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# MEASURING REAL AND FINANCIAL CYCLES IN LUXEMBOURG: AN UNOBSERVED COMPONENTS APPROACH

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# MEASURING REAL AND FINANCIAL CYCLES IN LUXEMBOURG: AN UNOBSERVED COMPONENTS APPROACH

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Abstract. We use unobserved components time series models to extract real and financial cycles for Luxembourg over the period 1980Q1-2018Q2. We find that financial cycles are longer and have larger amplitude compared to standard business cycles. Furthermore, financial cycles are highly correlated with cycles in GDP. We compare our results to other approaches to measure financial cycles and show how unobserved components models can serve to evaluate uncertainty and to monitor cyclical developments in real time. Overall, our estimates indicate that in mid 2018 both real and financial cycles in Luxembourg were close to zero, with financial conditions near their long-run trend.

JEL Codes: C22, C32, E30, E50, G01.

Keywords: financial cycles, unobserved component time series models, Luxembourg.

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## Résumé Non Technique

Dans la poursuite de leur objectif de stabilité des prix, les banques centrales cherchent à limiter les déviations de l'activité économique, mesurée par le PIB, par rapport à son niveau potentiel de long terme. Le *cycle des affaires* désigne les fluctuations de l'activité par rapport à cette tendance, mais aussi les cycles plus ou moins simultanés observés pour d'autres variables telles que la productivité, la consommation, l'investissement, les heures travaillées, la participation au marché du travail ou le taux de chômage.

La crise financière des années 2007-2008 a rappelé aux économistes que ce cycle des affaires, ou cycle réel, peut être lié à un *cycle financier* distinct, affectant les prix des actifs, le volume du crédit et le niveau d'endettement des ménages, des entreprises et des institutions financières. L'intérêt des banques centrales pour ce cycle financier provient non seulement du besoin d'étalonner de nouveaux outils macro-prudentiels, mais également des effets potentiels du cycle financier sur l'évolution de l'activité économique et du niveau des prix.

Concernant le Luxembourg, en novembre 2017 la Banque centrale européenne a souligné la croissance "soutenue" du crédit au secteur privé non financier. En mars 2018, lors de son examen du Luxembourg au sein du semestre européen, la Commission européenne a identifié des risques potentiels associés à la croissance continue des prix immobiliers et de l'endettement de ménages. En avril 2018, le Fonds monétaire international a également conclu, dans le cadre de sa consultation annuelle, que la croissance des prix immobiliers au Luxembourg pourrait conduire à un endettement excessif des ménages.

Dans ce contexte, il paraît important d'évaluer la position des variables réelles et financières au Luxembourg par rapport à leur tendance historique. Dans ce but, nous appliquons dans ce papier le modèle de séries temporelles dit *à composantes inobservées* à l'étude des cycles réels et financiers. Par contraste avec les méthodes univariées mises en œuvre par Giordana et Gueddoudj (Cahier BCL 103), le modèle à composantes inobservées permet (i) d'estimer la durée et l'amplitude des cycles à partir des données, (ii) d'effectuer une décomposition cycle-tendance de manière simultanée pour plusieurs variables réelles et financières, en tenant compte d'éventuels liens entre variables et (iii) de quantifier l'incertitude statistique de façon formelle.

Selon nos résultats, l'économie luxembourgeoise se trouvait proche de sa tendance de long terme au cours des deux premiers trimestres de 2018. En particulier, le PIB réel se trouvait près de son niveau tendanciel, avec un écart de production pratiquement nul en 2018. Quant aux prix immobiliers, leur composante cyclique affichait des valeurs très limitées en 2018. Ce résultat confirme les conclusions d'analyses plus structurelles de l'offre et de la demande pour le marché immobilier luxembourgeois. Ainsi, en 2018 la Revue de Stabilité Financière de la BCL a noté que "les indicateurs suggèrent une évolution des prix immobiliers plus ou moins en ligne avec les fondamentaux". D'autre part, le FMI, lors de sa consultation de

2018 au titre de l'Article IV, a remarqué que les prix immobiliers semblent cohérents avec les tendances sous-jacentes du marché. Concernant les prêts bancaires au secteur privé non financier, ils se situaient légèrement au-dessus de leur tendance historique, tandis que les prêts aux ménages avaient rejoint leur tendance après un pic cyclique en 2009. Finalement, les prêts aux sociétés non financières s'étaient rétablis après un creux prononcé en 2014 et se trouvaient, au début 2018, légèrement au-dessus de leur tendance de long terme.

"The old and apparently still persistent notion of 'the' business cycle, as a single, simple, self-generating cycle [. . . ] is a myth. Instead of one cycle, there are many co-existing cycles, constantly aggravating or neutralizing each other, as well as co-existing with many non-cyclical forces."

— Irving Fisher (1933), p. 338.

## 1. Introduction

In pursuing price stability, central banks generally act to limit deviations from potential GDP, a concept that reflects sustainable long-run growth. The "business cycle" refers to GDP fluctuations around this trend, but also to related cycles in other real variables such as productivity, consumption, investment, hours worked, labor market participation, and unemployment. The Great Financial Crisis reminded economists that this "business cycle" may be linked to a separate "financial cycle" that affects asset prices, credit volumes, and leverage among households, firms, and financial institutions.[1] Central bank interest in this "financial cycle" is motivated not only by the need to calibrate new macro-prudential tools, but also by the impact that the financial cycle can have on the outlook for the real economy and for price stability.

Regarding Luxembourg, in November 2017 the European Central Bank Financial Stability Review noted that credit to the non-financial private sector was "buoyant." In the context of the European Semester, the March 2018 European Commission country report for Luxembourg noted that house prices continued to rise and that household indebtedness represented a potential source of risk. In April 2018, the International Monetary Fund Article IV consultation with Luxembourg also concluded that rising real estate prices could lead to excessive household indebtedness.

In this policy context, it is important to assess the position of real and financial variables relative to their historical trend. Giordana and Gueddoudj (2016) presented a first attempt to characterize the financial cycle in Luxembourg using turning point analysis and univariate band-pass filters. This paper extends their analysis in several directions.

First, Giordana and Gueddoudj followed Drehmann, Borio, and Tsatsaronis (2012) in using the Christiano-Fitzgerald (2003) band-pass filter and turning point analysis. However, these methods require *ex ante* choices regarding the length of the cycle that are inevitably arbitrary at some level and restrict the duration of the cycles that one then extracts from the data.[2] Instead, we prefer to estimate the structural time series models with unobserved

[1]The work by Irving Fisher (1933) is an early example of these real-financial linkages. Borio (2014) describes the resurgence of the "financial cycle" in economic thought.

[2]An additional limitation of the Christiano-Fitzgerald filter, shared with the Baxter-King filter, is that it is subject to leakages across frequencies. The Corbae-Ouliaris (2006) filter provides a better approximation of the ideal band-pass filter by resorting to frequency domain methods.

components introduced by Harvey (1991) and Harvey and Koopman (1997). Not only are these models agnostic *a priori* about the duration and amplitude of cycles in the data, but their estimated parameters allow proper inference about duration and amplitude, as well as formal testing of statistical hypotheses.

Second, while Giordana and Gueddoudj analyze each variable in isolation, we prefer the multivariate approach in Chen, Kontonikas, and Montagnoli (2012), Galati, Hindrayanto, Koopman, and Vlekke (2016), Melolinna and Tóth (2016), Rünstler and Vlekke (2015, 2018), or Rots (2018). These studies conduct a joint trend-cycle decomposition of several financial variables simultaneously and allow cyclical fluctuations in financial variables to interact with real cycles in GDP. A team from the ESCB Working Group on Econometric Modelling developed Bayesian estimation codes for this purpose that we apply below to long quarterly series for Luxembourg. The report produced by the WGEM team was published as WGEM (2018).

Third, our unobserved components approach allows a more careful analysis of uncertainty. For example, we explore model uncertainty by comparing univariate and multivariate estimates of cycle duration, persistence, and volatility. We also consider data uncertainty by comparing one-sided filtered estimates of the cycle (similar to real-time estimates) to two-sided smoothed estimates. Finally, we evaluate parameter uncertainty by comparing full-sample estimates of the cycle to filtered estimates based on parameters estimated on the subsample up to 2007Q3, when the financial crisis began to unfold.

Our main finding is that in mid 2018 both real and financial cycles in Luxembourg were close to zero. In particular, the cyclical component in house prices took only very limited values in 2018. This result is consistent with the conclusions of more structural analyses of supply and demand factors in the Luxembourg housing market. Indeed, in 2018 the BCL Financial Stability Review noted that the evolution of house prices was more or less in line with economic fundamentals. Similarly, the IMF remarked in its 2018 Article IV survey of Luxembourg that “house prices appear consistent with underlying trends.”

Total bank loans to the private non-financial sector were only slightly above their historical trend, while the cyclical component of loans to households declined since 2009 and remained close to zero. Finally, loans to non-financial corporations recovered from a deep trough in 2014 and were moderately above trend. These findings are consistent with those based on more standard band-pass filters, both as provided here and as published in the BCL Revue de Stabilité Financière.

Section 2 below provides a brief review of the recent literature on real and financial cycles. Section 3 describes our empirical approach and describes the data. Section 4 then reports the resulting stylized facts about real and financial cycles in Luxembourg, while Section 5 reports the results of several robustness checks evaluating different sources of uncertainty. Finally, Section 6 concludes.

## 2. An Overview of the Literature on Real and Financial Cycles

The Great Financial Crisis drew attention to the links between financial variables and the real economy. At the time, theoretical models focused on the role of collateral constraints, as in the "financial accelerator" model developed by Bernanke, Gertler, and Gilchrist (1996, 1999) or the model of credit cycles developed by Kiyotaki and Moore (1997). However, in these models financial factors only amplify the magnitude or enhance the persistence of economic shocks. Borio (2014), among others, argued that financial crises cannot be captured adequately by simply grafting such "financial frictions" onto otherwise well-behaved general equilibrium models, because they lack the medium-term perspective needed to understand the financial cycle, which is longer than the business cycle.

In fact, Claessens, Kose, and Terrones (2011, 2012) provided evidence that financial cycles are characterized by longer duration and greater amplitude than conventional business cycles. This finding resulted from turning point analysis and univariate band-pass filters applied to real and financial variables from a set of advanced and emerging market economies. Aikman, Haldane, and Nelson (2015) and Hiebert, Peltonen, and Schüler (2015) reached similar conclusions using estimated spectral densities. This frequency domain approach had already appeared in Comin and Gertler (2006), who identified medium-term cycles in US GDP but did not consider possible links to financial cycles.

Claessens, Kose, and Terrones (2012) noted that business cycle recessions accompanied by financial disruptions tend to be longer and deeper. Similarly, Jordà, Schularick, and Taylor (2013) observed that more credit-intensive booms often lead to deeper recessions and slower recoveries. Hubrich et al. (2013) also reported evidence suggesting that the link between financial variables and output was tighter during recessions than during recoveries. All these observations seem consistent with claims by Schularick and Taylor (2012), Gourinchas and Obstfeld (2012), and Aikman, Haldane, and Nelson (2015) that lagged credit growth is a significant predictor of financial crises.

However, these studies assume that financial crises and recessions are known *a priori*, treating them as isolated exogenous events and focusing on the behavior of the economy near the identified turning points. Instead, Gadea Rivas and Perez-Quiros (2015) stress the uncertain nature of recession dating in real time, noting that while the credit-to-GDP ratio may be high before turning points, it is often high and rising throughout long expansions without triggering a recession until the end. Their empirical results confirm that credit build-up significantly affects economic growth, while credit does not appear to improve turning-point forecasts once the uncertainty in dating recessions is taken into account. These authors conclude that credit may help to describe the past in full-sample analysis, but cannot help to infer the future out-of-sample.

The complexity of the link between credit and the real economy is also illustrated by the literature on "creditless recoveries," including Biggs, Mayer, and Pick (2009), Abiad, Dell'Ariccia, and Li (2011), and Takáts and Upper (2013), who found that declining bank credit to the private sector is not necessarily harmful to growth. There is also evidence that fluctuations in financial variables can serve to predict output growth throughout the cycle, and not just financial crises. This more applied literature includes Goodhart and Hofmann (2008), Adrian, Estrella, and Shin (2010), Ng (2011), Guarda and Jeanfils (2012), and Hubrich et al. (2013).

Our analysis below limits itself to the trend-cycle decomposition of real and financial variables in Luxembourg. We ask whether the common finding that financial cycles are longer than real cycles also applies for the Luxembourg economy. We also estimate the amplitude and persistence of cycles in different variables and test for similar cycles. Finally, we quantify the links across real and financial cycles in Luxembourg.

## 3. Empirical Approach

In this section, we set up the structural time series model used to extract the real and financial cycles from the data. We also discuss the estimation method. Finally, we provide a brief description of our dataset.

3.1. **The unobserved components time series model.** Let $y_t$ denote a vector of $n$ time series observed at dates $t = 1, \ldots, T$. Following Harvey and Koopman (1997), the *unobserved components time series model* (UCTSM) decomposes $y_t$ into three components: a trend $\mu_t$, a cycle $x_t$, and an irregular component $\epsilon_t$:

$$y_t = \mu_t + x_t + \epsilon_t.$$

The three components are not separately observed, hence the name of the model. Instead, identification is achieved through statistical restrictions on the behavior of each component.

First, the vector of irregular components $\epsilon_t$ is assumed to be normally and independently distributed with mean zero and diagonal covariance matrix $\Sigma_\epsilon$:

$$\epsilon_t \sim \mathcal{N}(0_n, \Sigma_\epsilon).$$

Therefore, all irregular components are by construction orthogonal one to another.

Second, the vector of stochastic trends evolves according to

$$\begin{aligned}\mu_t &= \mu_{t-1} + \beta_{t-1} + \eta_t,\\ \beta_t &= \beta_{t-1} + \zeta_t,\end{aligned}$$

with

$$\eta_t \sim \mathcal{N}(0_n, \Sigma_\eta), \quad \zeta_t \sim \mathcal{N}(0_n, \Sigma_\zeta).$$

This specification assumes seemingly unrelated trends, as the covariance matrices $\Sigma_\eta$ and $\Sigma_\zeta$ may not be diagonal. The standard deviations of the level and slope innovations associated with variable $i$, respectively $\eta_{it}$ and $\zeta_{it}$, control the smoothness of its trend. If $\sigma_{\zeta i} = 0$, the trend reduces to a random walk with drift that is not very smooth. If in addition $\sigma_{\eta i} = 0$, it becomes a deterministic linear time trend. Instead, if $\sigma_{\eta i} = 0$ and $\sigma_{\zeta i} > 0$, the trend turns into an integrated random walk that is relatively smooth.[3] A key part of our empirical analysis will thus be to determine the appropriate degree of smoothness of the trends, which will determine the relative importance of the trend and cyclical components.

Third, the vector of cyclical components is specified as in Rünstler and Vlekke (2015):

$$x_t = A\psi_t + A^\star \psi_t^\star,$$

where $A$ and $A^\star$ are generic real matrices of size $n \times n$, $\psi_t = (\psi_{1t}, \ldots, \psi_{nt})'$ and $\psi_t^\star = (\psi_{1t}^\star, \ldots, \psi_{nt}^\star)'$ are two $n \times 1$ vectors of stochastic cycles evolving according to

$$(1 - \phi_i L)\left(I_2 - \rho_i \begin{bmatrix} \cos\lambda_i & \sin\lambda_i \\ -\sin\lambda_i & \cos\lambda_i \end{bmatrix} L\right)\begin{bmatrix} \psi_{it} \\ \psi_{it}^\star \end{bmatrix} = \begin{bmatrix} \kappa_{it} \\ \kappa_{it}^\star \end{bmatrix}, \; i = 1, \ldots, n,$$

where $L$ is the lag operator and

$$\begin{bmatrix} \kappa_{it} \\ \kappa_{it}^\star \end{bmatrix} \sim \mathcal{N}(0_2, \sigma_{\kappa i}^2 I_2).$$

Here, $0 \leq \lambda_i \leq \pi$ is the frequency in radians of the stochastic cycle $\psi_{it}$, while $0 < \phi_i, \rho_i < 1$ measure its decay. Compared to the simpler specification of stochastic cycles in Harvey (1991), introducing a second autoregressive root helps to match the high persistence of macroeconomic and financial variables. Additional zero restrictions on the entries of $A$ and $A^\star$ are necessary to ensure identification.

When discussing our empirical results, we find it convenient to report the standard deviations of the cyclical component, which we denote $\sigma_c = \mathrm{std}(x_t)$, instead of the standard deviations of the innovations, $\sigma_\kappa$. Indeed, while $\sigma_c$ is not a structural parameter of the model, in the sense that it depends on $\phi$, $\rho$, and $\sigma_\kappa$, it has a more natural interpretation since it measures directly the cyclical volatility of the variable.[4]

Finally, as discussed in Durbin and Koopman (2012), the model is closed by appropriate initial conditions for the trend and cyclical components.

3.2. **Estimation.** We estimate the model by Bayesian methods. To form the likelihood function of our sample $(y_1, \ldots, y_T)$, we use the state-space representation of the UCTSM:

$$y_t = Z\alpha_{t-1} + u_t,$$
$$\alpha_t = W\alpha_{t-1} + v_t,$$

where $Z$ and $W$ are matrices reflecting the structure of the model, $\alpha_t$ is an unobserved state vector containing the trends and cyclical components of interest, and $u_t$ and $v_t$ are two

[3]More generally, Harvey and Trimbur (2003) discuss how to fine-tune the smoothness of the trend by increasing its integration order.

[4]In the univariate setting, the cyclical variance is given by $\sigma_c^2 = \sigma_\kappa^2/[(1-\rho^2)(1-\phi^2)]$.

vectors of shocks appropriately formed from the model's various disturbances. We complete the likelihood function by formulating a prior distribution for the model parameters.[5]

Given the resulting estimates, we use the Kalman smoothing recursion to infer the sample realizations of the unobserved trend, cyclical, and irregular components of the series. In Section 4, we use efficient full-sample estimates $\alpha_{t|T} = E(\alpha_t|y_1, \ldots, y_T)$ to discuss the properties of real and financial cycles in Luxembourg. In Section 5, we rely instead on real-time estimates $\alpha_{t|t} = E(\alpha_t|y_1, \ldots, y_t)$ to study the ability of the model to track economic developments in real time.

3.3. **Data.** We extract the real and financial cycles from quarterly time series of real GDP ($Y_t$), real credit ($C_t$), and real residential property (house) prices ($P_t$) for Luxembourg.

Since financial cycles are generally longer than business cycles, they require a long sample period for their study. Quarterly data for Luxembourg GDP is only available starting in 1995Q1, so we have to extend it back to 1980Q1 by applying the Chow-Lin interpolation to the annual series in the European Commission AMECO database. The quarterly series for Luxembourg house prices is only available starting in 2007Q1, so we extend it back to 1980Q1 by interpolating the annual residential property price index calculated by the BCL. Regarding credit to the private non-financial sector, we avoid the broad measure from the BIS dataset because it appears to include a significant volume of bonds issued by multinationals on the Luxembourg stock market: this measure of credit reflects economic activity abroad, bearing little relationship to Luxembourg's GDP. Instead, we focus on bank loans to resident households[6] and bank loans to resident non-financial corporations, as well as the sum of these variables, which we refer to as bank loans to the private non-financial sector. Quarterly data on bank loans is only available starting in 1997Q4 , so we extend it back to 1980Q1 using the growth rates from internal estimates of bank loans to euro area households and non-financial corporations.[7] The estimation sample ends in 2018Q2.

[5]We assume standard Beta distributions for the autoregressive coefficients $\phi$ and $\rho$, constrained to the range [0, 1). We assume a Gamma distribution for the $\lambda$ parameter controlling the cycle frequency and an Inverse Gamma distribution for the $\sigma$ parameters capturing the standard deviation of the innovations, constraining them to be non-negative. Finally, we assume Normal distributions centered at zero for the parameters capturing the covariances and correlations between innovations in multivariate models. Tables 4 to 6 in Appendix A provide more information on the prior distributions. See Harvey, Trimbur, and Van Dijk (2007) for a discussion of prior distributions for UCTSMs.

[6]Mortgages represent nearly 85% of all bank loans to households, so the results are qualitatively unaffected when the analysis is repeated with mortgages only.

[7]These internal estimates may be of poorer quality, but they make it possible to use a longer sample, as required to study financial cycles. Since this data-induced uncertainty only affects the first half of the sample, we expect estimated cycles for recent observations to be less affected.

We use the Tramo-Seats software package to seasonally adjust all variables. Real GDP is available in chain-linked volumes, while the financial series are deflated using the national index of consumer prices.[8] All variables enter the model in logarithms.

## 4. Stylized Facts on Financial Cycles in Luxembourg

This section reports our main findings. We present the estimates of real and financial cycles in Luxembourg obtained from the UCTSMs and discuss their properties, establishing a set of stylized facts. Furthermore, we compare our results with those derived from the more common Christiano-Fitzgerald band-pass filter.

Following Rünstler and Vlekke (2015), we restrict the standard deviations of the slope innovations $\zeta_t$ to 0.001 in all our estimation exercises. This restriction, which can be seen as an infinitely tight prior in our Bayesian framework, ensures that the UCTSMs identify trends that are relatively smooth and evolve slowly over time. Without this constraint, medium-term movements in the variables would be largely reflected in the trend component, although we wish to capture them in the cyclical component.

4.1. **Univariate estimates.** As a first pass at establishing the core properties of the variables, we start by fitting univariate models to the series. This step is also useful for testing purposes, as it allows us to assess whether the parameters defining cyclical behavior are the same across variables. We report selected point estimates in Table 1 and plot the resulting decompositions in Figures 1 to 5. Table 4 in the appendix presents the full set of estimates.

Consider first the top panel of Table 1, which shows the results for unrestricted univariate models. In the first row, we see that the UCTSM extracts GDP cycles slightly longer than standard business cycles, with a period just above 8 years. These real cycles are fairly persistent, with autoregressive coefficients close to 0.70. Rows 2 to 4 correspond to the credit variables. The point estimates of the cyclical parameters imply three notable features: (i) Credit cycles are longer than the standard business cycle, with a period ranging from 12 to 18 years. (ii) They are also more persistent, as shown by the larger autoregressive parameters. (iii) Lastly, credit cycles are more volatile than real cycles, especially for total bank loans and bank loans to non-financial corporations. Looking at the fourth row, we find that the cyclical component of real house prices has similar properties, as it is associated with a long period of about 18 years, autoregressive coefficients above 0.80, and a high standard deviation.

Figures 1 to 5 provide a visual representation of the decompositions. In Figure 1, we can see that the trend in GDP is flexible enough to track most variations in the level of the

[8]Our results are not sensitive to using alternative price indicators such as the GDP deflator or the Harmonized index of consumer prices.

Table 1. Cyclical estimates for univariate UCTSM models.

| | Persistence | | Period (years) | Volatility |
|---|---|---|---|---|
| | $\phi$ | $\rho$ | $2\pi/4\lambda$ | $\sigma_c$ |
| *Unrestricted models* | | | | |
| GDP $Y$ | 0.73 | 0.70 | 8.23 | 0.03 |
| Bank loans to private non-financial sector $C_T$ | 0.90 | 0.91 | 13.64 | 0.11 |
| Bank loans to households $C_H$ | 0.86 | 0.89 | 17.79 | 0.06 |
| Bank loans to non-financial corporations $C_{NFC}$ | 0.85 | 0.88 | 11.86 | 0.17 |
| House prices $P$ | 0.84 | 0.93 | 17.55 | 0.15 |
| *Restricted model: Similar cycles in bank loans to private non-financial sector and house prices* | | | | |
| Bank loans to private non-financial sector $C_T$ | 0.87 | 0.91 | 16.82 | 0.10 |
| House prices $P$ | 0.87 | 0.91 | 16.82 | 0.15 |
| Bayes factor: $BF = 0.38$ | | | | |
| *Restricted model: Similar cycles in bank loans to households and house prices* | | | | |
| Bank loans to households $C_H$ | 0.80 | 0.93 | 18.12 | 0.06 |
| House prices $P$ | 0.80 | 0.93 | 18.12 | 0.16 |
| Bayes factor: $BF = 0.04$ | | | | |
| *Restricted model: Similar cycles in bank loans to non-financial corporations and house prices* | | | | |
| Bank loans to non-financial corporations $C_{NFC}$ | 0.84 | 0.90 | 16.00 | 0.21 |
| House prices $P$ | 0.84 | 0.90 | 16.00 | 0.12 |
| Bayes factor: $BF = 1.87$ | | | | |

*Note.* The estimates are posterior means computed from the random-walk Metropolis-Hastings algorithm with two chains of 50,000 draws each. Parameters $\phi$ and $\rho$ measure the persistence of the cyclical component, $2\pi/4\lambda$ is its period (expressed in years), and $\sigma_c$ is its standard deviation. For restricted models, the Bayes factors test the null hypothesis of common cycles across credit ($C$) and house prices ($P$): $\phi_C = \phi_P$, $\rho_C = \rho_P$, and $\lambda_C = \lambda_P$. A value of $BF$ below one signals that the data support the restrictions.

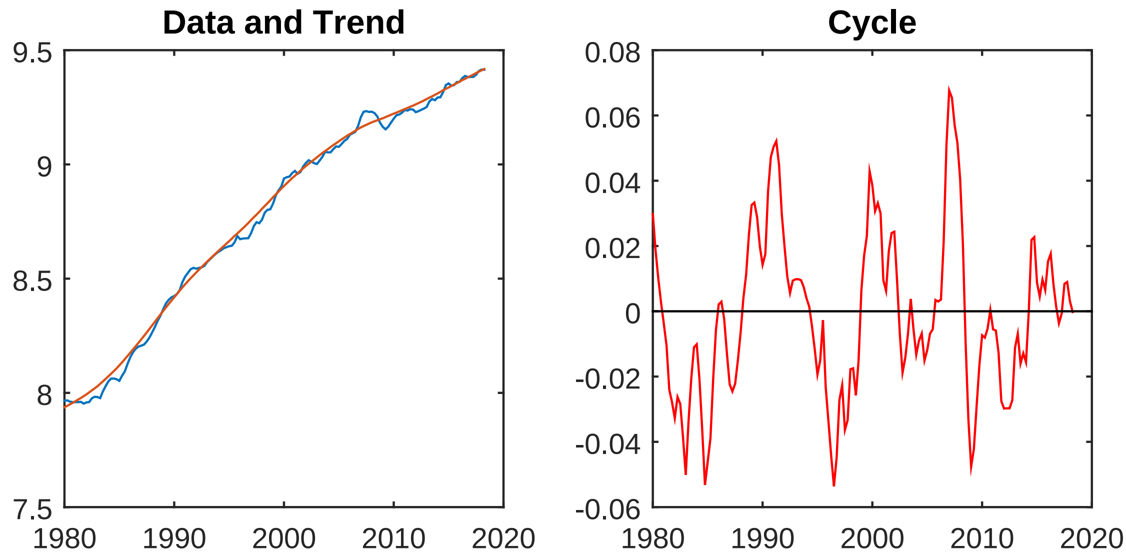
series, resulting in real cycles that last less than 10 years and are of plausible amplitude.[9] Instead, it is clear from Figures 2 to 5 that the trends in real credit and house prices ignore much of the medium-term fluctuations, resulting in long-lasting financial cycles with larger amplitude.[10] We also note that the cyclical components extracted from the credit variables, although not identical, follow relatively similar patterns over time. Hence, they may convey similar information regarding the state of the financial cycle in Luxembourg.

These decompositions also provide an interpretation of recent economic developments in Luxembourg. Between 2005 and 2007-2009, Luxembourg experienced a period of sustained

[9]Peaks and troughs broadly match those of an output gap estimate obtained using a Hodrick-Prescott filter with standard settings. In particular, the 2007Q2 peak is around 6% and the 2009Q2 trough is around -5%. Both approaches find a cyclical component near zero in 2018Q1 and Q2.

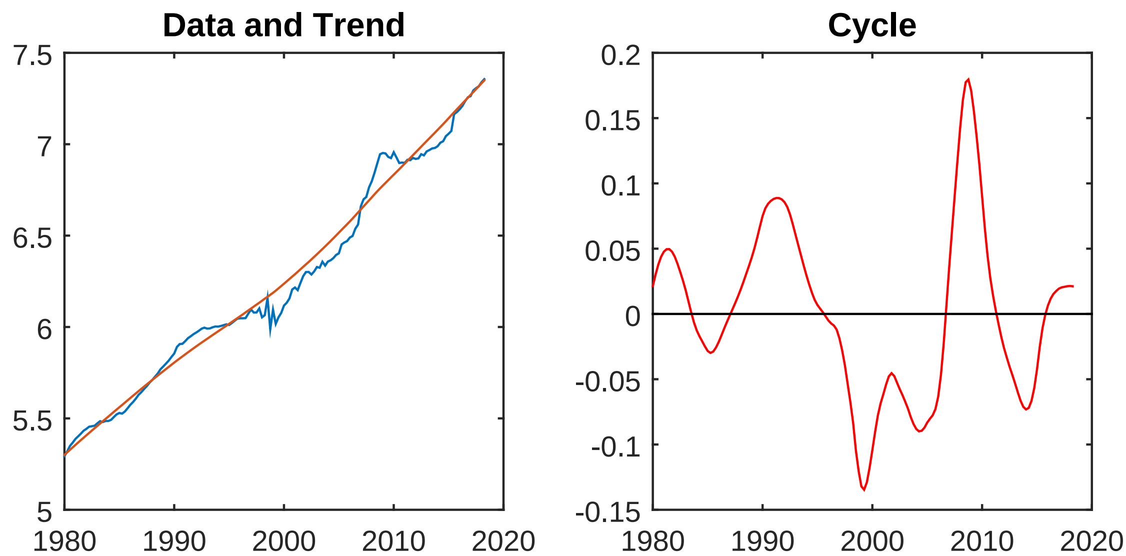
[10]The cycles in real credit are much more smooth than those in real GDP or house prices. This reflects the lower short-term volatility of credit, which is a stock variable.

FIGURE 1. Univariate trend-cycle decomposition: GDP.



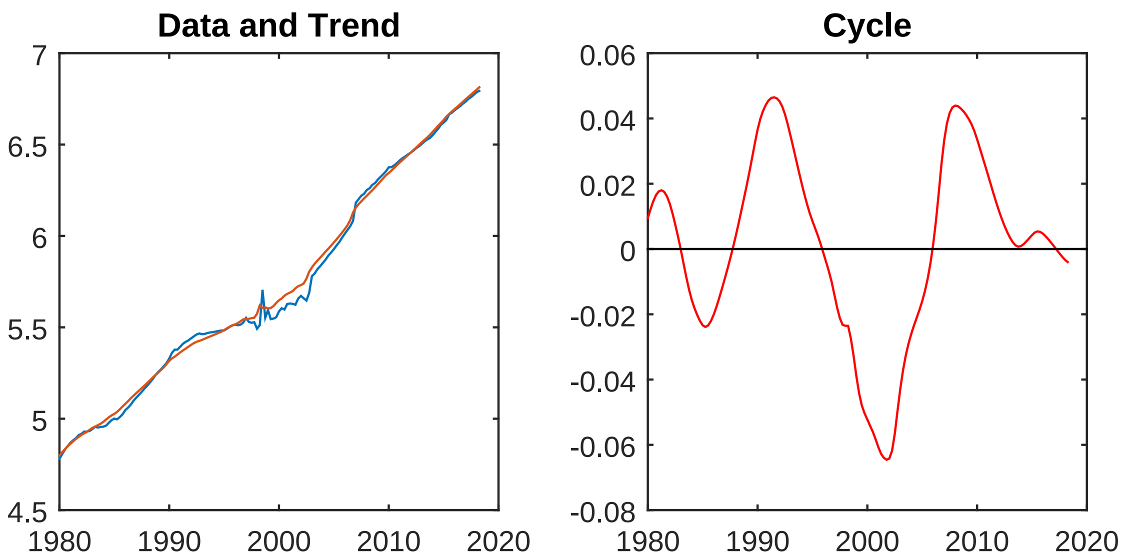

*Notes.* The original time series (in natural logs, seasonally adjusted) appears in dark blue, while the full-sample smoothed estimates of the model-based components are in red.

FIGURE 2. Univariate trend-cycle decomposition: Bank loans to private non-financial sector.



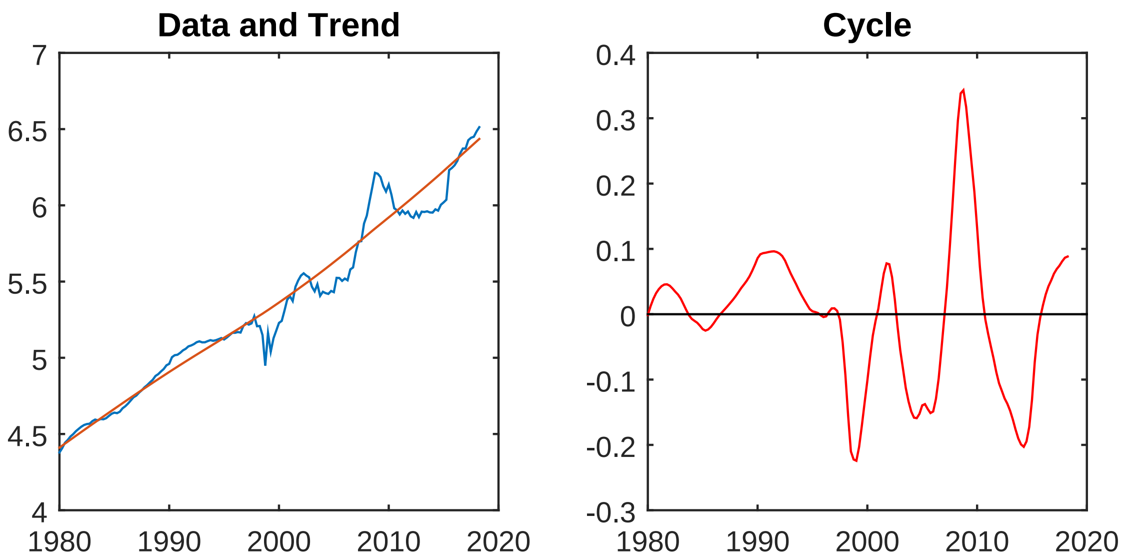

*Notes.* The original time series (in natural logs, seasonally adjusted) appears in dark blue, while the full-sample smoothed estimates of the model-based components are in red.

FIGURE 3. Univariate trend-cycle decomposition: Bank loans to households.



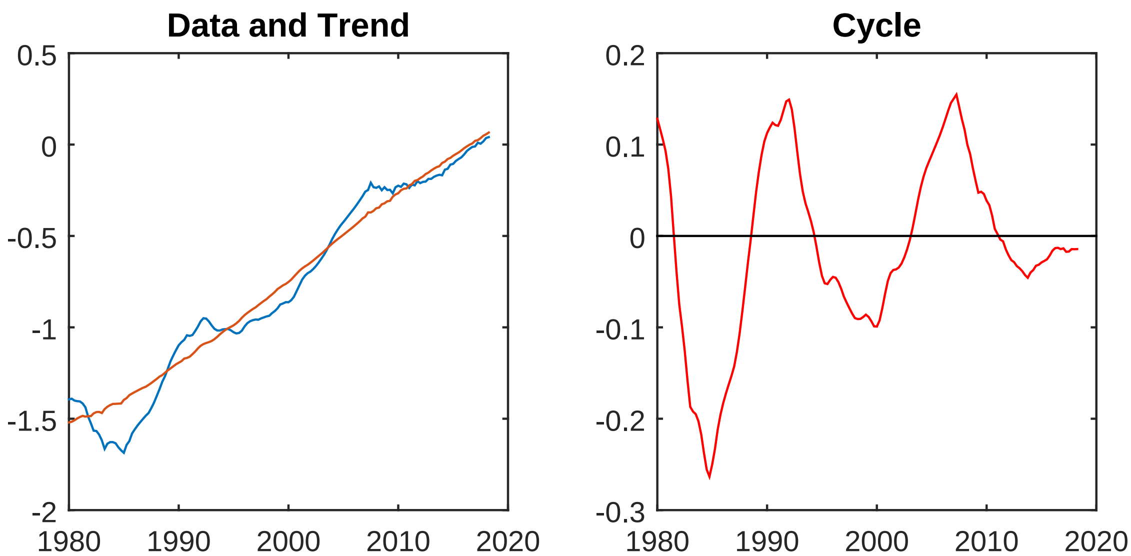

*Notes.* The original time series (in natural logs, seasonally adjusted) appears in dark blue, while the full-sample smoothed estimates of the model-based components are in red.

FIGURE 4. Univariate trend-cycle decomposition: Bank loans to non-financial corporations.




*Notes.* The original time series (in natural logs, seasonally adjusted) appears in dark blue, while the full-sample smoothed estimates of the model-based components are in red.

FIGURE 5. Univariate trend-cycle decomposition: Real house prices.




*Notes.* The original time series (in natural logs, seasonally adjusted) appears in dark blue, while the full-sample smoothed estimates of the model-based components are in red.

growth in credit and house prices. All financial cycle estimates turned positive, reaching peaks ranging from 5 to 35% with respect to the long-run trend. Retrospectively, this now appears as a time of growing financial risk. After 2007 and the onset of the economic crisis, the cycle in house prices began to decline and the cycle in credit quickly followed. The cyclical downturn in house prices lasted until 2013, while credit dynamics were slightly more complex. In particular, loans to non-financial corporations reached a through in 2014 and are recovering since then, while the positive cycle in loans to resident households was much smaller leading up to the crisis but also appears to be more persistent. As for the current situation, the estimates suggest that in mid 2018 the financial cycle in Luxembourg is close to zero. There is no evidence of a positive cyclical component in house prices. Bank loans to non-financial corporations are progressively recovering from the last recession and loans to households are close to their long-term trend.

The next step of our analysis is to test whether the financial variables share *similar cycles*, meaning that the parameters defining the persistence and the period of the cyclical components are the same across variables.[11] Indeed, the unrestricted univariate models suggest that the cyclical components in bank loans and in house prices share important properties that could reflect common dynamics, which could in turn be interpreted as defining the financial cycle in Luxembourg. Here, we use the Bayes factor to test the joint

[11]We do not consider the possibility that all series — that is, both GDP and financial variables — share similar cycles. Our unrestricted point estimates strongly suggest that this is not the case, and Rünstler and Vlekke (2015) show that this restriction is rejected for the five largest Euro area countries.

null hypothesis that $\phi_C = \phi_P$ and $\rho_C = \rho_P$ and $\lambda_C = \lambda_P$, where $C$ refers to credit and $P$ to house prices.[12]

We run a separate test for each of our three measures of credit. We report the associated restricted parameter estimates in the bottom panels of Table 1. For total bank loans to the private non-financial sector and for bank loans to households, the Bayes factors indicate that the restrictions are supported by the data. Furthermore, for these two credit variables the common parameters estimated in the restricted model do not differ much from those estimated in the unrestricted model, except for a marked rise in the period of credit cycles. On the other hand, the similar-cycle restriction is rejected for bank loans to non-financial corporations, mostly because the cycle in this credit variable has a shorter period than the cycle in house prices.

Overall, the results provide strong empirical evidence that in Luxembourg real bank loans to the private non-financial sector and to households share similar cycles with house prices. In the next section, we embed this property in a multivariate UCTSM. However, since bank loans to non-financial corporations appear to have distinct cyclical behavior, we exclude this variable from the multivariate model. The latter identifies financial cycles based on joint movements in GDP, house prices, and bank loans to the private non-financial sector or bank loans to households.

4.2. **Multivariate estimates.** Univariate models assume that the cyclical components extracted from two different variables are statistically independent. On this basis, the estimated cycles would be of little use to study the relationship between real and financial variables. We address this shortcoming by turning to multivariate UCTSMs. Namely, we estimate a tri-variate model including real GDP, real house prices, and real credit (we consider bank loans to the private non-financial sector and bank loans to households). Allowing for contemporaneous correlations among the innovations to the trend components and defining all the cyclical components from the same set of stochastic cycles ($A$ and $A^\star$ are no longer identity matrices), these multivariate UCTSMs are tailored to study joint dynamics in a common framework. In light of our univariate estimates, we further impose similar cycles for the two financial variables (credit and house prices).

In multivariate models, the interpretation of parameters differs from the univariate case because the cyclical coefficients $\phi$, $\rho$, and $\lambda$ pertain to the stochastic cycles $\psi_t$ and $\psi_t^\star$, which are now combined in the unobserved cyclical components $x_t$. To characterize the latter, we follow Rünstler and Vlekke (2015) and rely on the spectral generating function implied by the estimated UCTSMs. We present in Table 2 some key statistics for the cyclical components obtained from the tri-variate models and relegate the point estimates

[12]The Bayes factor assesses the relative likelihood of two competing hypotheses. Given the unrestricted model $M_u$, the restricted model $M_r$, and the dataset $D$, the Bayes factor is defined as $BF = P(D \mid M_u)/P(D \mid M_r)$. Hence, $BF < 1$ provides evidence in favor of the restricted model $M_r$.

Table 2. Cyclical estimates for multivariate models.

| Model estimated from bank loans to private non-financial sector | | | | | Model estimated from bank loans to households | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | $Y$ | $C_T$ | $P$ | | | $Y$ | $C_H$ | $P$ |
| Period | $2\pi/4\lambda$ | 9.87 | 15.78 | 16.07 | Period | $2\pi/4\lambda$ | 9.39 | 14.43 | 14.52 |
| Volatility | $\sigma_c$ | 0.07 | 0.12 | 0.16 | Volatility | $\sigma_c$ | 0.06 | 0.07 | 0.13 |
| | | Phase shift (years) | | | | | Phase shift (years) | | |
| | | $Y$ | $C_T$ | $P$ | | | $Y$ | $C_H$ | $P$ |
| | $Y$ | | 3.61 | −0.68 | | $Y$ | | 3.65 | −1.15 |
| Coherence | $C_T$ | 0.41 | | 3.08 | Coherence | $C_H$ | 0.46 | | 1.72 |
| | $P$ | 0.53 | 0.47 | | | $P$ | 0.67 | 0.84 | |

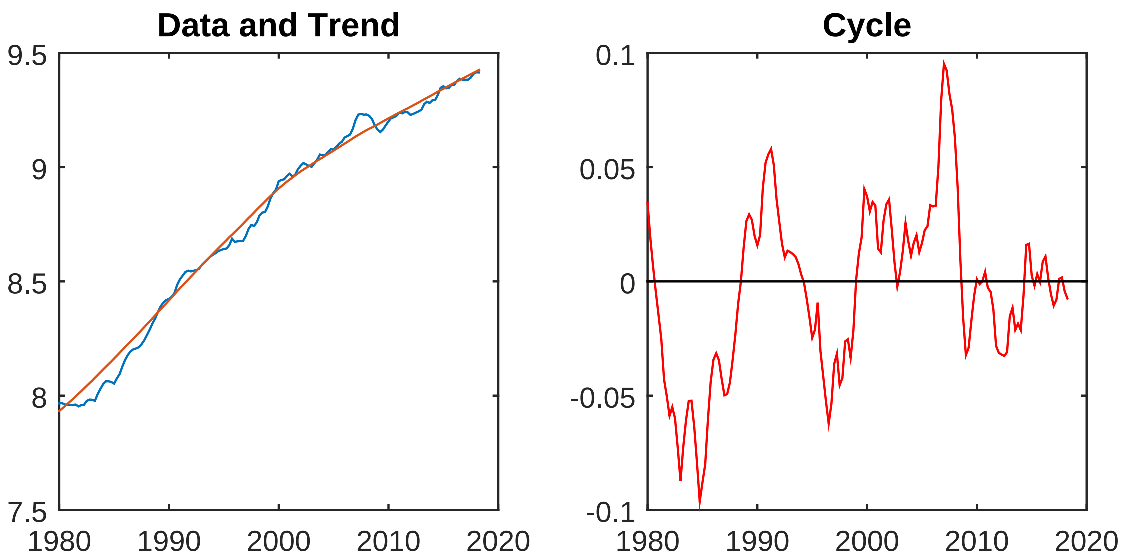
*Note.* The estimates correspond to posterior means, computed from the random-walk Metropolis-Hastings algorithm with two chains of 50,000 draws each. $\sigma_c$ corresponds to the standard deviation of the cyclical component. Coherences and phase shifts are averages over all frequencies. A positive phase shift means that the row series leads the column series. Reported coherences and phase shifts are all statistically significant at the 5% level.

of the parameters to Tables 5 and 6 in Appendix A. Visually, the associated trend-cycle decompositions strongly resemble those obtained from univariate models and are omitted to save space. One exception is real GDP, whose estimated trend becomes much smoother in the multivariate models as illustrated in Figure 6.

We obtain three main results. First, estimated GDP cycles for Luxembourg have a longer period and a larger amplitude when obtained from multivariate UCTSMs rather than from univariate models. Indeed, while the average cycle length for GDP is about 8 years in Table 1, it ranges from 9 to about 10 years in Table 2. This falls outside the 8 to 32 quarters conventionally regarded as business-cycle frequencies. Furthermore, the volatility of the estimated GDP cycle increases by more than half and reaches 7%. Hence, estimating the GDP and financial cycles jointly attributes more of the medium-term movements in output to the cycle and less to the trend, as is visible when comparing the decomposition in Figure 6 with that in Figure 1. Rünstler and Vlekke (2015) obtain similar results using data from the US and the largest European economies.

Second, we confirm that the financial cycle in Luxembourg is typically longer and more pronounced than the GDP cycle. In particular, the average length for both credit and house prices cycles is close to 15 years and their standard deviations range from 7% to 16%. Contrasting these estimates with those derived from univariate decompositions, we see that joint estimation increases the length of credit cycles and lowers the length of house price cycles. This is an immediate consequence of the similar-cycle assumption but, as demonstrated by the statistical tests reported above, it involves no significant loss of fit.

FIGURE 6. Multivariate trend-cycle decomposition: Real GDP.




*Notes.* The original time series (in natural logs, seasonally adjusted) appears in dark blue, while the full-sample smoothed estimates of the model-based components are in red.

Third, we find a close link between real and financial cycles in Luxembourg. Table 2 reports the coherence between cycles, a symmetric measure ranging between 0 and 1 (see Croux, Forni, and Reichlin, 2001). The coherence between GDP cycles and credit cycles ranges from 0.40 to 0.45, and the coherence between GDP cycles and house price cycles is even higher. The coherence between house prices and bank loans to households is very high at 0.84, nearly twice the coherence between house prices and bank loans to the private non-financial sector. This probably reflects the overwhelming share of mortgages in bank loans to households. These statistics, which are computed as averages over the whole frequency band, suggest a strong relationship between the three time series. In particular, the high coherence between GDP cycles and financial cycles may explain why the former are longer when estimated by multivariate rather than univariate methods.

The phase shifts provide further information by identifying lead-lag patterns. As can be seen from the table, credit cycles tend to lag GDP cycles in Luxembourg by about 3 years. Using the Corbae-Ouliaris filter, Igan, Kabundi, Nadal de Simone, Pinheiro, and Tamirisa (2011) found that credit cycles lag GDP cycles in 7 out of 18 advanced economies (Luxembourg excluded), while they lead in 8 countries. WGEM (2018) also reported that credit cycles lag GDP cycles on average across 17 EU countries. Table 2 also indicates that Luxembourg house price cycles are roughly coincident with GDP cycles, a situation that Igan et al. found in 7 out of 18 countries. Averaging across 17 EU countries, WGEM (2018) reported that house price cycles lag GDP cycles by only 3-4 months. Finally, Table 2 indicates that in Luxembourg credit cycles lag cycles in house prices. Igan et al. found a similar result in 9 out of 18 countries, with house price cycles leading in only 5 countries. For the 10 EU countries with longer samples, WGEM (2018) reported that credit cycles lag house price cycles by just over 3 months on average.

It is also interesting to contrast our estimates of duration and amplitude for Luxembourg with those obtained for other countries with the same empirical approach (Rünstler and Vlekke, 2015).[13] In terms of GDP cycles, an average length of 9 years in Luxembourg is very much in line with the estimates for France, Italy, the UK, and the US.[14] The output cycle in Luxembourg appears more volatile than in these other countries, which may not be very surprising given the size of the economy, its openness, and its sensitivity to foreign shocks.[15] Regarding credit and house prices cycles, Luxembourg is very similar to France or Italy.[16]

4.3. **Comparison with the Christiano-Fitzgerald filter.** We close this section with a comparison between our UCTSMs and the band-pass filter of Christiano and Fitzgerald (2003, CF hereafter), which provides an alternative tool to extract real and financial cycles from the data. Without going into too much detail, band-pass filters decompose time series into orthogonal contributions located at different frequencies and identify the cyclical components by selecting only the contributions from a specified frequency band. This is in contrast with UCTSMs, which identify the cycles from statistical restrictions imposed on the dynamics of different components within the model.

We consider two CF filters. The first filter follows the standard business-cycle literature (see, e.g., Canova, 1998) and defines cycles based on the frequency band of 8 to 32 quarters. The second filter acknowledges the presence of pronounced medium-run movements in both GDP and financial variables and instead focuses on a wider frequency band of 32 to 120 quarters, as in Drehmann, Borio, and Tsatsaronis (2012). Figure 7 displays the estimated cycles obtained from these two filters, together with the cyclical components identified by the multivariate UCTSMs. It is readily apparent that UCTSM cycles are highly correlated with the medium-term cycles identified by the extended CF filter, and much less with the shorter cycles identified by the CF filter restricted to the conventional business-cycle band of 8 to 32 quarters. Indeed, the correlations between the UCTSM cycles and the CF(32,120) cycles range from 0.83 to 0.94 for the four variables, while for the CF(8,32) filter they range from 0.19 to only 0.43.

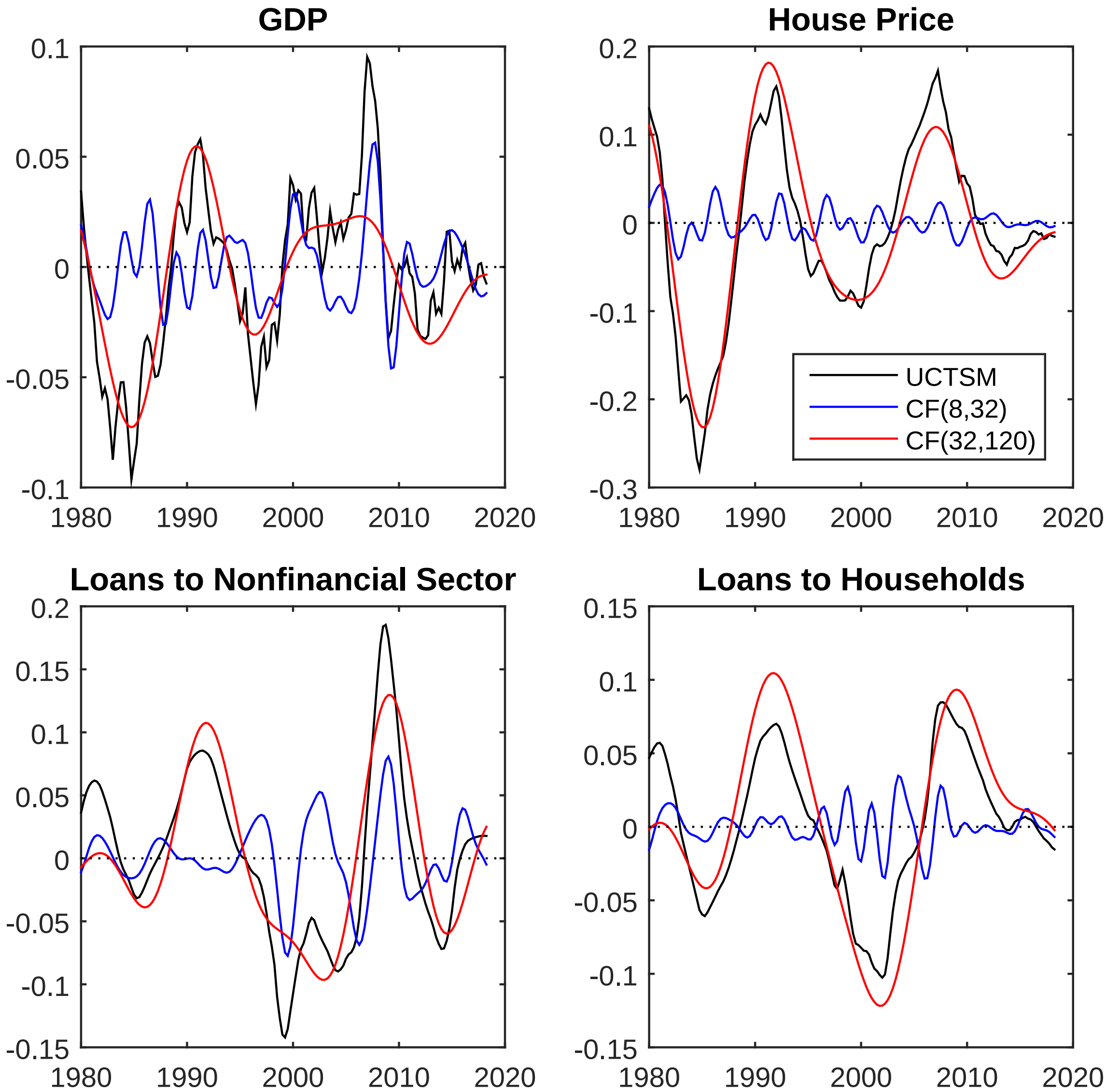
[13]One caveat to this comparison is that Rünstler and Vlekke (2015) estimate their UCTSMs on much longer samples than we do, with observations starting in the early 1970's.

[14]Averaging across 17 EU countries, WGEM (2018) finds a longer cycle length of 12 years.

[15]WGEM (2018) reports a standard deviation around 0.03 on average across 10 EU countries.

[16]WGEM (2018) reports an average cycle length around 14 years for both house prices and total credit. Average cycle volatility was 0.10 for house prices and 0.07 for total credit.

FIGURE 7. Comparing cyclical estimates: UCTSM vs. CF filters.




*Notes.* UCTSM corresponds to the multivariate model for real GDP, total real credit, and real house prices. CF corresponds to the Christiano-Fitzgerald band-pass filter and the numbers in parentheses indicate the frequency band (in quarters) isolated by each filter.

We conclude that the UCTSMs identify real and financial cycles for Luxembourg that closely correspond to the medium-term cycles that would result from the Drehmann et al. (2012) filtering exercise. This confirms that in Luxembourg, as in other European countries, financial cycles have longer duration than would be captured using conventional business-cycle frequencies. The finding that in mid 2018 financial cycles in Luxembourg were close to zero appears remarkably robust across methods.

Finally, we emphasize that the similarity between the cycles estimated from the UCTSMs and from the CF filter actually provides support for the former approach. First, the filtering exercise requires an *a priori* choice of the relevant frequency band, while the UCTSM is agnostic on the presence or significance of medium-term cycles, allowing the data to speak freely. Second, UCTSMs are more resilient to the endpoint bias that affects the Christiano-Fitzgerald filter at the beginning and end of the sample.[17] This last point is especially relevant for real-time analysis, to which we now turn.

## 5. Tracking the Cycles in Real Time

So far, our analysis has been based on full-sample estimates. For instance, in Figures 1 to 5, the cyclical components computed at each date are conditioned on knowledge of all subsequent observations up to the end of the available sample. In practice, policymakers must rely on real-time estimates based only on information available up to the current period. In this section we assess the ability of the UCTSMs to monitor Luxembourg's real and financial cycles in real time.

Adding a new observation to the sample increases the available information along two dimensions. First, conditional on existing parameter values, estimated cycles change because the new observation adds information that is relevant to the trend-cycle decomposition. We call this dimension *data uncertainty.*[18] Second, the model can be re-estimated with the new observation, leading to new parameter values which in turn change the estimated cycles. We call this dimension *parameter uncertainty.*

To deal with both dimensions, one would ideally evaluate the real-time performance of UCTSMs by re-estimating them period after period, computing the associated decompositions in a recursive fashion over time. The computational cost of Bayesian estimation makes this procedure unfeasible for our purposes.

Instead, we rely on two complementary exercises that allow us to disentangle the effects of the two sources of uncertainty. In the first exercise, we focus on data uncertainty by keeping the model parameters fixed at their full-sample values and computing one-sided filtered estimates of the cycle at each date, akin to pseudo real-time estimates.[19] In the second exercise, we focus instead on parameter uncertainty by estimating model parameters on a first subsample and then checking its ability to track full-sample estimates of the cycle in the second, non-overlapping subsample.

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[17] The CF filter is symmetric and therefore requires an equal number of observations before and after each period to estimate the cycle at that given date. For this reason, approximate solutions must be used at the start and end of the sample.

[18] In the discussion below, we ignore the impact of revisions to previously released observations. In practice, this appears to be quantitatively less important (WGEM, 2018).

[19] For obvious reasons, we allow for a training period (of five years) at the start of the sample.

TABLE 3. Properties of pseudo real-time cyclical estimates.

| | Correlation with smoothed estimates | Volatility relative to smoothed estimates | Noise-to-signal ratio |
|---|---|---|---|
| GDP | 0.76 | 0.63 | 0.58 |
| Bank loans to private non-financial sector | 0.75 | 0.51 | 0.74 |
| Bank loans to households | 0.85 | 0.51 | 0.60 |
| House prices | 0.80 | 0.48 | 0.56 |

*Note.* Statistics computed from the multivariate UCTSMs.

5.1. **Data uncertainty.** In the first experiment, we follow Rünstler and Vlekke (2015) and use the full-sample parameter estimates to compute one-sided filtered estimates of the cycles, $\alpha_{t|t} = E(\alpha_t|y_1, \ldots, y_t)$, as well as two-sided smoothed estimates after a 20-period lag, $\alpha_{t|t+20} = E(\alpha_t|y_1, \ldots, y_{t+20})$.[20] These additional five years of data are enough to dissipate most of the short-run data uncertainty, while preserving enough 'future' observations for the two-sided estimates.

We evaluate the reliability of these pseudo real-time estimates of the cycle along three dimensions: their correlations with the smoothed estimates, their volatility relative to that of the smoothed estimates, and the noise-to-signal ratio corresponding to the volatility of the revision from the one-sided filtered estimate relative to the volatility of the smoothed estimate. We report these statistics in Table 3.

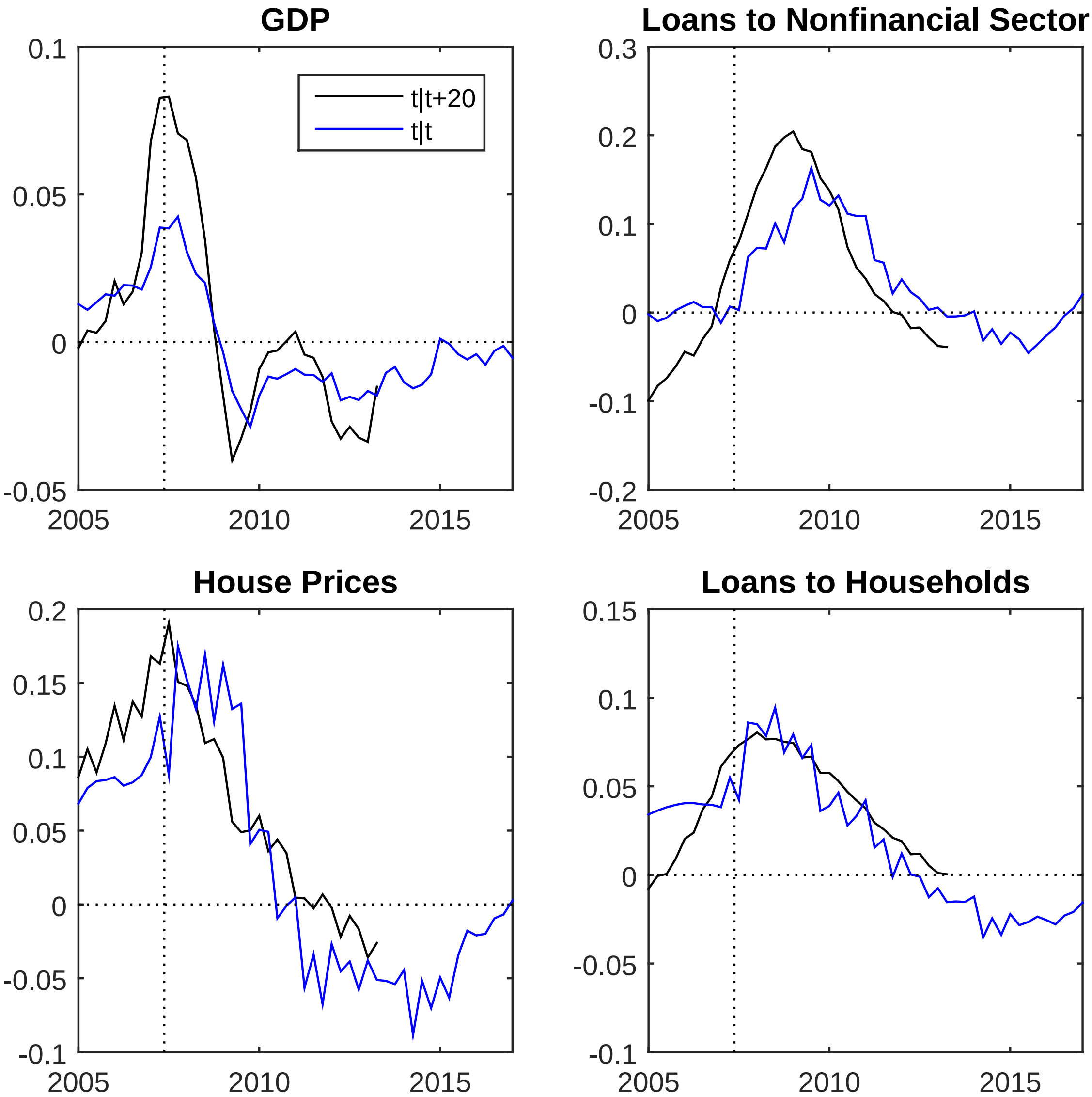
We find that the pseudo real-time estimates are highly correlated with the smoothed estimates, suggesting that real-time analysis with UCTSMs can provide useful information about real and financial cycles in Luxembourg. However, pseudo real-time estimates tend to underestimate the size of the cycles (relative volatility below one) and contain an important share of noise (the revisions are more than half as volatile as the final estimates). Interestingly, bank loans to households seems to produce relatively more accurate real-time estimates than bank loans to the private non-financial sector.

5.2. **Parameter uncertainty.** In the second experiment, we estimate UCTSM parameters up to 2007Q2 and use them to compute pseudo real-time estimates starting from 2007Q3. This estimation subsample is long enough to identify the parameters of the model and there remains enough variability in the data in the subsequent periods to check the ability of the model to track large cycles. In Figure 8, we report one-sided filtered estimates of the cycles, as well as two-sided smoothed estimates conditioned on the 20 subsequent observations.

The figure suggests that parameter uncertainty has only a limited effect on estimates of real and financial cycles in Luxembourg. Starting with GDP, the turning point in 2007Q3

[20]Intuitively, one-sided filtered estimates exploit only information available up to date $t$ and can thus be interpreted as pseudo real-time estimates. Two-sided smoothed estimates, on the other hand, also exploit information from future periods that mitigates data uncertainty.

FIGURE 8. Real-time estimates with subsample parameter estimates.




*Notes.* Black lines correspond to two-sided smoothed estimates of the cyclical components conditioned on data up to 20 periods ahead, while blue lines are pseudo real-time (one-sided) estimates. Vertical dashed lines mark 2007Q2, the end of the estimation subsample.

is correctly identified by the filtered estimate, even though it occurs after the end of the estimation sample. Furthermore, filtered estimates provide an adequate evaluation of the magnitude of the subsequent collapse in economic activity, relative to the lower estimate of the peak in 2007Q2. Things look even better for house prices and bank loans to households, as the filtered estimates are able to pin down the turning point in 2009Q1, almost two years beyond the window used for parameter estimation. The performance is slightly worse for bank loans to the private non-financial sector, whose decline is only identified after about a one-year delay. Still, this lag originates more from data uncertainty than from parameter uncertainty, since a similar delay occurs when cycles are obtained from one-sided filters using parameters estimated over the full sample. Overall, we conclude from our experiments that UCTSMs provide useful real-time monitoring tools.

## 6. Conclusion

This paper establishes several stylized facts about real and financial cycles in Luxembourg using multivariate structural unobserved component time series models estimated from real GDP, real credit, and real house prices. First, estimates of the business cycle in Luxembourg are longer and more volatile than those obtained from more conventional filtering methods. In particular, we find that the Luxembourg business cycle extends over 9 to 10 years. Although this exceeds the conventional business cycle frequencies of 8 to 32 quarters, it is consistent with results found for other advanced economies when the interactions between real and financial variables are taken into account. Second, the financial cycle in Luxembourg is longer than the cycle in GDP, as also found in other countries: for both credit and house prices, cycle duration is close to 15 years. Financial cycles in Luxembourg are also more volatile than the business cycle. Third, we find evidence of close links between real and financial cycles in Luxembourg: GDP cycles have a coherence with credit cycles close to 50%, while that with house price cycles reaches 60%. Credit cycles in Luxembourg tend to lag GDP cycles, consistent with evidence from other countries, while house prices cycles appear to be more coincident with GDP cycles. Fourth, our results suggest that in mid 2018 the financial cycle in Luxembourg was close to zero, with financial conditions near their long-run trend. In particular, there is no evidence that real house prices were significantly above their long-run trend in the first two quarters of 2018. This is consistent with the findings of more structural models published in the BCL 2018 Financial Stability Review or the IMF 2018 Article IV consultation for Luxembourg.

Two subsample exercises assess the uncertainty surrounding our estimates of real and financial cycles in Luxembourg. To evaluate data uncertainty, we compare the one-sided filtered estimates of the cycle (similar to real-time analysis) with the two-sided smoothed estimates that exploit information in later observations. The two versions of the cycle are highly correlated, suggesting that real-time analysis can provide useful information, although it is liable to underestimate the extent of cyclical fluctuations and may only identify turning points after a delay. To evaluate parameter uncertainty, we re-estimate the model on the subsample ending in 2007Q3 and compare the resulting (one-sided) filtered estimates of the cycle to smoothed estimates obtained from full-sample parameter estimates. Parameters estimated on pre-crisis data provide useful estimates of the cycle, closely tracking those obtained with full-sample parameter estimates, even during the financial crisis when the model accurately captures the turning points in GDP, house prices, and bank lending to households.

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## Appendix A. Baseline Point Estimates

In this appendix, we report the point estimates of the parameters of the univariate and multivariate UCTSMs discussed in the paper. Some of these estimates appear also in Tables 1 and 2.

Table 4. Prior and posterior distributions for unrestricted univariate models.

| Parameter | Prior distribution | | | Posterior distribution | |
|---|---|---|---|---|---|
| | Distribution | Mean | SD | Mean | SD |
| *Cyclical parameters* | | | | | |
| $\rho_Y$ | Beta | 0.70 | 0.10 | 0.697 | 0.075 |
| $\phi_Y$ | Beta | 0.70 | 0.10 | 0.732 | 0.082 |
| $\lambda_Y$ | Gamma | 0.20 | 0.07 | 0.191 | 0.068 |
| $\rho_{C_T}$ | Beta | 0.85 | 0.10 | 0.914 | 0.038 |
| $\phi_{C_T}$ | Beta | 0.85 | 0.10 | 0.897 | 0.061 |
| $\lambda_{C_T}$ | Gamma | 0.10 | 0.04 | 0.115 | 0.039 |
| $\rho_{C_H}$ | Beta | 0.85 | 0.10 | 0.890 | 0.072 |
| $\phi_{C_H}$ | Beta | 0.85 | 0.10 | 0.859 | 0.116 |
| $\lambda_{C_H}$ | Gamma | 0.10 | 0.04 | 0.088 | 0.034 |
| $\rho_{C_{NFC}}$ | Beta | 0.85 | 0.10 | 0.880 | 0.053 |
| $\phi_{C_{NFC}}$ | Beta | 0.85 | 0.10 | 0.846 | 0.070 |
| $\lambda_{C_{NFC}}$ | Gamma | 0.10 | 0.04 | 0.133 | 0.046 |
| $\rho_P$ | Beta | 0.85 | 0.10 | 0.933 | 0.052 |
| $\phi_P$ | Beta | 0.85 | 0.10 | 0.838 | 0.111 |
| $\lambda_P$ | Gamma | 0.10 | 0.04 | 0.089 | 0.027 |
| *Shocks* | | | | | |
| $\sigma_{\epsilon_Y}$ | Inv.Gamma | 0.005 | Inf. | 0.002 | 0.001 |
| $\sigma_{\epsilon_{C_T}}$ | Inv.Gamma | 0.005 | Inf. | 0.016 | 0.001 |
| $\sigma_{\epsilon_{C_H}}$ | Inv.Gamma | 0.005 | Inf. | 0.015 | 0.002 |
| $\sigma_{\epsilon_{C_{NFC}}}$ | Inv.Gamma | 0.005 | Inf. | 0.025 | 0.002 |
| $\sigma_{\epsilon_P}$ | Inv.Gamma | 0.005 | Inf. | 0.004 | 0.001 |
| $\sigma_{\eta_Y}$ | Inv.Gamma | 0.002 | Inf. | 0.002 | 0.001 |
| $\sigma_{\eta_{C_T}}$ | Inv.Gamma | 0.002 | Inf. | 0.002 | 0.001 |
| $\sigma_{\eta_{C_H}}$ | Inv.Gamma | 0.002 | Inf. | 0.010 | 0.004 |
| $\sigma_{\eta_{C_{NFC}}}$ | Inv.Gamma | 0.002 | Inf. | 0.001 | 0.001 |
| $\sigma_{\eta_P}$ | Inv.Gamma | 0.002 | Inf. | 0.006 | 0.004 |
| $\sigma_{\kappa_Y}$ | Inv.Gamma | 0.005 | Inf. | 0.009 | 0.001 |
| $\sigma_{\kappa_{C_T}}$ | Inv.Gamma | 0.005 | Inf. | 0.006 | 0.001 |
| $\sigma_{\kappa_{C_H}}$ | Inv.Gamma | 0.005 | Inf. | 0.003 | 0.001 |
| $\sigma_{\kappa_{C_{NFC}}}$ | Inv.Gamma | 0.005 | Inf. | 0.015 | 0.003 |
| $\sigma_{\kappa_P}$ | Inv.Gamma | 0.005 | Inf. | 0.008 | 0.002 |

*Note.* The posterior distribution is constructed from the random-walk Metropolis-Hastings algorithm with two chains of $50,000$ draws each. The acceptance rate is close to 0.30 and standard tests confirm convergence to a stationary distribution. The standard deviations of all slope innovations are set to 0.001.

Table 5. Prior and posterior distributions for tri-variate models: With $C_T$.

| Parameter | Prior distribution | | | Posterior distribution | |
|---|---|---|---|---|---|
| | Distribution | Mean | SD | Mean | SD |
| *Cyclical parameters* | | | | | |
| $\rho_1$ | Beta | 0.70 | 0.10 | 0.660 | 0.080 |
| $\phi_1$ | Beta | 0.70 | 0.10 | 0.673 | 0.087 |
| $\lambda_1$ | Gamma | 0.20 | 0.07 | 0.187 | 0.065 |
| $\rho_2$ | Beta | 0.85 | 0.10 | 0.910 | 0.045 |
| $\phi_2$ | Beta | 0.85 | 0.10 | 0.861 | 0.090 |
| $\lambda_2$ | Gamma | 0.10 | 0.04 | 0.090 | 0.028 |
| $a_{11}$ | Inv.Gamma | 0.005 | Inf. | 0.008 | 0.001 |
| $a_{22}$ | Inv.Gamma | 0.005 | Inf. | 0.004 | 0.002 |
| $a_{33}$ | Inv.Gamma | 0.005 | Inf. | 0.003 | 0.002 |
| $a_{12}$ | Normal | 0.00 | 0.005 | $-0.001$ | 0.002 |
| $a_{21}$ | Normal | 0.00 | 0.005 | 0.001 | 0.002 |
| $a_{23}$ | Normal | 0.00 | 0.005 | 0.001 | 0.004 |
| $a_{31}$ | Normal | 0.00 | 0.005 | 0.000 | 0.002 |
| $a_{32}$ | Normal | 0.00 | 0.005 | 0.000 | 0.004 |
| $a^{\star}_{12}$ | Normal | 0.00 | 0.005 | 0.002 | 0.003 |
| $a^{\star}_{21}$ | Normal | 0.00 | 0.005 | $-0.002$ | 0.003 |
| $a^{\star}_{23}$ | Normal | 0.00 | 0.005 | 0.001 | 0.004 |
| $a^{\star}_{31}$ | Normal | 0.00 | 0.005 | 0.000 | 0.004 |
| $a^{\star}_{32}$ | Normal | 0.00 | 0.005 | 0.004 | 0.006 |
| *Shocks* | | | | | |
| $\sigma_{\epsilon_Y}$ | Inv.Gamma | 0.005 | Inf. | 0.002 | 0.001 |
| $\sigma_{\epsilon_{C_T}}$ | Inv.Gamma | 0.005 | Inf. | 0.016 | 0.001 |
| $\sigma_{\epsilon_P}$ | Inv.Gamma | 0.005 | Inf. | 0.005 | 0.001 |
| $\sigma_{\eta_Y}$ | Inv.Gamma | 0.002 | Inf. | 0.001 | 0.001 |
| $\sigma_{\eta_{C_T}}$ | Inv.Gamma | 0.002 | Inf. | 0.001 | 0.001 |
| $\sigma_{\eta_P}$ | Inv.Gamma | 0.002 | Inf. | 0.002 | 0.001 |
| *Correlations* | | | | | |
| Corr($\eta_Y$,$\eta_{C_T}$) | Normal | 0.00 | 0.10 | $-0.001$ | 0.098 |
| Corr($\eta_Y$,$\eta_P$) | Normal | 0.00 | 0.10 | $-0.003$ | 0.098 |
| Corr($\eta_{C_T}$,$\eta_P$) | Normal | 0.00 | 0.10 | 0.000 | 0.100 |

*Note.* The posterior distribution is constructed from the random-walk Metropolis-Hastings algorithm with two chains of $50,000$ draws. The acceptance rate is close to 0.30 and standard tests confirm convergence to a stationary distribution. The standard deviations of all slope innovations are set to 0.001.

TABLE 6. Prior and posterior distributions for tri-variate models: With $C_H$.

| Parameter | Prior distribution | | | Posterior distribution | |
|---|---|---|---|---|---|
| | Distribution | Mean | SD | Mean | SD |
| *Cyclical parameters* | | | | | |
| $\rho_1$ | Beta | 0.70 | 0.10 | 0.646 | 0.077 |
| $\phi_1$ | Beta | 0.70 | 0.10 | 0.670 | 0.085 |
| $\lambda_1$ | Gamma | 0.20 | 0.07 | 0.181 | 0.063 |
| $\rho_2$ | Beta | 0.85 | 0.10 | 0.931 | 0.056 |
| $\phi_2$ | Beta | 0.85 | 0.10 | 0.767 | 0.135 |
| $\lambda_2$ | Gamma | 0.10 | 0.04 | 0.082 | 0.023 |
| $a_{11}$ | Inv.Gamma | 0.005 | Inf. | 0.008 | 0.001 |
| $a_{22}$ | Inv.Gamma | 0.005 | Inf. | 0.003 | 0.001 |
| $a_{33}$ | Inv.Gamma | 0.005 | Inf. | 0.004 | 0.002 |
| $a_{12}$ | Normal | 0.00 | 0.005 | 0.001 | 0.002 |
| $a_{21}$ | Normal | 0.00 | 0.005 | 0.001 | 0.002 |
| $a_{23}$ | Normal | 0.00 | 0.005 | 0.002 | 0.002 |
| $a_{31}$ | Normal | 0.00 | 0.005 | 0.000 | 0.002 |
| $a_{32}$ | Normal | 0.00 | 0.005 | 0.005 | 0.003 |
| $a^{\star}_{12}$ | Normal | 0.00 | 0.005 | 0.003 | 0.002 |
| $a^{\star}_{21}$ | Normal | 0.00 | 0.005 | 0.000 | 0.004 |
| $a^{\star}_{23}$ | Normal | 0.00 | 0.005 | $-0.001$ | 0.002 |
| $a^{\star}_{31}$ | Normal | 0.00 | 0.005 | 0.004 | 0.004 |
| $a^{\star}_{32}$ | Normal | 0.00 | 0.005 | $-0.001$ | 0.004 |
| *Shocks* | | | | | |
| $\sigma_{\epsilon_Y}$ | Inv.Gamma | 0.005 | Inf. | 0.002 | 0.001 |
| $\sigma_{\epsilon_{C_H}}$ | Inv.Gamma | 0.005 | Inf. | 0.017 | 0.001 |
| $\sigma_{\epsilon_P}$ | Inv.Gamma | 0.005 | Inf. | 0.005 | 0.001 |
| $\sigma_{\eta_Y}$ | Inv.Gamma | 0.002 | Inf. | 0.001 | 0.001 |
| $\sigma_{\eta_{C_H}}$ | Inv.Gamma | 0.002 | Inf. | 0.002 | 0.001 |
| $\sigma_{\eta_P}$ | Inv.Gamma | 0.002 | Inf. | 0.002 | 0.001 |
| *Correlations* | | | | | |
| Corr($\eta_Y$,$\eta_{C_H}$) | Normal | 0.00 | 0.10 | 0.003 | 0.097 |
| Corr($\eta_Y$,$\eta_P$) | Normal | 0.00 | 0.10 | $-0.002$ | 0.097 |
| Corr($\eta_{C_H}$,$\eta_P$) | Normal | 0.00 | 0.10 | $-0.001$ | 0.102 |

*Note.* The posterior distribution is constructed from the random-walk Metropolis-Hastings algorithm with two chains of 50,000 draws. The acceptance rate is close to 0.30 and standard tests confirm convergence to a stationary distribution. The standard deviations of all slope innovations are set to 0.001.

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