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Joint Decomposition of Business and Financial Cycles: Evidence from Eight Advanced Economies*

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Abstract

We discuss a model-based simultaneous decomposition of multiple time series in short-term and medium-term cyclical dynamics. We associate short-term dynamic features with the business cycle and medium-term dynamic features with the financial cycle. For eight advanced economies, we analyse a set of macroeconomic and financial time series data. A strong and common finding among all economies is the co-cyclicality of medium-term cycles, especially those corresponding to house price and gross domestic product variables. We also find empirical evidence that the house price is partly driven by the credit cycle. Most cyclical movements in the country-specific time series appear to be driven by domestic rather than global factors.

I. Introduction

We present and discuss a multivariate unobserved components time series model (UCTSM) for the joint estimation and signal extraction of short-term and medium-term cycles from a dataset of macroeconomic and financial variables. In recent years, various contributions have investigated the existence of medium-term cyclical

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movements in the economy. Comin and Gertler (2006) argue that medium-term oscillations are typically not detected by conventional business cycle filters and they tend to be captured in the long-term trend dynamics. They argue that medium-term business cycles are caused by high-frequency shocks that influence the pace of research, development and technology adoption; these shocks produce business cycles of greater length and more volatility when compared to conventionally extracted business cycles. Furthermore, Correa-López and de Blas (2012) and Comin *et al.* (2014) describe another mechanism that may lead to more medium-term cycles: the transmission of technology from leading countries towards follower countries. Examples of this propagation channel include the spread of the steam-engine technology from the United Kingdom to Europe in the 19th century, and the spread of information-technology goods and services from the United States (US) to the rest of the world at the turn of the millennium.

During the global financial crisis, another explanation for the existence of medium-term cycles emerged that focuses on the medium-term fluctuations of financial variables. It is argued that such fluctuations are associated with a so-called financial cycle. This cycle is typically characterized by the co-movement of the medium-term cycles in credit (usually defined as total credit), the credit-to-GDP ratio (where GDP is gross domestic product) and house prices. A important finding from this literature is that peaks in the medium-term oscillations of these variables coincide with onsets of financial crises; see, for example Drehmann, Borio and Tsatsaronis (2012), Borio (2014), Borio, Furfine and Lowe (2001), Schularick and Taylor (2012), Igan and Loungani (2012) and Aikman, Haldane and Nelson (2015). Furthermore, there is evidence that booms and busts in the financial sector have macroeconomic consequences: the excessive build-up of credit exerts a negative influence on economic growth and increases the probability of remaining in a recession; see, for example Gadea Rivas and Pérez-Quirós (2015) and Schularick and Taylor (2012).

In our empirical study, we aim to bridge these two research directions using a recently developed methodology that decomposes a panel of macroeconomic and financial time series into four dynamic components: a long-term trend, a medium-term cycle, a short-term cycle movements and an irregular component; see Koopman and Lucas (2005) for a detailed discussion of the methodology. The model belongs to the class of multivariate UCTMs. The model decomposes a panel of time series into latent dynamic variables; see, for example Chen, Kontonikas and Montagnoli (2012), De Bonis and Silvestrini (2014), Galati *et al*. (2016), Koopman, Lit and Lucas (2016) and Rünstler and Vlekke (2018). The main advantage of the methodology compared to other approaches, including vector autoregressive models and non-parametric one-sided bandpass filters (see e.g. Aikman *et al*., 2015; Schüler, Hiebert and Peltonen, 2015), is that it enables simultaneous extraction of the short-term and medium-term cycles. Furthermore, the interrelations between the extracted cycles can be modelled in a parsimonious manner. Finally, our approach does not require ex ante assumptions on the length of the duration of the cycle, which is necessary in popular non-parametric statistical filters such as the Hodrick and Prescott (1997) and Christiano and Fitzgerald (2003) filter. These ex ante restrictions introduce the risk of missing parts of the cyclical dynamics (European Central Bank, 2018) or, conversely, the extraction of spurious cycles (Murray, 2003).

We analyse the cyclical oscillations for eight advanced economies: the G7 countries (i.e. the US, the United Kingdom, Japan, Canada, Germany, France and Italy) and the Netherlands. Our sample period is 1970–2015. We use quarterly data on real GDP and monthly data on real industrial production as our macroeconomic variables. The advantage of adding the monthly industrial production series is that our modelling framework can be formulated in terms of the higher monthly frequency instead of the quarterly frequency. This enables updating the model on a more timely, monthly, basis. In the business cycle literature it is well acknowledged that short-term cycles of industrial production and GDP are closely aligned with each other (Burns and Mitchell, 1946).[1] Our financial variables are quarterly figures on credit volumes and house prices, in line with the aforementioned literature on financial cycles.

We make several contributions to the existing UCTSM literature on business and financial cycles. First, we decompose cyclical dynamics that have been documented in the literature into two components: a short-term cycle and a medium-term cycle; see also Koopman *et al*. (2016). The Kalman filter enables extracting the short-term and medium-term cycles in a straightforward fashion. The separation of the cycle in a short-term cycle and a medium-term cycle is potentially important. Recent research shows that extraction of only the medium-term cycle can lead to spurious cycles. Moreover, if the frequency of crises changes, focusing on the medium-term cycle can lead to missing important signals (Schüler, 2018). Second, we extend previous studies that have used the UCTSM framework by using variables with both quarterly and monthly frequencies in a parsimonious and joint modelling framework; see also Valle e Azevedo, Koopman and Rua (2006). Third, we extend recent work on the international coherence of business and financial cycles (e.g. Meller and Metiu, 2015), by analysing the international linkages of both the short-term and medium-term cycles using the methodology of Mink, Jacobs and de Haan (2012).

Our main results can be summarized as follows. First, we show that credit and house prices are largely driven by the medium-term cycle, while the macroeconomic variables are equally driven by the short-term and medium-term cycle. Second, for most countries, the co-movement between the cycles of the financial- and macroeconomic variables is mainly present in the medium-term. Third, we find strong correlation between the medium-term cyclical movements of house prices and GDP. Fourth, we find no evidence for strong concordance between the medium-term credit and house price cycles in four of the eight countries in our sample. Finally, the cross-country concordance between the short-term and medium-term cycles of the financial and macroeconomic variables is low. Hence, the short-term and medium-term cycles seem to be largely driven by domestic factors instead of global factors.

The remainder of the paper is organized as follows. Section II describes the dataset and highlights some stylized features of the macroeconomic and financial time series. Section III describes our modelling approach and discusses the estimation and signal extraction method. Section IV presents our main empirical results. Section V concludes.

[1]Even though the share of industrial production in total output has been falling since the seminal work of Burns and Mitchell (1946), this stylized fact is still relevant, also in recent years (Astolfi *et al*., 2016).

II. Dataset and stylized facts

Dataset

The main sources of our time series are databases maintained by the OECD and the BIS.[2] The time series for GDP, industrial production and nominal house prices are taken from the OECD. All nominal credit variables are taken from BIS. We use the volume of credit to the private non-financial sector as the credit variable in sections (Stylized facts–Concordance of extracted cycles between countries) and present the robustness of our findings to the definition of the credit variable in section (Alternative credit variables).

We use deflated series for all variables. GDP and industrial production are deflated at the source by the respective national statistical agencies. Our nominal credit and house price series are deflated with the country-specific CPI-index in the OECD database. All series are seasonally adjusted. GDP and industrial production are seasonally adjusted at the source[3], while house prices and credit are seasonally adjusted using the Census X–12 ARIMA method.

Stylized facts

Figure 1 presents the raw time series of the variables we analysed, for the US. The large peaks and troughs in both credit and house prices stand out. Clearly visible are the large increases in both credit and house prices starting in the mid-1990s, and the subsequent decrease during and following the global financial crisis of 2008–09. To keep the main text contained, we included the time series for the other G7 countries and the Netherlands in the Online Appendix. Overall, the other country results all show periods of build-up and subsequent decline in both house prices and credit. However, the timing and size of the rise and fall in house prices seem to differ markedly between countries.

To get insight into the duration of the cyclical oscillations in the time series, we have analysed the spectral densities. Spectral density estimates originate from the periodograms of variables, they are locally smooth estimates thereof, and offer insight into where the mass of the cyclical oscillations in a time series occurs. Analysing the spectral densities can give further guidance on whether it is sensible to extract multiple cycles. Figure 2 presents the spectral density estimates for the US variables. Since the spectral densities are symmetric between $-\pi$ and π, we only present the plots for the interval $[0,\pi]$, where 1 on the horizontal axis stands for π, 0.5 for 0.5π, etc.[4] When interpreting the spectra it is often more convenient to think in terms of the period rather than its frequency. If we define the frequency of a cycle as λ, the average period

[2]The time series from the OECD database are publicly available via https://data.oecd.org/economy.htm. The time series from the BIS data are publicly available via http://www.bis.org/statistics/totcredit.htm.

[3]Most statistical agencies adopt the Census X12–ARIMA method for seasonal, trading day and holiday effect adjustments; see the metadata for industrial production and GDP in the OECD database for more information.

[4]All sample spectral densities are based on a lag length of 96 quarters (24 years).

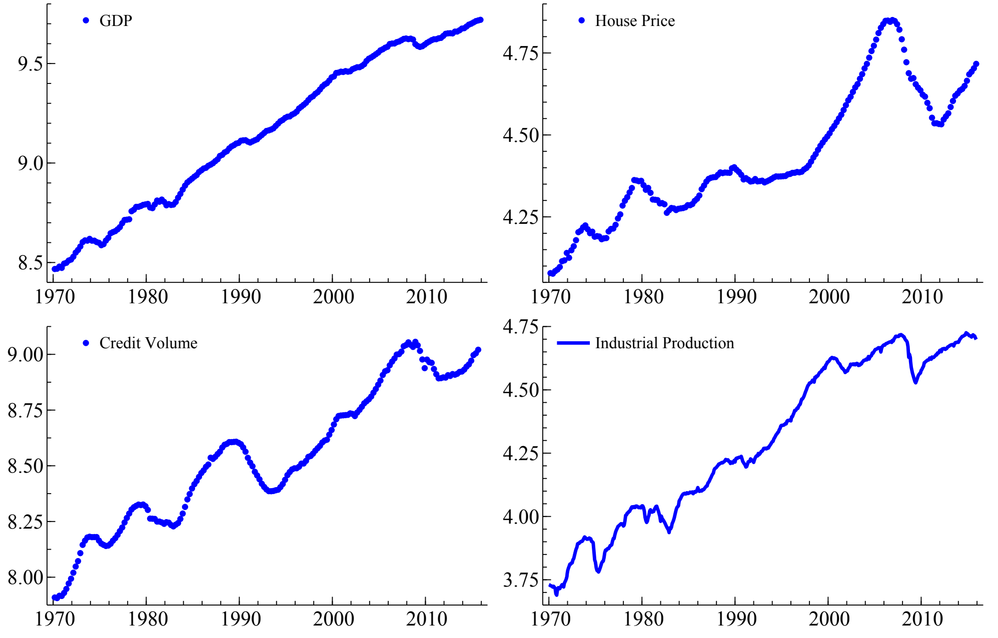

Figure 1. Time series of US gross domestic product, house prices, credit and industrial production. All series are deflated, seasonally adjusted and in logs.

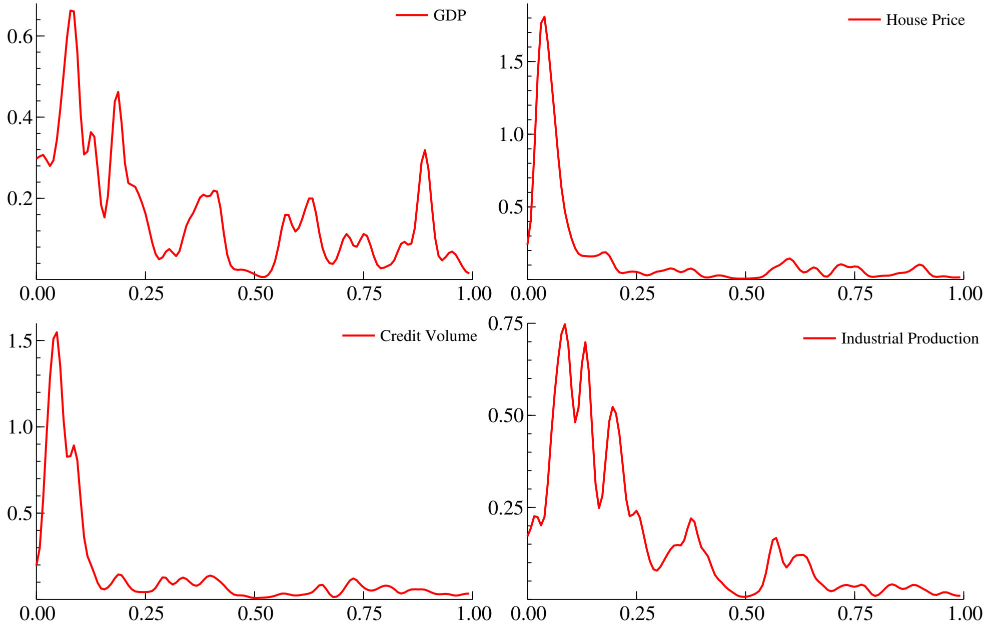

Figure 2. Spectral densities of time series of US gross domestic product, house prices, credit and industrial production. All series are deflated, seasonally adjusted and in log-differences.

of the cycle is $2\pi/\lambda$. The area under the line can be viewed as how much of the variability in the time series is due to a certain frequency.

The first (visible) peak in the spectral density of US GDP is estimated at approximately 0.02π, which translates into a cycle with an average period of $\frac{2\pi}{0.02\pi} = 100$ quarters, or 25 years. This peak can be viewed as an indication of how much of the variability of GDP can be captured by medium-term cycles. The second peak is at 0.08π, which translates into a period of $6\frac{1}{4}$ years. Given the dating of recessions, the latter seems to be related to the 'traditional' business cycle frequency fluctuations in the range from 0.5 to 8 years; see, for example Baxter and King (1999) and Christiano and Fitzgerald (2003). The third and fourth peaks occur at 0.13π and 0.19π, which translate to 3.8 and 2.6 years respectively. Both peaks are lower than the peak in the spectral density at 0.08π. This indicates that most business cycle frequencies occur within an average period of $6\frac{1}{4}$ years, but there are also shorter business cycle fluctuation. Furthermore, there are some local peaks in the spectral density above approximately 0.25π (2 years). For our study, these fluctuations are not of key interest and can be seen as remaining seasonal and noise anomalies in the data.

Figure 2 also shows the spectral densities for house prices (top-right panel), credit (bottom-left panel) and industrial production (bottom-right panel). The spectral density for industrial production is very similar to the spectral density of GDP. There is a small peak at an average cycle-length of approximately 25 years, and peaks at cycles of approximately 6, 4 and 3 years. The spectral densities of house prices and credit are quite different. Both series show peaks at a cycle-length of approximately 13 years. In contrast to GDP and industrial production there is not much cyclical movement at the higher business cycle frequency. The only other visible peaks in the spectra are concentrated in the cyclical frequency that we associate with remaining seasonality or noise anomalies in the data.

In the Online Appendix, we present the estimated spectral densities for the other G7 countries and the Netherlands. Overall, the estimated spectral densities are similar to the results for the US, as the spectral densities of GDP and industrial show peaks at medium-term frequencies of roughly 25–30 years, and peaks at short-term frequencies between 2 to 6 years. Generally, the spectral densities for house prices and credit are heavily skewed to the right, with the mass of the cyclical oscillations concentrated between 13 and 25 years.

In the literature on extracting business and financial cycles, the analysis focuses on the decomposition of time series in a trend, a medium-term cycle and an irregular component; see the discussions, for example in Comin and Gertler (2006) and Rünstler and Vlekke (2018). The short-term cycle is typically excluded from the analysis. Based on our spectral density analysis, we departed from these analyses in the current literature, and consider the inclusion of two components in order to capture separately the medium-term cyclical and the short-term cyclical oscillations. We present formal likelihood-ratio tests of a model with a short-term cycle vs. the same model plus a medium-term cycle, after an exposition of the structure of our model in section (Unobserved components time series model). Our main conjecture from analysing the spectral densities for GDP, house prices, credit and industrial production is that the medium-term frequencies are dominant in house prices and credit, whereas the short-term fluctuations are dominant for GDP and industrial production.

III. Modelling approach

Unobserved components time series model

The empirical analysis is based on a multivariate UCTSM which aims to describe the dynamic behaviour of the time series and their dynamic interdependencies. The component structure of the model is similar to the one described in Koopman and Lucas (2005). The model is for a four-dimensional time series vector y_t which is given by

$$y_t = \begin{bmatrix} y_t^{\text{GDP}} \\ y_t^{\text{HP}} \\ y_t^{\text{CRED}} \\ y_t^{\text{IP}} \end{bmatrix} = \begin{bmatrix} \text{real GDP (GDP)} \\ \text{real house price (HP)} \\ \text{real credit (CRED)} \\ \text{real industrial production (IP)} \end{bmatrix}, \quad t = 1, \ldots, T. \tag{1}$$

All variables in the observation vector y_t are in logs. The time index t is for a monthly frequency and T is the number of monthly observations. The modelling framework can treat time series of monthly and quarterly frequencies simultaneously in one model. The model is formulated in terms of the monthly time index while the quarterly variable (GDP) is subject to the standard convention of placing the quarterly value in the third month of a quarter and insert missing values in the first and second month of a quarter; see, for example Durbin and Koopman (2012). In this solution, y_t has missing values but the methods below can handle missing observations.

The UCTSM for y_t is given by

$$y_t = \mu_t + A\gamma_t + B\psi_t + \varepsilon_t,\ \varepsilon_t \overset{i.i.d.}{\sim} \mathcal{N}(0, \Sigma_\varepsilon),\ t = 1, \ldots, T, \tag{2}$$

where we represent the long-term trend by the 4×1 vector μ_t, the short-term cycle component by γ_t, the medium-term cycle by ψ_t, the irregular component by ε_t, which is assumed normally ($\mathcal{N}$) independent and identically distributed (*i.i.d.*) with mean zero and a diagonal variance matrix Σ_ε, and matrices A and B are coefficient matrices. We assume that each series in y_t has its own trend component and its own irregular component but the individual cyclical components in the vectors γ_t and ψ_t can be shared among the four series in y_t. The unknown weights for each series to each individual cycle are provided by elements in matrices A and B.

The trend component μ_t is specified as in Valle e Azevedo *et al*. (2006) and Koopman and Lucas (2005). In particular, the trend vector μ_t is formulated as the integrated random walk process

$$\mu_{t+1} = \mu_t + \beta_t, \quad \beta_{t+1} = \beta_t + \zeta_t,\ \zeta_t \overset{i.i.d.}{\sim} \mathcal{N}(0, \Sigma_\zeta). \tag{3}$$

where β_t is the growth, gradient or slope component of μ_t and ζ_t is the innovation or disturbance driving the time-varying trend component. The disturbances ε_t and ζ_t are mutually and serially independent of each other. The variance matrix Σ_ζ is assumed diagonal. The role of each component in μ_t is to account for the low-frequencies or long-term dynamics in the corresponding time series in y_t.

The cycle components in γ_t and ψ_t are modelled via a stochastic dynamic specification as proposed by Harvey (1989) and Harvey and Koopman (1997) and are given by

$$\begin{pmatrix} \gamma_{t+1} \\ \gamma^*_{t+1} \end{pmatrix} = \phi_\gamma \left[\begin{pmatrix} \cos\lambda_\gamma & \sin\lambda_\gamma \\ -\sin\lambda_\gamma & \cos\lambda_\gamma \end{pmatrix} \otimes I_N \right] \begin{pmatrix} \gamma_t \\ \gamma^*_t \end{pmatrix} + \begin{pmatrix} \kappa_t \\ \kappa^*_t \end{pmatrix}, \quad \kappa_t, \kappa^*_t \overset{i.i.d.}{\sim} \mathcal{N}(0, \Sigma_\kappa),$$

$$\begin{pmatrix} \psi_{t+1} \\ \psi^*_{t+1} \end{pmatrix} = \phi_\psi \left[\begin{pmatrix} \cos\lambda_\psi & \sin\lambda_\psi \\ -\sin\lambda_\psi & \cos\lambda_\psi \end{pmatrix} \otimes I_N \right] \begin{pmatrix} \psi_t \\ \psi^*_t \end{pmatrix} + \begin{pmatrix} \omega_t \\ \omega^*_t \end{pmatrix}, \quad \omega_t, \omega^*_t \overset{i.i.d.}{\sim} \mathcal{N}(0, \Sigma_\omega), \tag{4}$$

where the frequency λ_j is measured in radians, $0 \leq \lambda_j \leq \pi$, and the persistence coefficient or damping factor ϕ_j ensures a stationary process, that is $0 < \phi_j < 1$, for $j=\gamma,\psi$. The average period or length of the stochastic cycle is given by $2\pi/\lambda_j$. The cycles γ_t and ψ_t are both stationary dynamic processes. To distinguish the short-term cycle γ_t from the medium-term cycle ψ_t, we impose the restriction that $\lambda_\gamma > \lambda_\psi$.

The unobserved component vectors μ_t, γ_t and ψ_t represent unique multivariate dynamic processes which are assumed to be independent processes of each other. Also, within each multivariate process, the element processes are also assumed to be independent of each other. Hence, we have a diagonal variance matrix Σ_j, for all $j=\zeta,\kappa,\omega,\varepsilon$. The dynamic dependence structure among the variables in y_t is specified only through the matrices A and B. The matrices A and B select and weight the appropriate cycle processes in γ_t and ψ_t for each of the individual series. The structures of the matrices A and B can, for example, be designed such that the GDP cycle is the same as the credit and house price cycles (up to a scaling factor). The designs of matrices A and B are subject to identification since not all elements in A and B can be identified. We can restrict A and B to be lower triangular matrices, with ones on the leading diagonals. Alterations of rows and columns in A and B can take place to allow for some flexibility. The specification of our multivariate dynamic model is completed with appropriate initial conditions for μ_1 (non-stationary trend), γ_1 and ψ_1 (stationary cycles); see Durbin and Koopman (2012).

Similar cycles

In our analysis, we assume that the cyclical components are ‘similar’. Under this assumption, the frequency λ_j and persistence ϕ_j in (4) have the same values for all individual cycles in γ_t for $j=\kappa$ and in ψ_t for $j=\omega$. Given that the peaks and troughs of the cycles (their amplitudes) are determined by the variances of the disturbances driving the cycle component, they can still be different for different time series. The statistical properties and implications of similar cycles, both in the time and frequency domain analyses, are discussed in Harvey and Koopman (1997). We statistically verify whether frequency λ_j and persistence ϕ_j can have the same value for all variables in y_t. We do so by adopting the approach as in Galati *et al.* (2016) by using standard likelihood ratio tests based on univariate UCTSMs.

We formally test for the existence of the two cycles (short-term and medium-term) for all variables, based on a standard likelihood-ratio (LR) tests; also see Rünstler and Vlekke (2018) and Galati *et al.* (2016). Hence we verify whether each time series is better characterized by a model with a long-term trend, a short-term cycle and a medium-term cycle, against a model with a long-term trend and one (short-term) cycle. The parameters in these univariate UCTSMs are estimated using quarterly data. Table 1 reports the LR-test values. The null hypothesis in favour of the model with one cycle is rejected for all countries and all time series at high significance levels, for most variables and most countries. There are only 2 of the 32 LR-test values that are not significant at the 95% confidence level.

State space methodology

Multivariate UCTSMs can be formulated as a linear Gaussian state space model that is given by the observation equation $y_t = Z\alpha_t + \varepsilon_t$, with state vector α_t, and the state updating equation $\alpha_{t+1} = T\alpha_t + \eta_t$, where Z and T are system matrices that determine the dynamic properties of y_t, and, together with the variance matrices for ε_t and η_t, contain the parameters of the model. The state vector consists of the unobserved components μ_t, γ_t and ψ_t, together with auxiliary variables such as γ_t^* and ψ_t^* in (4). The disturbance vectors are part of the vectors ε_t and η_t. The specific details of our state space formulations are outlined in the Online Appendix.

Once the model is represented in state space form, the Kalman filter and related state space methods can be applied. We estimate the unknown parameters by the

TABLE 1

Parameter estimates of LR-test for the G7 countries and the Netherlands

	Likelihood-Ratio test			
	GDP	*HP*	*CRED*	*IP*
United States	29***	26***	26***	47***
United Kingdom	7*	41***	21***	n.a.†
Japan	13***	86***	21***	23***
Canada	24***	7*	44***	33***
Germany	14***	33***	70***	22***
France	11**	34***	26***	17***
Italy	87***	88***	10**	51***
Netherlands	2	55***	28***	10**

Notes: The table reports the χ^2-test value of the likelihood-ratio test for specification with both a short-term and medium-term cycle vs. a specification with only a short-term cycle. All variables have quarterly frequency and are estimated with a signal-to-noise ratio of $6.25*10^{-4}$. Positive entries indicate the likelihood of the two-cycle specification is higher than the one-cycle specification, That is including two cycles in our model is significantly better/worse than one cycle. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

† n.a. indicates that the model-specification with one-cycle does not converge.

method of maximum likelihood; the numerical maximization of the likelihood function with respect to the parameter vector requires the Kalman filter to compute the log-likelihood function repeatedly. Given these estimates, we obtain prediction residuals from the Kalman filter and use these for diagnostic checking and model evaluations. We obtain the smoothed estimates of the unobserved trend, short-term and medium-term cycle and the irregular component from a smoothing method; for further discussion, see Durbin and Koopman (2012) on the state space methodology and Harvey (1989) on the general trend-cycle model.

Estimation strategy

It is not feasible to estimate the parameters of our multivariate dynamic model directly via the numerical maximization of the log-likelihood function with respect to all parameters. In practice, feasible estimation requires various restrictions and parameter transformations. To facilitate a smooth estimation process further, we pre-select a fixed value for the signal-to-noise ratio, $q = \sigma^2_{\zeta,j}/\sigma^2_{\varepsilon,j}$ for j = 1, 2, 3, 4. For example, Harvey and Jaeger (1993) advocate the value q = 1/1,600 which achieves a good balance between smoothness and some stickiness in the long-term trend μ_t; they deduct that this value produces the same trend function as the one advocated by Hodrick and Prescott (1997) filter for quarterly time series data. In case of monthly time series, one could consider the signal-to-noise ratio 1/14400. As an alternative, a grid of signal-to-noise ratios can be considered and the one that produces the highest maximized likelihood function is selected. In our empirical work, we only consider a grid of the two values $\{1/1{,}600; 1/14{,}400\}$ and then make a choice of q for all series, for each country separately.

The full estimation process proceeds in four steps. First, we estimate all parameters under the restriction of a fixed signal-to-noise ratio value $q \in \{1/1{,}600, 1/14{,}400\}$. Second, in addition we set the damping factors for the short (ϕ_γ) and medium-term (ϕ_ψ) cycles fixed at their values in the first step and re-estimate the remaining parameters. The damping factors have a big impact on the dynamic properties of the cycles and this strategy make the estimation of the other parameters more robust against spurious estimates. The damping factors must lie within the unit circle with a maximum value of 0.99. Third, we re-estimate all factor loading parameters again while all other parameters are fixed at their estimates in the second step. Fourth, we choose between the models with a high or low signal-to-noise ratio on the basis of their maximized likelihood value. For most countries, this estimation strategy leads to a model with a higher signal-to-noise ratio. Only for the two countries of the Netherlands and the United Kingdom, the UCTSM is taken with a lower signal-to-noise ratio.

Our model is different from the UCTSMs adopted in earlier studies, in several ways. Galati *et al*. (2016) and De Bonis and Silvestrini (2014) use univariate UCTSMs and do no study cyclical comovements. Chen *et al*. (2012) present a Bayesian treatment of multivariate UCTSMs for five time series.

We abstract from so-called phase-shifts as introduced by Rünstler (2004) and used in the analyses of Valle e Azevedo *et al*. (2006), Chen *et al*. (2012), Koopman *et al*. (2016), and Rünstler and Vlekke (2018). The cycle model specification with phase-shifts is costly in terms of the number of parameters. Also, given these earlier studies, we anticipate that the impact of estimated phase-shifts on the overall analysis is relatively small. For example, Chen *et al*. (2012) find that the phase-shifts between medium-term cycles are not statistically significant; a finding that is corroborated by Koopman *et al*. (2016). Moreover, by specifying matrices A and B as lower-triangular in our model, we allow for correlation within the short-term cycles and within the medium-term cycles. These correlation structures are not considered by Koopman *et al*. (2016) while Rünstler and Vlekke (2018) does account for such correlations but in a different manner.

International concordance of cycles

For each country, the parameters of the multivariate UCTSM are estimated using state space methods. It is of interest to check the coherence between the extracted cycles from the different countries. To verify whether the extracted short-term and medium-term cycles have a high inter-country coherence, we consider 'synchronicity' and 'similarity' measures, as proposed by Mink *et al.* (2012).[5] The idea is that the coherence of cycles at any point in time is driven by whether or not cycles are simultaneously above or below trend level (synchronicity) and whether the cycles have the same amplitude (similarity). The synchronicity measure captures whether the cycle of a country and a predefined reference cycle coincide, regardless of their amplitudes. To examine the overall synchronicity and similarity among our set of countries, a synthetic reference cycle is formed, which is defined as the median cycle of the individual cycles, following Mink *et al*. (2012) and European Central Bank (2018). Synchronicity and similarity of the individual country cycles with the reference cycles are then calculated and averaged across countries. We denote the cycle of country i, for variable j at time t by $c_t^{i,j}$ and the reference cycle r for variable j at time t by $c_t^{r,j}$ and n is the number of countries. The *overall* synchronicity measure for variable j is defined as:

$$\theta_t^j = \frac{1}{n}\sum_{i=1}^{n}\frac{c_t^{i,j}c_t^{r,j}}{|c_t^{i,j}c_t^{r,j}|}, \tag{5}$$

while overall similarity is defined as:

$$\zeta_t^j = 1 - \frac{\sum_{i=1}^{n}|c_t^{i,j}c_t^{r,j}|}{\sum_{i=1}^{n}|c_t^{i,j}|}. \tag{6}$$

Both measures can vary between 0 and 1, where 0 means that there is no synchronicity/similarity and 1 means that there is perfect synchronicity/similarity. Perfect synchronicity indicates that all cycles are simultaneously above/below trend

[5]Alternatively, the signal extraction and international concordance of the short- and medium term cycles for all countries considered could be modelled in one comprehensive state-space model. Given the large number of parameters involved, it requires a different modelling strategy. We leave this for future research.

level. Perfect similarity indicates that the absolute difference between the cycles is zero; that is, cycles have an identical amplitude.

IV. Empirical results

In this section, we discuss our empirical findings on the basis of the UCTSMs for the G7 countries and the Netherlands. In order to keep the main discussion contained, we limit our discussion to the final estimated coefficients in the UCTSMs as reported in Tables 2 and 3. The Online Appendix shows an extended set of residual diagnostics. The variance of the prediction residuals for the house price and credit variables are very small, indicating that the model has a good fit explaining he movement for these variables. For GDP, the errors are somewhat bigger but still very small (on average less than 2% of the variance of the extracted cycle). Formal residual diagnostics, that is normality, serial correlation, heteroscedasticity, indicate the null-hypothesis of normality and heteroskedasticity cannot be rejected at the 1% level. There is weak autocorrelation in the disturbances, but this seems to be primarily caused by some serial correlation during the oil crises in the 1970*s*.

Short-term cycle

Table 2 shows the estimated results for the short-term cycles, γ_t and contains information on the average duration (p_γ), standard deviation (×100) and persistence (ϕ_γ) of the short-term cycles. The standard deviation equals the root of the diagonal elements in the variance matrix (Σ_γ). Finally, Table 2 reports the loading-matrices (A) for the short-term cycles. Remember, the short-term cyclical signal for y_t is a composite of four separate similar cycles since we have the term $A\gamma$ in the measurement equation. The loading matrices A reveal whether there is any co-cyclicality between the short-term cycles. We distinguish statistical significance levels of 10%, 5% and 1%, which are denoted as *, ** and *** respectively. Our empirical results point to some interesting finding, that can be summarized as follows.

First, averaged over all countries in our sample, the average duration of the short-term cycle is 5.3 years. We find the longest average duration of the short-term cycle (7.9 years) for the Netherlands. The shortest duration (3.3 years) is estimated for Japan. Generally, the estimated cycle duration coincide with those based on the more conventional band-pass filter frequency range setting of [1.5,8] years (see e.g. Baxter and King, 1999; Christiano and Fitzgerald, 2003).

Second, there is strong evidence for co-cyclicality between the short-term cycles of GDP and industrial production, given the statistically significant loadings in all countries we considered.

Third, we find no empirical evidence for commonality between the short-term cycles of housing and GDP. This implies that the short-term fluctuations in house prices are largely independent of the short-term fluctuations of GDP.

Fourth, we find little evidence for co-cyclicality between the short-term cycles of credit and GDP. For the majority of countries analysed, we find no statistically

TABLE 2

Parameter estimates of multivariate unobserved components time series model (UCTSM) short-term cycle, 1970Q1–2015Q4

	United States				*United Kingdom*			
p_γ	5.4				6.7			
ϕ_γ	0.99				0.99			
std. dev. D_γ	1.69	0.69	1.48	3.64	1.48	4.98	1.32	1.72
loading matrix A	GDP	HP	CRED	IP	GDP	HP	CRED	IP
γ_{GDP}	1.00	—	—	1.00	—	—	—	—
γ_{HP}	−0.02	1.00	—	—	1.79	1.00	—	—
γ_{CRED}	0.25	1.26	1.00	—	0.20	0.30	1.00	—
γ_{IP}	1.82***	1.51	−0.07	1.00	1.11**	0.11	0.27	1.00
	Japan				Canada			
p_γ	3.3				7.1			
ϕ_γ	0.98				0.99			
std. dev. D_γ	1.23	1.17	0.94	5.19	2.10	2.90	3.47	4.46
loading matrix A	GDP	HP	CRED	IP	GDP	HP	CRED	IP
γ_{GDP}	1.00	—	—	—	1.00	—	—	—
γ_{HP}	0.48	1.00	—	—	−0.14	1.00	—	—
γ_{CRED}	0.01	−0.04	1.00	—	0.94*	0.25	1.00	—
γ_{IP}	3.26***	0.43	−1.99	1.00	1.97***	0.02	−0.19	1.00
	Germany				France			
p_γ	4.5				3.6			
ϕ_γ	0.97				0.98			
std. dev. D_γ	1.14	0.60	0.51	3.22	0.68	0.81	0.32	2.39
loading matrix A	GDP	HP	CRED	IP	GDP	HP	CRED	IP
γ_{GDP}	1.00	—	—	1.00	—	—	—	—
γ_{HP}	−0.09	1.00	—	—	0.52	1.00	—	—
γ_{CRED}	0.07	−0.57	1.00	—	0.08	−0.13	1.00	—
γ_{IP}	2.82***	0.34	−0.46	1.00	3.14***	0.86	2.31	1.00
	Italy				Netherlands			
p_γ	3.8				7.9			
ϕ_γ	0.97				0.99			
std. dev. D_γ	1.17	4.12	0.52	3.15	2.04	3.28	2.91	3.23
loading matrix A	GDP	HP	CRED	IP	GDP	HP	CRED	IP
γ_{GDP}	1.00	—	—	—	1.00	—	—	—
γ_{HP}	−0.38	1.00	—	—	−0.06	1.00	—	—
γ_{CRED}	0.33	0.00	1.00	—	0.88*	−0.16	1.00	—
γ_{IP}	2.54***	−0.10	1.81	1.00	1.45**	0.03	0.53	1.00

Notes: The table reports the estimates of persistence ϕ_γ, the period p_γ in years ($p=2\pi/\lambda$), 100x the root of the diagonal of the variance-matrix (standard-deviation) D_γ for the short cycle (γ). A denotes the loading matrices for the short-term cycle. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

significant entries in the A-matrices measuring the co-cyclicality between the short-term credit and short-term GDP cycle. Canada and the Netherlands are the only exceptions to this finding. This might indicate a more prominent role for credit as a means of financing businesses and households in the economies of these countries. This is

TABLE 3

Parameter estimates of multivariate unobserved components time series model (UCTSM) medium-term cycle, 1970Q1–2015Q4

	United States				*United Kingdom*			
p_ψ	13.6				18.4			
ϕ_ψ	0.99				0.99			
std. dev. D_ψ	0.73	3.33	3.88	2.51	2.56	5.89	6.33	6.63
loading matrix B	GDP	HP	CRED	IP	GDP	HP	CRED	IP
ψ_{GDP}	1.00	—	—	—	1.00	—	—	—
ψ_{HP}	2.77***	1.00	—	—	1.19*	1.00	—	—
ψ_{CRED}	4.48***	−0.25	1.00	—	0.80	0.16	1.00	—
ψ_{IP}	1.91*	−0.19	−0.58	1.00	2.42***	−0.36**	−0.03	1.00
	Japan				Canada			
p_ψ	9.2				22.3			
ϕ_ψ	0.99				0.99			
std. dev. D_ψ	1.33	3.46	3.37	3.76	0.86	7.87	6.82	4.10
loading matrix B	GDP	HP	CRED	IP	GDP	HP	CRED	IP
ψ_{GDP}	1.00	—	—	—	1.00	—	—	—
ψ_{HP}	1.45**	1.00	—	—	8.43***	1.00	—	—
ψ_{CRED}	1.73***	0.42*	1.00	—	−1.98	1.28*	1.00	—
ψ_{IP}	2.70***	−0.26	0.06	1.00	3.17**	−0.80**	0.24	1.00
	Germany				France			
p_ψ	9.3				16.2			
ϕ_ψ	0.99				0.99			
std. dev. D_ψ	0.39	7.57	4.61	2.46	1.08	4.20	3.15	3.14
loading matrix B	GDP	HP	CRED	IP	GDP	HP	CRED	IP
ψ_{GDP}	1.00	—	—	—	1.00	—	—	—
ψ_{HP}	1.80***	1.00	—	—	1.54*	1.00	—	—
ψ_{CRED}	1.10	6.56	1.00	—	1.58***	−0.07	1.00	—
ψ_{IP}	1.69	−12.64	0.29	1.00	2.66***	−0.17	−0.41*	1.00
	Italy				Netherlands			
p_ψ	14.7				23.7			
ϕ_ψ	0.99				0.99			
std. dev. D_ψ	0.39	7.57	4.61	2.46	1.75	7.37	4.14	5.22
loading matrix A	GDP	HP	CRED	IP	GDP	HP	CRED	IP
ψ_{GDP}	1.00	—	—	—	1.00	—	—	—
ψ_{HP}	19.58***	1.00	—	—	3.56***	1.00	—	—
ψ_{CRED}	2.78	2.90***	1.00	—	0.45	0.96**	1.00	—
ψ_{IP}	2.32	−0.83	2.32	1.00	1.71***	−0.48	2.62**	1.00

The table reports the estimates of persistence ϕ_ψ, the period p_ψ in years ($p=2\pi/\lambda$), 100x the root of the diagonal of the variance-matrix (standard-deviation) D_ψ for the medium-term cycle (ψ). B denotes the loading matrices for the medium-term cycle. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

corroborated by the relatively high percentage of private credit by deposit money to GDP in Canada and the Netherlands, respectively, 165% and 112%. With the exception of the United Kingdom (131%), and Japan (103%), the rest of the countries in our sample fall well below 100%. The United States only has a 51% share of private credit by deposit money to GDP (World Bank Group, 2020).

In summary, for most of the countries in our sample we find little evidence of significant linkages between the short-term GDP cycle on the one hand and the short-term credit and house price cycle on the other hand.

Medium-term cycle

Table 3 shows the estimates for the medium-term cycles ψ_t and contains information on the average duration (p_ψ), standard deviation (×100) and persistence (ϕ_ψ) of them medium-term cycles. Table 3 also shows the loading matrices $B\gamma$. We distinguish statistical significance levels of 10%, 5% and 1%, which are denoted as *, ** and *** respectively. The results can be summarized as follows.

First, the average duration of the medium-term cycle (p_ψ) in our sample of countries varies from 9.2 years in Japan to 23.7 years in the Netherlands. The estimated cycle lengths lie within the 8–30 years boundaries that are usually found for the financial cycle; see Aikman *et al*. (2015), Borio (2014) and Drehmann *et al*. (2012). Moreover, they lie within the boundaries of the medium-term cycle for GDP as documented in Comin and Gertler (2006) and Comin *et al*. (2014) who take the medium-term frequency as representing cycles with periods between 8 and 50 years, while the high frequency corresponds to cycles with periods between 1.5 and 8 years.

Second, for most countries, the standard deviation of the medium-term cycles (ψ_t) of GDP and industrial production are usually just as 'important' as the standard deviation of the short-term cycles (γ_t), as can be seen from a comparison of D_ψ and D_γ in Tables 2 and 3 ($D_\psi \approx D_\gamma$) respectively. By contrast, for most countries, we find the medium-term cycles of the financial variables are more important than the short-term cycle ($D_\psi >> D_\gamma$). This implies that the medium-term cycle is much more dominant than the short-term cycle in explaining the cyclical variability for the financial variables. Figure 3 clearly confirms this finding; it plots the data and the smoothed components for the four US time series; similar plots for the other G7 countries and the Netherlands are available in the Online Appendix. Overall, these figures confirm the finding for the United States: the medium-term cycle is rather dominant in explaining cyclical variations.

Third, the loading matrices B reveal strong, and statistically significant, co-cyclicality between house prices and GDP, for all countries. This outcome supports the notion that medium-term fluctuations in GDP are partly caused by boom-bust patterns in house prices.

Fourth, the direct relation between the medium-term cycles of GDP and credit is more complex. In only three countries, that is the US, Japan and France, we find strong co-cyclicality between both cycles. In three of the other countries, that is Canada, Italy and the Netherlands, we find strong evidence for 'indirect' commonality between the medium-term cycles of credit and GDP. In these countries the medium-term cycles of house prices and credit share co-cyclicality, while in turn the medium-term cycles of house prices and GDP share commonality. This outcome might indicate that the house

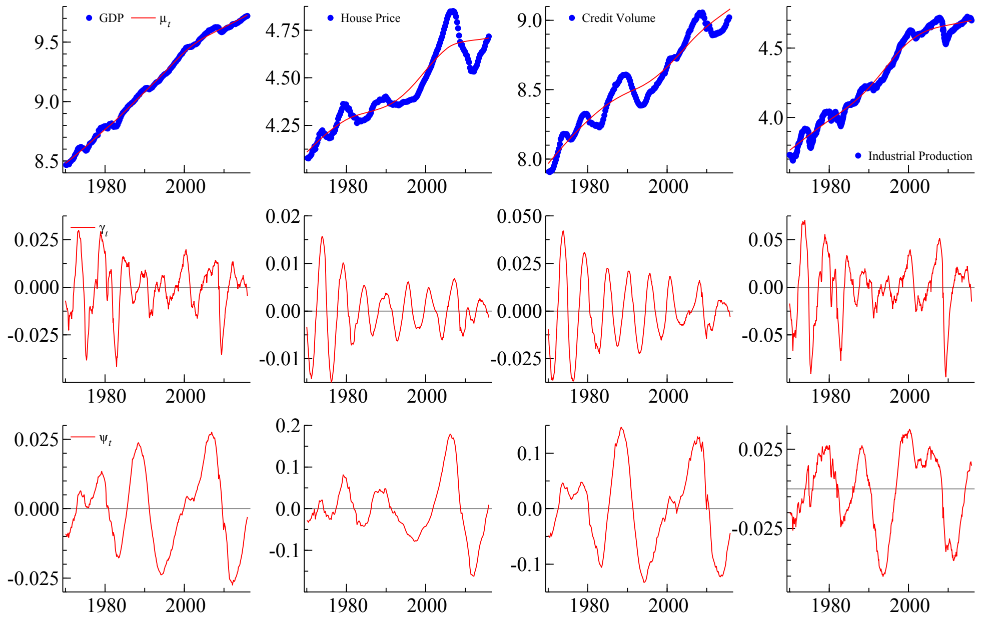

Figure 3. Time series United States with trend (μ_t), short-term cycle (γ_t) and medium-term cycle (ψ_t) components in gross domestic product, house prices, credit and industrial production. All series are deflated, seasonally adjusted and in logs.
Notes: The figure presents the fit (smoothed estimates) of the UCTSM model estimated for the United States. The top row shows the raw data (blue line) and trend (μ_t, red line) for GDP, house prices, credit and industrial production. The middle row presents the short-term cycle (γ_t) of the four series considered. The bottom row presents the medium-term cycle (ψ_t) of the four series considered.

price cycle is – at least partly – driven by the credit cycle. In the remaining two other countries, that is the United Kingdom and Germany, there is no discernible direct or indirect co-cyclicality between the medium-term cycles of credit and GDP. The mixed evidence might be related to structural features of credit markets, such as the share of mortgage in total credit (see e.g. Cerutti, Dagher and Dell'Ariccia, 2017) and the homeownership rate (see e.g. Rünstler and Vlekke, 2018; Comunale, 2020).

Overall, we find strong evidence for co-cyclicality between the medium-term cycles of GDP and house prices. The evidence for co-cyclicality between the medium-term cycles of GDP and credit is more complex. For some countries there is a direct relation, for some an indirect relation (via the medium-term house price cycle), and for some countries there is no clear relation. Lastly, we find only limited evidence for strong concordance between the medium-term cycles of credit and house prices.

Concordance of extracted cycles between countries

The intertwined nature of the medium-term cycles of credit, house prices and GDP on a country level, naturally raises the question whether, and to what extent, these cycles are synchronized across countries. This is an important question, especially for macroprudential policy makers that have to judge whether the build-up of excessive

TABLE 4

Number of business cycle peaks according to Harding and Pagan (2002) algorithm, 1970Q1–2015Q4

	United States	*Japan*	*Canada*	*United Kingdom*	*Germany*	*France*	*Italy*	*Netherlands*
	A. short-term cycle							
GDP	15	15	12	10	16	12	11	10
HP	9	15	7	14	14	16	15	7
CRED	9	15	8	12	13	15	12	11
	B. medium-term cycle							
GDP	5	8	12	11	6	12	6	7
HP	5	9	11	3	5	12	6	4
CRED	5	13	11	4	6	11	10	10

leverage in the global financial system affects the domestic financial system and whether this should be mitigated by macroprudential measures; see the discussions in Jeanne (2014) and Beirne and Friedrich (2014).

We can measure the international coherence for short-term and medium-term cycles by counting the number of months that cycles are in the same phase (a downturn or an upturn). When at least seven of the eight countries we analysed are in the same phase of the cycle, we mark this as a simultaneous upturn/downturn. We define a downturn as a period between a peak and through of the business cycle and a upturn as a period between a through and peak of the business cycle. We have determined the peaks and troughs in the cycle using the definitions and the algorithm of Harding and Pagan (2002).

Table 4 presents the number of cyclical peaks we found in the short- and medium term cycles. The short-term cycles of GDP, house price and credit volume all contain an average of 12 peaks, averaged over the eight countries we analysed. So, from peak to peak this constitutes approximately six business cycles in the period 1985–2015. The medium-term cycles have eight peaks on average, so approximately four cycles. The Online Appendix contains a set of tables showing the monthly dates of peaks and troughs in the short-term and medium-term cycle for all variables and all countries we analysed.

Table 5 presents our measures of international simultaneity for the short-term and medium-term cycles of GDP, house prices and credit. For most months, the short-term cycle phases are different; we observe different phases in 69%, 94% and 77% of the months for GDP, house prices and credit respectively. For the medium-term cycle, we observe different phases for GDP, house prices and credit in 74%, 77% and 79% respectively. We may conclude from these measures that the simultaneity of the international medium-term cycles is lower than the simultaneity of the international short-term cycles. The short-term housing price cycle shows least simultaneity of all variables. We find that periods with strong similarity are concentrated around major events such as the oil crises during the mid-1970s and the beginning of the 1980s, and the Great Recession of 2008–09.

TABLE 5

Simultaneity of business cycle upturns and downturns, 1970Q1–2015Q4, percent

	GDP	*HP*	*CRED*
	A. short-term cycle		
Upturn	18	3	11
Downturn	12	3	12
Not-simultaneous	69	94	77
	B. medium-term cycle		
Upturn	13	12	12
Downturn	14	11	9
Not-simultaneous	74	77	79

For a more formal description of the coherence of the business cycles we use the synchronicity and similarity measures of Mink *et al*. (2012), introduced in section (International concordance of cycles). An alternative is to consider the correlation between the cycles as a measure of cyclical coherence, using conventional Pearson's correlation coefficients. However, the correlation coefficient does not properly take into account that cycles can be in different phases (below/above trend level) or have different amplitudes. Moreover, the correlation coefficients are often not very discriminative. For example, in our sample, almost all pairwise country correlations are high and significant, while the cycles show very little similarity in terms of being above/below trend level or amplitude.6

Figure 4 shows the 10-year moving average overall synchronicity and similarity measures for the short-term cycles (left-hand panel) and long-term cycles (right-hand panel). The Figure points to several interesting results.

First, the similarity and synchronicity measures are relatively low. The overall synchronicity measure is usually lower than 0.5 and the similarity measure is lower than 0.3. This means that the short-term (and medium-term) cycles are only simultaneously above trend level in all countries less than half of the time. The amplitude of the cycles is only roughly equivalent 33% of the time. This limited concordance is in line with the low pairwise international cross-correlations of macroeconomic aggregates found by Ambler, Cardia and Zimmermann (2004).

Second, the overall cross-country co-movement of the medium-term cycles of GDP, credit and house prices has hardly changed since the 1980s. This seems to indicate that the medium-term credit and house price cycles depend more on country specificities than on global factors. The picture is quite different for the short-term cycle of GDP. According to the similarity and synchronicity measures, the international co-movement of the short-term GDP cycle has increased since 2000, coinciding with the most recent wave of increased globalization starting in the mid-1990s with the integration of China in the global economy. Note that we are analysing 10-year moving averages, that is the synchronicity and similarity measures in 2000 measure the average synchronicity and similarity in the period 1990Q1–2000Q1.

[6]Results available upon request from the authors.

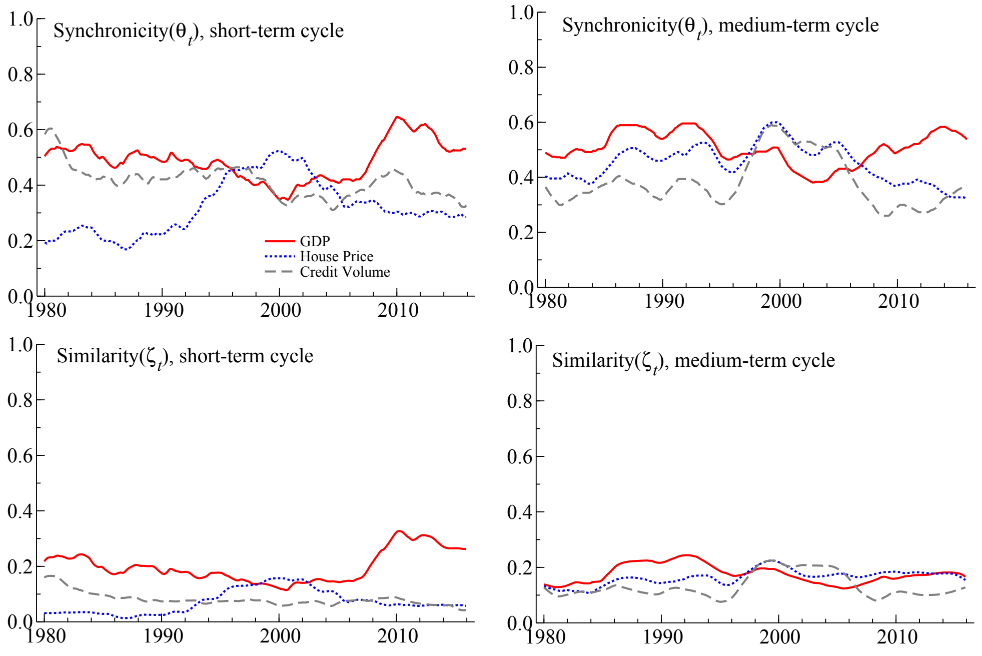

Figure. 4. Overall synchronicity (θ_t) and similarity (ζ_t) measures for the short-term and medium-term cycles of gross domestic product (GDP), house prices and credit, G7 countries and the Netherlands, 1970Q1–2015Q4.

Our findings appear to contradict with previous research on claims that global financial factors are important drivers of country-specific financial cycles (see e.g. Bekaert, Hoerova and Lo Duca, 2013; Bruno and Shin, 2015). We do find evidence for stronger international co-movement of the short-term cycles of the G7 countries. However, Bruno and Shin (2015) and Bekaert *et al.* (2013) use equity, bonds and other liquid assets as indicators to identify the financial cycle. Recent research (Rünstler *et al.*, 2018) indicates that the medium-term cycle of these indicators have very different properties than our credit variables both in terms of cycle length and volatility, so they are pretty much unrelated with each other. Furthermore, we have used a different selection of countries and a relatively short time period in our study.

Alternative credit variables

This section presents the outcome of our model when two alternative credit variables are used instead of our main variable, the volume of domestic bank credit to the private non-financial sector. The first alternative measure is credit from all sectors to the private non-financial sector. This credit variable includes cross-border-bank-lending and lending to the private sector by institutions (e.g. pension funds). The second alternative measure is credit from all sectors to households and non-profit institutions serving households. This variable excludes credit to private non-financial corporations, but includes lending by non-domestic banks and institutions. Parameter estimates using these alternative credit variables are presented in the Online Appendix.

Overall, the results for the model using alternative credit variables are in line with the main results presented in Tables 2 and 3. Minor differences occur mainly in the loading matrices B of the medium-term cycle. It would be interesting to see how recently proposed indicators of credit imbalances, such as leverage and the debt service ratios (see e.g. Juselius and Drehmann, 2015), would influence the results. However, the length of the available time-series is currently too short to reliably apply our methodology.[7]

Alternative synchronicity and similarity measures

We have verified our results on the synchronicity and similarity measures. The first check calculates the synchronicity and similarity measures leaving out Germany and Japan, because these countries have a relatively small duration or amplitude of the medium-term credit and house price cycles. However, the results are not very sensitive to excluding these countries. The outcomes are qualitatively the same as can be verified in the Online Appendix.

The second check analyses whether the synchronicity and similarity measures for the first-differenced cyclical measures, which we refer to as the 'swing'-synchronicity and 'swing'-similarity (see e.g. Meller and Metiu, 2015), differ from the outcomes described in section (International concordance of cycles). The swing measures indicate the directional change (swing synchronicity) and the absolute value of the size of the directional change (swing similarity) respectively. The results are shown in the Online Appendix; they are comparable to the outcomes presented in Figure 4. The main difference is that the swing measures are more compressed, indicating that the differences in the overall swing-synchronicity and swing-similarity between GDP, house prices and credit are smaller than the differences for the 'usual' measures.

V. Conclusion

We have discussed a model-based method for the joint extraction of unobserved components that represent long-term trend, short-term cycle, medium-term cycle and irregular noise. The method is based on a dynamic multivariate model for a country panel of mixed-frequency time series of macroeconomic and financial variables. The estimation procedure allows us to measure the concordance of cycles associated with different variables and countries. The international concordance of the extracted cycles is analysed using synchronicity and similarity measures.

In our empirical study, we have analysed GDP, monthly industrial production, credit volumes and house prices. The main findings of the study are as follows. First, the cyclical movements in time series of credit volumes and house prices are largely driven by the medium-term cycle. Second, for most countries, the co-movement

[7]The BIS database contains time series of the debt service ratios, but these only start in 1999Q1.

between the cycles of the financial and macroeconomic variables is limited to the medium-term. Third, for all countries considered, we find strong concordance between the medium-term cycles of house prices and GDP. The relation between the medium-term cycles of GDP and credit is more complex. We find strong concordance between both cycles in only three countries. However, in three other countries, we find some evidence of indirect concordance which implies that the medium-term cycles of credit and house prices share co-cyclicality while the medium-term cycles of house prices and GDP share commonality. This suggests that house price cycles and credit cycles are correlated, confirming the bidirectional relationship in the literature. Finally, the cross-country concordance of both the short-term and medium-term cycles of GDP, house prices and credit volume is low. Hence, the bulk of the cyclical movements appears to be driven by domestic rather than global factors.

Our outcomes confirm earlier findings of large medium-term cycles in credit volumes and house prices as well as the strong correlation between the medium-term cycles of house price and credit cycles (see e.g. Rünstler *et al*., 2018; Bulligan *et al*., 2019; Yan and Huang, 2020). Our study sheds new light on the estimation of both short and medium term cycles in one joint framework, and the co-cyclicality of GDP, house prices and credit. In light of our results an interesting avenue for future research are joint modelling of the international concordance of the short-term and medium-term GDP, house price and credit cycles in a joint UCTSM. Furthermore, a more in depth investigating into the propagation mechanisms and structural factors driving the (interaction) between the cycles seems a fruitful topic for future research.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Supplementary Material Online Appendix.