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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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Modeling the business and financial cycle in a multivariate structural time series model*

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Abstract

We consider a multivariate unobserved component time series model to disentangle the short-term and medium-term cycle for the G7 countries and the Netherlands using four key macroeconomic and financial time series. The novel aspect of our approach is that we simultaneously decompose the short-term and medium-term dynamics of these variables by means of a combination of their estimated cycles. Our results show that the cyclical movements of credit volumes and house prices are mostly driven by the medium-term cycle, while the macroeconomic variables are equally driven by the short-term and medium-term cycle. For most countries, the co-movement between the cycles of the financial and macroeconomic variables is mainly present in the medium-term. First, we find strong co-cyclicality between the medium-term cycles of house prices and GDP in all countries we analyzed. Second, 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 'indirect' concordance, i.e. the medium-term cycles of credit and house prices share co-cyclicality, while in turn the medium-term cycles of house prices and GDP share commonality. This outcome might indicate that the house price cycle is –at least partly– driven by the credit cycle. Lastly, the cross-country concordance of both the short-term cycles and the medium-term cycles of GDP, house prices and credit is low. Hence, the bulk of the cyclical movements seem to be driven by domestic rather than global factors.

Keywords: unobserved component time series model, Kalman filter, maximum likelihood estimation, short-term and medium-term cycles.
JEL classifications: C32, E32, G01.

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1 Introduction

We present a novel approach for the simultaneous estimation and extraction of short-term and medium-term cycles from a set of macroeconomic and financial variables. In recent years, many contributions have emerged that investigate the existence of medium-term cyclical movements in the economy. In a seminal paper, Comin and Gertler (2006) argue that medium-term oscillations are typically not detected by conventional business cycle filters, which tend to capture them into the long-term trend. They argue that medium-term business cycles are caused by high-frequency shocks that influence the pace of research, development and technology adoption, producing business cycles of greater length and volatility than conventionally analyzed. Further, Comin et al. (2014) and Correa-López and de Blas (2012) describe another mechanism causing medium-term cycles, i.e. the transmission of technology from countries that can be considered technology-leaders to 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 ict-goods and services from the United States to the rest of the world at the turn of the last 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. A important finding from this literature is that peaks in the medium-term oscillations of financial variables coincide with onsets of financial crises; see, for example, Drehmann et al. (2012) and Borio (2014). 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).

We aim to bridge these two research directions by studying a recently proposed approach that decomposes a panel of macroeconomic and financial time series into four dynamic components: the long-term trend, the medium-term cyclical dynamics, the short-term cyclical movements and the irregular component (see Koopman and Lucas, 2005). The model belongs to the class of unobserved components time series models (UCTSMs), which enable the dynamic decomposition of a panel of time series; see, for example, Chen et al. (2012), De Bonis and Silvestrini (2014), Galati et al. (2016), and Rünstler and Vlekke (2016). The main advantage of this approach compared to traditional approaches, such as non-parametric one-sided and bandpass filters (see e.g. Aikman et al., 2015, Schüler et al., 2015), is that it enables simultaneous extraction of the short-term and medium-term cycles. Furthermore, the interrelations between the extracted cycles can be modeled in a parsimonious manner. Finally, our approach does not require ex-ante assumptions on the length of the duration of the cycle. In particular, compared to non-parametric filters, the UCTSM does not need prior assumptions on the length of the cycles.

We make several contributions to the existing literature on medium-term cycles. First, we decompose oscillations that have been documented in the literature into two components: a short-term cycle and a medium-term cycle. The Kalman filter enables extracting the short-term and medium-term cycles in a straightforward fashion. Second, we extend recent work on the international coherence of business and financial cycles (for example, Meller and Metiu, 2015), by analyzing the international linkages of both the short-term and medium-term cycles using the methodology of Mink et al. (2012). Third, we extend previous studies that have used the UCTSM framework by using variables with both quarterly and monthly frequencies in a parsimonious and joint modeling framework.

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 house prices and gross domestic product (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 2 describes the dataset and highlights some stylized features of the macroeconomic and financial time series. Section 3 describes our modeling approach and discusses the estimation and signal extraction method. Section 4 presents our main empirical results. Section 5 concludes.

2 Dataset and stylized facts

2.1 Dataset

We estimate short-term and medium-term cycles of four key macroeconomic and financial time series for eight advanced economies, i.e. the so-called G7 countries (the United States, 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 modeling 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). 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). Our main financial time series are quarterly data on credit volumes and house prices. These variables have been commonly used as proxies for the financial cycle in earlier work of Borio et al. (2001), Drehmann et al. (2012), Schularick and Taylor (2012), Igan and Loungani (2012) and Aikman et al. (2015), amongst others. We use the volume of domestic bank credit to the private non-financial sector as our main credit variable.

The main sources of our time series are databases maintained by the OECD and the BIS.[1]

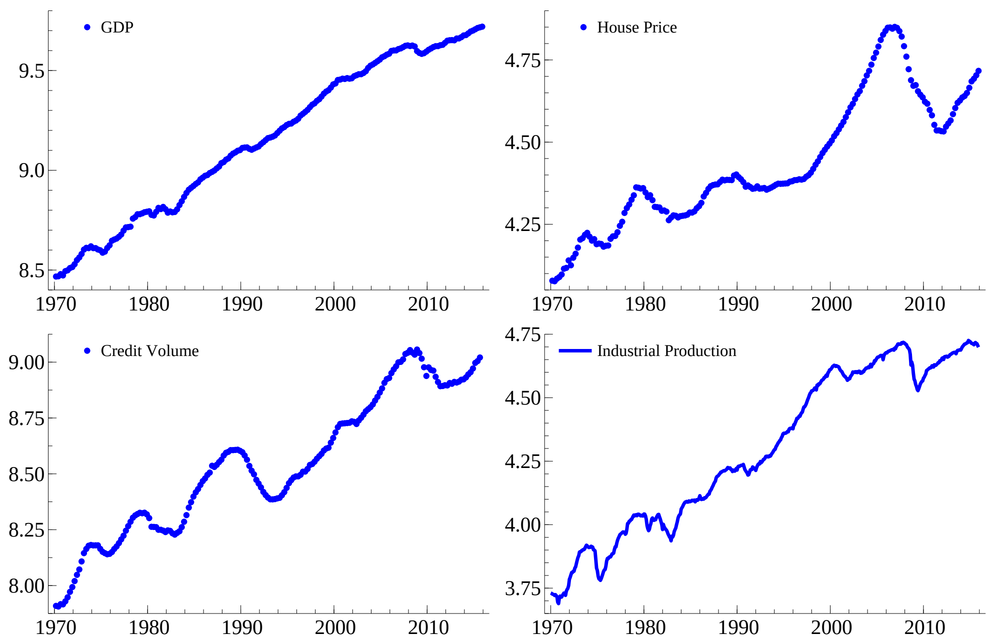
[1] The time series from the OECD database are publicly available via `https://data.oecd.org/economy.htm`.

Our GDP, industrial production and nominal house prices series are taken from the former. All nominal credit variables are taken from the BIS-database. We use deflated series for all variables. GDP and industrial production are deflated at the source. 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, while house prices and credit are seasonally adjusted using the Census X–12 method.

2.2 Stylized facts

Figure 1 presents the raw time series of the variables we analyzed, for the United States. 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 2008–2009. To keep the main text contained, we included the time series for the other G7 countries and the Netherlands in Figure 4 to Figure 10 in Appendix A.2. Overall, the other country results all show periods of build-up and subsequent downfalls in both house prices and credit. However, the timing and size of the rise and fall in house prices seems to differ markedly between countries.

Figure 1: GDP, house prices, credit and industrial production in the United States. All series are deflated, seasonally adjusted and in logs.

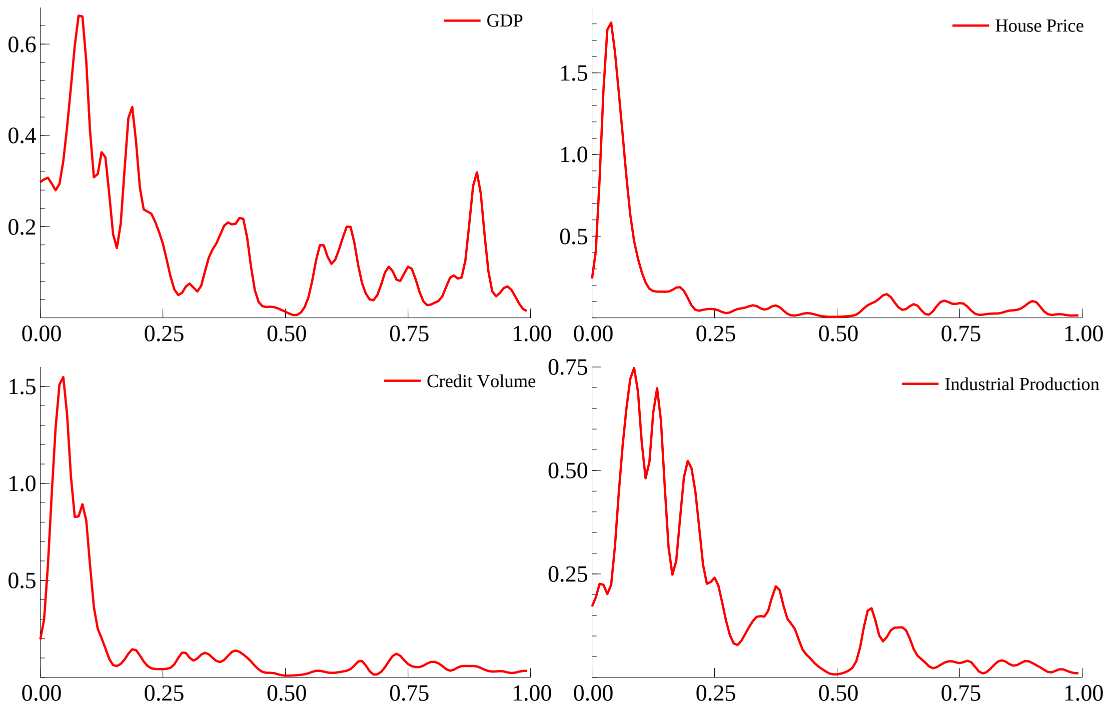


To get more insight into the possibility of multiple cycles in our times series we analyzed the spectral densities. Spectral density estimates originate from the periodograms of variables (they are locally smooth estimates thereof), and offer insight into where the mass of the cyclical oscillations in the data occurs. Analyzing the spectral densities can give further guidance on whether it is sensible to extract a short-term and medium-term cyclical component. Figure 2

The times series from the BIS data area publicly available via `http://www.bis.org/statistics/totcredit.htm`.

presents the spectral density estimates for the US variables. Since the spectral densities are symmetric between -π 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.[2] 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 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.

Figure 2: Spectral densities United States for GDP, house prices, credit and industrial production. All series are deflated, seasonally adjusted and in log-differences.



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 to a period of $6\frac{1}{4}$ years. Given the dating of economic recessions, the latter seems to be related to the business cycle frequency. The third and fourth peak 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 so much of interest. They can be seen as seasonality or noise 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

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

cycle-length of approximately 25 years, and peaks at cycles of approximately 6, 4 and 3 years, respectively. The spectral densities of the house prices and credit are quite different from the aforementioned densities. Both 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 seasonality or noise in the data.

Figure 11 to Figure 17 in Appendix A.3 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 United States, i.e. the spectral densities of GDP and industrial show peaks at medium-term frequencies of roughly 25 to 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 to 25 years.

The literature on medium-term cycles typically decomposes the times series in a trend, one (medium-term) cycle and an irregular component (see e.g. Comin and Gertler, 2006 and Rünstler and Vlekke, 2016). Based on the results above, we decided to depart from the standard set-up in the literature and add a component that captures the medium-term cycle, i.e. we decompose our time series into a long-term trend, a short-term cycle, a medium-term cycle, and an irregular components. Our main conjecture from analyzing 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.

3 Modeling approach

3.1 Unobserved Components Time Series Models

We introduce a multivariate unobserved components time series model (UCTSM) to describe the dynamic behavior of the four series and there interdependencies as described in Koopman and Lucas (2005), i.e.:

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

where y_t represents the time-series observation vector at time t, and is defined as follows:

$$y_t = \begin{bmatrix} y_t^{\text{GDP}} \\ y_t^{\text{HP}} \\ y_t^{\text{CRED}} \\ y_t^{\text{IP}} \end{bmatrix} = \begin{bmatrix} \text{real GDP (GDP)} \\ \text{real house price (HP)} \\ \text{real credit (CRED)} \\ \text{real industrial production (IP)} \end{bmatrix}, \qquad t = 1, \ldots, T, \tag{2}$$

where t is a monthly time index. All variables in the observation vector are in logs. The long-term trend is represented by the vector μ_t and the cycle components by γ_t (short-term cycle) and ψ_t (medium-term cycle). We assume that ε_t is normally distributed, with mean zero and a diagonal covariance matrix Σ_ε. The irregular component ε_t in eq. (1) is introduced to allow for measurement noise in the observations. Following Valle e Azevedo et al. (2006) and Koopman and Lucas (2005), the trend μ_t is specified as an integrated random walk process:

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

The role of μ_t is to filter out the low-frequencies or long-term dynamics from the data.

The cycle components γ_t and ψ_t have the stochastic dynamic specification proposed by Harvey (1989), and are defined as

$$\begin{pmatrix} \gamma_{t+1} \\ \gamma^*_{t+1} \end{pmatrix} = \phi_\gamma \begin{bmatrix} \cos\lambda_\gamma \mathcal{I}_N & \sin\lambda_\gamma \mathcal{I}_N \\ -\sin\lambda_\gamma \mathcal{I}_N & \cos\lambda_\gamma \mathcal{I}_N \end{bmatrix} \begin{pmatrix} \gamma_t \\ \gamma^*_t \end{pmatrix} + \begin{pmatrix} \kappa_t \\ \kappa^*_t \end{pmatrix}, \qquad \begin{pmatrix} \kappa_t \\ \kappa^*_t \end{pmatrix} \overset{i.i.d.}{\sim} \mathcal{N}(0, I_2 \otimes \Sigma_\kappa), \tag{4}$$

and

$$\begin{pmatrix} \psi_{t+1} \\ \psi^*_{t+1} \end{pmatrix} = \phi_\psi \begin{bmatrix} \cos\lambda_\psi \mathcal{I}_N & \sin\lambda_\psi \mathcal{I}_N \\ -\sin\lambda_\psi \mathcal{I}_N & \cos\lambda_\psi \mathcal{I}_N \end{bmatrix} \begin{pmatrix} \psi_t \\ \psi^*_t \end{pmatrix} + \begin{pmatrix} \omega_t \\ \omega^*_t \end{pmatrix}, \qquad \begin{pmatrix} \omega_t \\ \omega^*_t \end{pmatrix} \overset{i.i.d.}{\sim} \mathcal{N}(0, I_2 \otimes \Sigma_\omega), \tag{5}$$

where the frequency λ_j is measured in radians, $0 \leq \lambda_j \leq \pi$, and the persistence ϕ_j is the damping factor, $0 < \phi_j < 1$, for $j = \gamma, \psi$. The average period or length of the stochastic cycles is given by $2\pi/\lambda_j$. The cycles γ_t and ψ_t are both stationary dynamic processes.

The unobserved components μ_t, γ_t, and ψ_t are assumed to represent unique dynamic processes and are independent of each other. However, the covariances between the disturbances driving a particular component are typically non-zero, and imply a dependence structure amongst the variables and their dynamic characteristics. The matrices A and B are introduced to determine this dependence structure. The matrices A and B scale the cycles γ_t and ψ_t for each of the individual series. By inspection of the 'cycle loading' matrices A and B we can test whether the GDP cycle is the same as the credit and house price cycles. For identification of the cycle disturbance variances (Σ_κ and Σ_ω), the loading-matrices A and B in eq. (1) are restricted to be lower triangular matrices with unity as diagonal elements. The model is completed with appropriate initial conditions for trend μ_1 and cycles (γ_1, ψ_1), as discussed in Durbin and Koopman (2012).

3.2 Similar cycles

In our analysis, we assume that the cycles are 'similar', following Galati et al (2016). Under this assumption, the frequency λ_j and persistence ϕ_j in eqs. (4)–(5) have the same values for the four variables in our estimation. However, the peaks, troughs and scales of the cycles, as determined by the variances and covariances of the disturbances driving the components, can still be different under these 'similar' restrictions. The implications for the properties of similar cycles, both in the time- and frequency-domain analyses, are discussed in Harvey and Koopman (1997).

3.3 State space methodology

Multivariate UCTSMs can be formulated in the general linear state space model as 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 contains the unobserved components μ_t, γ_t and ψ_t, together with auxiliary variables such as γ_t^* and ψ_t^* in eqs. (4)–(5). The various disturbances are placed in an appropriate manner in the vectors ε_t and η_t. The state-space setup of the dynamic factor model is outlined in Appendix A.1.

Once the model is represented in state space form, the Kalman filter and related state space methods can be applied. We estimate the unknown static parameters by the method of maximum likelihood; numerical maximization requires the Kalman filter to compute the loglikelihood function. Given these estimates, we obtain prediction residuals for diagnostic checking and model evaluation from the Kalman filter. We obtain the smoothed estimates of the unobserved trend, short-term and medium-term cycle and the irregular component from a smoothing method; see Durbin and Koopman (2012) and Harvey (1989) for further details on the trend-cycle model and the state space methodology.

3.4 Estimation strategy

Following Harvey and Jaeger (1993) we restrict the signal-to-noise ratio, $\sigma_\zeta^2/\sigma_\epsilon^2$. The tightness of the signal-to-noise ratio is a matter of choice. Harvey and Jaeger (1993) choose the signal-to-noise ratio $6.25E^{-4}$ to ensure smoothness and some stickiness of the long-term trend μ_t. They show this choice equals the preferred setting of the Hodrick and Prescott (1997) filter for quarterly data. An alternative would be to choose an even tighter setting. We opted for an alternative signal-to-noise ratio of $6.94E^{-5}$, equaling the monthly setting of the Hodrick and Prescott filter. For each country analyzed, we choose the signal-to-noise setting with the highest estimated likelihood value as our baseline .[3]

We estimate the model in four steps. First, we run the model by fixing the signal-to-noise ratios to either the loose ($6.25E^{-4}$) or tight ($6.94E^{-5}$) signal-to-noise ratio. Second, we re-run the model with the same signal-to-noise ratio and fix the damping factor for the short (ϕ_γ) and medium-term (ϕ_ψ) cycles at the values in the previous run. These restrictions assume that the cycles are somewhat more volatile than the unrestricted estimates. Furthermore, it insures against spurious estimates. We restrict the damping factors to lie within the unit circle with a maximum value of 0.99. Third, we re-run the model with all coefficients fixed at the estimates in the second step, except for the factor loadings. Fourth, we choose between the models with a loose and tight signal-to-noise ratio based on their estimated likelihood value. For most countries, this estimation strategy led to choosing the model with a loose signal-to-noise ratio. In only two countries, i.e. the Netherlands and the United Kingdom, the UCTSM with the tighter signal-to-noise ratio was chosen.

[3] Alternatively, the estimated likelihood value could be maximized over a grid of signal-to-noise ratio's. We leave this for future research.

4 Empirical results

In this section we discuss the outcome of the UCTSMs for the countries we analyzed. In order to keep the main discussion contained, we limit our presentation to the estimated coefficients in the UCTSMs in Table I. Figures 18–25 in Appendix A.4 show the raw data and the estimated components (long-term trend, short-term cycle and medium-term cycle) for the variables considered for the G7 countries and the Netherlands, respectively.

4.1 Short-term cycle

We start our discussion with the short-term cycles, γ_t. Panel A in Table I shows the average duration (p_γ) and persistence (ϕ_γ) of the short-term cycles. Note that γ_t consists of four separate similar cycles. Furthermore, the variance of the cycles (the diagonal D_γ of the covariance matrix Σ_γ) is shown. Finally, panel A shows the loading-matrices (A) for the short-term cycles. The loading matrices A reveal whether there is any co-cyclicality between the short-term cycles. Grey cells indicate the coefficients are statistically significant. We distinguish statistical significance levels of 10%, 5% and 1%, which are denoted as *,** and ***, respectively. Our empirical results point to some interesting findings, that can be summarized as follows.

First, averaged over the 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. All cycles are statistically significant, as can be seen from the elements on the diagonal, D_γ, of the variance matrix Σ_γ in Table I. Generally, the estimated cycle durations coincide with those based on the more conventional band-pass filter frequency range setting of $[\frac{1}{2},8]$ years (see e.g. Baxter and King, 1999 and 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.This seems to indicate that the short-term cycle of industrial production is a good approximation for the short-term cycle of GDP.

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 six out of the eight countries analyzed, we find no statistically significant entries for the short-term credit cycles in the loading-matrices. However, we do find strong co-cyclicality between the short-term credit and GDP cycles in Canada and the Netherlands. This might indicate a more prominent role for credit as a means of financing businesses and households in these economies.

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.

Table I: Parameter estimates of multivariate UCTSM for G7 countries and the Netherlands

A. Short-term cycle	United States				United Kingdom				Japan				Canada			
p_γ	5.4				6.7				3.3				7.1			
ϕ_γ	0.99				0.99				0.98				0.99			
variance D_γ	0.0003	0.0000	0.0002	0.0013	0.0002	0.0025	0.0002	0.0003	0.0002	0.0001	0.0001	0.0027	0.0004	0.0008	0.0012	0.0020
loading matrix A	GDP	HP	CRED	IP	GDP	HP	CRED	IP	GDP	HP	CRED	IP	GDP	HP	CRED	IP
γ_{GDP}	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
γ_{HP}	-0.02	1.00	0.00	0.00	1.79	1.00	0.00	0.00	0.48	1.00	0.00	0.00	-0.14	1.00	0.00	0.00
γ_{CRED}	0.25	1.26	1.00	0.00	0.20	0.30	1.00	0.00	0.01	-0.04	1.00	0.00	0.94*	0.25	1.00	0.00
γ_{IP}	1.82***	1.51	-0.07	1.00	1.11**	0.11	0.27	1.00	3.26***	0.43	-1.99	1.00	1.97***	0.02	-0.19	1.00
	Germany				France				Italy				Netherlands			
p_γ	4.5				3.6				3.8				7.9			
ϕ_γ	0.97				0.98				0.97				0.99			
variance D_γ	0.0001	0.0000	0.0000	0.0010	0.0000	0.0001	0.0000	0.0006	0.0001	0.0017	0.0000	0.0010	0.0004	0.0011	0.0008	0.0010
loading matrix A	GDP	HP	CRED	IP	GDP	HP	CRED	IP	GDP	HP	CRED	IP	GDP	HP	CRED	IP
γ_{GDP}	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
γ_{HP}	-0.09	1.00	0.00	0.00	0.52	1.00	0.00	0.00	-0.38	1.00	0.00	0.00	-0.06	1.00	0.00	0.00
γ_{CRED}	0.07	-0.57	1.00	0.00	0.08	-0.13	1.00	0.00	0.33	0.00	1.00	0.00	0.88*	-0.16	1.00	0.00
γ_{IP}	2.82***	0.34	-0.46	1.00	3.14***	0.86	2.31	1.00	2.54***	-0.10	1.81	1.00	1.45**	0.03	0.53	1.00
B. Medium-term cycle	**United States**				**United Kingdom**				**Japan**				**Canada**			
p_ψ	13.6				18.4				9.2				22.3			
ϕ_ψ	0.99				0.99				0.99				0.99			
variance D_ψ	0.0001	0.0011	0.0015	0.0006	0.0007	0.0035	0.0040	0.0044	0.0002	0.0012	0.0011	0.0014	0.0001	0.0062	0.0047	0.0017
loading matrix B	GDP	HP	CRED	IP	GDP	HP	CRED	IP	GDP	HP	CRED	IP	GDP	HP	CRED	IP
ψ_{GDP}	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
ψ_{HP}	2.77***	1.00	0.00	0.00	1.19*	1.00	0.00	0.00	1.45**	1.00	0.00	0.00	8.43***	1.00	0.00	0.00
ψ_{CRED}	4.48***	-0.25	1.00	0.00	0.80	0.16	1.00	0.00	1.73***	0.42*	1.00	0.00	-1.98	1.28**	1.00	0.00
ψ_{IP}	1.91*	-0.19	-0.58	1.00	2.42***	-0.36**	-0.03	1.00	2.70***	-0.26	0.06	1.00	3.17**	-0.80**	0.24	1.00
	Germany				France				Italy				Netherlands			
p_ψ	9.3				16.2				14.7				23.7			
ϕ_ψ	0.99				0.99				0.99				0.99			
variance D_ψ	0.0001	0.0003	0.0004	0.0005	0.0001	0.0018	0.0010	0.0010	0.0000	0.0057	0.0021	0.0006	0.0003	0.0054	0.0017	0.0027
loading matrix B	GDP	HP	CRED	IP	GDP	HP	CRED	IP	GDP	HP	CRED	IP	GDP	HP	CRED	IP
ψ_{GDP}	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
ψ_{HP}	1.80***	1.00	0.00	0.00	1.54*	1.00	0.00	0.00	19.58***	1.00	0.00	0.00	3.56***	1.00	0.00	0.00
ψ_{CRED}	1.10	6.56	1.00	0.00	1.58***	-0.07	1.00	0.00	2.78	2.90***	1.00	0.00	0.45	0.96**	1.00	0.00
ψ_{IP}	1.69	-12.64	0.29	1.00	2.66***	-0.17	-0.41*	1.00	2.32	-0.83	2.32	1.00	1.71***	-0.48	2.62**	1.00

The table reports the estimates of persistence ϕ_γ and ϕ_ψ, the period p_γ and p_ψ in years ($p = 2\pi/\lambda$), the diagonal of the variance-matrix D_γ for the short cycle (γ) and medium-term cycle (ψ), respectively. A and B denote the loading matrices for the short-term and medium-term cycle, respectively. Significant estimates in these matrices are highlighted in grey. *,** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

4.2 Medium-term cycle

Panel B of Table I shows the estimates for the medium-term cycles ψ_t, the average cycle durations (p_ψ), cycle persistences (ϕ_ψ), the diagonal D_ψ of the covariance matrix Σ_ψ and the loading matrices B. The results can be summarized as follows.

First, the average duration of the medium-term cycle (p_ψ) varies from 9.2 years in Japan to 23.7 years in the Netherlands. All cycles are statistically significant given the elements in D_ψ. The estimated cycle lengths lie within the boundaries that are usually found for the so-called 'financial cycle' (see e.g. Borio, 2014 and Drehmann et al., 2012).

Second, for most countries, the variance of the medium-term cycles (ψ_t) of GDP and industrial production are economically just as important as the variance of the short-term cycles (γ_t), as can be seen from a comparison of D_ψ and D_γ in Table I ($D_\psi \approx D_\gamma$). By contrast, for most countries, we find the medium-term cycles of the financial variables are economically much 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.

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

Fourth, the direct relation between the medium-term cycles of GDP and credit is more complex. In only three countries, i.e. the United States, Japan and France, we find strong co-cyclicality between both cycles. In three of the other countries, i.e. 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 price cycle is –at least partly– driven by the credit cycle. In the remaining two other countries, i.e. the United Kingdom and Germany, there is no discernible direct or indirect co-cyclicality between the medium-term cycles of credit and GDP.

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.

4.3 International concordance of short-term cycles and medium-term cycles

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 extend, these cycles are synchronized across countries. This is an important question, especially for macro-prudential policy makers that have to judge whether the build-up of excessive leverage in the global financial system affects the domestic financial system and whether this should be mitigated by macro-prudential measures (see e.g. Jeanne, 2014 and Beirne and Friedrich, 2014).

In order to determine if the short-term and medium-term cycles have a high coherence we use the so-called 'synchronicity' and 'similarity' measures proposed by Mink et al. (2012). 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. 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 $c_t^{r,j}$. Following Mink et al. (2012), we define a synthetic reference cycle, that is defined as the median cycle for the G7 countries and the Netherlands. The *overall* synchronicity measure for variable j is defined as:

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

while overall similarity is defined as:

$$\zeta_t^j = 1 - \frac{\sum_{i=1}^{n} |c_t^{i,j} c_t^{r,j}|}{\sum_{i=1}^{n} |c_t^{i,j}|}. \tag{7}$$

Both measures can vary between 0 and 1, where 0 means that there is no synchronicity/similarity and 1 means that their is perfect synchronicity/similarity. Perfect synchronicity indicates that all cycles are simultaneously above/below trend level. Perfect similarity indicates that the absolute difference between the cycles is zero, meaning that the cycles have an identical amplitude.

Alternatively, we could have used 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.[4]

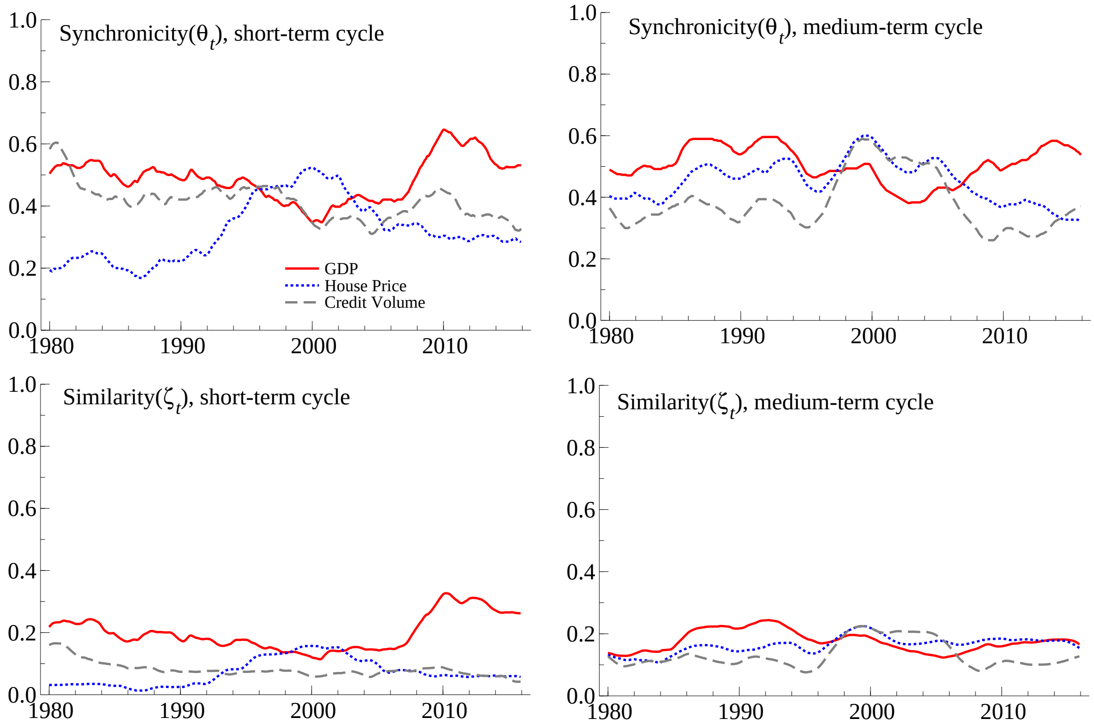
Figure 3 shows the 10–year moving average overall synchronicity and similarity measures for the short-term cycles (left-hand panel) and long-term cycles (right-hand panel). The Figure points to several interesting results.

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 percent of the time. This limited concordance is in line with the low pairwise international cross-correlations of macroeconomic aggregates found by Ambler et al. (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.

[4] Results available upon request from the authors.

Figure 3: Overall synchronicity (θ_t) and similarity (ζ_t) measures for the short-term and medium-term cycles of GDP, house prices and credit, G7 countries and the Netherlands



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 analyzing 10-year moving averages, so the synchronicity and similarity measures in 2000.I tell us something about these measures in the period 1990.I–2000.I.

Overall, our findings seem to contradict with previous research that claims that global financial factors are important drivers of country-specific financial cycles (see e.g. Bruno and Shin, 2015 and Bekaert et al., 2013). We do find evidence for stronger international co-movement of the short-term cycles of the G7 countries. Admittedly, our sample of countries and time period are relatively short. We leave it to future research to investigate the international co-movement of the short-term and medium-term financial cycles in more depth.

4.4 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. Tables of the parameter estimates using these alternative credit variables are shown in Table II and Table III in Appendix A.5, respectively.

Overall, the model outcomes using the alternative credit variables are in line with the main results presented in Table I. 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 method.[5]

4.5 Alternative synchronicity and similarity measures

We conducted two checks to corroborate 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 shown in Figure 26 in Appendix A.5.

The second check analyzes 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 4.3. 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 Figure 27 in Appendix A.5. Overall, the results are comparable to the outcome presented in Figure 3. The main difference is that the swing measures are more compressed. This indicates that the differences in the overall swing-synchronicity and swing-similarity between GDP, house prices and credit are smaller than the differences for the 'normal' synchronicity and similarity measures.

5 Conclusion

This paper presents a novel method for extracting the long-term trend, short-term and medium-term cycles and irregular component from a mixed frequency dataset in a multivariate setting. The model structure allows us to analyze the concordance of cycles associated with different variables and countries. The international concordance of the extracted cycles is analyzed using the synchronicity and similarity measures proposed by Mink et al. (2012).

The main findings of our paper can be summarized as follows. First, the cyclical movement of credit volumes and house prices are largely driven by the medium-term cycle. Second, for most countries, the co-movement 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 indirect concordance,

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

i.e. the medium-term cycles of credit and house prices share co-cyclicality, while in turn the medium-term cycles of house prices and GDP share commonality. This outcome might indicate that the house price cycle is –at least partly– driven by the credit cycle. Lastly, the cross-country concordance of both the short-term and medium-term cycles of GDP, house prices and credit is low. Hence, the bulk of the cyclical movements seems to be driven by domestic rather than global factors.

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A Appendix

A.1 State space representation unobserved components time series model

The equations of our multivariate UCTSM, eqs. (1)–(5), can be cast in the general state space form. Below we illustrate the setup for four variables ($N = 4$). The measurement and transition equations are defined in eq. (8) and eq. (9), respectively:

$$y_t = Z\alpha_t + \varepsilon_t, \qquad \varepsilon_t \sim N(0, H), \tag{8}$$

$$\alpha_{t+1} = T\alpha_t + \nu_t, \qquad \nu_t \sim N(0, Q), \tag{9}$$

where $y_t = (y_{1,t}, \ldots, y_{N,t})'$, $\varepsilon_t = (\varepsilon_{1,t}, \ldots, \varepsilon_{N,t})'$, and $H = \text{diag}(\sigma^2_{\varepsilon_1}, \ldots, \sigma^2_{\varepsilon_N})$. The state vector α_t is given by the $(6N \times 1)$ vector

$$\alpha_t = (\mu_t, \beta_t, \gamma_t, \gamma_t^*, \psi_t, \psi_t^*)',$$

where $\mu_t = (\mu_{1,t}, \ldots, \mu_{N,t})'$ is the long-term trend, $\beta_t = (\beta_{1,t}, \ldots, \beta_{N,t})'$ is the slope, $(\gamma_t, \gamma_t^*)' = (\gamma_{1,t}, \ldots, \gamma_{N,t}, \gamma^*_{1,t}, \ldots, \gamma^*_{N,t})'$ is the short-term cycle, and $(\psi_t, \psi_t^*)' = (\psi_{1,t}, \ldots, \psi_{N,t}, \psi^*_{1,t}, \ldots, \psi^*_{N,t})'$ is the medium-term cycle. The measurement-transition Z matrix is given by

$$Z = \begin{bmatrix} I_N & 0_{N\times N} & A & 0_{N\times N} & B & 0_{N\times N} \end{bmatrix},$$

with A and B are $(N \times N)$ lower triangular matrices with ones on the diagonal. The state-transition matrix T is given by

$$T = \begin{bmatrix} I_N & I_N & 0_{N\times 2N} & 0_{N\times 2N} \\ 0_{N\times N} & I_N & 0_{N\times 2N} & 0_{N\times 2N} \\ 0_{2N\times N} & 0_{2N\times N} & S & 0_{2N\times 2N} \\ 0_{2N\times N} & 0_{2N\times N} & 0_{2N\times 2N} & L \end{bmatrix},$$

with S and L are $(2N \times 2N)$ matrices defined as follow

$$S = \phi_\gamma \begin{bmatrix} \cos\lambda_\gamma I_N & \sin\lambda_\gamma I_N \\ -\sin\lambda_\gamma I_N & \cos\lambda_\gamma I_N \end{bmatrix}, \qquad L = \phi_\psi \begin{bmatrix} \cos\lambda_\psi I_N & \sin\lambda_\psi I_N \\ -\sin\lambda_\psi I_N & \cos\lambda_\psi I_N \end{bmatrix}.$$

The state-disturbance vector ν_t is given by

$$\nu_t = \begin{bmatrix} 0_{N\times 1} \\ \zeta_t \\ \kappa_t \\ \kappa_t^* \\ \omega_t \\ \omega_t^* \end{bmatrix},$$

where $\zeta_t = (\zeta_{1,t}, \ldots, \zeta_{N,t})'$ are the slope-disturbances, $(\kappa_t, \kappa_t^*)' = (\kappa_{1,t}, \ldots, \kappa_{N,t}, \kappa^*_{1,t}, \ldots, \kappa^*_{N,t},)'$ are the short-term cycle disturbances, and $(\omega_t, \omega_t^*)' = (\omega_{1,t}, \ldots, \omega_{N,t}, \omega^*_{1,t}, \ldots, \omega^*_{N,t},)'$ are the

medium-term cycle disturbances.
Lastly, the $(6N \times 6N)$ disturbance matrix Q in the transition equation is defined as:

$$Q = \text{diag}\left[0_{N\times N} \quad \Sigma_\zeta \quad I_2 \otimes \Sigma_\kappa \quad I_2 \otimes \Sigma_\omega\right],$$

where Σ_ζ is the variance matrix of the slope-disturbances, Σ_κ is the variance matrix of the short-term cycle disturbances, and Σ_ω is the variance matrix of the medium-term cycle disturbances. In the paper Σ_ζ is restricted to be diagonal, i.e. $\Sigma_\zeta = \text{diag}(\sigma^2_{\zeta_1}, \ldots, \sigma^2_{\zeta_N})'$ and that the signal-to-noise ratio $(\sigma^2_{\zeta_i}/\sigma^2_{\varepsilon_i})$ is fixed to a certain number for each $i = 1, \ldots, N$.

A.2 Figures raw data

Figure 4: GDP, house prices, credit and industrial production in the United Kingdom. All series are deflated, seasonally adjusted and in logs.

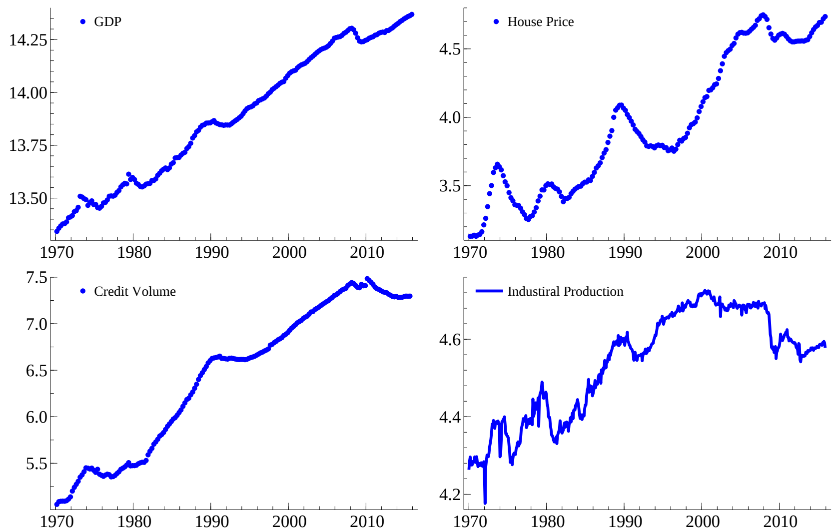


Figure 5: GDP, house prices, credit and industrial production in Japan. All series are deflated, seasonally adjusted and in logs.

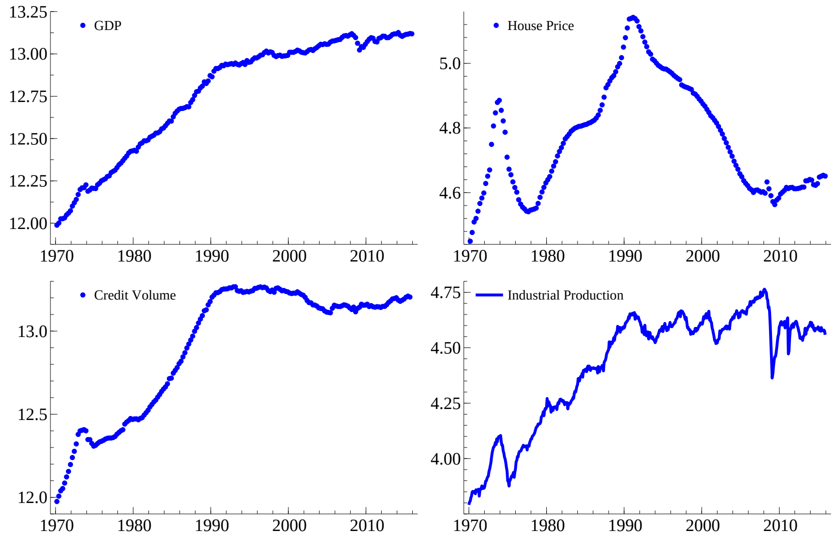


Figure 6: GDP, house prices, credit and industrial production in Canada. All series are deflated, seasonally adjusted and in logs.

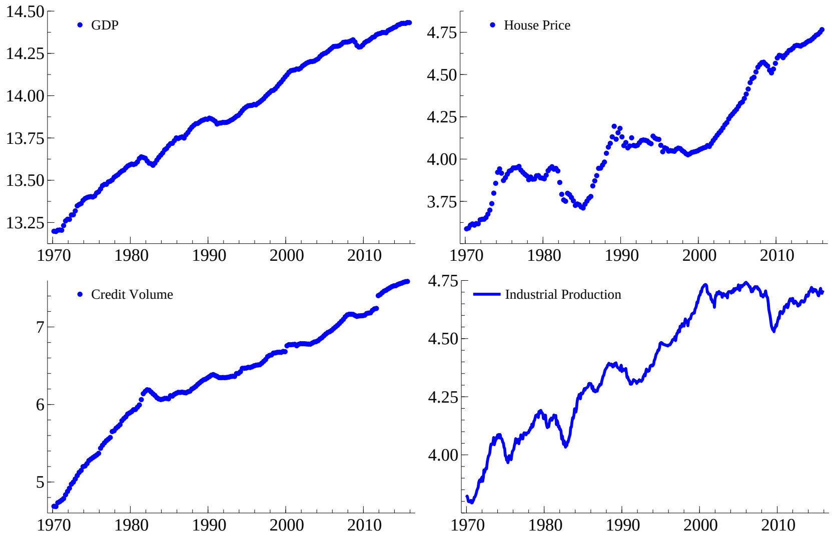


Figure 7: GDP, house prices, credit and industrial production in Germany. All series are deflated, seasonally adjusted and in logs.

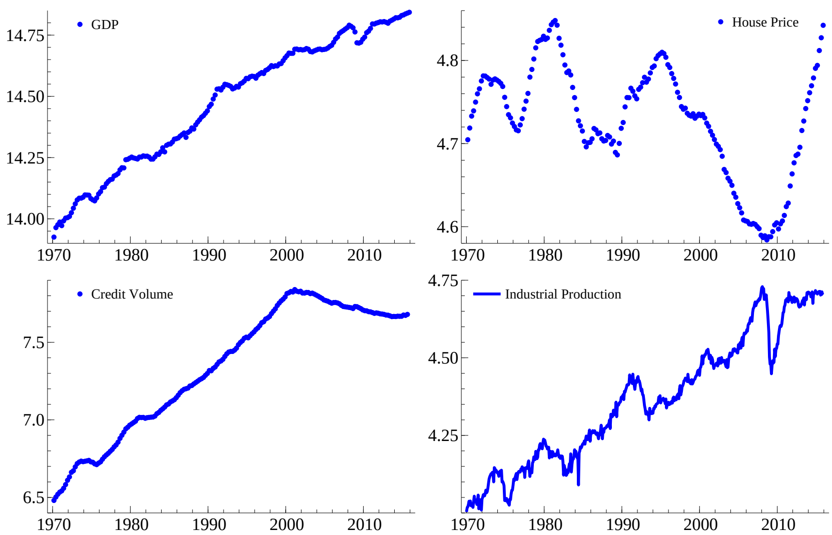


Figure 8: GDP, house prices, credit and industrial production in France. All series are deflated, seasonally adjusted and in logs.

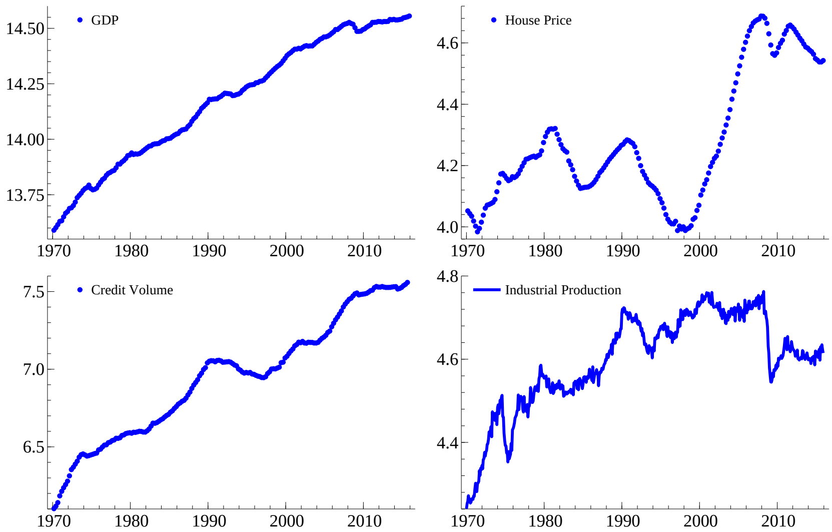


Figure 9: GDP, house prices, credit and industrial production in Italy. All series are deflated, seasonally adjusted and in logs.

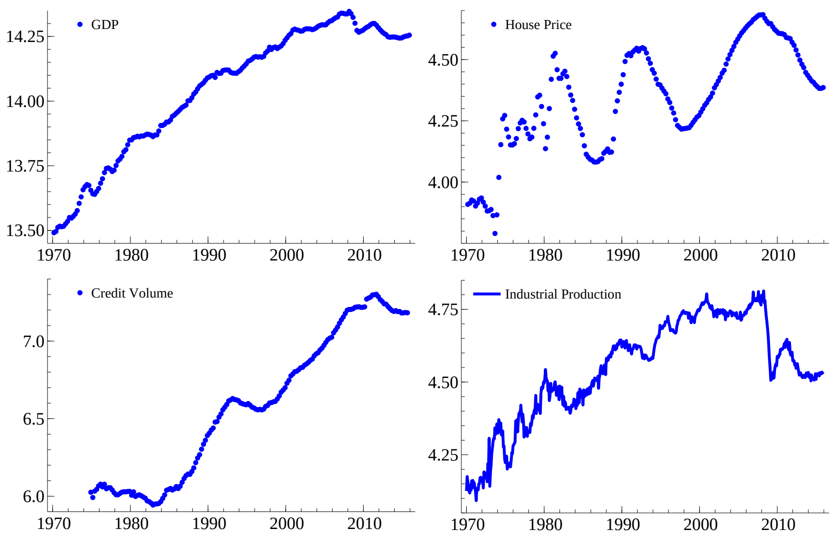
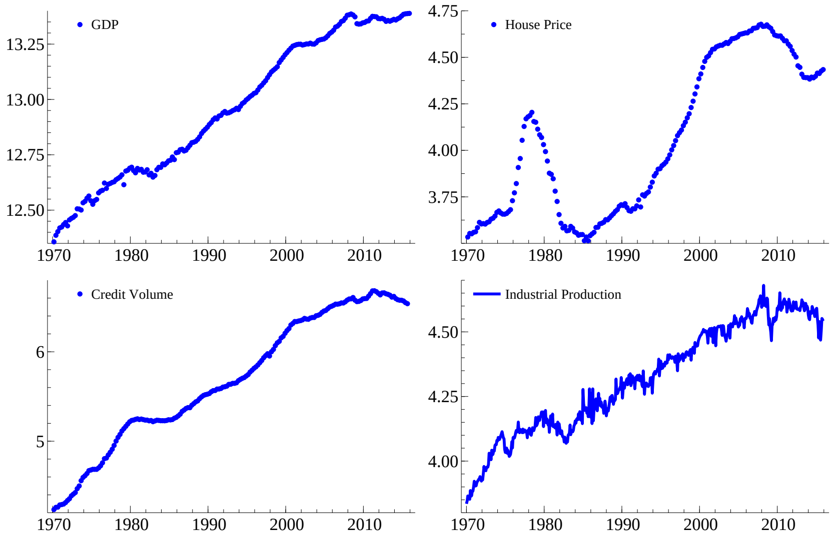


Figure 10: GDP, house prices, credit and industrial production in the Netherlands. All series are deflated, seasonally adjusted and in logs.



A.3 Spectral densities

Figure 11: Spectral densities United Kingdom for GDP, house prices, credit and industrial production. All series are deflated, seasonally adjusted and in log-differences.

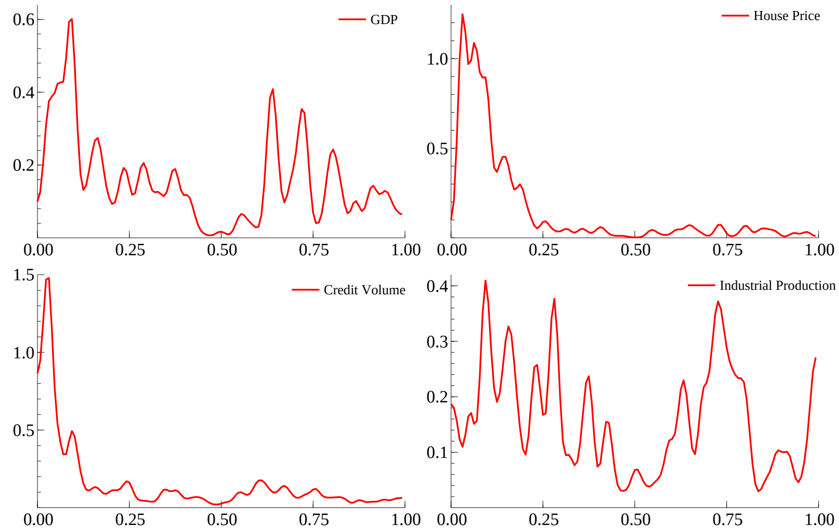


Figure 12: Spectral densities Japan for GDP, house prices, credit and industrial production. All series are deflated, seasonally adjusted and in log-differences.

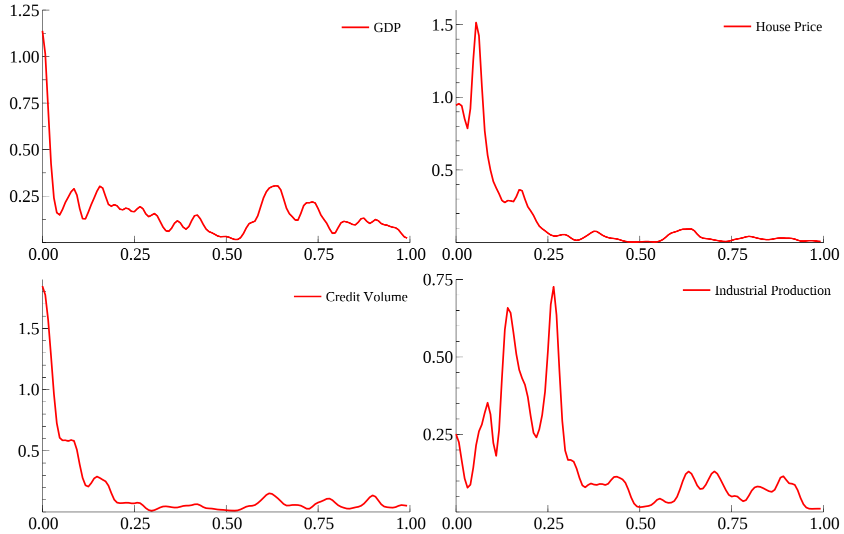


Figure 13: Spectral densities Canada for GDP, house prices, credit and industrial production. All series are deflated, seasonally adjusted and in log-differences.

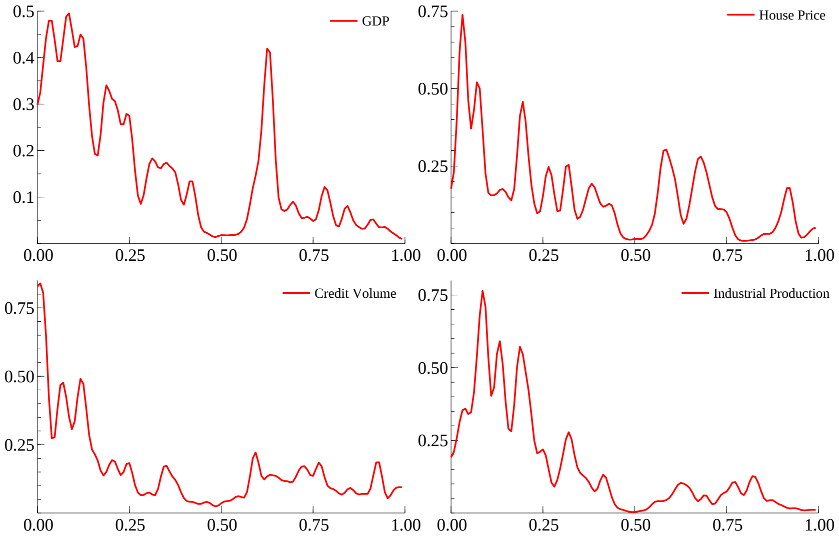


Figure 14: Spectral densities Germany for GDP, house prices, credit and industrial production. All series are deflated, seasonally adjusted and in log-differences

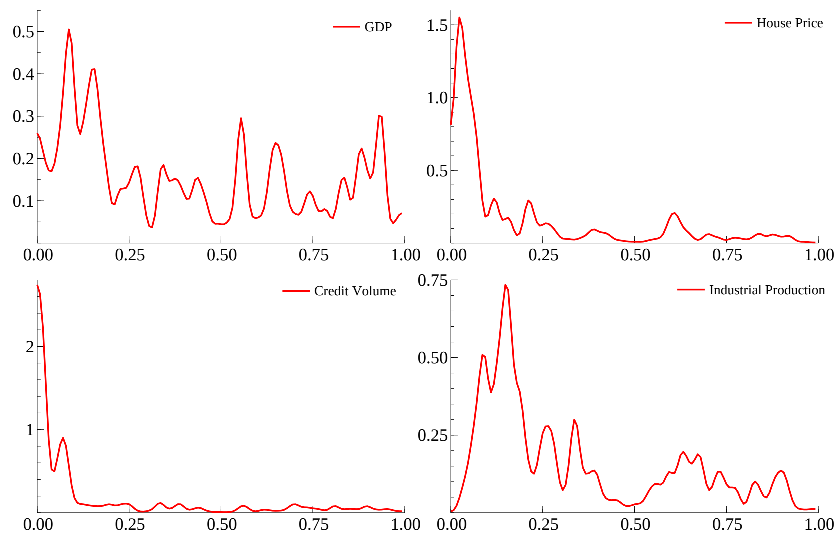


Figure 15: Spectral densities France for GDP, house prices, credit and industrial production. All series are deflated, seasonally adjusted and in log-differences

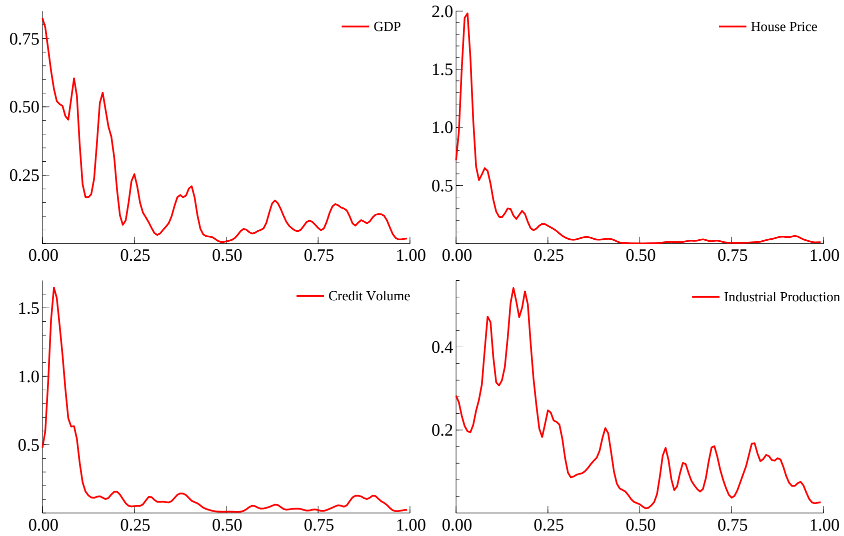


Figure 16: Spectral densities Italy for GDP, house prices, credit and industrial production. All series are deflated, seasonally adjusted and in log-differences

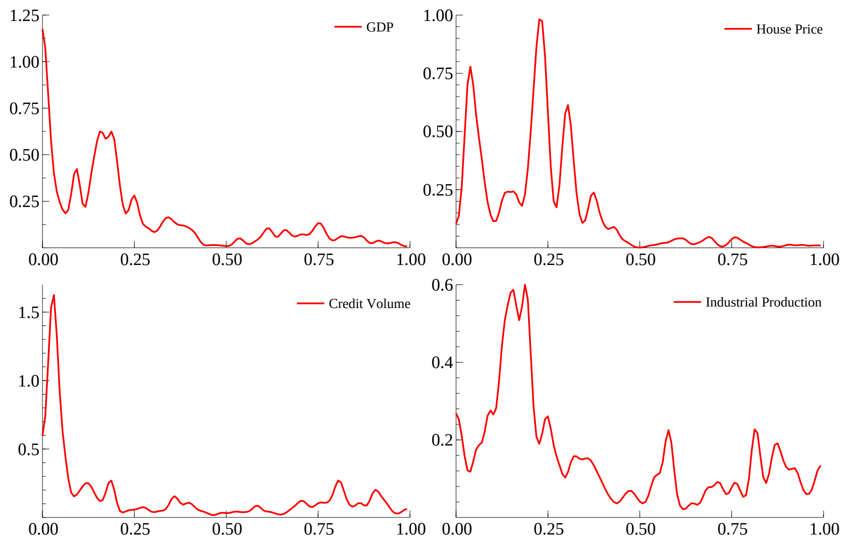
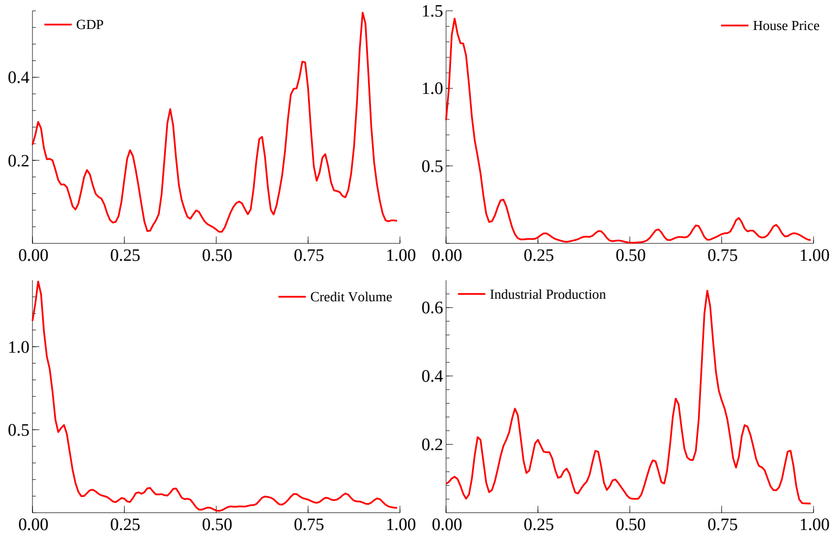
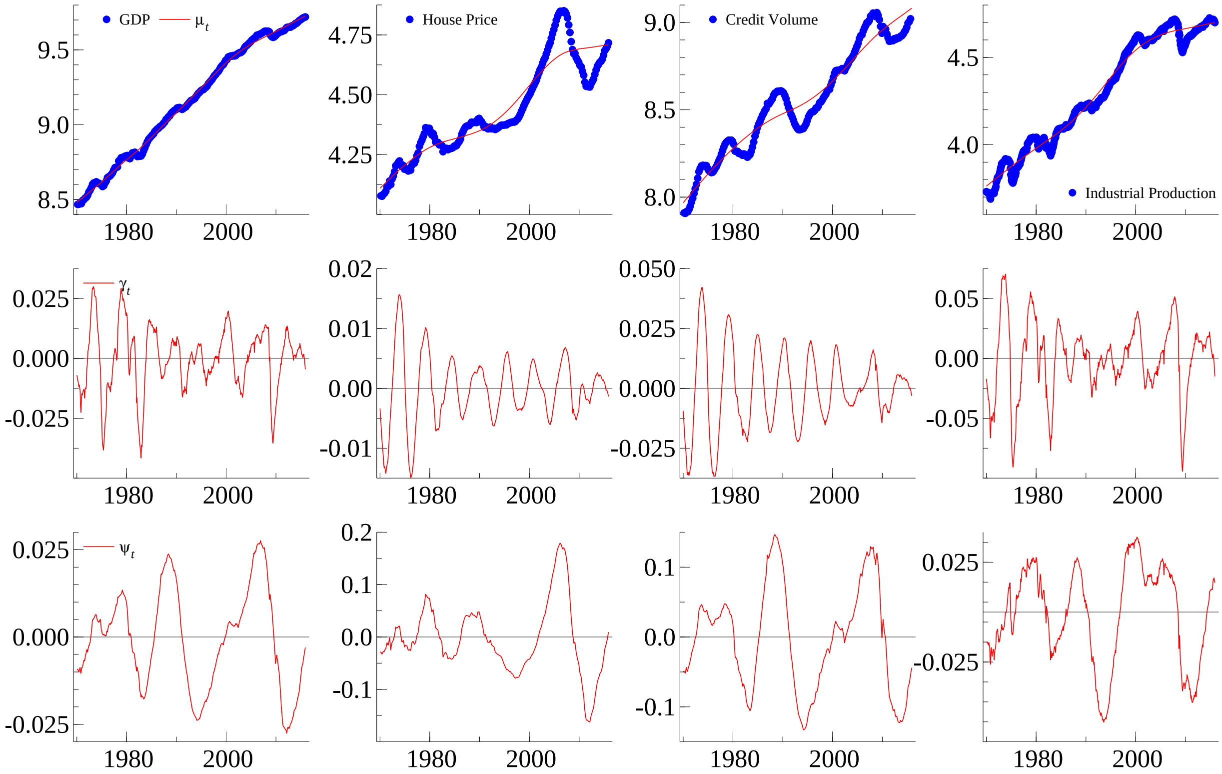


Figure 17: Spectral densities the Netherlands for GDP, house prices, credit and industrial production. All series are deflated, seasonally adjusted and in log-differences



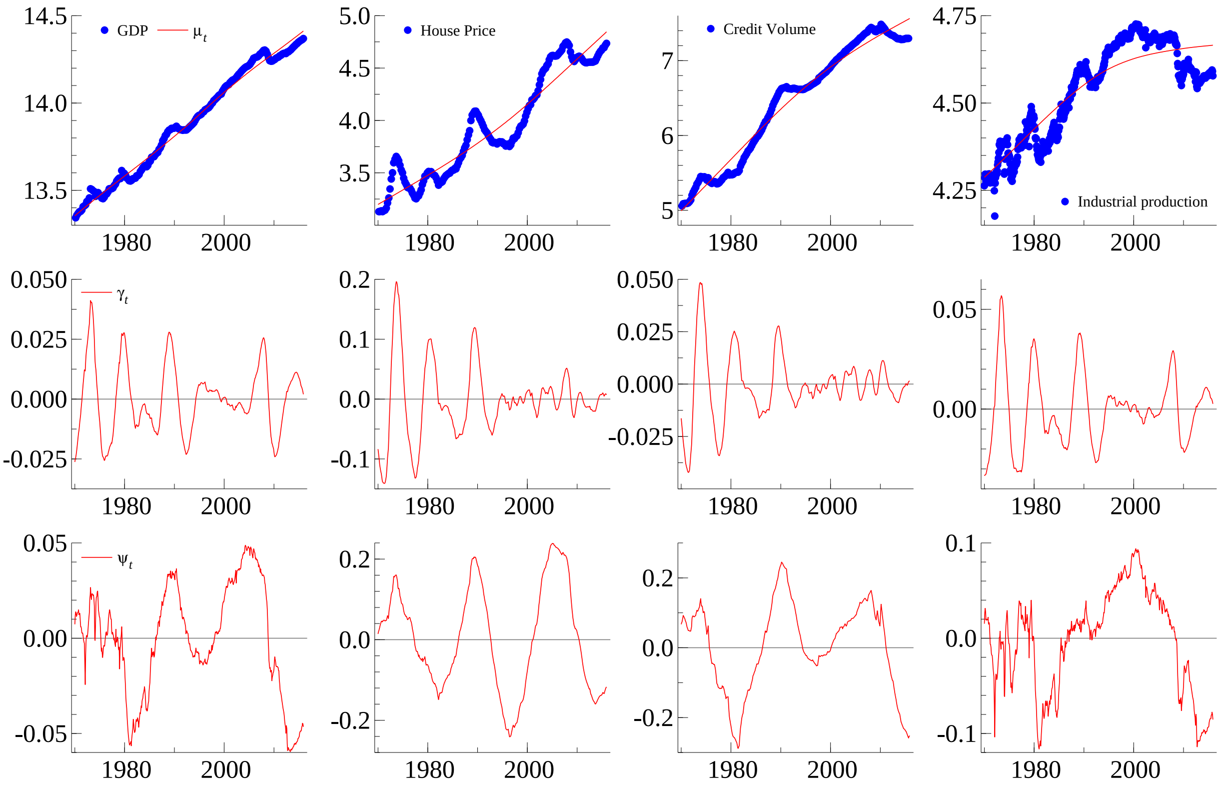
A.4 Figures on UCTSM decomposition

Figure 18: Time series United States with trend (μ_t), short-term cycle (γ_t) and medium-term cycle (ψ_t) components in GDP, house prices, credit and industrial production. All series are deflated, seasonally adjusted and in logs.



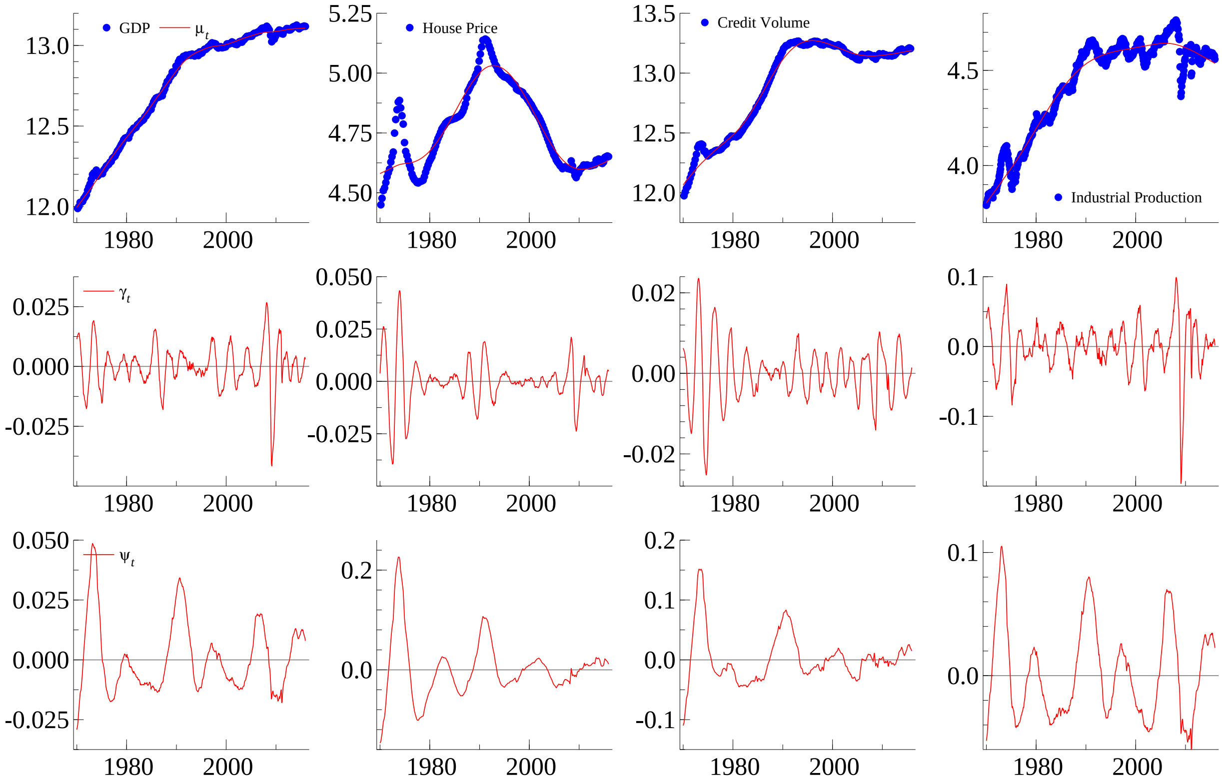
The figure presents the fit (smoothed estimates) of the model estimated in Table I for the United States. The top row shows the raw data (blue line) and trend (μ_t, red line) for GDP, house prices, credit and industrial production. The middle row presents the short-term cycle (γ_t) of the four series considered. The bottom row presents the medium-term cycle (ψ_t) of the four series considered.

Figure 19: Time series United Kingdom with trend (μ_t), short-term cycle (γ_t) and medium-term cycle (ψ_t) components in GDP, house prices, credit and industrial production. All series are deflated, seasonally adjusted and in logs.



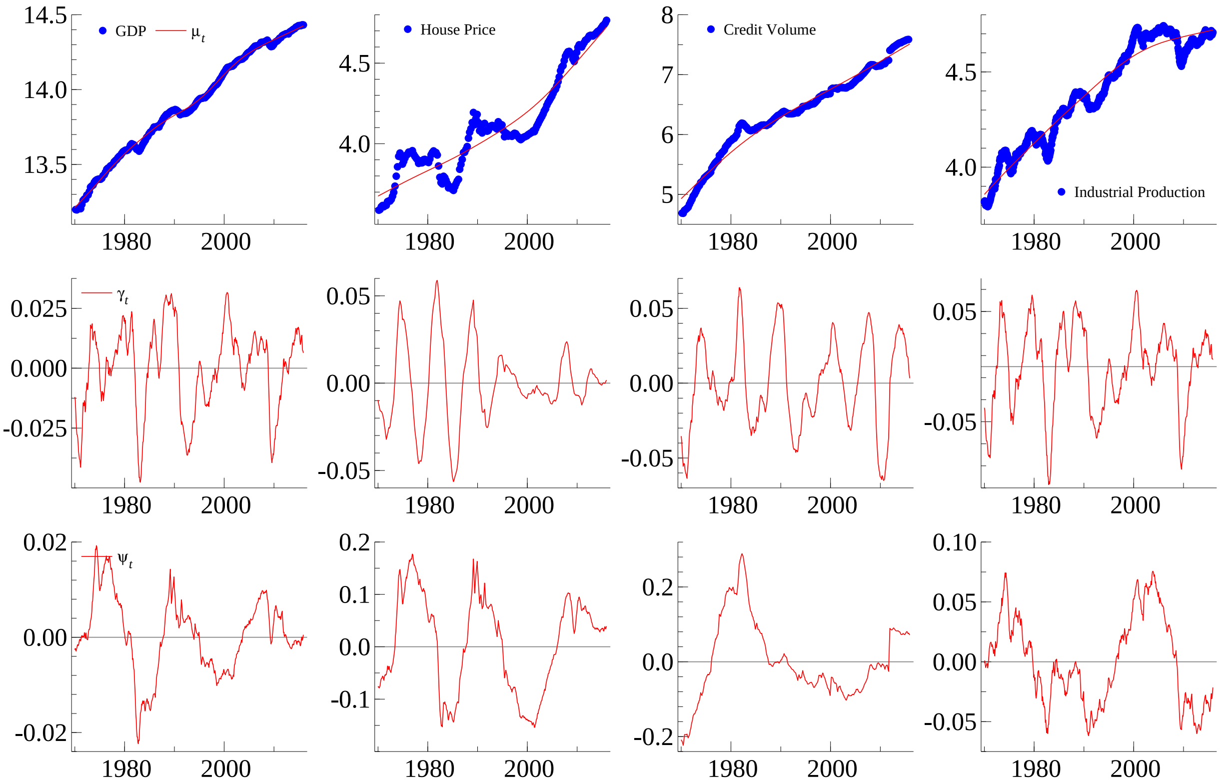
See notes on Figure 18.

Figure 20: Time series Japan with trend (μ_t), short-term cycle (γ_t) and medium-term cycle (ψ_t) components in GDP, house prices, credit and industrial production. All series are deflated, seasonally adjusted and in logs.



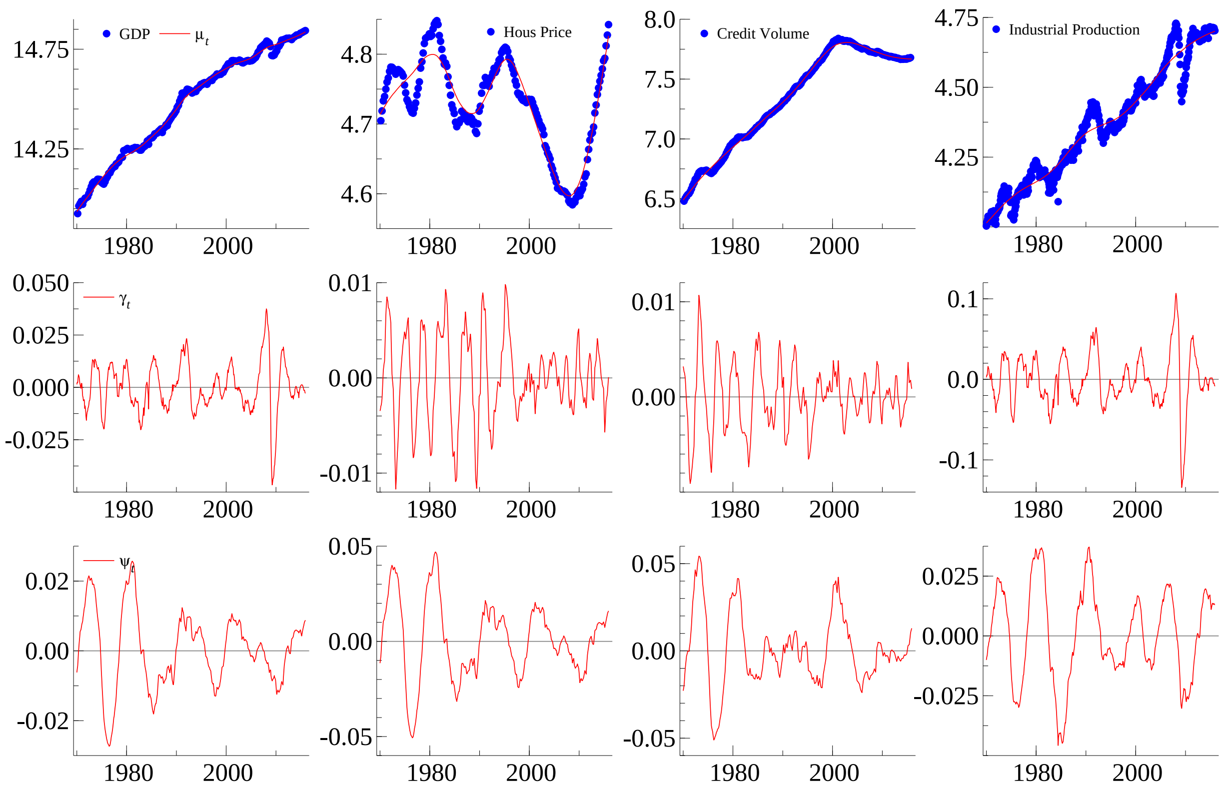
See notes on Figure 18.

Figure 21: Time series Canada with trend (μ_t), short-term cycle (γ_t) and medium-term cycle (ψ_t) components in GDP, house prices, credit and industrial production. All series are deflated, seasonally adjusted and in logs.



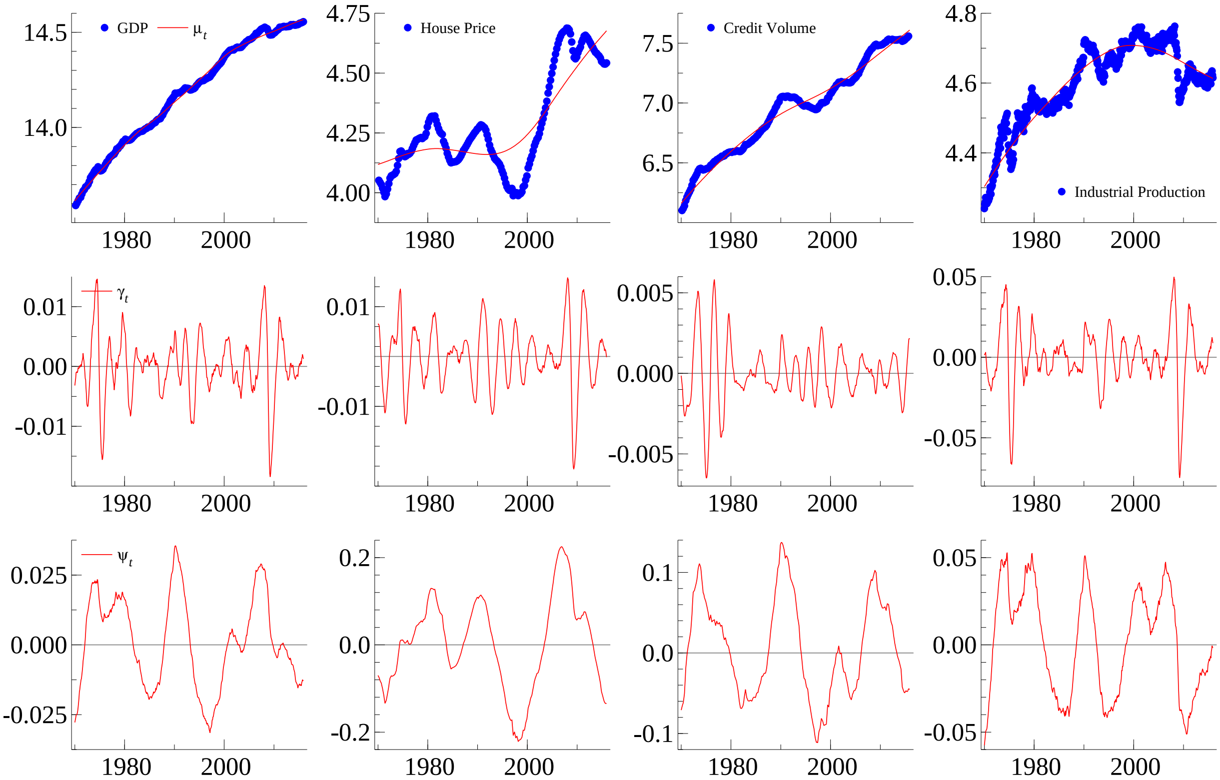
See notes on Figure 18.

Figure 22: Time series Germany with trend (μ_t), short-term cycle (γ_t) and medium-term cycle (ψ_t) components in GDP, house prices, credit and industrial production. All series are deflated, seasonally adjusted and in logs.



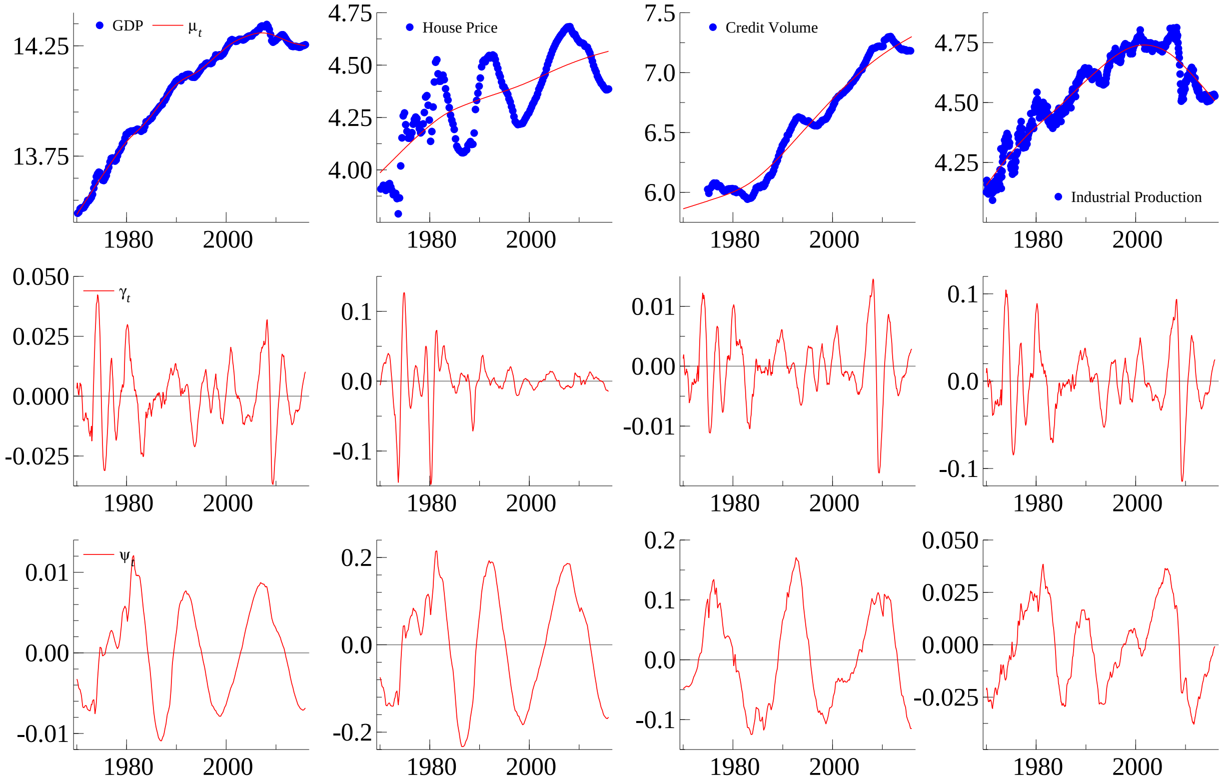
See notes on Figure 18.

Figure 23: Time series France with trend (μ_t), short-term cycle (γ_t) and medium-term cycle (ψ_t) components in GDP, house prices, credit and industrial production. All series are deflated and in logs.



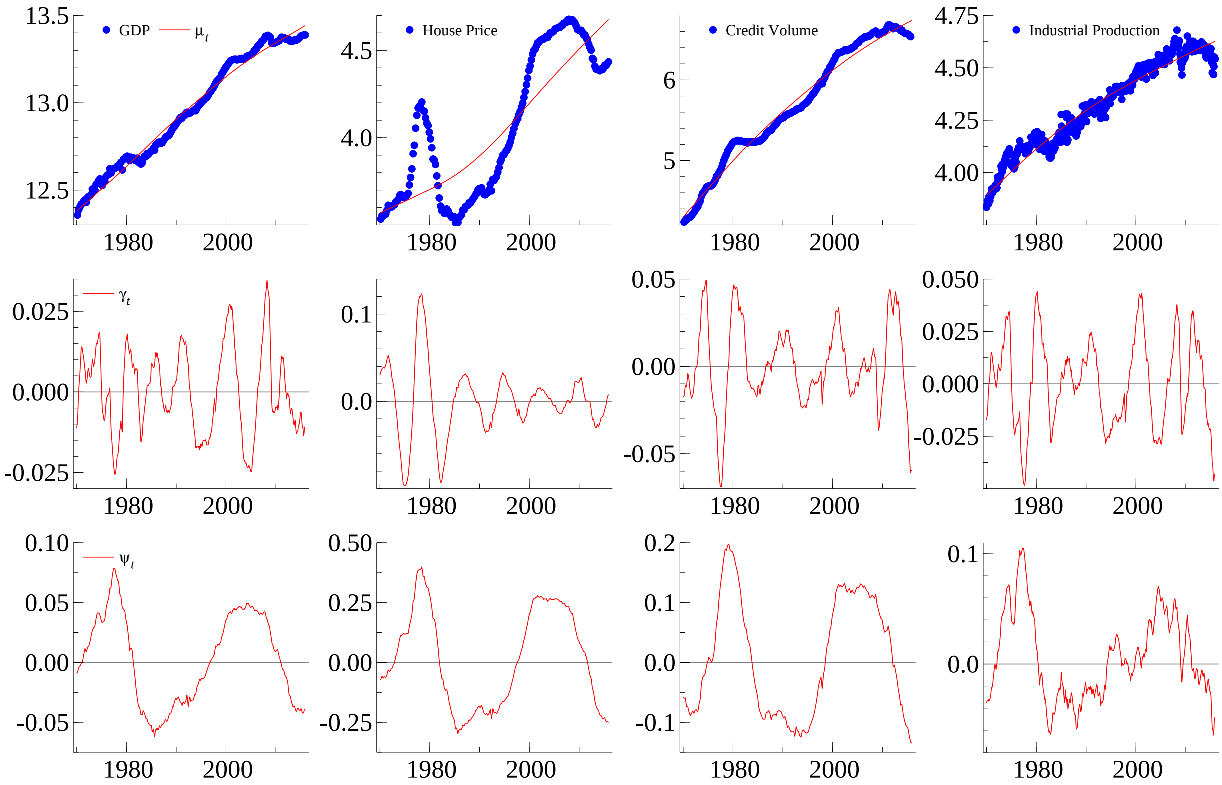
See notes on Figure 18.

Figure 24: Time series Italy with trend (μ_t), short-term cycle (γ_t) and medium-term cycle (ψ_t) components in GDP, house prices, credit and industrial production. All series are deflated, seasonally adjusted and in logs.



See notes on Figure 18.

Figure 25: Time series the Netherlands with trend (μ_t), short-term cycle (γ_t) and medium-term cycle (ψ_t) components in GDP, house prices, credit volume and industrial production. All series are deflated, seasonally adjusted and in logs.



See notes on Figure 18.

A.5 Alternative measures of concordance and credit variables

Figure 26: Overall synchronicity (θ) and similarity (ζ) measures for the short-term and medium-term GDP, house price and credit cycle, G7 countries and the Netherlands excluding Germany and Japan

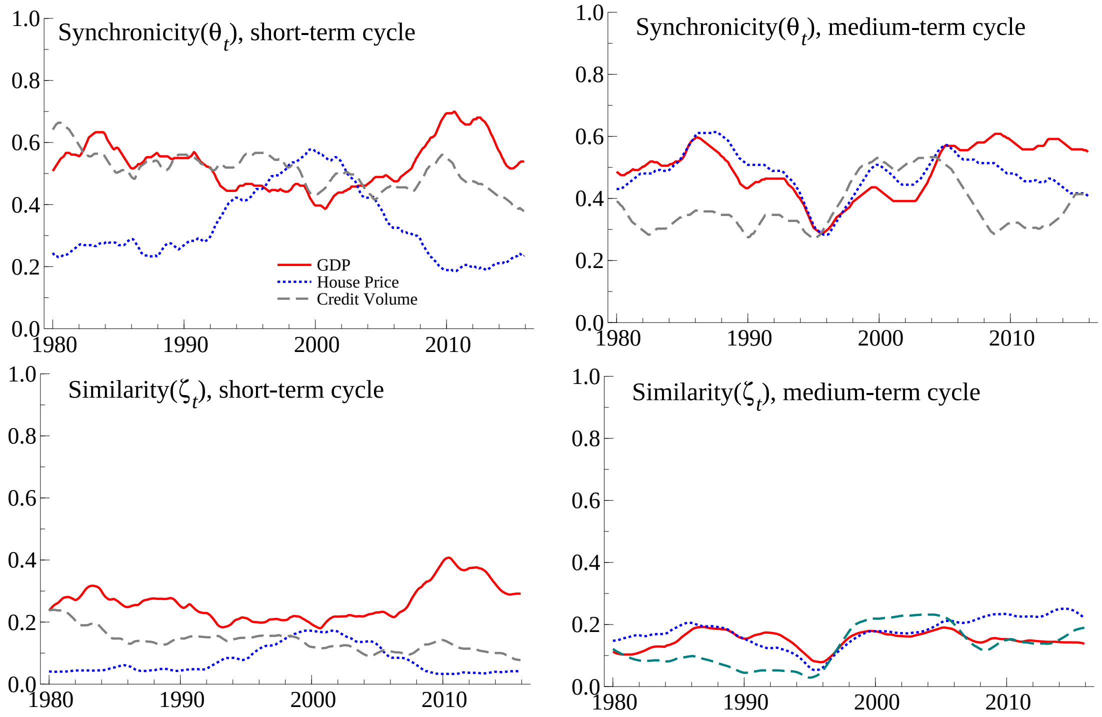


Figure 27: Overall swing synchronicity (θ) and swing similarity (ζ) measures for the short-term and medium-term GDP, house price and credit cycle, G7 countries and the Netherlands

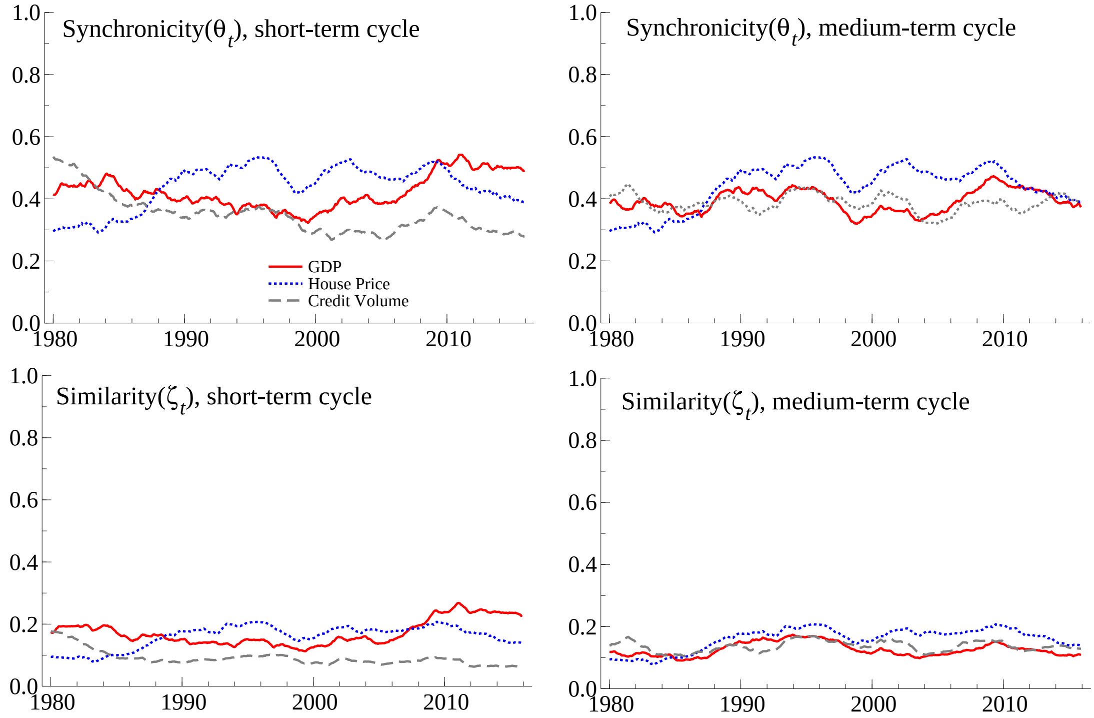


Table II: Parameter estimates of multivariate UCTSM for G7 countries and the Netherlands with alternative credit variable outstanding credit (all sectors) to non-financial corporations

A. Short-term cycle	United States				United Kingdom				Japan				Canada			
p_γ	6.71				6.80				3.34				7.03			
ϕ_γ	0.99				0.98				0.98				0.99			
variance D_γ	0.0004	0.0003	0.0002	0.0021	0.0004	0.0016	0.0003	0.0015	0.0001	0.0001	0.0001	0.0029	0.0004	0.0001	0.0002	0.0023
loading matrix A	GDP	HP	CRED	IP	GDP	HP	CRED	IP	GDP	HP	CRED	IP	GDP	HP	CRED	IP
γ_{GDP}	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
γ_{HP}	-0.10	1.00	0.00	0.00	0.83*	1.00	0.00	0.00	0.45	1.00	0.00	0.00	13.29***	1.00	0.00	0.00
γ_{CRED}	0.28	0.42	1.00	0.00	0.36	0.09	1.00	0.00	-0.08	0.18	1.00	0.00	0.43	0.42	1.00	0.00
γ_{IP}	1.79***	0.26	0.31	1.00	1.87***	0.05	-0.01	1.00	4.00***	0.28	-2.18	1.00	3.19***	-0.41	-0.22	1.00
	Germany				France				Italy				Netherlands			
p_γ	3.96				6.07				3.00				6.76			
ϕ_γ	0.97				0.98				0.98				0.98			
variance D_γ	0.0001	0.0000	0.0000	0.0008	0.0001	0.0002	0.0001	0.0011	0.0001	0.0017	0.0001	0.0007	0.0002	0.0005	0.0003	0.0013
loading matrix A	GDP	HP	CRED	IP	GDP	HP	CRED	IP	GDP	HP	CRED	IP	GDP	HP	CRED	IP
γ_{GDP}	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
γ_{HP}	-0.01	1.00	0.00	0.00	0.33	1.00	0.00	0.00	-0.31	1.00	0.00	0.00	-0.10	1.00	0.00	0.00
γ_{CRED}	-0.09	-0.39	1.00	0.00	0.12	-0.41	1.00	0.00	-0.17	-0.05	1.00	0.00	0.43	-0.22	1.00	0.00
γ_{IP}	2.85***	0.03	0.38	1.00	2.84***	0.62	0.36	1.00	2.47***	-0.10	1.82**	1.00	2.66***	0.23	0.58	1.00

B. Medium-term cycle	United States				United Kingdom				Japan				Canada			
p_ψ	15.98				17.00				8.23				14.34			
ϕ_ψ	0.99				0.99				0.99				0.98			
variance D_ψ	0.0002	0.0065	0.0032	0.0004	0.0001	0.0033	0.0047	0.0009	0.0001	0.0011	0.0006	0.0009	0.0000	0.0037	0.0005	0.0006
loading matrix B	GDP	HP	CRED	IP	GDP	HP	CRED	IP	GDP	HP	CRED	IP	GDP	HP	CRED	IP
ψ_{GDP}	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
ψ_{HP}	6.03***	1.00	0.00	0.00	6.35***	1.00	0.00	0.00	2.18***	1.00	0.00	0.00	0.24	1.00	0.00	0.00
ψ_{CRED}	1.02	3.93***	1.00	0.00	1.39	8.75***	1.00	0.00	1.70***	0.26	1.00	0.00	0.42*	0.60	1.00	0.00
ψ_{IP}	1.32	-0.80	0.41	1.00	0.88	-4.22	0.32	1.00	2.91***	-0.43	0.11	1.00	2.28***	-1.61	-0.31	1.00
	Germany				France				Italy				Netherlands			
p_ψ	9.05				17.72				14.33				12.63			
ϕ_ψ	0.99				0.99				0.99				0.99			
variance D_ψ	0.0001	0.0003	0.0002	0.0008	0.0000	0.0017	0.0008	0.0005	0.0000	0.0000	0.0000	0.0000	0.0002	0.0035	0.0009	0.0004
loading matrix B	GDP	HP	CRED	IP	GDP	HP	CRED	IP	GDP	HP	CRED	IP	GDP	HP	CRED	IP
ψ_{GDP}	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
ψ_{HP}	0.76**	1.00	0.00	0.00	7.63***	1.00	0.00	0.00	0.60	1.00	0.00	0.00	4.57***	1.00	0.00	0.00
ψ_{CRED}	0.67	0.37	1.00	0.00	0.10	0.89	1.00	0.00	0.43	0.11	1.00	0.00	1.06	3.87***	1.00	0.00
ψ_{IP}	2.07**	-0.24	-1.32	1.00	1.63	-0.83	0.24	1.00	2.51***	-0.07	-0.21	1.00	1.03	-2.01	-0.71	1.00

The table reports the estimates of persistence ϕ_γ and ϕ_ψ,the period p_γ and p_ψ in years ($p = 2\pi/\lambda$), the diagonal of the variance-matrix D_γ for the short cycle (γ) and medium-term cycle (ψ), respectively. A and B denote the loading matrices for the short-term and medium-term cycle, respectively. Significant estimates in these matrices are highlighted in grey. *,** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table III: Parameter estimates of multivariate UCTSM for G7 countries and the Netherlands with alternative credit variable outstanding credit (all sectors) to households and NPISH

A. Short-term cycle	United States				United Kingdom				Japan				Canada			
p_γ	4.28				7.03				3.18				6.13			
ϕ_γ	0.98				0.98				0.97				0.99			
variance D_γ	0.0000	0.0000	0.0000	0.5176	0.0011	0.0062	0.0007	0.0035	0.0001	0.0001	0.0001	0.0018	0.0000	0.0000	0.0000	0.0000
loading matrix A	GDP	HP	CRED	IP	GDP	HP	CRED	IP	GDP	HP	CRED	IP	GDP	HP	CRED	IP
γ_{GDP}	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
γ_{HP}	-2.83	1.00	0.00	0.00	0.91**	1.00	0.00	0.00	0.47	1.00	0.00	0.00	-0.46	1.00	0.00	0.00
γ_{CRED}	1.95	0.21	1.00	0.00	0.56	0.25	1.00	0.00	0.04	0.32	1.00	0.00	0.44	-0.05	1.00	0.00
γ_{IP}	21.10*	0.63	1.16	1.00	1.82***	-0.03	0.11	1.00	3.23***	0.68	-1.71	1.00	2.23***	0.05	1.90*	1.00

	Germany				France				Italy				Netherlands			
p_γ	5.15				3.71				3.56				4.88			
ϕ_γ	0.99				0.98				0.98				0.98			
variance D_γ	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002	0.0018	0.0003	0.0012	0.0008	0.0050	0.0031	0.0044
loading matrix A	GDP	HP	CRED	IP	GDP	HP	CRED	IP	GDP	HP	CRED	IP	GDP	HP	CRED	IP
γ_{GDP}	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
γ_{HP}	-0.18	1.00	0.00	0.00	0.54	1.00	0.00	0.00	0.12	1.00	0.00	0.00	0.45	1.00	0.00	0.00
γ_{CRED}	0.08	0.87	1.00	0.00	0.56	-0.17	1.00	0.00	0.06	-0.39**	1.00	0.00	-0.34	-0.27	1.00	0.00
γ_{IP}	2.77***	-0.47	0.18	1.00	3.41***	0.81	0.75	1.00	2.51***	-0.13	-1.17	1.00	2.88***	-0.05	1.01	1.00

B. Medium-term cycle	United States				United Kingdom				Japan				Canada			
p_ψ	12.49				17.56				8.39				14.23			
ϕ_ψ	0.99				0.99				0.99				0.99			
variance D_ψ	0.0005	0.0010	0.0008	0.0015	0.0000	0.0019	0.0038	0.0013	0.0001	0.0011	0.0005	0.0014	0.0000	0.0000	0.0000	0.0000
loading matrix B	GDP	HP	CRED	IP	GDP	HP	CRED	IP	GDP	HP	CRED	IP	GDP	HP	CRED	IP
ψ_{GDP}	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
ψ_{HP}	0.28	1.00	0.00	0.00	7.49***	1.00	0.00	0.00	1.18	1.00	0.00	0.00	6.19***	1.00	0.00	0.00
ψ_{CRED}	0.58**	0.46***	1.00	0.00	-0.44	1.85***	1.00	0.00	1.47***	0.24	1.00	0.00	1.34	0.15	1.00	0.00
ψ_{IP}	1.67***	0.03	-0.35	1.00	2.15	-0.73	0.41	1.00	2.***	-0.24	0.55	1.00	2.69**	-0.61	-0.56	1.00

	Germany				France				Italy				Netherlands			
p_ψ	10.25				18.61				14.87				10.4			
ϕ_ψ	0.99				0.99				0.90				0.99			
variance D_ψ	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0074	0.0043	0.0010	0.0001	0.0016	0.0001	0.0000
loading matrix B	GDP	HP	CRED	IP	GDP	HP	CRED	IP	GDP	HP	CRED	IP	GDP	HP	CRED	IP
ψ_{GDP}	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
ψ_{HP}	1.85***	1.00	0.00	0.00	1.13*	1.00	0.00	0.00	5.62	1.00	0.00	0.00	4.91***	1.00	0.00	0.00
ψ_{CRED}	0.55	-2.45**	1.00	0.00	0.36	0.20	1.00	0.00	16.40***	-0.05	1.00	0.00	1.13	0.00	1.00	0.00
ψ_{IP}	2.25**	-0.82	-2.36	1.00	2.17***	-0.09	-0.24	1.00	2.79	-0.03	-1.75	1.00	0.40	0.05	0.02	1.00

The table reports the estimates of persistence ϕ_γ and ϕ_ψ, the period p_γ and p_ψ in years ($p = 2\pi/\lambda$), the diagonal of the variance-matrix D_γ for the short cycle (γ) and medium-term cycle (ψ), respectively. A and B denote the loading matrices for the short-term and medium-term cycle, respectively. Significant estimates in these matrices are highlighted in grey. *,** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

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