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CHARACTERIZING THE LUXEMBOURG FINANCIAL CYCLE: ALTERNATIVES TO STATISTICAL FILTERS

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Characterizing the Luxembourg financial cycle: alternatives to statistical filters

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Abstract

This paper studies the cyclical properties of bank loans to non-financial corporations, bank loans to households, bank loans to the non-financial private sector and house prices in Luxembourg, by applying two methodologies to decompose and characterize the cycles. First, we use an unobserved components model (UCM) to extract classical cycles. We find evidence of medium-term cycles in the loan series over the sample 1980 Q1 to 2019 Q1. The non-financial corporation credit cycle is the most volatile and of larger duration compared to the other credit cycles. The length of the house price cycle in Luxembourg is estimated at 13.8 years. A dynamic synchronicity measure between households' credit cycle and the house price cycle reveals that these cycles are sometimes synchronous. However, the early warning properties of the univariate unobserved components model are limited despite its good pseudo real-time estimates. A wavelet analysis complements the findings of the univariate UCM by providing growth cycles of financial variables. We show that these growth cycles could be useful as complementary information in financial cycle analysis. A coherence wavelet analysis is also conducted. The main findings show that the credit growth cycles of non-financial corporations and of the non-financial private sector are highly coherent with respect to households' credit growth cycle. The household credit cycle often precedes house price growth. From a macroprudential policy perspective, these results support the use of complementary methodologies for assessing the financial cycle and confirm earlier studies on the limited role of the household credit cycle in the evolution of the house price cycle.

Keywords: credit cycle, wavelet analysis, unobserved components model, house prices

JEL codes: C30, E32, E51

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Résumé non technique

L'analyse des causes sous-jacentes à la crise financière de 2007-2008 a corroboré les thèses qui attribuent aux variables financières, et notamment à l'évolution du crédit, un rôle important dans la matérialisation des crises financières. Le volume des crédits accordés aux ménages et aux sociétés non financières augmente en période de croissance économique et décroît en phase de repli économique. Cette procyclicité favorise l'augmentation des prix des actifs et entretient une croissance du volume des crédits jusqu'à un certain niveau. Au-delà de ce seuil, une phase de décroissance du volume de crédit s'ouvre moyennant une potentielle crise bancaire, ou pour le moins une période d'instabilité financière. Cette alternance entre les phases d'expansion excessive du crédit et les phases de ralentissement de la dynamique du crédit décrit le cycle de crédit. Les études empiriques sur l'analyse du cycle de crédit ont montré une coïncidence entre certaines crises financières et les pics du cycle de crédit, confirmant ainsi le rôle du cycle du crédit dans l'instabilité financière. Néanmoins, plusieurs études empiriques montrent que l'étude singulière du cycle de crédit demeure insuffisante pour identifier les périodes de vulnérabilités financières susceptibles de conduire à une crise financière. Une identification appropriée de ces moments critiques peut être fournie par l'analyse du cycle financier dont le cycle de crédit est une composante.

Diverses études s'accordent sur une description parcimonieuse du cycle financier par une double analyse des cycles de crédit et des prix immobiliers. Dans le cadre de la conduite de la politique macroprudentielle, l'estimation du cycle financier demeure un exercice nécessaire qui permet d'apporter des évidences empiriques à la constitution du jugement d'expert, facteur important dans la prise de décision des autorités macroprudentielles.

Au cours de la période récente, l'économie luxembourgeoise a été caractérisée par une croissance soutenue des crédits et des prix immobiliers qui ont conduit le Comité du Risque Systémique (CdRS) luxembourgeois à relever le taux de coussin de fonds propres contracycliques à un niveau de 0,25 % applicable dès le 1er janvier 2020. Cette décision fait écho à la persistance des développements enregistrés (i) du niveau du crédit bancaire accordé aux sociétés non financières (avec une croissance annuelle nominale de 8,1 % en 2018 T4), (ii) du niveau d'endettement des ménages (171,3 % du revenu disponible en 2018 T4) et de (iii) la croissance soutenue des prix immobiliers (avec une croissance annuelle nominale de 9,26 % en 2018 T4). Ces diverses évolutions sont susceptibles d'amplifier les vulnérabilités cycliques et par

conséquent, de conduire à des périodes d'instabilité financière.
Dans ce contexte, une évaluation appropriée des variables de crédits et des prix immobiliers par rapport à leur tendance de long terme permettrait d'identifier la position de ces variables dans leurs cycles respectifs et, partant, d'anticiper la matérialisation de vulnérabilités cycliques systémiques. Dans cet objectif, l'extraction des composantes cycliques est menée au moyen de deux méthodologies : les modèles à composantes inobservées permettent d'extraire un cycle en niveau, tandis que la décomposition en ondelettes fournit un cycle de croissance. Ces choix méthodologiques visent à pallier les insuffisances de certaines méthodes statistiques, notamment les filtres statistiques très usités dans l'extraction des cycles. Les modèles à composantes inobservées permettent une décomposition cycle-tendance à partir des données empiriques sans hypothèse préalable sur la durée des cycles. La décomposition par la méthode des ondelettes permet d'identifier les fréquences les plus significatives dans les fluctuations d'une série temporelle et offre, en outre, la possibilité d'analyser les co-mouvements entre deux séries temporelles dans un espace fréquentio-temporel.

Les résultats de cette étude, menée sur la période 1980 T1- 2019 T1, indiquent que les variables de crédits sont caractérisées par des cycles d'une durée moyenne de 8,91 ans pour le crédit bancaire au secteur privé non financier, 8,71 ans pour les crédits bancaires aux ménages et 9,03 ans pour les crédits bancaires aux sociétés non financières, selon le modèle à composantes inobservées. Les prix de l'immobilier résidentiel au Luxembourg se caractérisent par une composante cyclique d'une durée de 13,8 ans. Au premier trimestre 2019, le cycle du crédit au secteur privé non financier atteint 1,6 %, entretenu principalement par le cycle de crédit aux sociétés non financières qui atteint 5,5 %. Le niveau du crédit aux ménages est légèrement au-dessus de sa tendance de long terme (0,28 % en 2019 T1) tandis que le cycle des prix immobiliers atteignait 4,5 % en 2018 T4. Les mesures de corrélation et de synchronicité montrent que les composantes cycliques des crédits accordés aux ménages, aux sociétés non financières et au secteur privé non financier au Luxembourg sont fortement corrélées et synchrones. Le cycle de crédit des ménages est souvent synchrone avec le cycle des prix immobiliers. La décomposition par la méthode des ondelettes complète les résultats susmentionnés. À partir des mesures de cohérences, nous constatons une corrélation plus faible entre le cycle des prix de l'immobilier et l'ensemble des cycles de crédit, alors que ces derniers sont très corrélés entre eux sur la période considérée.

Au niveau de la politique macroprudentielle, ces résultats sont très utiles. Premièrement, ils permettent de quantifier la durée du cycle financier et fournissent ainsi des informations pertinentes sur la durée du cycle financier. Deuxièmement, la diversité des approches permet de réduire les erreurs d'appréciation fondées exclusivement sur les méthodes statistiques. Troisièmement, ces résultats corroborent des études antérieures sur le rôle limité du cycle du crédit aux ménages luxembourgeois sur le cycle des prix immobiliers.

"The financial cycle denotes self-reinforcing interactions between perceptions of value and risk, attitudes towards risk and financing constraints, which translate into booms followed by busts." Borio (2014)

1 Introduction

Financial cycle analysis has gained momentum since the Great Financial Crisis (GFC), and has lead to an intensive literature on the links between financial and business fluctuations (see for instance, Jordà *et al.*, 2011; Schularick and Taylor, 2012; Hubrich *et al.*, 2013), on stylized facts of the financial cycle (Borio, 2012; Drehmann *et al.*, 2012) and on the methodological aspects of the cycle extraction (ECB, 2018). These issues are relevant for financial stability as well as the macroprudential policy decision-making process. Indeed, estimates of cyclical components provide relevant inputs for macroprudential policy tools, especially the countercyclical capital buffer.

The idea that outsized financial booms could lead to future banking distress has been explored in a large strand of the literature, and Minsky (1977) and Kindleberger (1978) pioneered the study of the inherent procyclicality between credit cycle and business fluctuations. The underlying intuition is straightforward: in good times, risk appetite is high as investors' confidence is strong, thus leading to substantial increases in asset prices and credit growth. Empirically, several papers provide evidence that financial crises are often preceded by credit booms, in particular Reinhart and Rogoff (2009), Schularick and Taylor (2012), Aikman *et al.* (2015), among others. The increased severity of economic recessions during credit busts has been emphasized by Jordà *et al.* (2011) and Claessens *et al.* (2012).

A growing literature aiming at nuancing the negative role of credit booms in economic fluctuations shows that the build-up of vulnerabilities should not be assessed solely based on credit booms (as measured by the credit-to-GDP gap[1]) but also by the identification of house price bubbles. Thus, Barrell *et al.* (2017) argued for a clear distinction between credit booms associated with price bubbles and those which 'fund productive investment', as the latter do not generally pose a threat. The use of macroprudential tools to correct for a productive investment credit boom could be detrimental to economic activity while not contributing to financial stability. Against this background, Borio (2012) and Drehmann *et al.* (2012) argued that the financial cycle can be parsimoniously described by credit and property prices. In

[1]It should be recalled that the Hodrick-Prescott (HP) filter is the common methodology used for the measurement and calculation of the credit-to-GDP gap as in ESRB/2014/1 recommendation on guidance for setting countercyclical buffer rates.

fact, these variables co-vary closely at low frequencies. Thus, several studies showed that credit volumes and house prices in advanced economies can be characterized by medium-term cyclical components. The longer amplitude and duration of the financial cycle relative to the business cycle is commonly observed in the literature (e.g., Claessens *et al.*, 2011) and Drehmann *et al.* (2012) found the average length of financial cycles to be 16 years. The longer duration is explained by the build-up of financial imbalances that could culminate in financial crises (see for instance Claessens *et al.*, 2011; Drehmann *et al.*, 2012; Borio, 2012).

Concerning the methodological aspects of cycle extraction, Claessens *et al.* (2011, 2012) used a turning point analysis while Aikman *et al.* (2015) based their analysis on a band-pass filter, and Drehmann *et al.* (2012) and Schüler *et al.* (2015) opted for the two methodologies. Employing a band pass filter required the use of a frequency band. By pre-specifying frequency bands, non-parametric filters risk omitting relevant parts of the cyclical dynamics or, as stated by Murray (2003) and the ECB (2018), filtering spurious cycles. As detailed in Rünstler and Vlekke (2016), the main conclusion of Drehmann *et al.* (2012) on the intrinsic characteristics of financial and business cycles relies mainly on the choice of frequency bands, that do not overlap and, consequently, cycles extracted using this methodology are, by construction, uncorrelated. In Schüler *et al.* (2015), this inconsistency is addressed by using cross-spectral densities in order to obtain the relevant frequency bands but, according to Rünstler and Vlekke (2016), this ignores information in the auto spectrum. Regarding the shortcomings of the turning point analysis, *ad hoc* assumptions on cyclical properties negatively impact the quality of the analysis.

Another strand of the literature relies on univariate structural time-series models, as in De Bonis and Silvestrini (2014) or the multivariate approach of Chen *et al.* (2012). Unlike non-parametric filters, univariate structural models provide additional information regarding the dynamic properties of financial cycles. Wavelet analysis has been increasingly used in cyclical analysis since it provides estimations of the dominant frequency of fluctuations in specific time-series and could measure the strength of the co-movement among time-series. Some studies that use wavelet analysis include Scharnagl and Mandler (2016), ECB (2018), Verona (2016). Finally, one of the key outputs of the financial cycle analysis is the assessment of the relevance of the extracted cyclical component. In order to detect the build-up of financial booms in real time and with reasonable confidence, early warning indicators are used. As stated by many studies, deviations of credit or assets prices from long-run trends breaching certain critical thresholds are able to identify the build-up of vulnerabilities reasonably well. Moreover, real-time estimates properties are assessed in order to gauge the usefulness of the model for policymakers.

In this paper, we shed light on the characteristics of the Luxembourg financial cycle, by using two alternative methodologies that do not rely on statistical filters. First, as it minimizes the risk of extracting spurious cycles, a univariate structural model is used. Second, a wavelet analysis should provide an overview of the most relevant cyclical frequencies, thus allowing to obtain a growth cycle estimate. This analysis covers three bank credit series for the non-financial private sector (NFPS) and its components, households (HH) and non-financial corporations (NFC)[2], and house prices over the period spanning 1980 Q1 to 2019 Q1. We are interested in three questions that are of relevance for macro-prudential policy; first, what are the defining characteristics of the different cycles in Luxembourg? Second, how is the house price cycle related to the structural characteristics of the national housing market? Third, how reliable are real-time estimates of the cycles and how reliable are the early warning properties of the cycles? The key findings of this study are as follows. First, we find medium-term cycles in Luxembourg's financial series, with an average cycle length of 8.91 years for loans to the non-financial private sector, 8.71 years for household credit and 9.03 years for non-financial corporations credit, according to the univariate unobserved components model. House prices in Luxembourg are characterized by a cyclical component with a period of 13.8 years. Standard deviations of credit cycles range from 6% to 9%, while the house price cycle has a standard deviation of 8%. All credit cycles are in ascending phase in 2019 Q1 with a gap[3] for credit to the non-financial private sector of 1.6%, while the cycle of the credit to the non-financial corporations and to the households reached 5.5% and 0.28%, respectively. The cycle of house prices reached, in 2018 Q4, 4.5%. Correlation and synchronicity measures show that credit cycles in Luxembourg are highly correlated and synchronous. The household credit cycle is sometimes synchronous with the house price cycle. Second, we assess the properties of cyclical components obtained by the unobserved components model through a static evaluation procedure, as described in Drehmann and Juselius (2014). We find that this model has limited early warning properties. Real-time estimates of all credit and house price cycles give

[2]According to the strict definition of the BCL, the total bank credit to non-financial private sector is composed of total bank credit to households and total bank credit to non-financial corporations.

[3]We use 'gaps' and 'cycles' interchangeably.

good results, in particular for the credit to the non-financial private sector and the credit to households. Third, the wavelet analysis complements the above-mentioned findings. Based on coherence measures, we find weaker coherence between the house price cycle and all credit cycles while the latter are highly coherent over the considered period. However, the additional information provided by wavelet analysis should be interpreted with caution.

These findings may have implications for the conduct of macroprudential policy. First, they give relevant information on the length of the financial cycle. Second, they support an assessment of the financial cycle by complementary methodologies. Third, these results confirm earlier studies on the limited role of the Luxembourg's household credit cycle on the house price cycle.

The remainder of the paper is organized as follows. Section 2 provides a review of the literature on credit and financial cycles. Section 3 introduces the methodologies. Section 4 presents the results of each methodology to decompose and characterize the financial cycle. Section 5 concludes.

2 Related literature

The literature on the credit cycle, and more broadly on the financial cycle, originated with the pioneering papers of Minsky (1977) and Kindleberger (1978). In contrast to the mainstream economic literature, Minsky (1977) considered the evolution of credit as a key source of financial instability and not just as an amplifier. According to Minsky (1986), instability is an intrinsic feature of financial systems since permanent stability cannot be achieved. Kindleberger (1978) relies on a cliometrical analysis to highlight the pro-cyclical role of credit in banking crises.

Against this background, the Great Financial Crisis (GFC) initiated a new body of literature on credit cycle analysis. Several papers find evidence of the importance of credit booms in systemic banking crises (e.g., Mendoza and Terrones, 2008; Schularick and Taylor, 2012, Aikman *et al.*, 2015). Indeed, Claessens *et al.* (2012), Drehmann *et al.* (2012) and Borio (2014) among other, show that the build-up of financial imbalances, as driven by financial cycles, might culminate in financial crises. Financial cycle analysis provides evidence that more severe recessions occur when they coincide with financial crises (see for instance, Reinhart and Rogoff, 2009; Jordà *et al.*, 2011, Claessens *et al.*, 2012; Schularick and Taylor, 2012) and underpinned the usefulness of financial cycle analysis in the conduct of macroprudential and monetary policies (ECB, 2018; Gadanecz and Jayaram, 2016).

More broadly, several studies (e.g., Schularick and Taylor, 2012; Hubrich *et al.*, 2013) focus on the links between financial cycles and business cycles. Hubrich *et al.* (2013) found that the combined contribution from five financial shocks to GDP reached about one-third. Some theoretical models, as in Bernanke *et al.* (1999) and Kiyotaki and Moore (1997), clarified the role of credit and asset prices in the evolution of macroeconomic aggregates. The ECB (2018) shows that in most EU countries (including Luxembourg), credit cycles and house price cycles are much more volatile and longer than business cycles. For most EU countries, the estimated length of house price cycles and credit cycles is about 10-12 years, which is similar to business cycles.

Several papers provided some stylized facts of financial cycles. Borio (2014) and Drehman *et al.* (2012) agree on a parsimonious description of financial cycle by using credit and property prices. As explained by Borio (2014), this feature does not exclude alternative approaches to the financial cycle as done by Aikman *et al.* (2010), Schularick and Taylor (2012) and Jordá *et al.* (2011), which centered their analysis on the credit cycle, or as in English *et al.* (2005) and Ng (2011) which use several financial price and quantity variables in order to extract their common components. Borio (2014) and Drehman *et al.* (2012) advocate an approach to characterize the financial cycle by using credit to private non-financial sector and property prices since they covary closely at low frequencies and allow to capture the core features of the link between the financial cycle, the business cycle and financial crises.

As emphasized by Borio (2014), the financial cycle operates at the medium-term with a period between 16 and 20 years. Drehmann *et al.* (2012) showed that peaks in financial cycles are closely linked to financial crises. They highlighted that the length and amplitude of financial cycles has increased since the 1980's, thus reflecting financial deregulation and changes in monetary policies. Drehmann *et al.* (2012) documented the unfinished recessions phenomena that occurs when policy decisions fail to consider the financial cycle length. Such decisions may contain the effects of a recession in the short-term but at the expense of longer-term effects. The idea that a rapid credit growth leads inevitably to financial instability has been questioned since not all credit booms have resulted in financial crises. As advocated by Barell *et al.* (2018), some credit-to-GDP amplifications could be the result of project investments whose net present value could be positive. These credit booms could suffer from the setting of countercyclical measures while their role in financial instability is nonexistent. Barell *et al.* (2018) argued for a clear distinction between credit booms associated with house price bubbles and those that fund productive investment.

In spite of an extensive literature on the characterization of financial cycles, few papers address this issue specifically for Luxembourg. Giordana and Gueddoudj (2016) studied the Luxembourg financial cycle by using turning point analysis and band-pass filters. Notwithstanding the methodological shortcomings outlined in Section 3, Giordana and Gueddoudj (2016) showed that house price cycles are not synchronized with credit cycles, thus justifying that structural factors are the main drivers of house price growth. Based on the turning points approach, Giordana and Gueddoudj (2016) estimated the average length of the loans to non-financial private sector cycle at 13.4 years, those of loans to households at 11.25 years, and the cycle of loans to non-financial corporations at 9 years. House prices are characterized by a cycle of 13.5 years. These durations differ slightly when they applied the Christiano and Fitzgerald (2003) filter since the length of the credit to non-financial private sector, credit to households and credit to non-financial corporations cycles are of 8.7 years, 8.25 years and 8.8 years, respectively[4].

Guarda and Moura (2019) conducted a cyclical extraction on Luxembourg data using unobserved components models, estimated by Bayesian methods. The double analysis - univariate and multivariate - resulted in a financial cycle level close to zero in mid-2018. They showed that the cyclical component in house prices is limited, thus confirming the structural nature of house price growth in Luxembourg. They found that the cycle of credit to the non-financial private sector in Luxembourg is slightly above its historical trend whereas for credit to households, it has declined since 2009 and is close to zero. The cyclical component of loans to non-financial corporations is moderately above its historical trend. Regarding the cycle's duration, Guarda and Moura (2019) found that, in Luxembourg, the cycle of loans to non-financial corporations is shorter (11.8 years) compared to that of loans to households (17.8 years) and loans to the non-financial private sector (13.6 years). House prices are characterized by a cycle with a period of 17.5 years. The limited literature on the characterization of the Luxembourg financial cycle should be put in perspective with the assessments provided by international institutions. At the European level, several studies suggest the presence of a more mature financial cycle

[4] It should be mentioned that the two methodologies are applied to different data set since the turning point approach analyzes the classical cycle and the frequency-based approach is applied on growth rates.

in Luxembourg, which are indicative of potential vulnerabilities for financial stability. For instance, the ECB Financial Stability Review of November 2018 highlights the buoyant lending dynamics in Luxembourg while the IMF FSAP of May 2017 for Luxembourg flagged the potential vulnerabilities that could emerge from the residential real estate market.

Given the importance of the financial cycle in macroprudential policy making and the calibration of cyclical macroprudential instruments, it is important to have an accurate estimation of the state of the cycle. Below, we describe some methodologies for estimating the state of the cycles in Luxembourg.

3 Methodologies

Financial cycle analysis is intended to determine the period and possible turning points of the cycle and several methodologies have been developed for extracting the cycle. The classical methodologies - turning point analysis and statistical filters, have been frequently used in business cycle analysis. The filter based on the wavelet transform is increasingly used in financial cycle analysis and offers a possible alternative to statistical filters. Finally, the unobservable component models allow to minimize the probability to extract spurious cycles since these models are tailored to each time-series. These methodologies are outlined below.

3.1 Statistical methodologies

Among the statistical filters, two types of filters are commonly used to extract the cyclical component of a time-series. The Hodrick-Prescott (1981) filter is a smoothing method that allows to estimate the long-term trend of a time-series. This filter represents a tradeoff between the smoothness of the trend component and the minimization of the variance of the cyclical component, as given in equation 1.

$$Min \sum_{t=1}^{T} (Y_t^c)^2 + \lambda \sum_{t=2}^{T-1} [(Y_{t+1}^G - Y_t^G) - (Y_t^G - Y_{t-1}^G)]^2 \tag{1}$$

Where Y_t^c and Y_t^G are the cyclical and trend components, respectively. The trend component will be more linear as the smoothing factor, λ, increases, thus leading to a more fluctuating cyclical component. The HP filter therefore allows to obtain a linear filter for each observation, which takes the form of a symmetrical moving average for the central values of Y_t. As stated by Fournier (2000), the filter loses its symmetrical propriety for end points, thereby leading to a difference in the phase of the trend and the original time-series. According to Singleton (1988), the HP filter is a good approximation of a high-pass filter when it is applied to a stationary time-series. The ESRB recommendation ESRB/2014/1 provides a methodology for calibrating the countercyclical capital buffer according to which the standardized credit-to- GDP gap is obtained from an HP filter with a smoothness factor of 400 000 when applied to quarterly data. The large value of the smoothing parameter reflects the longer duration of the credit cycle. The Basel Committee on Banking Supervision (BCBS) has motivated the choice of lambda by an empirical study which shows that trends provided by an HP filter with a smoothness factor $\lambda = 400000$ better replicate the long-term trend, in accordance with the work of Ravn and Uhlig (2002) on the need to determine λ according to the estimated duration of the cyclical component and the data frequency. Nevertheless, several shortcomings in the HP filter credit-to-GDP gap have been identified. For instance, in the aftermath of prolonged boom/bust cycles, credit-to-GDP gaps resulting from the HP filter can be systematically biased downward and may underestimate cyclical risks[5].

Another class of filter is the band-pass filter, which allows to extract the cyclical component of a time-series by specifying a range or band for the frequency of the cycle. For this purpose, the lower bound should be chosen in order to exclude the irregular component of the time-series and the upper bound is set appropriately in order to exclude the trend. Generally, the band-pass filter takes a two-sided moving average of the data and the cycle is filtered by the frequency band. The main difference between band-pass filters is linked to the method used to compute the moving average. The most common band-pass filters in the economic literature are fixed length symmetric filters in which the same lead and lag lengths are fixed. For instance, the filter developed by Baxter and King (1995) is a band-pass filter defined in the frequency domain. This filter is based on a minimization problem for the gap between the "ideal" filter gain and the Fourier transform of weights a_k of the cyclical component :

$$\min_{a_k} \int_{-\pi}^{\pi} |\beta(\omega) - \alpha(\omega)|^2 \, d\omega \tag{2}$$

where $\beta(\omega)$ is the ideal filter gain which takes the value 1 in the frequency interval $[\omega_1; \omega_2]$ and 0 outside this interval, and $[\omega_1; \omega_2]$ are the bounds of the cyclical component. The function $\alpha(\omega)$ is the Fourier transform of the weights a_k of the cyclical component. In the same vein, Christiano and Fitzgerald (2003) developed

[5]For more details, refer to Hamilton (2017) ; Lang and Welz (2017).

a filter based on an approximation of the "ideal" band pass filter. The univariate filtering methods are particularly popular in financial cycle extraction. Drehmann *et al.* (2012) and Aikman *et al.* (2015) found evidence for large medium-term cycles in credit volumes and house prices using band-pass filters. The main drawback of using band-pass filters is the ex-ante fixation of the cycle length by the choice of the frequency band, thus biasing the duration of cycles. Finally, turning point analysis allows to identify the peaks and troughs in the cycle of a time-series according to a set of rules as defined by Harding and Pagan (2002). Claessens *et al.* (2012) used turning point analysis and find evidence of large, medium-term cycles in credit volumes and house prices. The financial cycle, as obtained by the turning point analysis, is generally longer in period and larger in amplitude than the real GDP cycle. The cyclical component of credit and house prices tend to be highly synchronized within countries. These results are confirmed by Haavio (2012) for other countries using the same methodology. The set of rules defined in the turning points analysis, however, introduces some arbitrariness in cycle's extraction.

3.2 Wavelet analysis[6]

Wavelet analysis is a method that allows to separate the band frequencies of a signal. More precisely, wavelet analysis provides estimates of the spectral characteristics of a time-series as a function of time, thus allowing to estimate the different periodic components over time. It is analogous to the Fourier transform, which decomposes a time-series into its constituent sinusoids of different frequencies. Wavelet analysis offers the possibility to decompose a time-series into shifted and scaled versions of a function that has limited spectral band and duration in time. In spite of the intensive use of the discrete wavelet transform in economics, a growing body of the economic literature relies on the continuous wavelet transform (see for instance Crowley *et al.*, 2006; Aguiar-Conraria *et al.*, 2008; Scharnagl and Mandler, 2016). Wavelet analysis provides a useful toolkit for univariate and multivariate analyses. In the univariate case, the wavelet decompositions could be studied by traditional time-domain methods. Wavelet analysis also facilitates an analysis of the time-frequency dependencies between two time-series using tools such as the cross-wavelet power, the cross-wavelet coherency and the phase difference (Hudgins *et al.*, 1993; Aguiar-Conraria *et al.*, 2008).

According to Mallat (2000), Bigot (2008) and Aguiar-Conraria and Soares (2009),

[6]This section is heavily inspired by Aguiar-Conraria and Soares (2009, 2014).

a function $\psi(t)$ is a mother wavelet if $\psi \in L^2(\mathbb{R})$, with $L^2(\mathbb{R})$ the set of square integrable functions, and if it fulfills the admissibility condition defined by:

$$0 < C_\psi := \int_{-\infty}^{+\infty} \frac{|\Psi(f)|}{|f|} df < \infty \tag{3}$$

where $\Psi(f)$ denotes the Fourier transform of $\psi(t)$. In order to have unit energy, the wavelet ψ is normalized : $\|\psi\|^2 = \int_{-\infty}^{+\infty} |\psi(t)|^2 = 1$. As explained by Aguiar-Conraria and Soares (2009), the square integrability of ψ is a very smooth decay condition but in practice, the wavelets have much faster decay. For these functions, the admissibility condition is equivalent to requiring $\Psi(0) = \int_{-\infty}^{+\infty} \psi(t)dt = 0$, which translates the wave movement of the function ψ. The daughter wavelet $\psi_{s,\tau}$ could be obtained from a mother wavelet ψ by scaling it by s and translating it by τ:

$$\psi_{s,\tau}(t) := \frac{1}{\sqrt{|s|}} \psi \frac{t-\tau}{s} \tag{4}$$

With $s, \tau \in \mathbb{R}, s \neq 0$, where s is the scaling or dilatation parameter that controls the length of the wavelet and τ is the location parameter that indicates where the wavelet is centered. The scaling parameter allows the wavelet to stretch if $|s| > 1$ or to compress if $|s| < 1$.

The continuous wavelet transform (CWT) of a time-series $x(t) \in L^2(\mathbb{R})$ with respect to the wavelet ψ is a function $W_x(s,\tau)$ obtained by projecting $x(t)$, in the L^2 sense:

$$W_x(s,\tau) = \langle x, \psi_{s,\tau} \rangle = \int_{-\infty}^{+\infty} x(t) \frac{1}{\sqrt{|s|}} \psi^* \frac{t-\tau}{s} dt \tag{5}$$

Since the wavelet function can be complex, the wavelet transform may also be complex. The asterisk denotes the complex conjugation. We can divide the transform into its real part $R(W_x)$ and imaginary part $I(W_x)$. Furthermore, ψ should be chosen as *progressive* or *analytic* wavelet, i.e., to be such as $\Psi(f) = 0$ for $f < 0$ (for details, refer to Aguiar-Conraria and Soares, 2009). The admissibility condition guarantees that it is possible to recover $x(t)$ from its wavelet transform and *vice-versa*. The choice of the wavelet function is a crucial element to be taken into account. We refer to the economic literature which favours the Morlet wavelet (see for instance Aguiar-Conraria and Soares, 2009; Scharnagl and Mandler, 2016), for which a simplified version is given by:

$$\psi_\eta(t) = \pi^{-1/4} e^{i\eta t} e^{-\frac{t^2}{2}} \tag{6}$$

The choice of the value of η is also given by the economic literature: when $\eta > 5$, the wavelet can be considered as analytic. We follow the suggestion of Aguiar-Conraria and Soares (2009) and set $\eta = 6$ because the Morlet wavelet is centered at the point $(0, \frac{\eta}{2\pi})$ of the time-frequency plane and if $\eta = 6$, the frequency center is $\mu_f = \frac{6}{2\pi}$ and the relationship between the scale and frequency is $f = \frac{\mu_f}{s}$, which allows for a simpler interpretation.
In order to assess the relevance of a specific frequency in relation to others, it is enough to measure its inertia part with respect to the total variance. To this end, the (local) wavelet spectrum could be used:

$$S_x(s, \tau) = |W_x(s, \tau)|^2 \tag{7}$$

The power spectrum describes the evolution of the variance of a time-series at the different frequencies. According to Aguiar-Conraria and Soares (2009), the statistical significance of the wavelet power can be assessed against the null hypothesis that the data generating process is given by an AR(0) or AR(1) stationary process with a certain background power spectrum.
For the bivariate case, the cross-wavelet transform of two time-series $x(t), y(t)$ is the product of their respective wavelet transform:

$$W_{xy}(s, \tau) = W_x(s, \tau) W_y^*(s, \tau) \tag{8}$$

The cross-wavelet power, defined by $|W_{xy}(s, \tau)|$, gives the covariance between the time-series at each scale and frequency. In other words, it is a quantification of the similarity of the power of the two time-series. A measure of the local correlation, both in time and frequency of the two time-series is provided by the wavelet coherency measure:

$$R_{xy}(s, \tau) = \frac{|S(W_{xy}(s, \tau))|}{|S(W_{xx}(s, \tau))|^{1/2} \, |S(W_{yy}(s, \tau))|^{1/2}} \tag{9}$$

Where $S(.)$ is a smoothing operator in both time and scale (for details, see Aguiar-Conraria and Soares, 2009). Monte-Carlo simulation methods are used to assess the statistical significance of the estimated wavelet coherency. Finally, a useful tool for bivariate wavelet analysis is the phase-difference that estimates the separation of the oscillations in degrees between two waves having the same frequency and referenced to a common point in time. The phase of a time-series ϕ_x can be viewed as the position in the pseudo-cycle[7] of the series and the phase-difference is given by:

$$\phi_{x,y}(s,\tau) = tan^{-1}(\frac{I\{W_{xy}(s,\tau)\}}{R\{W_{xy}(s,\tau)\}}) \tag{10}$$

with $\phi_{x,y} \in [-\pi, \pi]$. If $\phi_{x,y} = 0$, the time-series move together at the specified frequency. Otherwise:

- If $\phi_{x,y} \in (0, \frac{\pi}{2})$, the series move in phase but y leads x;
- If $\phi_{x,y} \in (-\frac{\pi}{2}, 0)$, the series move in phase but x leads y;
- If $\phi_{x,y} = \pi(or - \pi)$, the series are characterized by an anti-phase relation;
- If $\phi_{x,y} \in (\frac{\pi}{2}, \pi)$, x is leading;
- If $\phi_{x,y} \in (-\pi, -\frac{\pi}{2})$, y is leading.

3.3 Unobserved components models

As an alternative methodology to statistical filters, the unobserved component models (UCM) aim to decompose a time-series into trends and cycles. The first unobserved components (UOC) model has been introduced by Harvey (1989), Harvey and Koopman (1997). The UOC model assumes that a time-series is a sum of both trend and cyclical components whose dynamics could be expressed explicitly.
As defined in Harvey and Koopman (1997), a structural time-series model decomposes a vector of n time-series $Y_t^{'}$ into a trend μ_t, a cycle C_t and an irregular component ϵ_t according to: :

$$Y_t = \mu_t + C_t + \epsilon_t \tag{11}$$

$$\mu_t = \beta_{t-1} + \mu_{t-1} + \nu_t \tag{12}$$

$$\beta_t = \beta_{t-1} + \zeta_t \tag{13}$$

with a normally and independently distributed $n \times 1$ vector of irregular components $\epsilon_t \sim N(0, \Sigma_\epsilon)$, and level $\nu_t \sim N(0, \Sigma_\nu)$ and slope innovations $\zeta_t \sim N(0, \Sigma_\zeta)$. β_t is a stochastic slope which depends of the disturbance term ζ_t. Cyclical components C_t

[7] As the phase of an oscillation or wave is the fraction of a complete cycle which fluctuates up and down around the time-axis, it is possible to simulate a cycle as a pseudo cycle rotating an unit circle and projecting onto time axis.

are defined from stochastic cycles with a bivariate stationary stochastic process for $\tilde{\psi}_{i,t} = (\psi_{i,t}, \psi^*_{i,t})'$:

$$(I_2 - \rho_i \begin{bmatrix} cos\lambda_i & sin\lambda_i \\ -sin\lambda_i & cos\lambda_i \end{bmatrix} L) \begin{bmatrix} \psi_{i,t} \\ \psi^*_{i,t} \end{bmatrix} = \begin{bmatrix} k_{i,t} \\ k^*_{i,t} \end{bmatrix} \tag{14}$$

with decay rate $0 < \rho_i < 1$ and frequency $0 < \lambda_i < \pi$, I_2 is a 2×2 identity matrix and L is the lag operator. Cyclical innovations $\tilde{k}_{i,t} = (k_{i,t}, k^*_{i,t})'$ are normally and independently distributed $\tilde{k}_{i,t} \sim NID(0, \sigma^2_{k,ii} I_2)$. The cyclical component is a linear combination of $\psi_{i,t}$ and $\psi^*_{i,t}$:

$$C_t = (A, A^*)\tilde{\psi}_{i,t} \tag{15}$$

where $A = (a_{ii})$ and $A^* = (a^*_{ii})$ are general matrices. The elements $\tilde{\psi}_{i,t} = (\psi_{i,t}, \psi^*_{i,t})$ of the $2n \times 1$ vector $\tilde{\psi}_t = (\psi'_t, \psi^{*'}_t)'$ follow stochastic processes with covariance matrix $E[\tilde{k}_t \tilde{k}'_t] = I_{2n}$. The innovations $\epsilon_t, \nu_t, \zeta_t$ and $\tilde{k}_t$ are mutually uncorrelated.

The parameters of the model $(A, A^*, \lambda_i, \rho_i)$ and standard deviations $(\Sigma_\nu, \Sigma_\zeta)$ are estimated either by maximum likelihood or by Bayesian techniques based on the Kalman filter. Unlike Guarda and Moura (2019), we estimate the UCM via the maximum likelihood while they use Bayesian techniques.

4 Luxembourg financial cycle : decomposition and characterization

In order to assess the position of the Luxembourg economy in the financial cycle, we use the BCL definition of the bank credit to non-financial private sector (NFPS) as the sum of credit to households (HH) and credit to non-financial corporations (NFC). We use quarterly data for these three credit variables and house prices for the period from 1980 Q1 until the 2019 Q1. All the data are obtained from the BCL website[8]. As credit decomposition is only available from 1999 Q1, we follow Giordana and Gueddoudj (2016) by extending credit to households and credit to NFCs back to 1980 by using fixed shares. The series evolve in a similar path over the period 1980-1999 and differ only with respect to their levels.

[8]All data are publicly available from the BCL website, except for the house price series, which has been constructed by the BCL. For this latter, the ending period is 2018 Q4.

4.1 Financial cycles : an approach by an univariate UCM

This section summarizes the results of the estimates of the Luxembourg financial cycle using the univariate UCM as developed by Harvey and Koopman (1997). Unlike the restricted versions of Rünstler and Vlekke (2016) and Guarda and Moura (2019) who use an extended version of the UCM proposed by Harvey and Koopman (1997), we choose not to impose any restrictions on the length of the credit and house price cycles. In our view, restricting the models to find similar cycles in credit and house prices reduces the advantages of the UCM by introducing *ad hoc* assumptions on the length of the cyclical components. Furthermore, we depart from distributional restrictions of bayesian estimations by adopting classical econometric methods to estimate our state-space specifications.

The output of the model should be assessed for policy purposes. To this end, two assessments are carried out. First, we conduct a static evaluation procedure, as detailed in Drehmann and Juselius (2014) in order to assess the early warning properties of the cycles provided by the univariate UCM. Second, an assessment of the performance of the univariate UCM with respect to its ability to identify the cyclical position in real time was conducted. We assess the effects of filter uncertainty by comparing one-sided and two-sided estimates of the cycles.

4.1.1 Stylized financial cycle facts

As mentioned, we use quarterly time-series of loans to non-financial corporations (NFC), loans to private households (HH), loans to the non-financial private sector (NFPS) and house prices (HP) for Luxembourg. All variables were seasonally adjusted using the Census X12 method, deflated by the National Index of Consumer Prices (NICP), and transformed in logarithms.

Table 1 provides the estimated parameters of the unrestricted univariate UCM and the respective decompositions are plotted in Figures 1 to 4. The estimates reveal pronounced cycles in all of the time series with average annual cycle lengths between 8.71 years and 13.8 years. We note that the NFC credit cycle is the longest with a duration of more than 9 years. The household credit cycle is estimated at 8.71 years, thus leading to an estimate of the duration of the non-financial private sector credit cycle of 8.9 years. These credit cycles are particularly persistent since all the estimated parameters ρ are above 0.95. According to the parameter σ_c, the NFC credit cycle is the more volatile. Regarding house prices, it should be noted that the estimated cycle is longer than all credit cycles and persistent. The house price cycle is less volatile than NFC and total credit cycles.

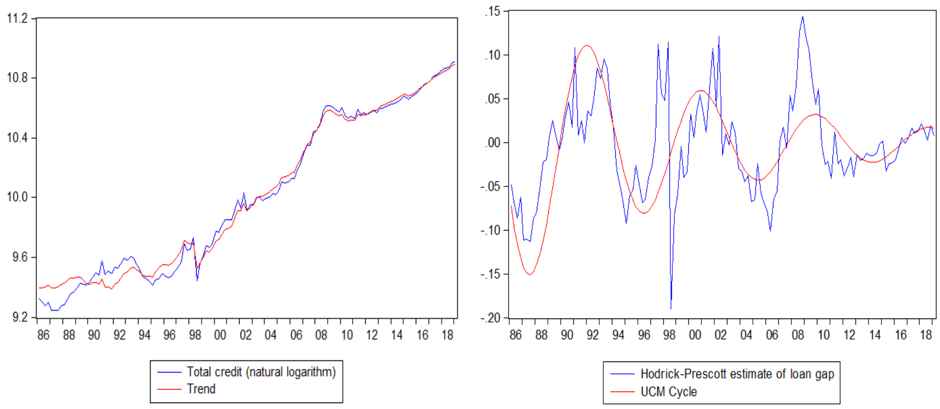
Based on Figures 1 to 4, three results can be emphasized: (i) at the beginning of the sample, the different credit cycles evolved along a similar path with the same peaks and troughs[9], (ii) over the remainder of the period, the household cycle and the NFPS cycle are closely connected while the NFC credit cycle differs in both phase and amplitude and (iii) the house price cycle has evolved along a different path than the other credit cycles since 1996 Q3. Figures 1 to 4 also show the cycle estimates resulting from the HP filter with a smoothness parameter of $\lambda = 1600$. The cycle estimates provided by the HP filter evolve along a similar path to those provided by the UCM estimates but differ substantially in amplitude. Furthermore, cycle estimates provided by the UCM are smoother and seem more accurate than those extracted by the HP filter. These estimates support some economic intuition regarding the growth of credit and house prices during 2007-2008. During this period, the peaks in the credit variables ranged from 3% to 22% with respect to their long-run trend and the peak of the house price cycle reached 6% compared to its long-run trend. However, it began to decline since 2016 Q2 while the credit variables began to decline at the end of 2008 through 2009. A trough in the house price cycle was observed in 2013 Q1 before a sustained recovery that lead to a gap with the long-run trend of house prices of 4.8% in 2018 Q4. The credit to non-financial private sector gap declined until 2014 Q2 and returned to an ascending phase one year before the NFC credit cycle. Nevertheless, it seems that the total credit cycle has a longer period than the NFC credit cycle, thus allowing the total credit cycle to be in phase with the NFC credit cycle during the last few years. The evolution of the household credit cycle seems poorly defined since 2008 Q4 due to the presence of several changes in household credit phases. According to these estimates, in 2019 Q1, the amplitude of the NFC credit cycle, household credit cycle and total credit cycle reached 5.5%, 0.28% and 1.6% respectively.

[9]This evolution is largely due to the extension procedure used to get a decomposition for households and NFC.

	Parameters	Total credit	NFC credit	HH credit	House prices
Cycles parameters	ρ	0.98**	0.95**	0.97**	0.99**
	λ	0.176**	0.174**	0.18**	0.114**
	$\frac{2\pi}{4\lambda}$	8.91	9.03	8.71	13.8
	σ_k	1.2E-09	0.0008**	7.8E-09	3.2E-10
	σ_c	0.07	0.09	0.06	0.08
Final State	μ_t	10.9**	10.01**	10.36**	4.92**
	β_t	0.012*	0.009**	0.014**	0.009**
	ψ_t	0.015**	0.054	0.002**	0.05**
	ψ_t^*	-0.005*	-0.0003	-0.0024**	0.02**
Log-Likelihood		235.9	148.04	299.7	443.06

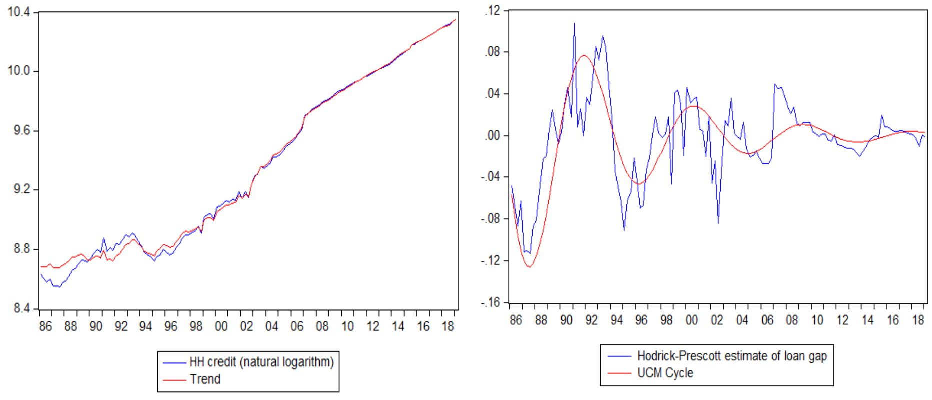
Note: This table gives the parameter estimates resulting from the univariate UCM without any restrictions. The ρ parameter measures the persistence of the cyclical component, $\frac{2\pi}{4\lambda}$ gives the cycle's duration (in years) and σ_c is the standard deviation of the estimated cycle. ** and * denote statistical significance at the 1% and 5% level, respectively.

Table 1: Main parameters estimates from univariate UCM



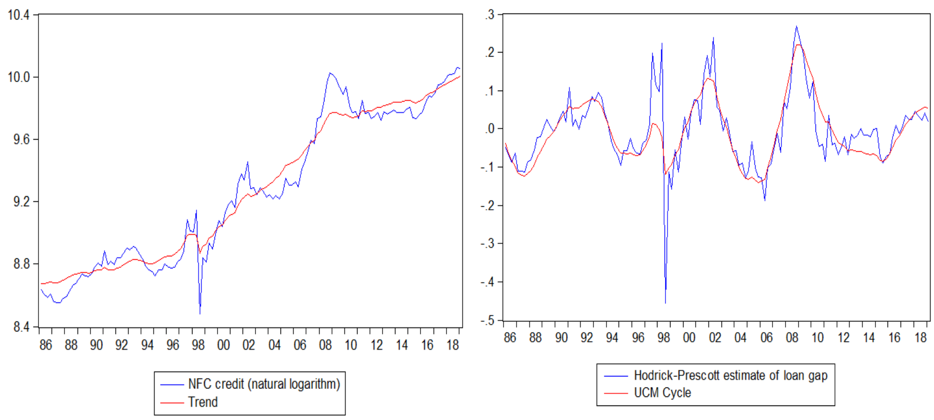
Note: In the left hand panel, the seasonally adjusted log time-series and its estimated trend from the UCM are shown in dark blue and red, respectively. In the right-side figure cycle estimates by UCM and by the HP filter ($\lambda = 1600$) appear in red and dark blue, respectively.

Figure 1: Trend-cycle decomposition - Credit to the non-financial private sector



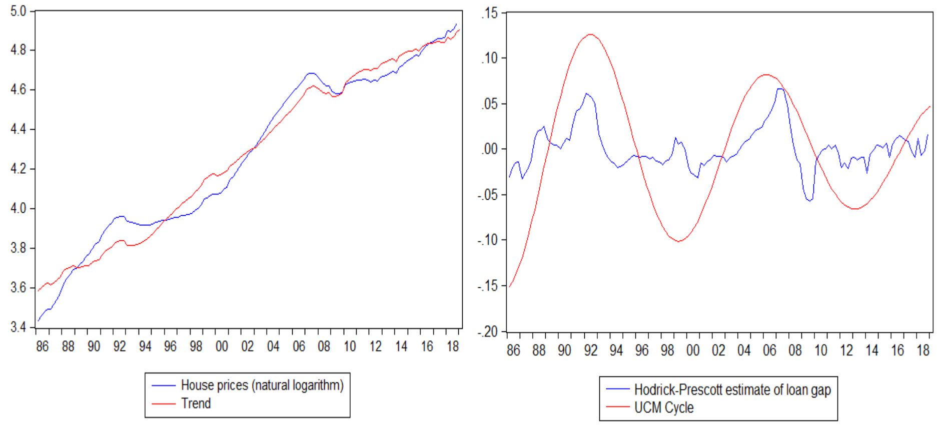
Note: In the left hand panel, the seasonally adjusted log time-series and its estimated trend from the UCM are shown in dark blue and red, respectively. In the right-side figure cycle estimates by UCM and by the HP filter ($\lambda = 1600$) appear in red and dark blue, respectively.

Figure 2: Trend-cycle decomposition - Credit to households



Note: In the left hand panel, the seasonally adjusted log time-series and its estimated trend from the UCM are shown in dark blue and red, respectively. In the right-side figure cycle estimates by UCM and by the HP filter ($\lambda = 1600$) appear in red and dark blue, respectively.

Figure 3: Trend-cycle decomposition - Credit to non-financial corporations



Note: In the left hand panel, the seasonally adjusted log time-series and its estimated trend from the UCM are shown in dark blue and red, respectively. In the right-side figure cycle estimates by UCM and by the HP filter ($\lambda = 1600$) appear in red and dark blue, respectively.

Figure 4: Trend-cycle decomposition - House prices

In order to assess the co-movements of the various credit cycles and the Luxembourg house price cycle, two measures are used. Table 2 shows correlation and synchronicity measures. The former is a simple linear correlation coefficient computed between each pair of estimated cycles. The synchronicity measure is constructed from a binary measure so that $\varphi_{ij}(t) = 1$ if cycles $c_i(t)$ and $c_j(t)$ are, at time t, of the same sign and $\varphi_{ij}(t) = -1$ if not. The average synchronicity between two cycles is then computed using:

$$\varphi_{ij} = \frac{1}{T}\sum_{t=1}^{T} \varphi_{ij}(t) \tag{16}$$

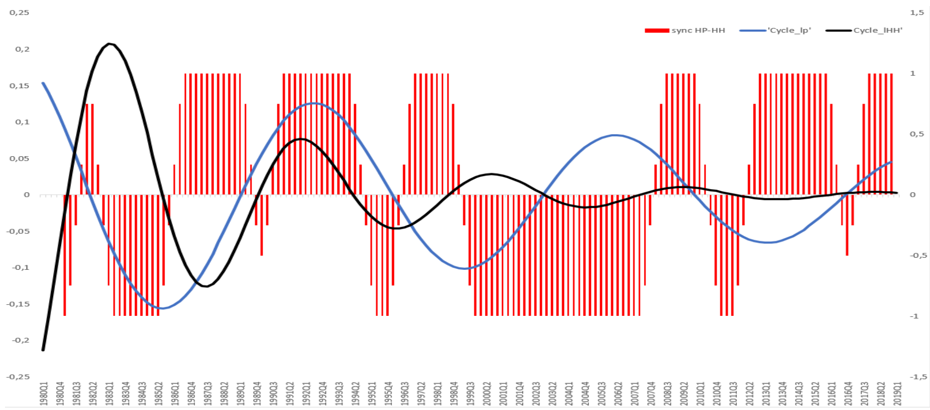
Where T is the number of observations and $-1 \leq \varphi_{ij} \leq 1$. In Table 2, the data above the main diagonal are correlations and the synchronicity measures are given below the main diagonal. These measures are complementary since linear correlations may fail to detect non-linear patterns in cyclical co-movements. As stated in ECB (2018), a correlation-based approach may not accurately reflect the degree of synchronicity between two co-moving cycles with opposite signs (above and below trend). The credit cycles are highly and positively correlated, albeit the household credit cycle is the more correlated with the non-financial private sector credit cycle. Correlations between the different credit cycles and the house price cycle are not significant. The synchronicity measures show that the household credit cycle and the private non-financial credit cycle are the more synchronous. Chart 5 shows the dynamic synchronicity measures between household credit and

	NFC	HH	NFPS	HP
NFC	1	0.729	0.789	-0.017
HH	0.783	1	0.962	-0.047
PNFS	0.796	0.885	1	0.064
HP	0.154	0.06	0.103	1

Note: This table gives correlations between each pair of variable above the diagonal and the respective synchronicity measure below the diagonal.

Table 2: Correlation and synchronicity measures

the house price cycles. Over the sample period, the household credit cycle and the house price cycle are sometimes synchronous. Nevertheless, the synchronicity of the household credit cyclical component and the house price cycle shows an important variation over time. In particular, the cycles are asynchronous between 1981 and 1986, in 1995-1996, between 1999 and 2007 and after 2010 until 2012. In spite of these episodes, the house price cycle and the household credit cycle have remained somewhat synchronous in the last years.



Note: Synchronicity measures are transformed to one-year moving average and given in red (right-hand scale). The house price cycle and the household credit cycle are shown in blue and black, respectively (left-hand scale).

Figure 5: Dynamic synchronicity between households credit and house price cycles

4.1.2 Assessment of early-warning properties and real time estimates

To assess the early warning properties of an indicator, Drehmann and Juselius (2014) defined both a static procedure and a dynamic procedure. As the dynamic procedure could only be applied to pooled data, we use the static evaluation procedure. Chart 6 shows the output of the static evaluation procedure when applied to Luxembourg data. The yellow, blue and gray lines show the estimated cycles for household credit, NFC credit and NFPS credit, respectively. The vertical red lines denote the start of a vulnerability period[10]. The quarters identified as being in a vulnerable period and the three quarters prior to each vulnerability period (in red gradient) are excluded from the analysis[11]. The blue shaded areas represent the evaluation period. This evaluation period begins from 5 years to 1 year prior to a vulnerability period. During this period, an indicator variable is computed depending on the value of the early warning indicator and whether this indicator is above or below a specified threshold, given by the black dashed line.

As depicted in Chart 6, credit cycles estimated using the UCM method are characterized by several boom-bust phases (in particular the NFC credit cycle) during the first evaluation period but they never breach the threshold, which has been fixed at 2 p.p. Moreover, in the quarters preceding the vulnerability period, the cycle estimates are in a bust phase, thus suggesting the absence of an actual crisis[12].

Regarding the second vulnerability period in 2001 Q3, the NFC credit cycle breached the threshold one quarter prior the vulnerability period. The household credit cycle and the total credit cycle estimates issued a signal five and six quarters before the vulnerability period, respectively. For the other vulnerability periods (2008 Q4 and 2009 Q1), the cycle estimates issued a signal during the evaluation period with the household credit cycle issuing a signal in 2007 Q3, or five quarters before the NFPS cycle breached the threshold. Nevertheless, a general assessment supports the poor early warning properties of these estimates since their noise-to-signal ratio is relatively high[13]. The build-up of the confusion matrix and of the

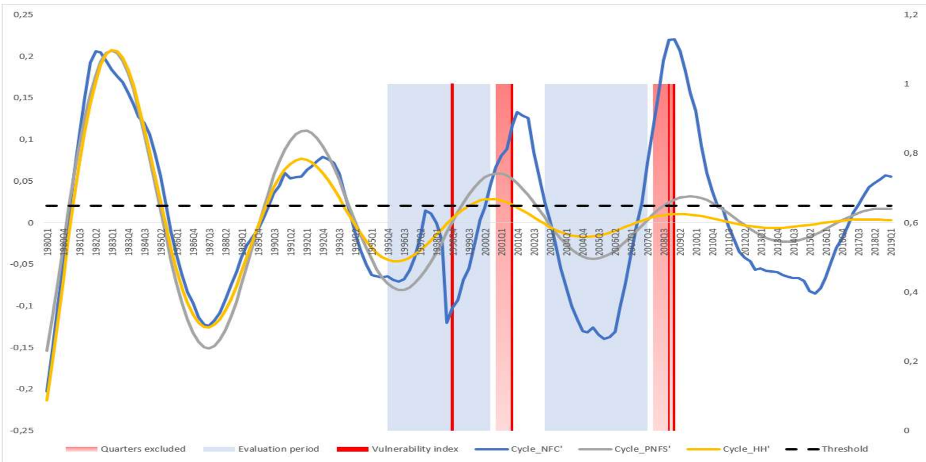
[10] The ESCB Heads of Research (HoR) crisis database can be used to identify periods of vulnerability. Nevertheless, the limited number of crises in Luxembourg, has an impact on the evaluation procedure. Consequently, we used the BCL vulnerability index.

[11] These quarters are excluded because an indicator with a good early-warning property should raise a signal in due time, i.e., before the countercyclical capital maintenance period, which is usually one-year.

[12] As a reminder, the vulnerability index measures the level of the vulnerability of the banking sector and could identify a period of vulnerability that does not necessarily materialize into an actual crisis.

[13] The computed noise-to-signal ratios for the NFC cycle, HH cycle and NFPS cycle are 55%, 84% and 54% respectively.

underlying ratios highlight a true positive rate of 66%, 33% and 33% for the NFC credit cycle, NFPS credit cycle and household credit cycle, respectively[14].



Note: The yellow, blue and gray lines give the estimated cycles of household credit, NFC credit and NFPS credit, respectively. The vertical red lines denote the start of vulnerability period. The red gradient delineates the excluded quarters. The blue shaded areas represent the evaluation period. The black dashed line gives the threshold.

Figure 6: Credit cycles and vulnerability index

In order to compute real-time estimates of cycles, we follow Rünstler and Vlekke (2016), ECB (2018) and Guarda and Moura (2019) by comparing the revisions of real-time with smoothed estimates $\hat{x}_{t|t} - \hat{x}_{t|t+h}$. Since the smoothed estimates ($\hat{x}_{t|t+h}$) are more precise than the real-time estimates ($\hat{x}_{t|t}$), the amplitude of the revisions provides an indication of the relative performance of the models. Three statistics are used to assess the quality of real-time estimates. Table 3 reports the sample standard deviations of the real-time estimates, the linear correlation between real-time estimates and the smoothed estimates and the Root Mean Square Error (RMSE) of revisions relative to the sample standard deviation of the smoothed estimates. Real-time estimates would be considered as useful if correlations and the relative volatility of one-sided estimates and noise ratios are close to one and zero, respectively. We choose to fix $h = 20$ which corresponds to 5 years. This period-lag seems appropriate in order to avoid short-run uncertainty. From table 3, we

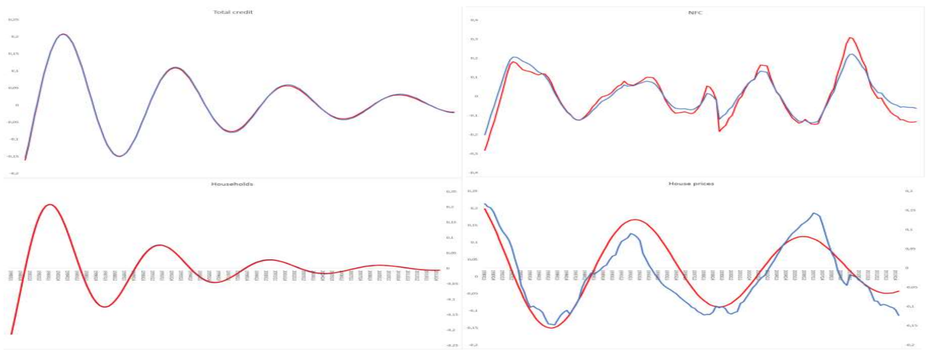
[14] These results could be explained by the vulnerability index since the latter identified only vulnerability periods and not the duration of potential "crisis". Against this framework, we note that credit cycles issued a signal after the vulnerability period that are considered, in the static evaluation procedure, as false positive signals.

find that the real-time estimates are highly correlated with the smoothed estimates, for all cycles. In other words, real-time estimates are relevant for characterizing the financial cycle. The good results for credit and house prices cycles are also supported by the low values of the RMSE. According to the standard deviations, it seems that the volatility of real-time estimates is lower than the volatility of smoothed estimates for total credit and household credit cycle, while the volatility of smoothed estimates is more important than the volatility of real-time estimates for NFC credit and house prices cycles. These findings are confirmed by Chart 7 that depicts the usefulness of the model since there are few differences between the real-time estimates and the smoothed estimates for the total credit and households credit cycles. Nevertheless, substantial deviations appear in the last observations for NFC credit, which may be relevant inputs to the policy decision-making process.

	Standard deviations	Correlations	RMSE
NFPS	0.993	0.999	0.03
HH	0.999	0.999	0.01
NFC	1.19	0.961	0.307
HP	1.162	0.878	0.49

Note: Standard deviations and RMSE of the real-time estimates are computed relatively to the sample standard deviations of the smoothed estimates $\hat{x}_{t|t+h}$. Correlations are simple linear correlations between the real-time estimates cycles and smoothed estimates cycles.

Table 3: Properties of Real-Time Estimates



Note: The blue line represents the real-time estimates and the red line gives the smoothed estimates.

Figure 7: Real-time estimates and smoothed estimates of cyclical components

4.2 Time-frequency characterization of the Luxembourg financial cycle : a wavelet analysis

Wavelet analysis is applied to the annual growth rate of credit variables and house prices in Luxembourg by taking the four-quarter difference for each time-series. This choice is motivated in the economic literature. Jolivaldt and Ahamada (2010) provided a comparative analysis between the statistical filters and wavelet filter and showed, based on simulations, that (i) the correlation between the estimated cycle and the theoretical cycle is higher when the cyclical component is stronger than the trend component, irrespective of the filter used; (ii) the wavelet filter is better suited when the cyclical component is dominant and; (iii) when the theoretical cycle is defined at low frequencies (as in the financial cycle). In this latter case, the extraction of the cycle is more accurate when the cyclical component is dominant, thus justifying the choice of the growth rate of the time-series instead of using the time-series in level. Moreover, as explained by Harding and Pagan (1999), the use of the de-trended time-series allows to compute its spectral density and the identification of the cycle could also be based on the identification of peaks in the spectral density.

The use of the growth rate affects the interpretation in relation to the classical cycle. An extensive discussion on the relevance of the growth cycle versus the classical cycle is provided by Harding and Pagan (1999). However, these different cycles can nevertheless be analyzed in a complementary way. Indeed, cycles extracted from growth rates can be expected to lead classical cycles. Classical cycle peaks are turning points at which a time-series changes from positive growth rates to negative growth rates and classical cycle troughs are turning points at which a time-series changes from negative growth rates back to positive growth rates. We follow the recommendations of Jolivaldt and Ahamada (2010) as well as the choice made by Aguiar-Conraria and Soares (2009, 2014), Scharnagl and Mandler (2016), and Verona (2016) by using the annual growth rate. The use of the (annual) growth rate differs from other methodologies, in particular from the turning point analysis[15].

Our empirical analysis uses quarterly data for the period from 1980 until the

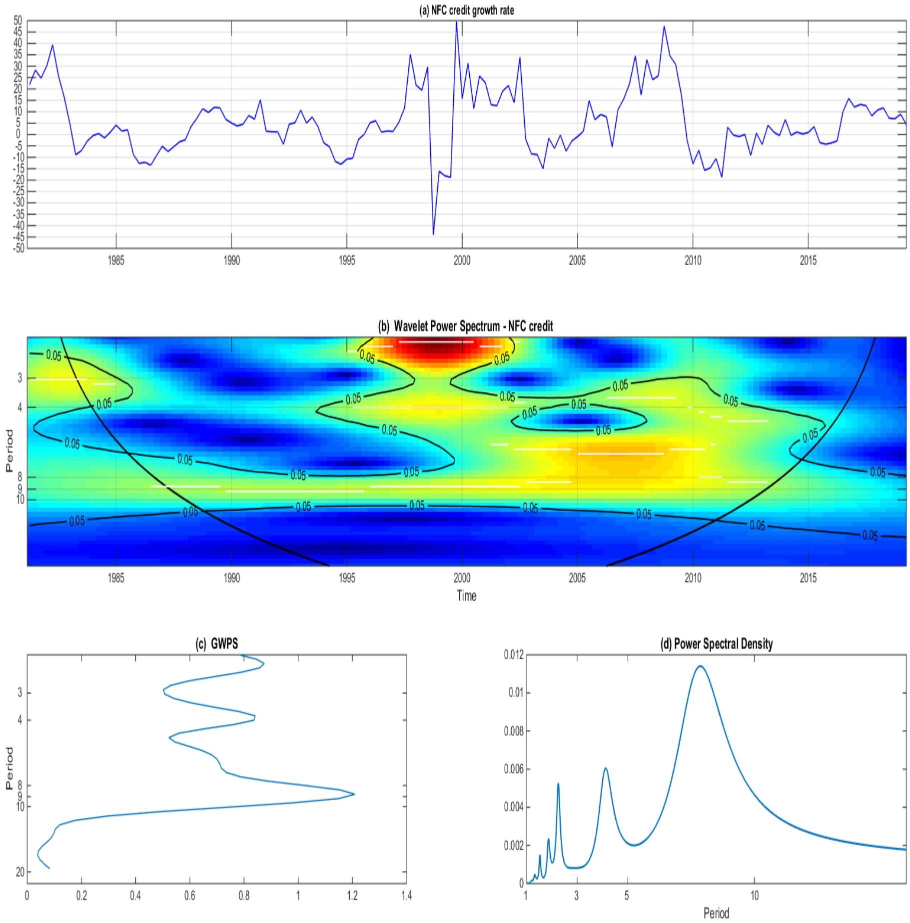
[15]It should be noted that the choice of the annual growth rate, as in Drehmann *et al.* (2012), Strohsal *et al.* (2015), ECB (2018) and Verona (2016) differs from Schüler *et al.* (2017), who use a quarter-on-quarter differencing, because of a lack of precision in the annual growth rate, for identifying turning points. According to Schüler *et al.* (2015), an annual transformation removes the higher frequency cycles when a quarterly transformation emphasizes them. In spite of this result, Schüler *et al.* (2015) conclude that there is no alteration in the relative significance of long-term cycles, in particular for financial variables.

first quarter of 2019 for three credit variables: loans to non-financial corporations (NFC), loans to households (HH), loans to the non-financial private sector (NFPS) and house prices (HP). All data series were seasonally adjusted using Census X12 and deflated by the National Index of Consumer Prices. We convert the series to annual growth rates.

4.2.1 Extraction and characterization of the Luxembourg financial cycle[16]

Figures 8, 9, 10 and 11 show **(a)** the growth rates of the different credit series and house prices, **(b)** their wavelet power spectra, **(c)** their global wavelet power spectrum and **(d)** their power spectral density. The wavelet power spectra provides a first time-frequency description of each series since it measures the variance of each time series at each time-frequency. On first inspection, the variability of the different credit series occurs at frequencies larger than 3 years while house prices are characterized by a cyclical component with a period larger than 9 years. Although the longer cycle in house prices occurs during the overall period, credit cycles are mainly characterized by a cyclical component with a period of around 9 years along with shorter cycles, around 4 years. More specifically, NFC credit is characterized by the prevalence of two frequencies - around 4 years and 10 years- but the shorter frequency is highly significant only from the year 2000 onwards. The 10-year cyclical oscillations are stable over the entire sample period considered. The global wavelet power spectrum confirms these observations since it is characterized by two significant peaks situated around 4 and 9 years. Household credit has an important variability with a frequency around 3-4 years until 1997 but at the same time, the frequency around 9 years prevails until 2006. This finding is confirmed by the global wavelet power spectrum, which shows an average of the wavelet power spectrum over the sample period. Two peaks emerge in the sub-graph (c) of Chart 9 at frequencies around 4 and 9 years. The wavelet power spectrum of the non-financial private sector credit series is, to some extent, a representation of the wavelet power spectrum of household credit and also of non-financial corporations. The 3-4 year frequency is characterized by significant variability since 1995 and also between 1980 to 1987. The 9-10 years frequency seems more relevant due to its stability over the period 1980-2019 as there is an important variance concentration around this frequency over time.

[16]These results are obtained by using the 2018 version of ASToolbox provided by Aguiar-Conraria and Soares and available at the following address: https://sites.google.com/site/aguiarconraria/joanasoares-wavelets.

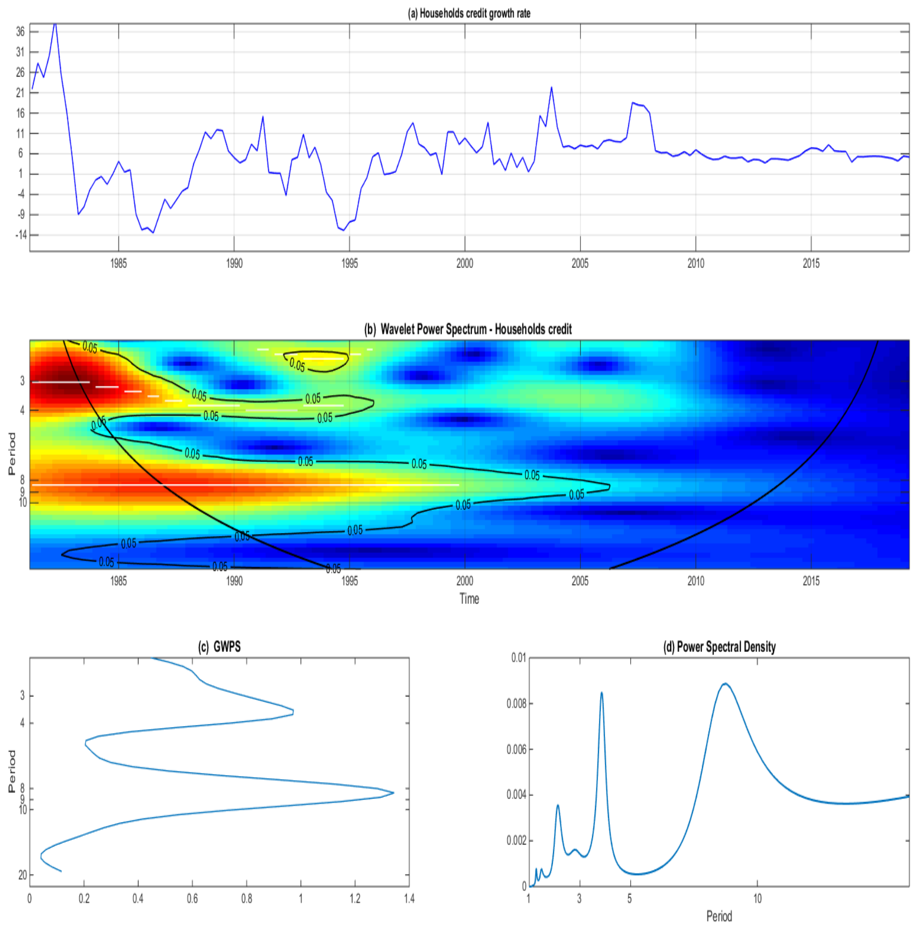


(a) NFC credit growth rate **(b)** Wavelet power spectrum - the black contour dotted by 0.05 designates the 5% significance level based on ARMA (1,1) null. The cone of influence, which indicates the region affected by edge effects, is shown with a thick black line. The color code for power range from blue (low power) to red (high power). The white lines show the maxima of the undulations of the wavelet power spectrum. **(c)** Global wavelet power spectrum - average wavelet power for each frequency. **(d)** Fourier power spectral density.

Figure 8: Wavelet decomposition of non-financial corporations credit growth rate

Chart 12 shows the cyclical components obtained from the sum of the three more relevant wavelet transforms[17]. We report in this chart the vulnerability index and the evaluation periods associated to the static evaluation procedure, as defined in the previous section. The interpretation of growth cycles, as given in Chart 12,

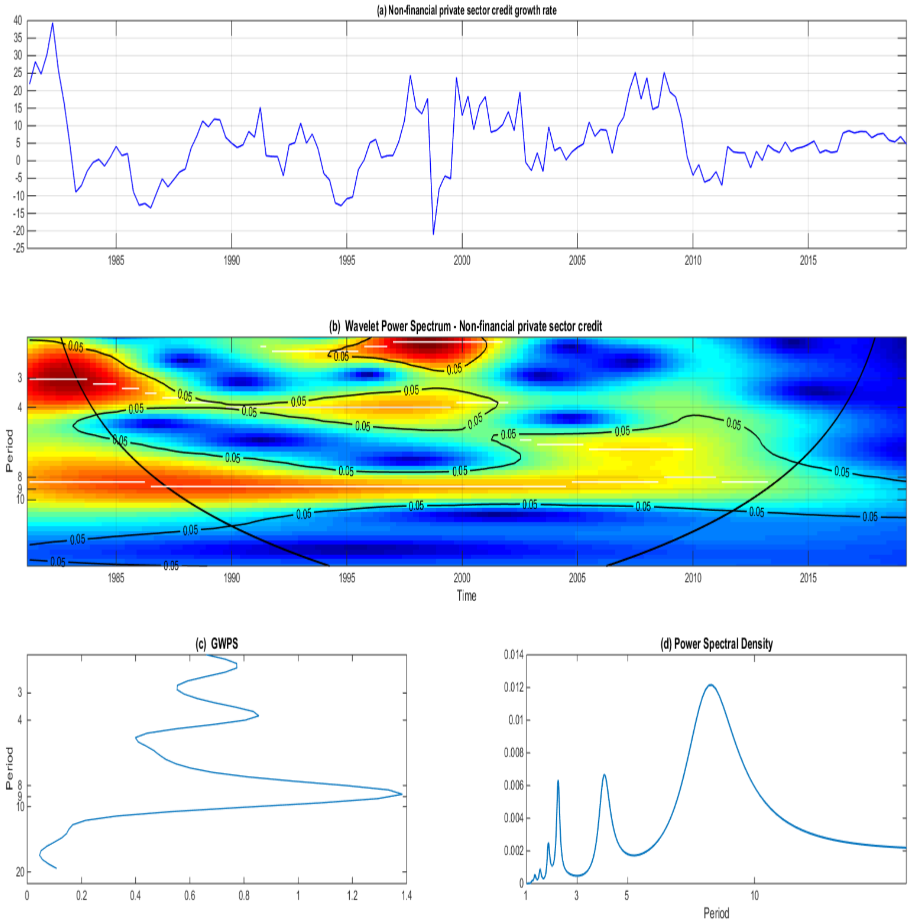
[17]The relevance of a wavelet transform with respect to the other is assessed by the global wavelet power spectrum.



(a) Households credit growth rate **(b)** Wavelet power spectrum - the black contour dotted by 0.05 designates the 5% significance level based on ARMA (1,1) null. The cone of influence, which indicates the region affected by edge effects, is shown with a thick black line. The color code for power range from blue (low power) to red (high power). The white lines show the maxima of the undulations of the wavelet power spectrum. **(c)** Global wavelet power spectrum - average wavelet power for each frequency. **(d)** Fourier power spectral density.

Figure 9: Wavelet decomposition of households credit growth rate

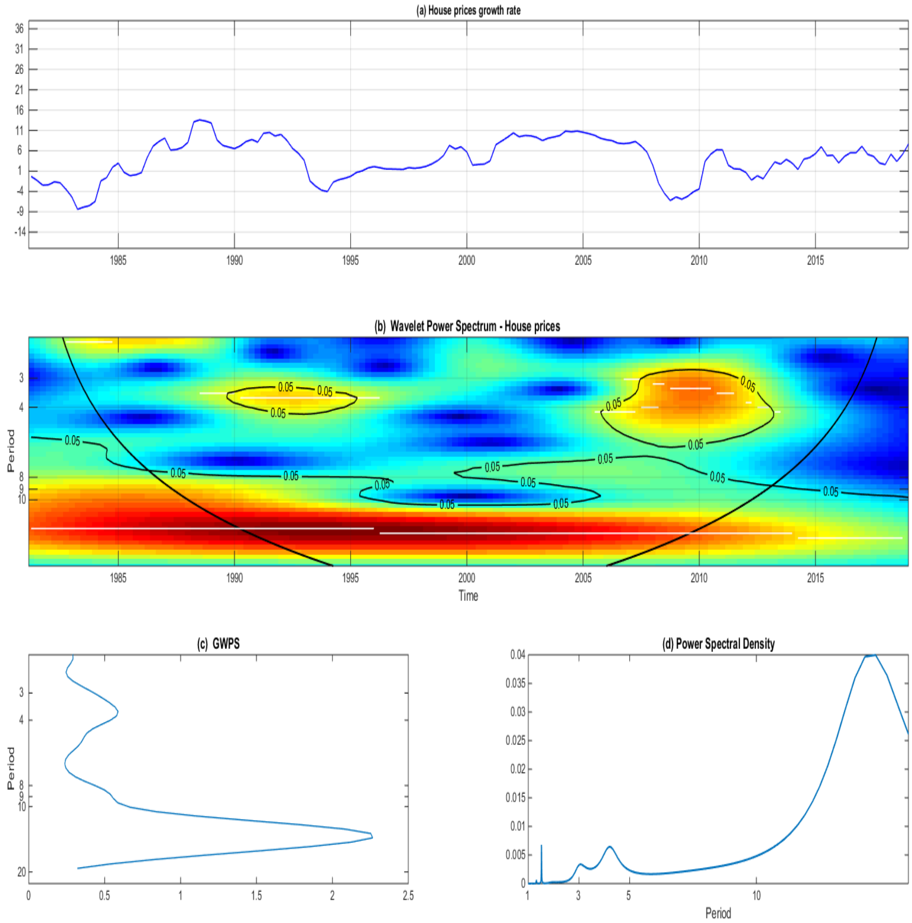
differs significantly from the previous analysis carried out in classical cycles, and it therefore seems relevant to highlight how these growth cycles can be informative for policy purposes. Thus, we note that growth cycles are, across the sample, at the beginning of an ascending phase when they enter into the evaluation period. Regarding the first evaluation period, the household growth cycle transitions from a negative growth rate to a positive growth rate in 1996 Q3, while the NFC growth



(a) NFPS credit growth rate **(b)** Wavelet power spectrum - the black contour dotted by 0.05 designates the 5% significance level based on ARMA (1,1) null. The cone of influence, which indicates the region affected by edge effects, is shown with a thick black line. The color code for power range from blue (low power) to red (high power). The white lines show the maxima of the undulations of the wavelet power spectrum. **(c)** Global wavelet power spectrum - average wavelet power for each frequency. **(d)** Fourier power spectral density.

Figure 10: Wavelet decomposition of non-financial private sector credit growth rate

cycle and the NFPS growth cycle breached 0 in 1997 Q2 and 1997 Q1 respectively. These movements occurred 9 quarters, 6 quarters and 7 quarters before the vulnerability period, respectively. They coincide, albeit not exactly, with the evolution of classical cycles. Indeed, as depicted by charts 13, which report growth cycles provided by the wavelet transform and classical cycles extracted by a Christiano



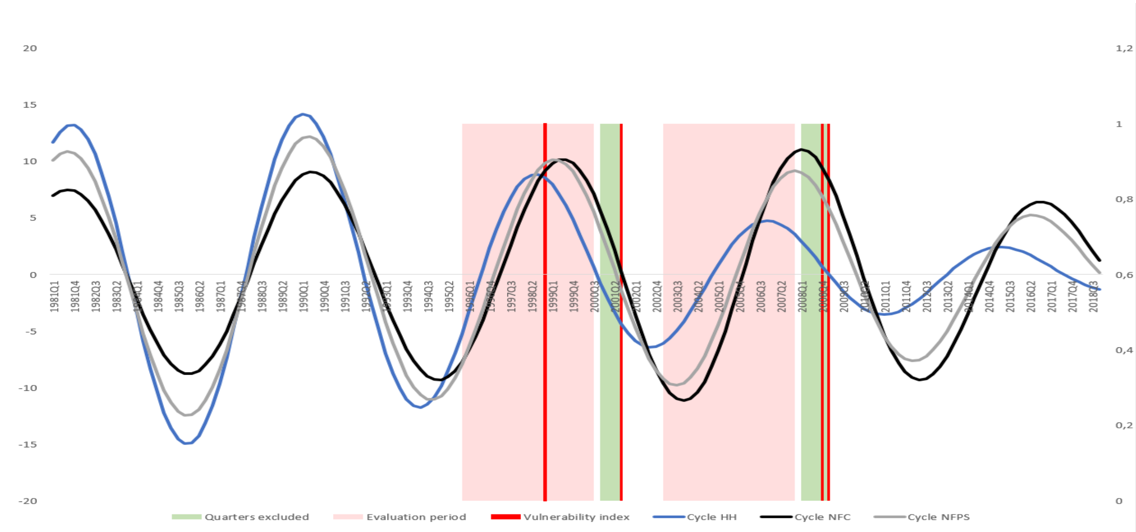
(a) House prices growth rate **(b)** Wavelet power spectrum - the black contour dotted by 0.05 designates the 5% significance level based on ARMA (1,1) null. The cone of influence, which indicates the region affected by edge effects, is shown with a thick black line. The color code for power range from blue (low power) to red (high power). The white lines show the maxima of the undulations of the wavelet power spectrum. **(c)** Global wavelet power spectrum - average wavelet power for each frequency. **(d)** Fourier power spectral density.

Figure 11: Wavelet decomposition of house prices growth rate

and Fitzgerald filter[18], it is possible to notice that peaks and troughs are almost opposed, thus suggesting that information provided from the growth cycle could be used to identify the evolution of the classical cycle. Based on this, the troughs in the household growth cycle in 2002 Q3, in the NFC growth cycle in 2003 Q4 and in the NFPS growth cycle in 2003 Q3 may provide a useful signal of the possible onset of a

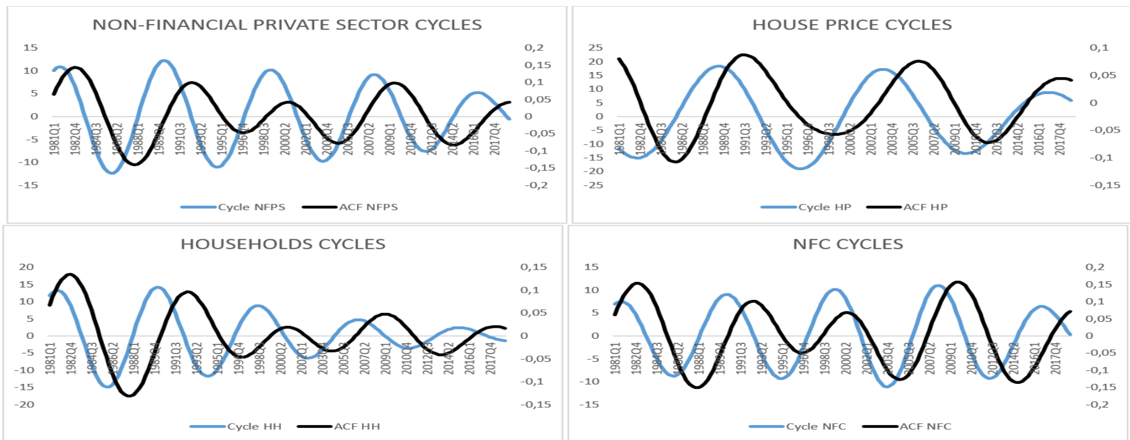
[18]We use an asymmetric Christiano-Fitzgerald filter with a windows of 32-60 quarters.

vulnerability period. This complementary information should be used with caution since it provides only partial information (given by the restricted number of selected wavelet transforms) and does not overcome the methodological shortcomings of the classical cycle extraction.



Note: These cyclical components are obtained from a wavelet transform. The blue, gray and black lines represent the household growth cycle, the NFPS growth cycle and the NFC growth cycle, respectively. The vertical red lines denote the start of a vulnerability period based on the BCLs vulnerability index. The green shaded area delineates the excluded quarters. The red shaded areas represent the evaluation period.

Figure 12: Growth cycle from wavelet decomposition



Note: The blue lines represent the wavelet growth cycles and the black lines show the ACF classical cycles.

Figure 13: Wavelet growth cycles and ACF level cycles

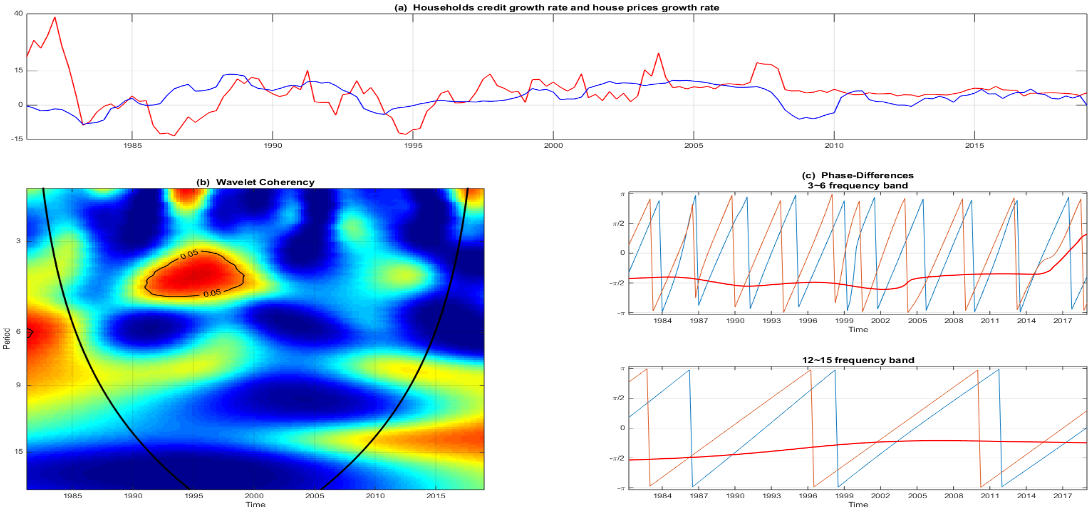
4.2.2 Coherence measures

As suggested by Borio (2012) and Drehmann *et al.* (2012), financial cycle analysis could be further supported by the joint analysis of the credit and house price cycles. Wavelet analysis can be a useful tool for assessing possible interactions and the evolution of different time-series in the time-frequency domain. Against this background, coherence and phase-difference measures could be used to assess to what extent (i) credit growth cycles are correlated with each other and (ii) credit growth cycles are connected to the house price cycle.

Charts 14 to 19 depict **(a)** the growth rate of credit and house prices **(b)** the wavelet coherency, which should be interpreted as a local correlation and **(c)** phase-differences for two frequency bands. From Chart 14, we note a high level of coherence between household credit and house prices between 1990 and 2000, as represented by the red ellipse. The other red areas are outside of the cone of influence and could be affected by edge effects[19].

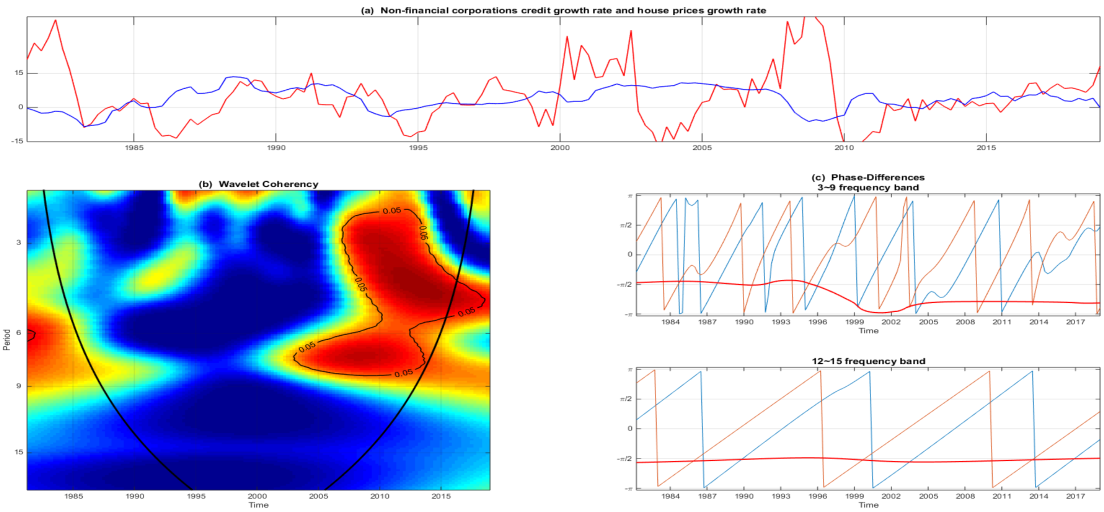
We choose to focus on the phase-difference in the 3-6 frequency band and the 12-15 frequency band since these bands correspond to the red area in sub-chart (b) of Chart 14. Regarding the 3-6 frequency band, household credit and house prices tend to evolve in phase with one another and household credit tends to lead house prices over the periods 1981-1988 and 2004-2017. In the 12-15 frequency band, the two series move in phase all the time with the household credit cycle leading the house price cycle. Some coherency can be identified between NFC credit and house prices according to the chart 15 for a frequency band between 3 to 9 years. The phase-difference is in contradiction to this finding, however, since from 1996, the phase-difference is roughly $-\pi$. Similar results emerge from Chart 16 regarding coherence between NFPS credit and house prices.

[19] As the wavelet transform is applied to a finite length time series, it could suffer from border distortions due to the fact that the values of the transform at the beginning and the end of the time series involve missing values of the series which are artificially imposed. Before applying the wavelet transform, one usually pads the series with zeros to avoid wrapping. The region affected by these edge effects is called the cone of influence. In this area of the time-frequency plane, the results are subject to border distortions and have to be interpreted carefully.



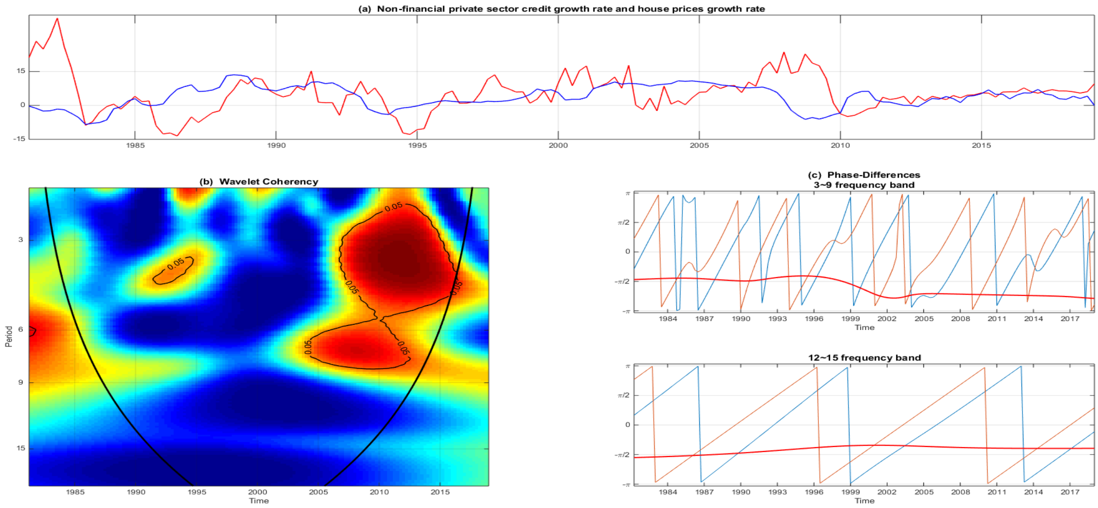
Note:**(a)** Household credit growth rate and house prices growth rate. **(b)** Wavelet coherency between household credit and house prices. The black contour designates the 5% significance level based on an ARMA (1,1) null. **(c)** Phase-differences at 3-6 years frequency band and 12-15 years frequency band.

Figure 14: Coherence and phase-differences measures between household credit and house prices



Note:**(a)** NFC credit growth rate and house prices growth rate. **(b)** Wavelet coherency between NFC credit and house prices. The black contour designates the 5% significance level based on an ARMA (1,1) null. **(c)** Phase-differences at 3-6 years frequency band and 12-15 years frequency band.

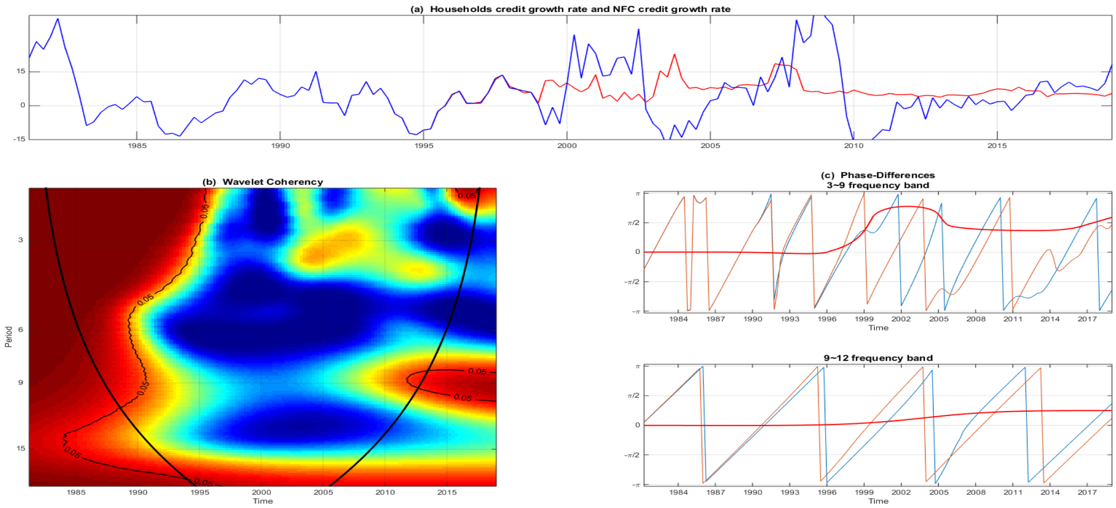
Figure 15: Coherence and phase-differences measures between non-financial corporation credit and house prices



Note:**(a)** NFPS credit growth rate and house prices growth rate. **(b)** Wavelet coherency between NFPS credit and house prices. The black contour designates the 5% significance level based on an ARMA (1,1) null. **(c)** Phase-differences at 3-6 years frequency band and 12-15 years frequency band.

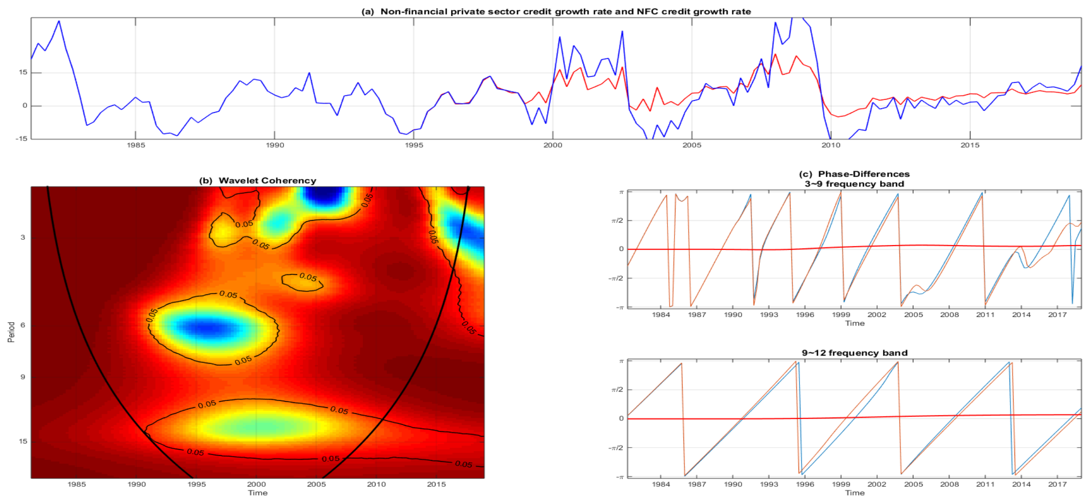
Figure 16: Coherence and phase-differences measures between NFPS credit and house prices

Regarding the coherence between credit growth rates, NFPS credit is highly correlated with NFC credit (Chart 18). This coherence is high across all periods and frequencies. Household credit shares common coherency with the NFPS and NFC series, in particular in the 9-15 frequency band. NFC credit leads NFPS credit, and household credit to an extent (see phase-difference of 9-12 frequency band of Chart 17). These findings are in line with those of the previous section since the credit series are weakly connected to house prices. Some coherencies characterize credit growth rates and house prices but not all the time and not across all frequencies. Based on these findings and on the shortcomings of the measures used, we can only conclude that there may be some similar evolution between household credit and house prices in Luxembourg.



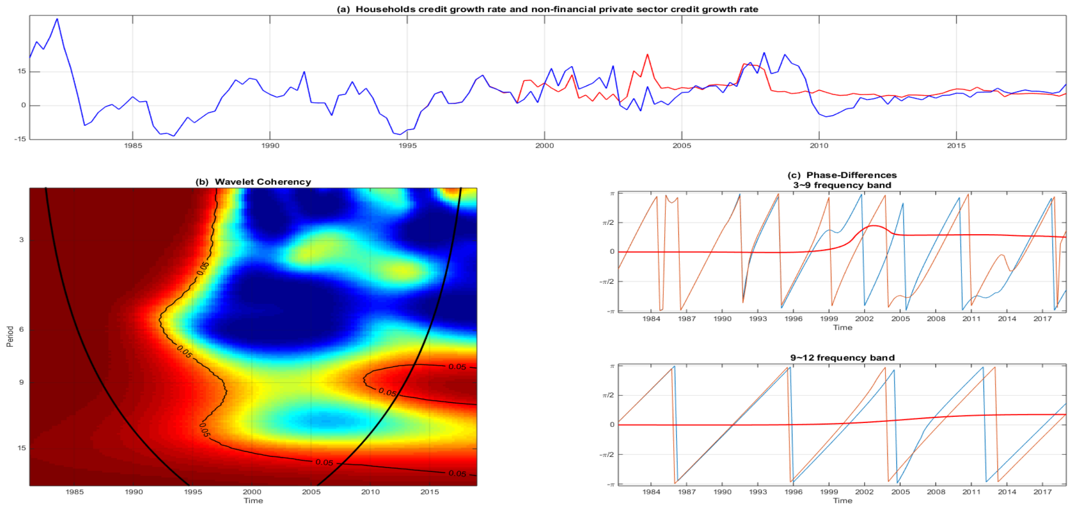
Note:**(a)** Households credit growth rate and NFC credit growth rate. **(b)** Wavelet coherency between households credit and NFC credit. The black contour designates the 5% significance level based on an ARMA (1,1) null. **(c)** Phase-differences in the 3-9 years frequency band and 9-12 years frequency band.

Figure 17: Coherence and phase-differences measures between household credit and non-financial corporations credit



Note:**(a)** Non-financial private sector credit growth rate and NFC credit growth rate. **(b)** Wavelet coherency between non-financial private sector credit and NFC credit. The black contour designates the 5% significance level based on an ARMA (1,1) null. **(c)** Phase-differences in the 3-9 years frequency band and 9-12 years frequency band.

Figure 18: Coherence and phase-differences measures between NFPS credit and non-financial corporation credit



Note:**(a)** Household credit growth rate and non-financial private sector credit growth rate. **(b)** Wavelet coherency between household credit and non-financial private sector credit. The black contour designates the 5% significance level based on an ARMA (1,1) null. **(c)** Phase-differences in the 3-9 years frequency band and 9-12 years frequency band.

Figure 19: Coherence and phase-differences measures between household credit and NFPS credit

5 Conclusion

The importance of the financial cycle for macroprudential policymaking has driven the work related to the cycles extraction, characterization and relevance for macroprudential purposes. The analysis of the financial cycle for Luxembourg is relevant for several reasons. First, the high level of household indebtedness in Luxembourg and lending to NFCs warrants a close monitoring of the evolution of the credit cycle and the potential drivers of this evolution. Second, the issues related to financial stability that emerged in the period following the crisis years have increased the importance of the financial cycle in helping to identify potential vulnerability periods that could be managed by the use of appropriate countercyclical macroprudential measures. Third, the assessment and estimation of the financial cycle for Luxembourg has relevance for the macroprudential policymaking process. Fourth, as the level of NFC debt in relation to GDP is particularly high in Luxembourg, an analysis of the NFC credit cycle (which is a component of the financial cycle) is essential. In the same vein, as household indebtedness is rising in the context of sustained increases in residential real estate prices, an assessment of the financial cycle should be conducted in order to identify the potential vulnerabilities that could arise from household credit growth.

Against this background, this paper addresses several issues linked to the financial cycle in Luxembourg. Using a univariate unobserved components model and wavelet analysis, we study the following issues: what are the characteristics of the financial cycle in Luxembourg? How, if at all, are the cyclical properties of credit cycle related to house price cycles? How reliable are real-time estimates of the various cycles and how good are the early warning properties of the cycles for predicting periods of potential vulnerability?

The key findings of the study can be summarized as follows. We observe medium-term cycles in financial series, with an average cycle length of 8.91 years for loans to the non-financial private sector, of 8.71 years for household credit and 9.03 years for NFC credit, according to the univariate unobserved components model. House prices in Luxembourg are characterized by a cyclical component of 13.8 years. Standard deviations of the various credit cycles range from 6% to 9%, while the house price cycle is characterized by a standard deviation of 8%. In 2019 Q1, the level of the cycle of credit to the non-financial private sector reached 1.6% while those for credit to NFCs and credit to households reached 5.5% and 0.28%, respectively. The house price cycle reached 4.5% in 2018 Q4. Correlation and synchronicity measures show that credit cycles are highly correlated and synchronous. The household credit cycle is sometimes synchronous with the house price cycle in Luxembourg.

We find that the univariate unobserved components model has limited early warning properties when applied to Luxembourg data. Real-time estimates of the credit and house price cycles give good results despite some deviations in the end-points for the cycle of credit to NFCs and cycle of house prices, which are more relevant for the policymaker. The wavelet analysis complements the above findings. Based on coherence measures, we find weaker coherence between the house price cycle and all credit cycles while the latter are highly coherent over the considered period. However, the additional information provided by the wavelet analysis should be interpreted with caution.

From a macroprudential perspective, these findings provide additional information on the length of the financial cycle in Luxembourg. These results can help to complement other information on the financial cycle in order to support macroprudential policymaking. In addition, our results confirm earlier studies on the limited role of the household credit cycle on the house price cycle suggesting that additional factors should be taken into account when assessing house prices

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