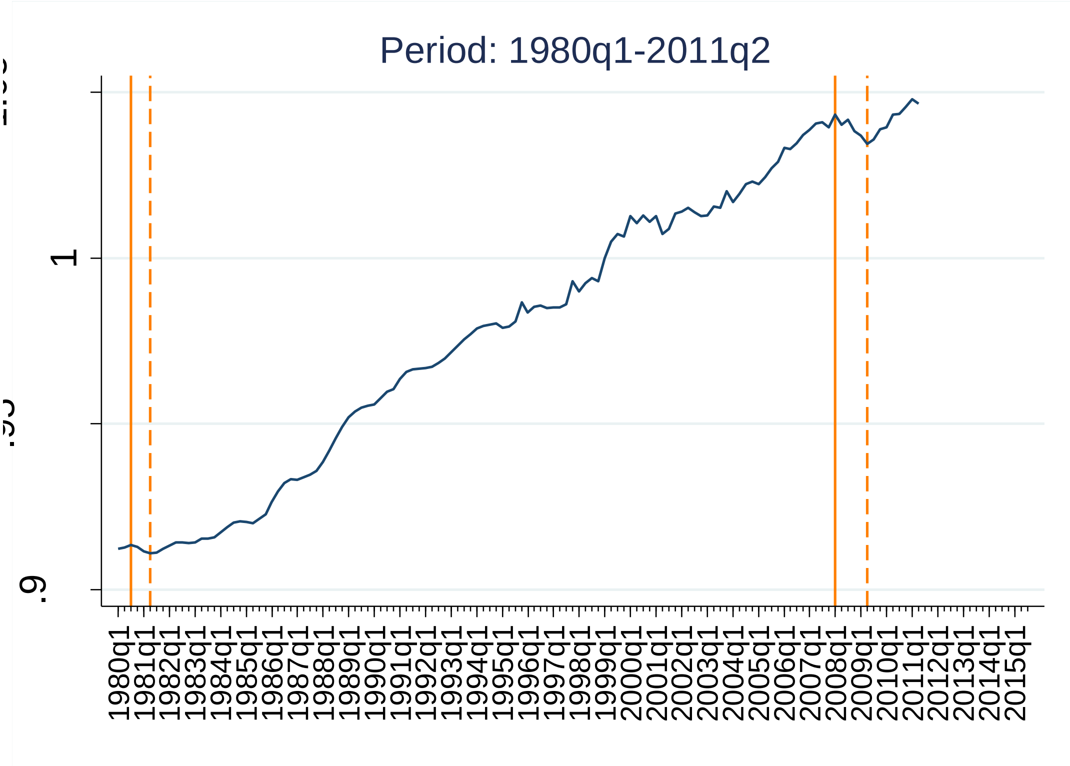
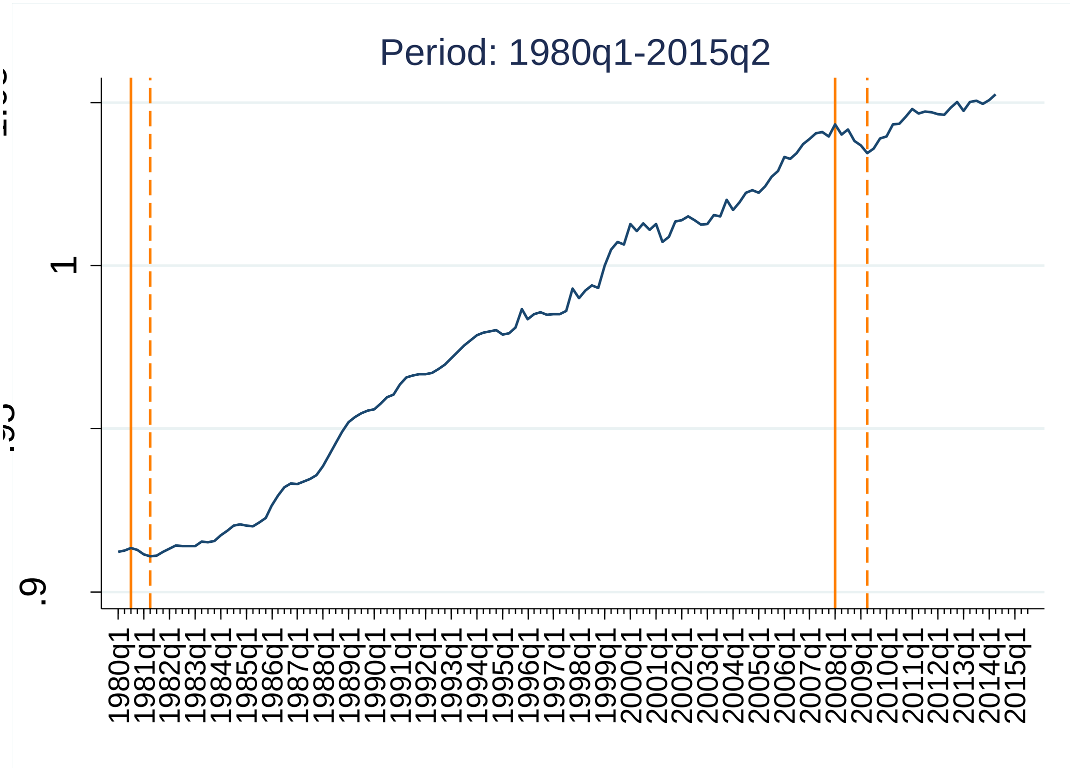
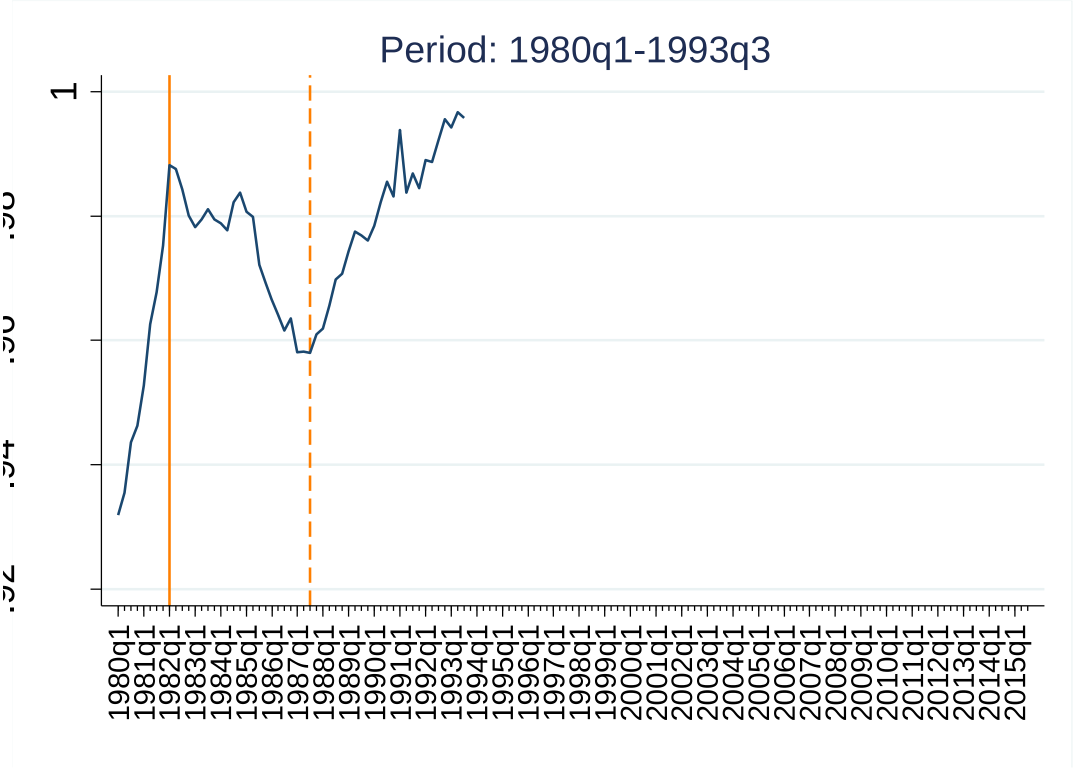
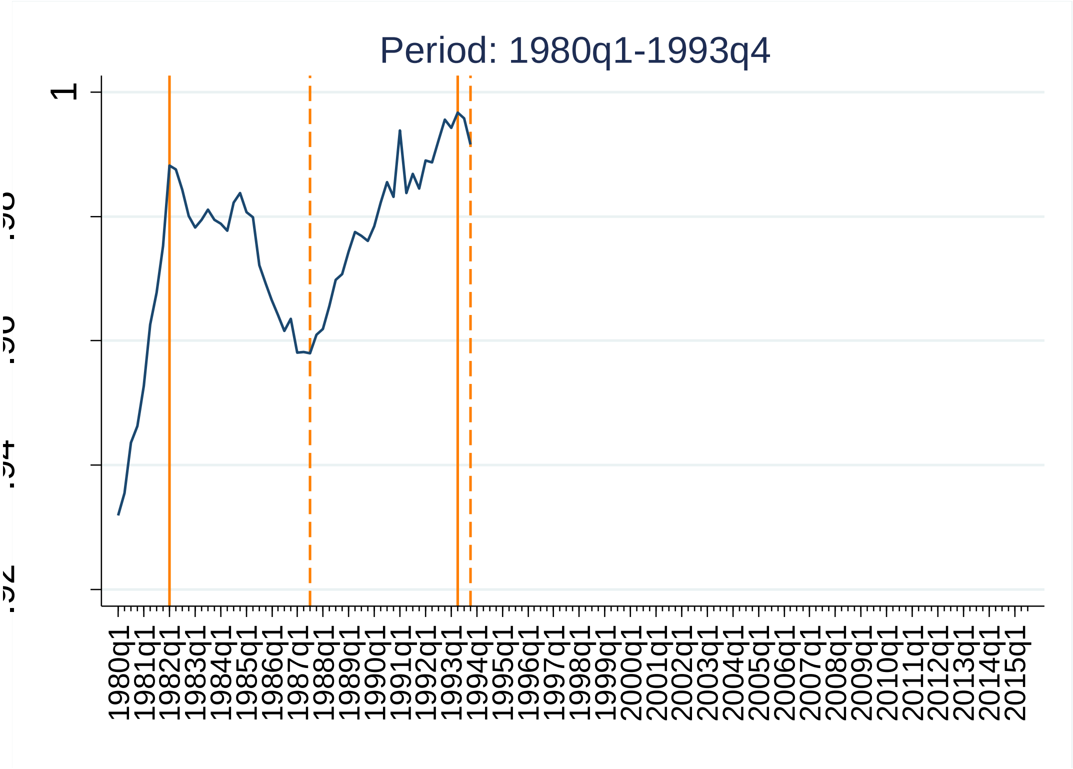




Source: Statec; BCL calculations

Figure 4: Peaks and troughs of Bank loans to domestic non-financial private sector (seasonally adjusted): pseudo real time analysis





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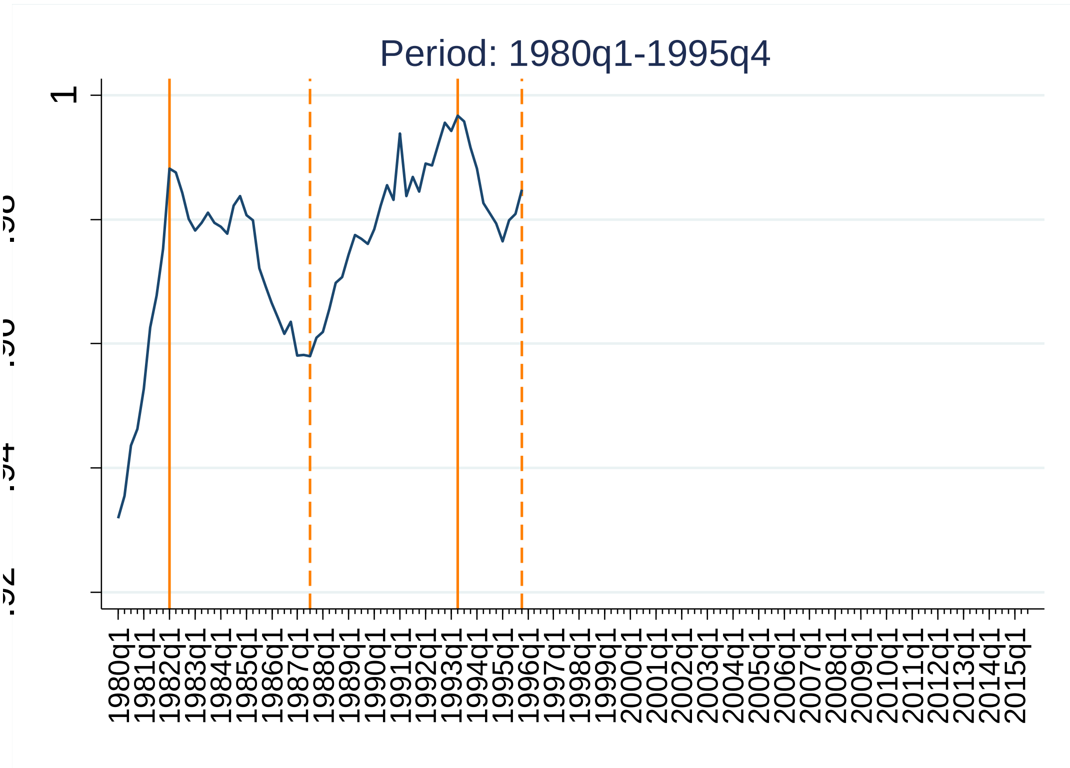

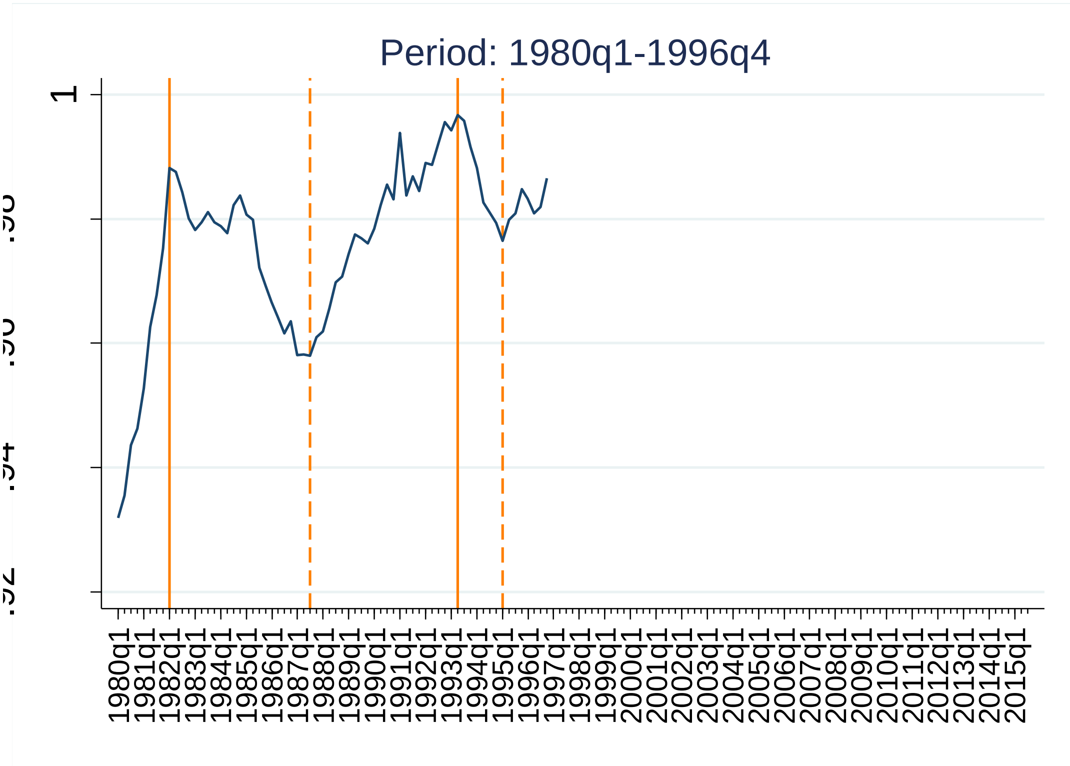

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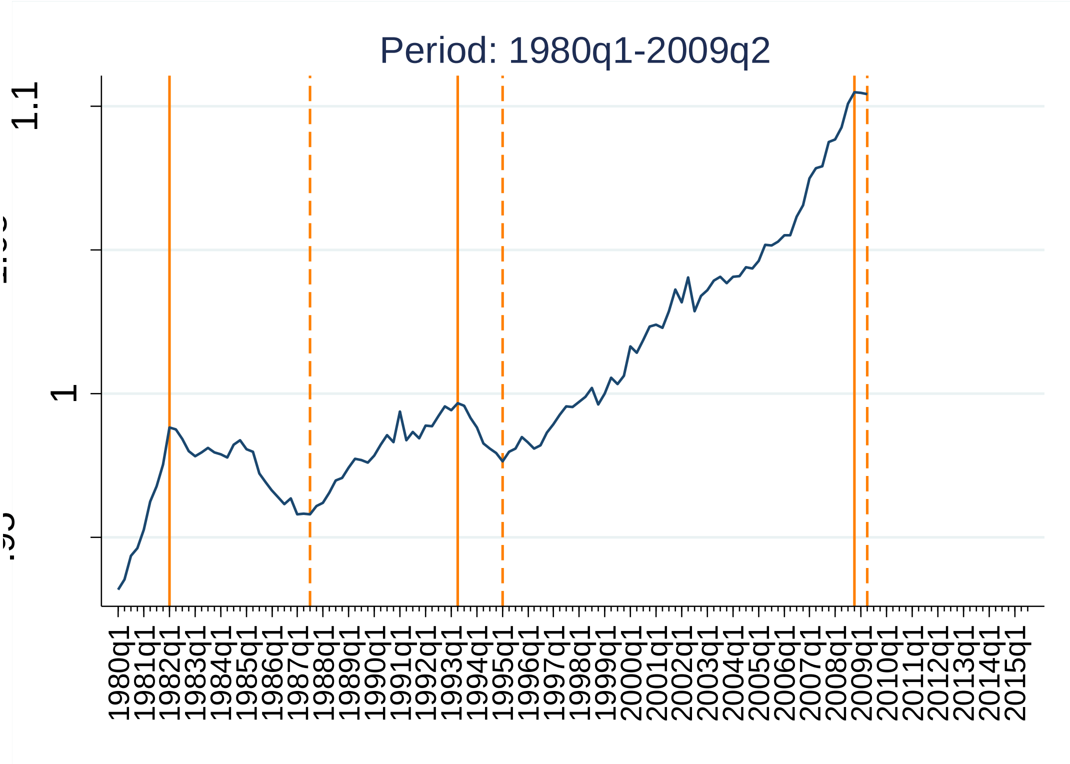
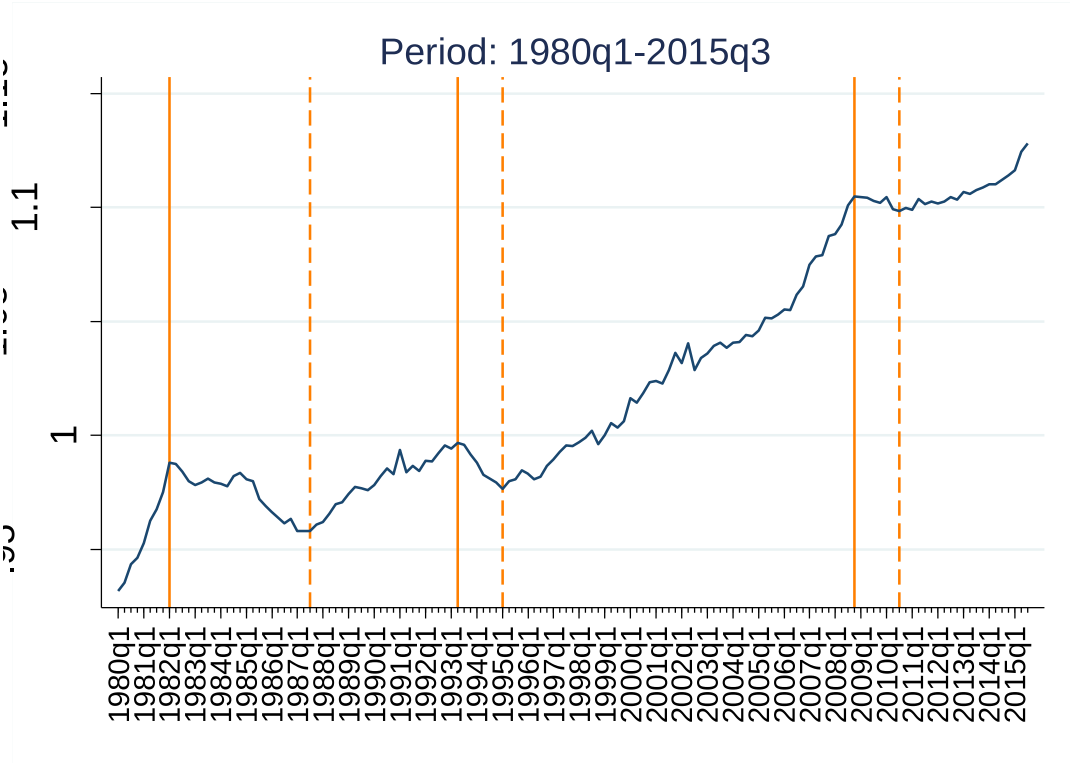




Source: BCL.

B Data sources and definitions

The following table describes how each variable is constructed. Most of the series have been obtained from the ECB Statistical Data Warehouse and then transformed in order to obtain the variables used in the study. All variables are set into real terms using a common deflator calculated on the basis of the Consumer Price Index. The seasonal adjustment is performed using Census X12 procedure.

Table 9: Individual series: definition and data sources

Variable	Definition
CPI	Consumer Price Index. Long series going back to 1980 on quarterly frequency series are obtained from the OECD MEI dataset (ECB Statistical Data Warehouse reference : MEI.Q.LUX.CPALTT01.IXOB).
GDP	Quarterly series of real Gross Domestic Product. Nominal quarterly series using ESA95 nomenclature were provided by Statec (available from 1995 onwards)*. Annual series going back to 1980 are obtained from the OECD MEI dataset and then interpolated (quadratic).
	Credit variables
CRNFS	Bank loans to private non-financial sector. The variable is available from BCL's official statistics since 1980q1 in local currency (Table 11.05). A fixed exchange rate has been used to convert it to euro (EUR=40.3399 LUF).
CRHH	Bank loans to households. The variable is available from BCL since 1999q1. On the basis of a fixed factor and an aggregate quarterly series CRNFS (Table 11.05), the bank credit to households has been extended back to 1980q1. The fixed factor is calculated as the average of the ratio of bank credit to households over CRNFS between 1999q1 and 2001q1.
CRNFC	Bank loans to non-financial corporations (NFCs). The variable is available from BCL since 1999q1. On the basis of a fixed factor and an aggregate quarterly series CRNFS (Table 11.05), the bank credit to NFCs has been extended back to 1980q1. The fixed factor is calculated as the average of the ratio of bank credit to households over CRNFS between 1999q1 and 2001q1.
DOMCRED	Credit to domestic non-financial private sector. The variable is available from IMF IFS (IFS.Q.137.3.12.$$$.Z.F.$$$ and IFS.Q.137.3.12.$$$.Z.W.$$$) and is intended to measure credit available from all possible sources to the non-financial sector. However, the suspicion remains that some residual intra-financial credit is included by construction. Last available period is 2013q4.
	Asset prices
HP	House prices. The variable is constructed by the BCL. Details on its construction are available in Di Filippo and Kaempff (2014).
EQ	Equity prices index (EuroStoxx 50). A series ranging from 1986q4 to 2014q2 was obtained from the ECB Statistical Data Warehouse.

* ESA95 series are no longer available as Statec has switched to the recently developed ESA2010 nomenclature for national accounts. However, ESA2010 data is only available up to 2000 impeding our analysis of medium-term cycles.

C CHRISTIANO AND FITZGERALD BAND-PASS FILTER

The CF filter has a steep frequency response function at the boundaries of the filter band (i.e. low leakage). It is an asymmetric filter that converges in the long run to an optimal filter. It is usually calculated in the following way:

Suppose one wishes to isolate the component of y_t with period of oscillation between p_u and p_l. where $2 \le p_l \le p_u < \infty$.

$$c_t = B_0 y_t + ... + B_{T-1} y_{T-1} + \tilde{B}_{T-1} y_T + ... + \tilde{B}_{t-1} y_1$$
$$B_j = \frac{\sin(jb) - \sin(ja)}{\phi j}, j \ge 1$$
$$B_0 = \frac{b-a}{\pi}$$
$$a = \frac{2\pi}{p_u}, b = \frac{2\pi}{p_l}$$
$$\tilde{B}_k = -0.5B_0 - \sum_{J=1}^{k-1} B_j$$

$\tilde{B}_{T-1},...,\tilde{B}_{t-1}$ are simple linear functions of the B_j's.

The parameters p_u and p_l are the cut-off cycle length in month. Cycles longer than p_l and shorter than p_u are preserved in the cyclical term c_t. Two types of cycle lengths are traditionally used for the short term (5,32) and for the long term (32,120) determination.

D THE TURNING-POINT ALGORITHM

In the following appendix we describe our implementation and calibration of Harding and Pagan (2002) algorithm and the one of Harding and Pagan (2006). First, the width of the search window to identify local extremes should be set. Second, in order to select peaks/troughs from the set of local extremes, censoring rules should be determined on the length of the cycle and its' phases. The censoring rules are applied iteratively in a specific order.

Our implementation of the algorithm is fully automatised, avoiding any *ad hoc* adjustment of the final output and maximising the reproduction of the results. In the first step, the censoring rules require that a trough immediately follows the peak; the peak (trough) with the higher (lower) level of the series is then chosen. In the second step, irregular cycles are combined in order to comply with censoring rules. These cycles are either too short or one of their phases does not take into account the minimum length. Our implementation of the algorithm automatically combines cycles not complying with censoring rules. This eliminates the necessity of any kind of ex-post manipulation of the outcome.

As regards the identification of the medium-term cycles we consider the proposal of Drehmann et al. (2012). The local extremes search window is set to nine quarters. Finally, we require that the minimum length of cycles and phases equals five years and two quarters, respectively.

In order to identify common peaks/troughs within the set of financial series, we consider the refinements introduced by Drehmann et al. (2012) to the calibration of Harding and Pagan's (2006) algorithm. More precisely, we consider the length of a cycle equal to five years and we require that all individual series have a turning-point as a necessary identification condition.

We follow Claessens et al. (2011) (page 9) for defining the features of financial cycles: "*The main characteristics of cyclical phases are their duration, amplitude, and slope. The duration of a downturn is the number of quarters, k, between a peak and the next trough. Likewise, the duration of an upturn is the number of quarters it takes for a variable* f_t *to reach its previous peak after the trough. The amplitude of a downturn,* A_c*, measures the change in* f_t *from a peak (*f_0*) to the next trough (*f_k*), i.e.,* $Ac=f_k-f_0$*. The amplitude of an upturn,* A_u*, measures the change in* f_t *from a trough (*f_k*) to the level reached in the first four quarters of an expansion (*f_{k+4}*), i.e.,* $Au=f_{k+4}-f_k$*. Lastly, the slope of a financial downturn is the ratio of the amplitude to the duration of the downturn. The slope of an upturn is the ratio of the change of a variable from the trough to the quarter at which it attains its last peak divided by the duration. Thus, the slope measures the violence of a given cyclical phase.*"

E. Bootstrap

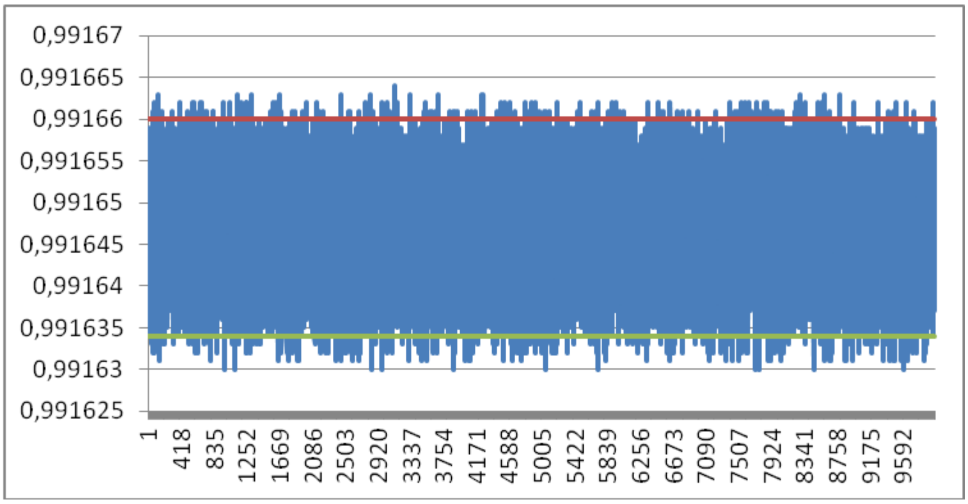
Change frequency robustness: The use of a parametric bootstrap

To precise the robustness of our frequency changes for the GDP variable, a bootstrapping sample is run from the statistical features of GDP. Then, a confidence interval for the value of the variance based on bootstrap estimates is built. While following this procedure, we expect that if we order the observations from the smallest to the largest, the interval containing 95% of the estimated variance (*EV*) values is a 95% confidence for the estimated variance. A bootstrap confidence interval generated as described below is called a percentile method confidence interval.

We used annual GDP data (provided by the STATEC) from 1995 to 2014 and increase the frequency by applying the quadratic algorithm (named GDP_BCL). Furthermore, we used quarterly GDP provided by the STATEC (named GDP_STATEC) for the same period (i.e. from 1995Q1 to 2014Q4) and ran a bootstrapping sample for each variable (GDP_BCL and GDP_STATEC). Lastly, we compared the estimated volatility of the two bootstrapping samples. While following this procedure, we computed the ratio of standard deviations for each bootstrapping sample (R=top/bottom, top= *the standard deviation of the bootstrapped GDP_BCL variable* and bottom= *the standard deviation of the bootstrapped GDP_STATEC variable*) and verify that Percentile (R(0.5))<R<Percentile(R(0.95))

The results are given by the following graph.

Figure E.1 Boostrap approach to validate the GDP frequency change



Within Figure E.1, the RATIO (blue line) represents the ratio of standard deviations for each bootstrapping sample as specified above. B1 (red line) stands for the superior percentile of the variance distribution (ratio). B2 (green line) is the inferior percentile of the variance distribution (ratio).

F. Aggregate index method

We use the equally weighted variance approach to calculate the financial index, which is considered to be the standard approach. The index is calculated based on the following equation:

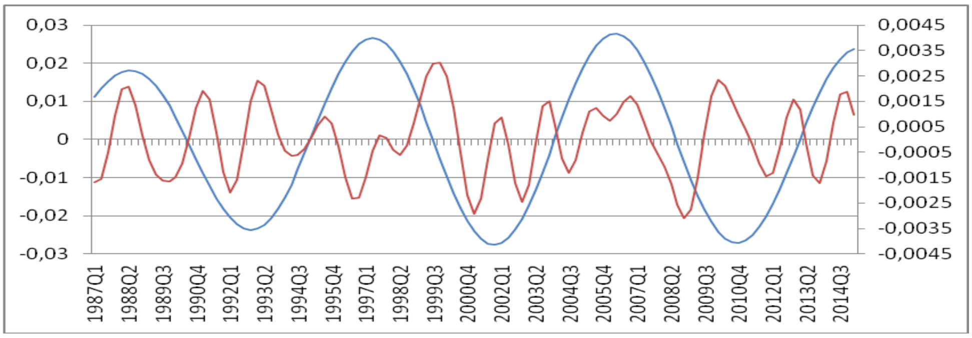
$$CI_t = \sum_{i=1}^{n} \frac{X_{it} - E(X_i)}{\sigma(X_i)} \qquad (1)$$
$$i = 1,\ldots 4$$

Where X_{it} are the i time series components, E is the mathematical expectations operator and σ is the standard deviation.

It should be noted that all variables are standardized.

The aggregated index decribed above is used to construct a composite financial index. Four variables (bank credit to household, bank credit to non-financial corporations, stock price index (*Euro Stoxx*) and house prices) have been used to measure the financial index.The financial index is used to deduct the cycle.

Figure F.1. Financial composite cycle component (*blue line, LHS*) and real cycle component (*red line, RHS*)



Source: Authors' calculations

Table F.1. Correlation coeficient matrix of the financial cycles according different methods

Correlation/Probability	CY_CDFs' ARITH	CY_ CDFs GOEM	CY_Standard Approach	CY_ Factor Analysis
CY_ CDFs ARITH	1.000000 -----			
CY_ CDFs GOEM	0.999452 0.0000	1.000000 -----		
CY_Standard Approach	0.965298 0.0000	0.964759 0.0000	1.000000 -----	
CY_Factor Analysis	0.523350 0.0000	0.528719 0.0000	0.325812 0.0000	1.000000 -----

G Methods for early detection of turning-points in the classical cycle

The appendix discusses the following methodologies implemented in Section 5: (i) *signals extraction approach* and (ii) *relevant models for the analysis of survival data*. These methodologies have been applied in various fields of research within different scientific disciplines (e.g. medicine, biology, engineering, sociology, economics).

For the purpose of the two methodologies mentioned above and given the fact that the financial indicators considered in this study have been set to a comparable scale and normalised, we build the dataset by pooling all the variables with the exception of the GDP (see Appendix B).

G.1 SIGNALS EXTRACTION APPROACH

The *signals extraction approach* is used to identify optimal thresholds which enable attaching a probability to an event given the observed value of the indicator. The criteria are obtained from the confusion matrix which is calculated at several cut-off values of the indicator distribution; there is one confusion matrix per cut-off value (see Table G.1). An important criterion to consider is the Area Under the Receiver Operating Characteristic Curve (AUROC). The AUROC provides the probability that the indicator's distribution conditional on the event under study stochastically dominates at the first order, the distribution conditional on the fact that the event did not occur (Hsieh and Turnbull, 1996).

Table G.1: Confusion matrix and definitions

	Condition		
Total population	pre-crisis	normal	
signal	True positive (TP)	False positive (FP)	PPV$^a = \frac{\sum \text{TP}}{\sum \text{signal}}$
no signal	False negative (FN)	True negative (TN)	NPV$^b = \frac{\sum \text{TN}}{\sum \text{no signal}}$
	True positive rate (TPR) $=$ 1 - Error of type I $= \frac{\sum \text{TP}}{\sum \text{Condition pre-crisis}}$	False positive rate (FPR) $=$ Error of type II $= \frac{\sum \text{FP}}{\sum \text{Condition normal}}$	

^{a} Positive Predictive Value

^{b} Negative Predictive Value

Noise-to-signal ratio: $\frac{\text{FP}}{\text{FP+TN}} / \frac{\text{TP}}{\text{TP+FN}}$

Loss function: L$= \theta$ (1-TPR) $+ (1-\theta)$ FPR, where the preference paramters θ represents the relative weight of errors of type 1.

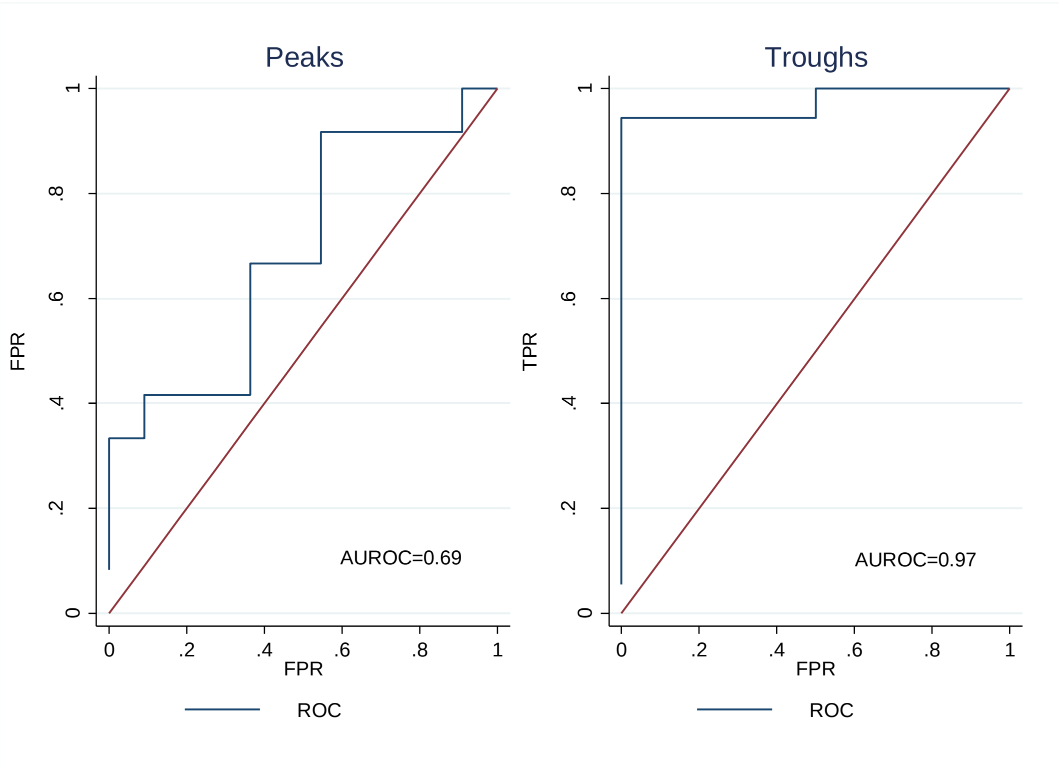
Usefulness $= min\,[\theta; 1-\theta] -$ L

We implement this approach to identify warning thresholds that would indicate the peaks/troughs in the *growth* cycle which are consistent with *classical* cycle turning-points in the quarters that follow. Accordingly, the left-hand-side variable (i.e. the event to be predicted) is defined on the basis of a 28-quarters window around the turning-point in the *classical* cycle. The width of the window affects the quality of the adjustment. In effect, if the width of the window is too short, excessive FPs would be accounted while, if it is too large too many FNs would be measured. Thus, we choose the width of the window in order to maximize the AUROC of early warning system to predict the peaks in the *classical* cycle (see Figure G.1).

We implement two alternative criteria for threshold selection: (i) the minimisation of the noise-to-signal ratio and, (ii) the minimisation of a loss function (see Table G.1 for definitions).

The basis of threshold selection is the maximisation of the number of predicted turning-points in the *classical* cycle. Therefore, we have selected the thresholds obtained by the minimisation of the regulators' loss function (with equal weighting of errors) which predicted 11 out of 18 peaks and 14 out of 18 troughs. The upper and bottom thresholds resulting from this criterion are equal to -0.001362 and 0.001186, respectively (these thresholds are drawn in Figure 1).

Figure G.1: Receiver Operating Characteristic Curve of the prediction of peaks in the classical cycle



G.2 SURVIVAL DATA ANALYSIS

The survival or duration analysis is based on statistical models aimed at dealing with the time duration until an event occurs. In our specific case, the occurrence of a turning-point in the *classical* cycle is the event of interest. Hence, given the lead/lag relationship between the peaks of *growth* and *classical* cycles, this kind of analysis allows us to determine the probability of classical turning-point in each quarter after a peak in the *growth* cycle.

The basic concepts for survival analysis are presented in what follows (Collet, 2003):

- **Survival function** represents the probability that the time of the event is later than some time *t,* i.e. $S(t) = \Pr(T > t) = \int_t^\infty f(u)du$ where *T* is a random variable denoting the time of the event.
- **Failure probability** is the complement of the survival function, i.e. $F(t) = \Pr(T \le t) = 1 - S(t)$.
- **Hazard function** or **hazard rate** is defined as the rate of the event in time *t* conditional on the fact the event has not been observed before *t*, i.e. $\lambda(t) = \frac{f(t)}{S(t)} = -\frac{S'(t)}{S(t)}$

The above functions can be either estimated non-parametrically or imposing a specific distributional assumption. The results presented in section 5 are based on a non-parametric estimation.

A dataset in a specific format has been built for performing the analysis in section 5. The dataset contains as many observations as the number of observed peaks in the *growth* cycle of the financial variables under study. The time variable is defined as the number of quarters after a peak in the *growth* cycle and until a *classical* peak takes place. If there is no *classical* peak after a *growth* cycle one, it is said that the observation is censured.

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