

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 or credit cycle. For eight advanced economies, we analyze a set of macroeconomic and financial time series data. A strong and common finding among all economies is the co-cyclicalities 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 financial cycle. Most cyclical movements in the country-specific time series appear to be driven by domestic rather than global factors.

Keywords: unobserved component time series model, Kalman filter, maximum likelihood estimation, short- and medium-term cycle.

JEL classification: C32, E32, G01.

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1 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 movements in the economy. Comin and Gertler (2006) argues 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 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 et al. (2012), Borio (2014), Borio et al. (2001), Schularick and Taylor (2012), Igan and Loungani (2012) and Aikman et al. (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 a 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 et al. (2012), De Bonis and Silvestrini (2014), Galati et al. (2016), Koopman et al. (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 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, 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 analyze the cyclical oscillations for eight advanced economies: the G7 countries (i.e. 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).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

¹Even 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).

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 modeling framework; see also Valle e Azevedo et al. (2006). Third, we extend recent work on the international coherence of business and financial cycles (e.g. 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).

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 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

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 2.2–4.3 and present the robustness of our findings to the definition of the credit variable in Section 4.4.

We use deflated series for all variables. GDP and industrial production are deflated at

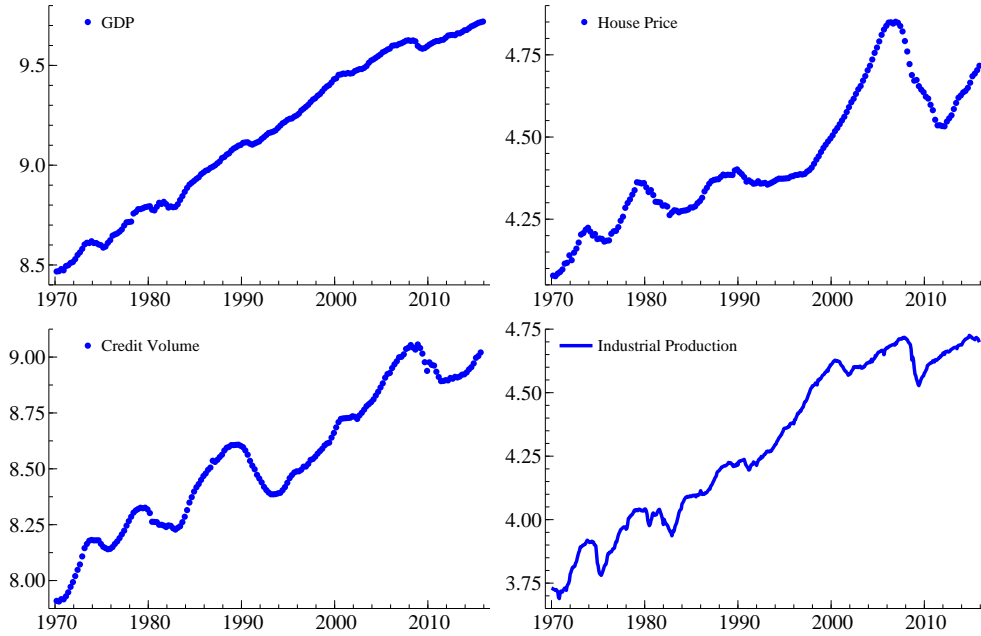
²The time series from the OECD database are publicly available via <https://data.oecd.org/economy.htm>. The time series from the BIS data are publicly available via <http://www.bis.org/statistics/totcredit.htm>.

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 source³, while house prices and credit are seasonally adjusted using the Census X-12 ARIMA method.

2.2 Stylized facts

Figure 1 presents the raw time series of the variables we analyzed, for the United States (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 2008–2009. 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 downfalls 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.

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

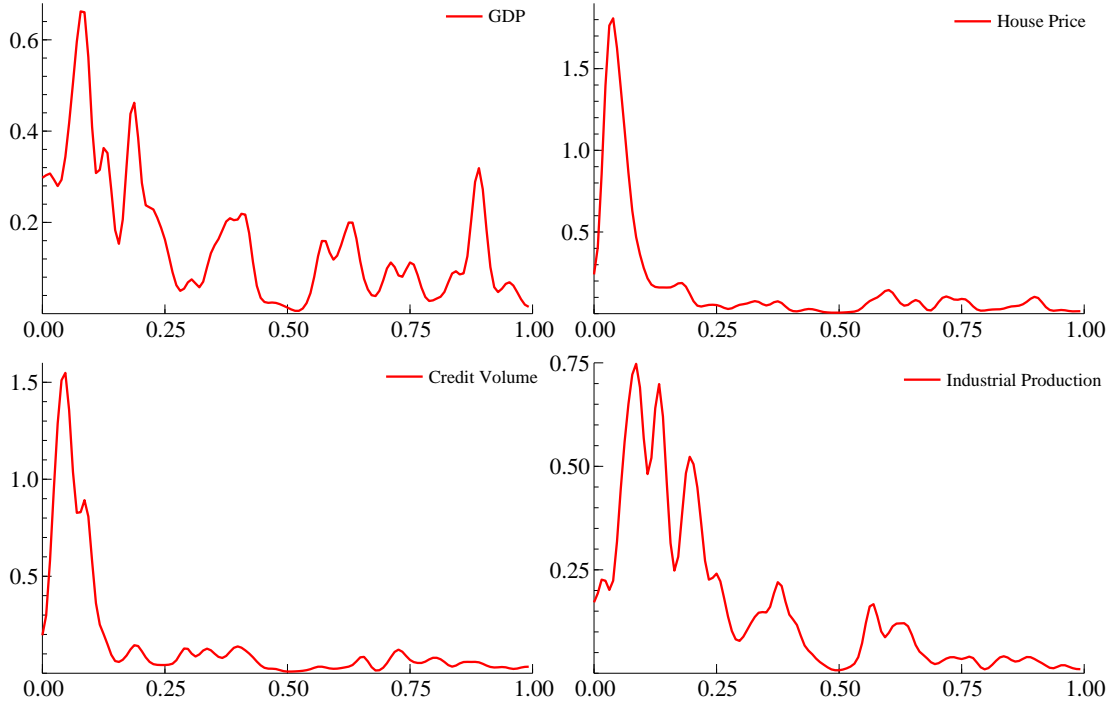


To get insight into the duration of the cyclical oscillations in the time series, we have analyzed the spectral densities. Spectral density estimates originate from the periodograms of

³Most 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.

variables, they are locally smooth estimates thereof, and offer insight into where the mass of the cyclical oscillations in a time series occurs. Analyzing 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 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 of time series of US 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 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

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

and King (1999) and Christiano and Fitzgerald (2003). 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 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 United States, as 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.

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 versus the same model plus a medium-term cycle, after an exposition of the structure of our model in Section 3.1. 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 Model

The empirical analysis is based on a multivariate UCTSM which aims to describe the dynamic behavior 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

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

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 modeling 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

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

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 is 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

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

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

$$\begin{aligned} \begin{pmatrix} \gamma_{t+1} \\ \gamma_{t+1}^* \end{pmatrix} &= \phi_\gamma \left[\begin{pmatrix} \cos \lambda_\gamma & \sin \lambda_\gamma \\ -\sin \lambda_\gamma & \cos \lambda_\gamma \end{pmatrix} \otimes I_N \right] \begin{pmatrix} \gamma_t \\ \gamma_t^* \end{pmatrix} + \begin{pmatrix} \kappa_t \\ \kappa_t^* \end{pmatrix}, \quad \kappa_t, \kappa_t^* \stackrel{i.i.d.}{\sim} \mathcal{N}(0, \Sigma_\kappa), \\ \begin{pmatrix} \psi_{t+1} \\ \psi_{t+1}^* \end{pmatrix} &= \phi_\psi \left[\begin{pmatrix} \cos \lambda_\psi & \sin \lambda_\psi \\ -\sin \lambda_\psi & \cos \lambda_\psi \end{pmatrix} \otimes I_N \right] \begin{pmatrix} \psi_t \\ \psi_t^* \end{pmatrix} + \begin{pmatrix} \omega_t \\ \omega_t^* \end{pmatrix}, \quad \omega_t, \omega_t^* \stackrel{i.i.d.}{\sim} \mathcal{N}(0, \Sigma_\omega), \end{aligned} \quad (4)$$

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 amongst the variables in y_t are 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 (upto 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).

3.2 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 the these univariate UCTSMs are estimated using quarterly data. Table I reports the LR-test values. The null hypothesis in favor 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 two of the thirty-two LR-test values that are not significant at the 95% confidence level.

3.3 State space methodology

Multivariate UCTSMs can be formulated as a linear Gaussian state space model that is given by the observation equation $y_t = Z\alpha_t + \epsilon_t$, 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

Table I: 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**

The table reports the χ^2 -test value of the Likelihood-ratio test for specification with both a short-term and medium-term cycle versus 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, i.e. 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.

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 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.

3.4 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, $q = \sigma_{\zeta,j}^2 / \sigma_{\varepsilon,j}^2$ 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.

3.5 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:

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

while overall similarity is defined as:

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

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

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

all cycles are simultaneously above/below trend level. Perfect similarity indicates that the absolute difference between the cycles is zero; that is, cycles have an identical amplitude.

4 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 Table II and Table III. The Online Appendix shows an extended set of residual diagnostics. The variance of the residuals for all house price and credit variables are extremely small compared to the the variance of the extracted cycles (on average less than $1E-10\%$), which indicates that the model has a near perfect fit explaining the 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, i.e. normality, serial correlation, heteroscedasticity, indicate the null-hypothesis of normality and heteroskedasticity can not 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 1970s.

4.1 Short-term cycle

Table II shows the estimated results for the short-term cycles, γ_t and contains information on the average duration (p_γ), standard deviation ($\times 100$) 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 II 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 findings, 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 and Christiano and Fitzgerald, 2003).

Second, there is strong evidence for co-cyclicalities 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-cyclicalities between the short-term cycles of credit and GDP. For the majority of countries analyzed, we find no statistically significant entries in the A -matrices measuring the co-cyclicalities 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.

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.

4.2 Medium-term cycle

Table III shows the estimates for the medium-term cycles ψ_t and contains information on the average duration (p_ψ), standard deviation ($\times 100$) and persistence (ϕ_ψ) of them medium-term cycles. Table III 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 to 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.

Table II: Parameter estimates of multivariate 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

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.

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 Table II and Table III ($D_\psi \approx D_\gamma$), respectively. By contrast, for most countries, we find the medium-term cycles of the financial variables are more important than the short-term cycle ($D_\psi \gg D_\gamma$). 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. Fig. 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-cyclicalities 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, i.e. the United States, Japan and France, we find strong co-cyclicalities 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-cyclicalities, 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-cyclicalities between the medium-term cycles of credit and GDP.

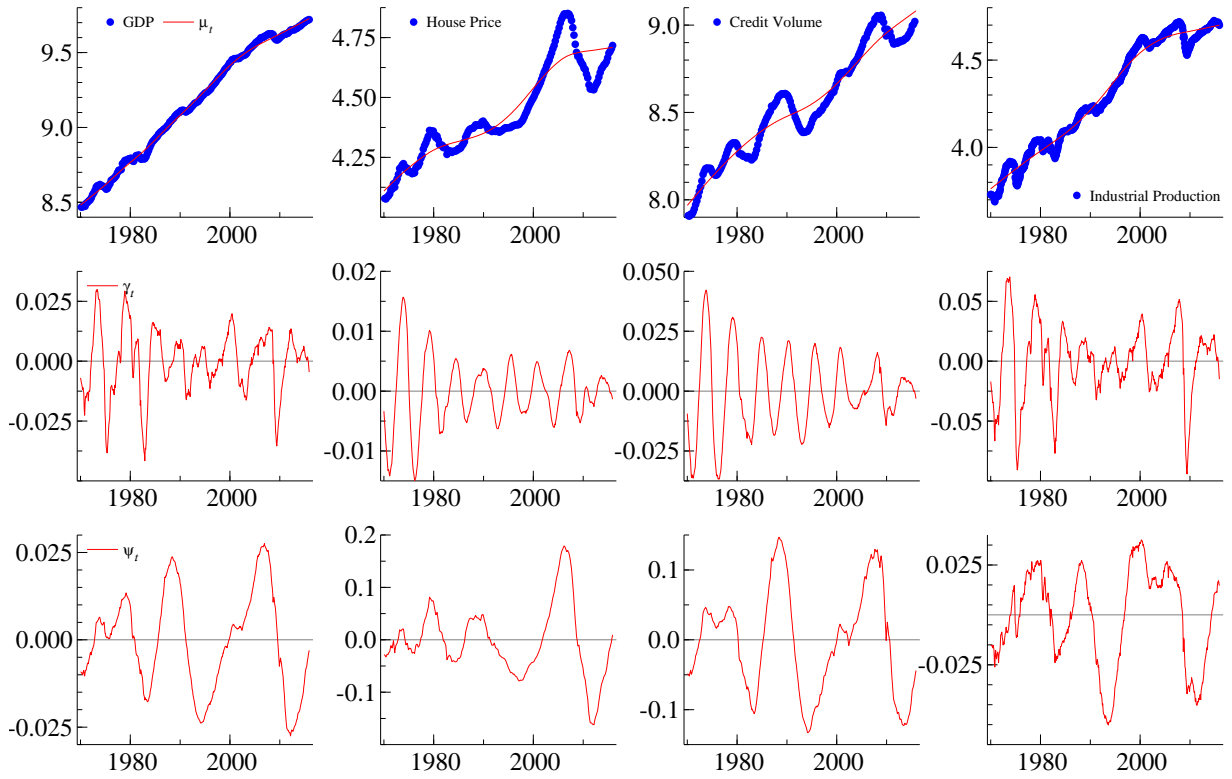
Overall, we find strong evidence for co-cyclicalities between the medium-term cycles of GDP and house prices. The evidence for co-cyclicalities between the medium-term cycles of GDP and credit is more complex. For some countries there is a direct relation, for some an indirect relation (via the medium-term 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.

Table III: Parameter estimates of multivariate 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.

Figure 3: 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 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.

Table IV: 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

4.3 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 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 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 analyzed 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 throughs in the cycle using the definitions and the algorithm of Harding and Pagan (2002).

Table IV 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 analyzed. So, from peak to peak this constitutes approximately 6 business cycles in the period 1985–2015. The medium-term cycles have 8 peaks on average, so approximately 4 cycles. The Online Appendix contains a set of tables showing the monthly dates of peaks and throughs in the short-term and medium-term cycle for all variables and all countries we analyzed.

Table V 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

Table V: 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

are different; we observe different phases in 69, 94 and 77 percent 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 percent, 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 2008–2009.

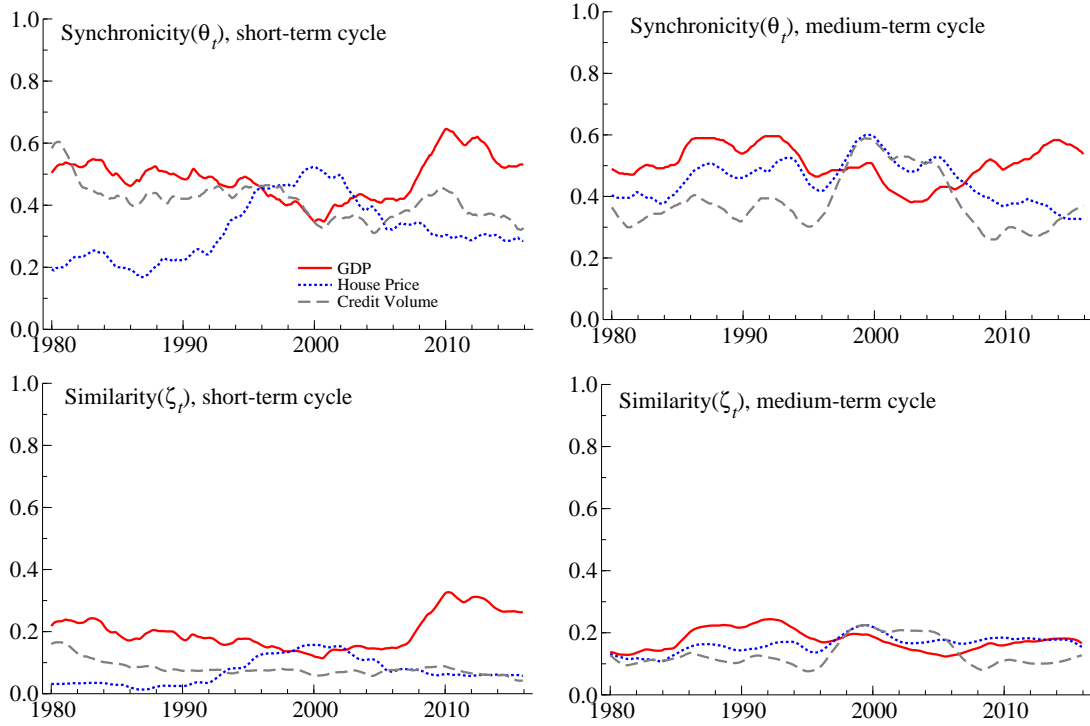
For a more formal description of the coherence of the business cycles we use the synchronicity and similarity measures of Mink et al. (2012), introduced in Section 3.5. An alternative is to consider the correlation between the cycles as a measure of cyclical coherence, using conventional Pearson’s correlation 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

⁶Results 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 GDP, house prices and credit, G7 countries and the Netherlands, 1970Q1–2015Q4.



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. 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, i.e. the synchronicity and similarity measures in 2000 measure the average synchronicity and similarity in the period 1990Q1–2000Q1.

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. 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. However, in the studies of Bruno and Shin (2015) and Bekaert et al. (2013), other indicator variables (e.g. equity, bonds and other liquid assets) are used for identifying the financial cycle. Furthermore, we have used a different selection of countries and a relatively short time period in our study.

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. 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 Table II and Table III. 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

4.5 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 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 3.5.

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

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.

5 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 analyzed using synchronicity and similarity measures.

In our empirical study we have analyzed gross domestic product (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 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-cyclicity while the medium-term cycles of house prices and GDP share commonality. The house price cycle is –at least partly– driven by the credit cycle. 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.

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ONLINE APPENDIX

A Figures raw data

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

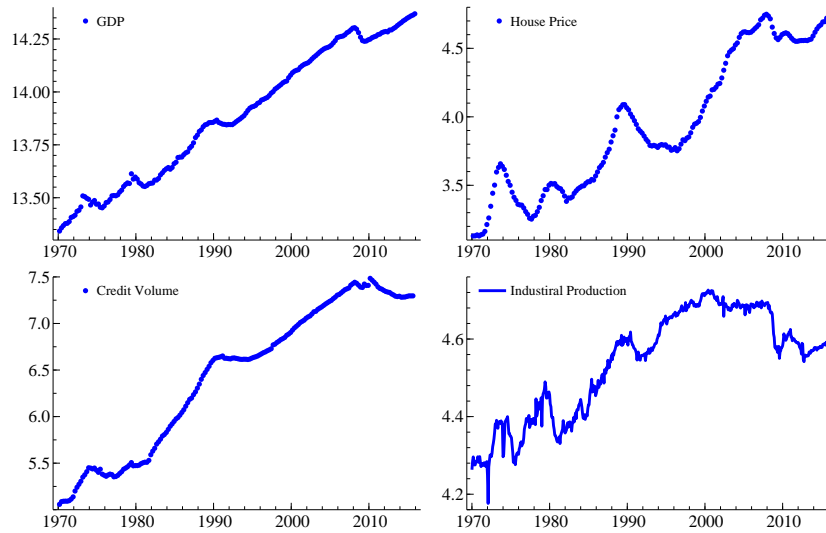


Figure A.2: GDP, house prices, credit and industrial production in Japan. All series are deflated, seasonally adjusted and in logs.

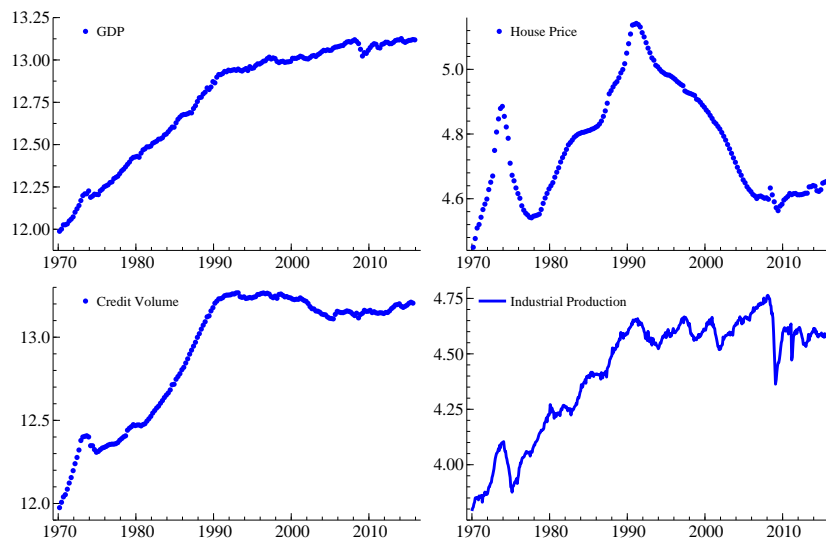


Figure A.3: GDP, house prices, credit and industrial production in Canada. All series are deflated, seasonally adjusted and in logs.

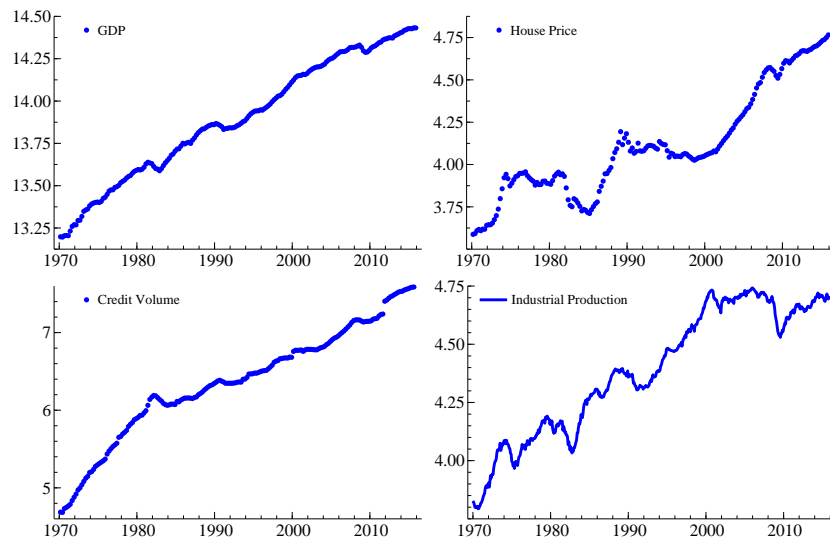


Figure A.4: GDP, house prices, credit and industrial production in Germany. All series are deflated, seasonally adjusted and in logs.

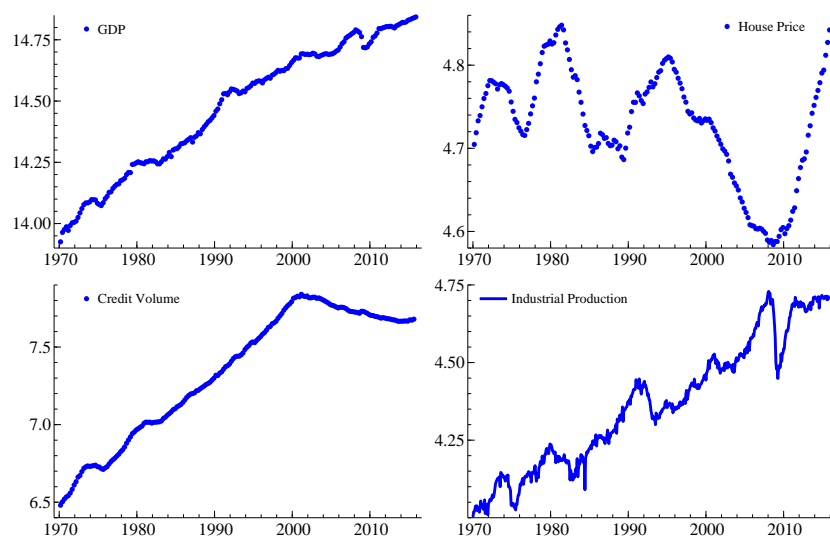


Figure A.5: GDP, house prices, credit and industrial production in France. All series are deflated, seasonally adjusted and in logs.

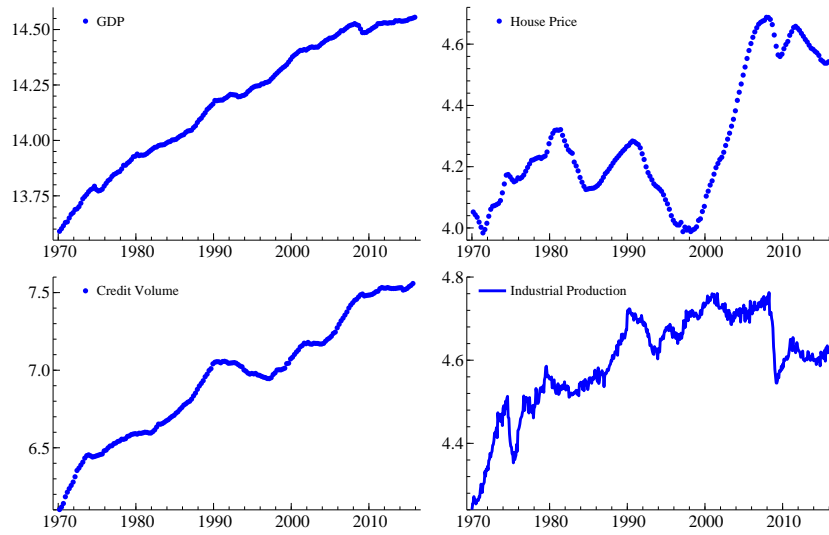


Figure A.6: GDP, house prices, credit and industrial production in Italy. All series are deflated, seasonally adjusted and in logs.

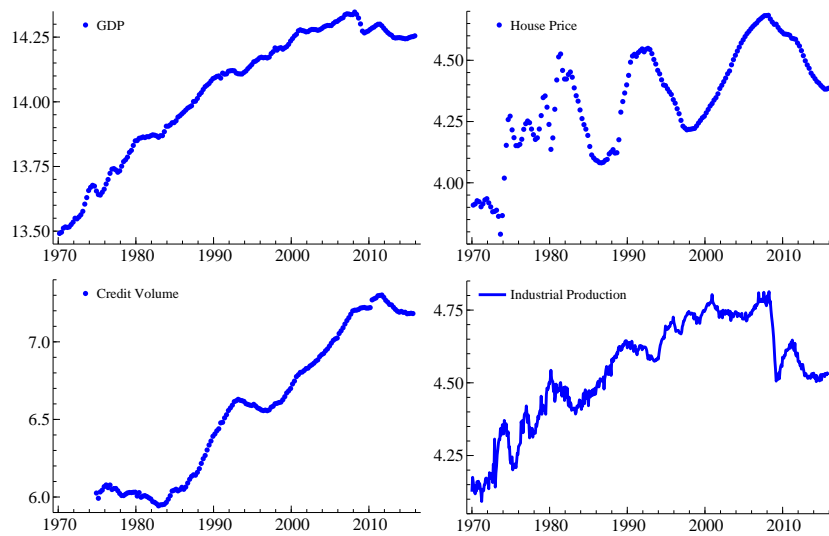
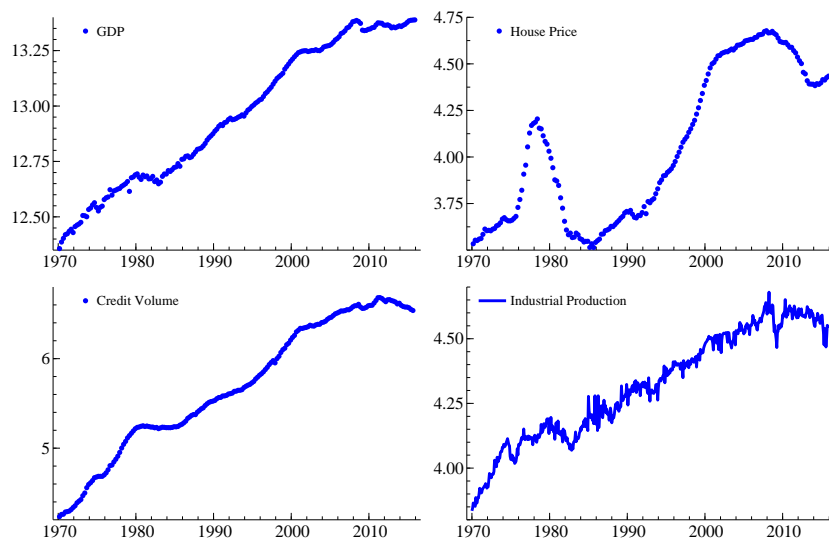


Figure A.7: GDP, house prices, credit and industrial production in the Netherlands. All series are deflated, seasonally adjusted and in logs.



B Spectral densities

Figure A.8: Spectral densities United Kingdom for GDP, house prices, credit and industrial production. All series are deflated, seasonally adjusted and in log-differences.

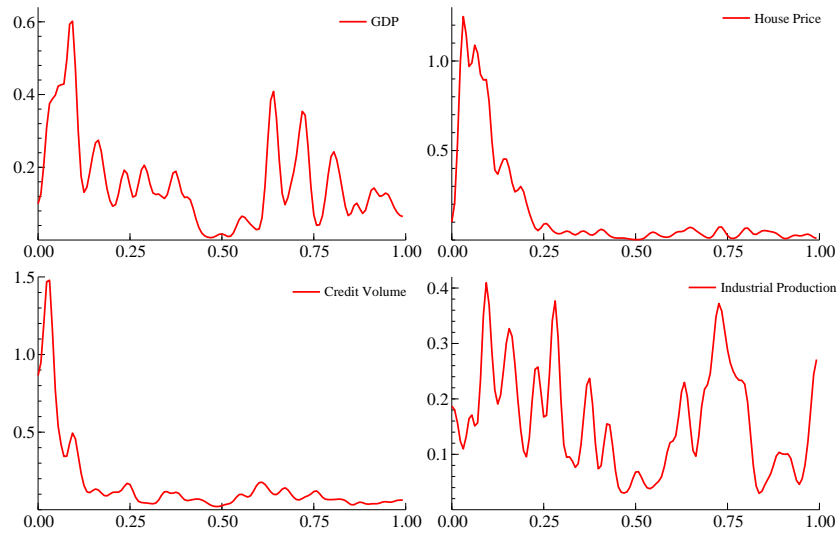


Figure A.9: Spectral densities Japan for GDP, house prices, credit and industrial production. All series are deflated, seasonally adjusted and in log-differences.

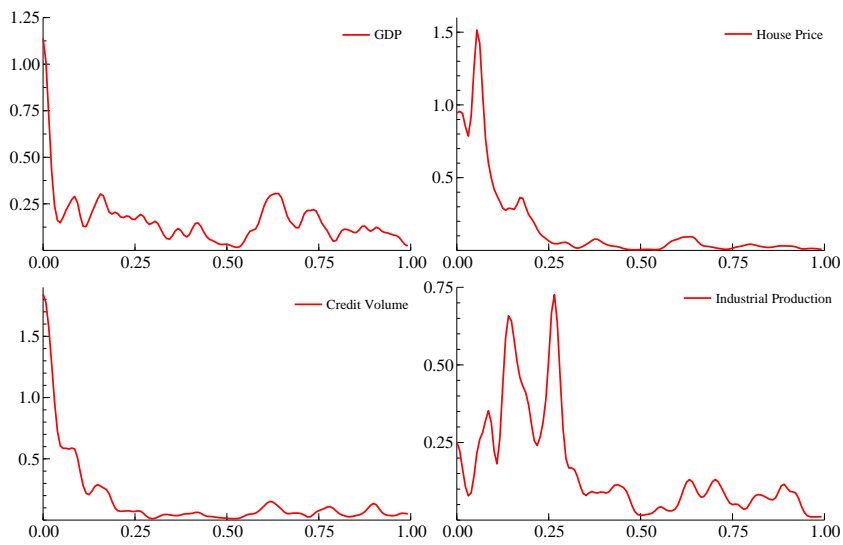


Figure A.10: Spectral densities Canada for GDP, house prices, credit and industrial production. All series are deflated, seasonally adjusted and in log-differences.

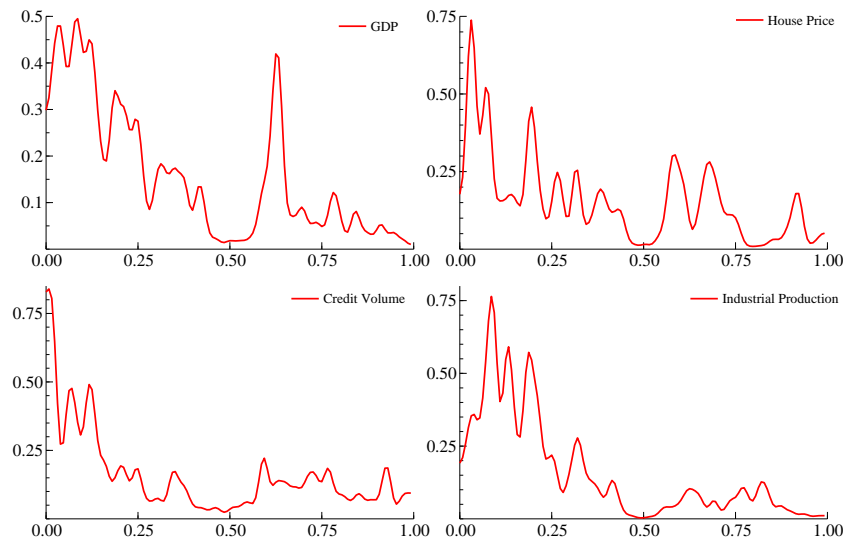


Figure A.11: Spectral densities Germany for GDP, house prices, credit and industrial production. All series are deflated, seasonally adjusted and in log-differences.

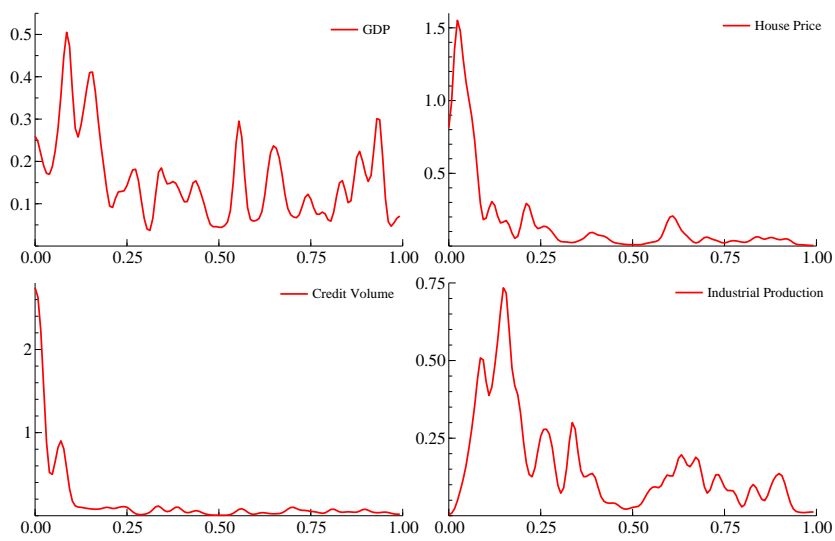


Figure A.12: Spectral densities France for GDP, house prices, credit and industrial production. All series are deflated, seasonally adjusted and in log-differences

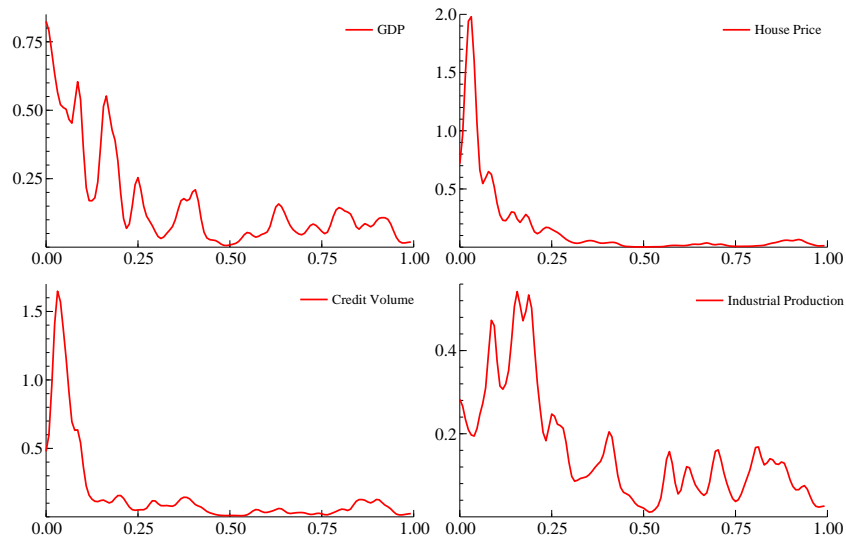


Figure A.13: Spectral densities Italy for GDP, house prices, credit and industrial production. All series are deflated, seasonally adjusted and in log-differences

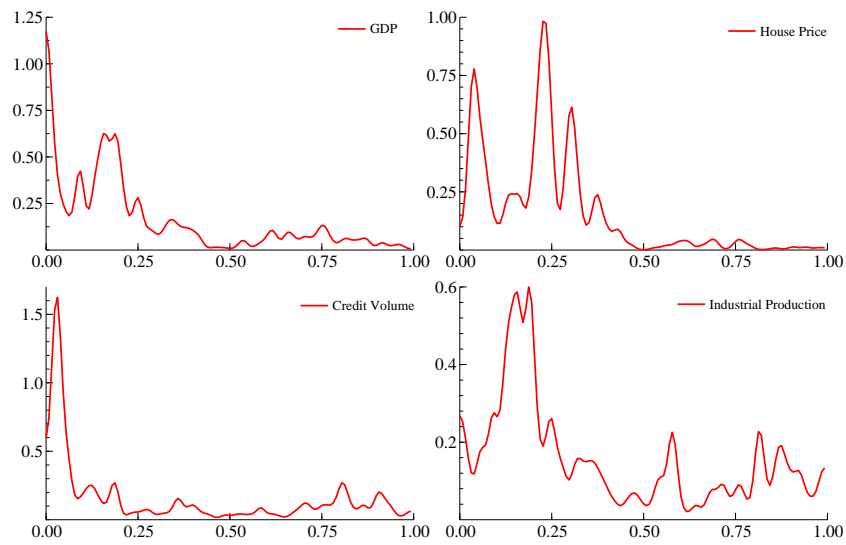
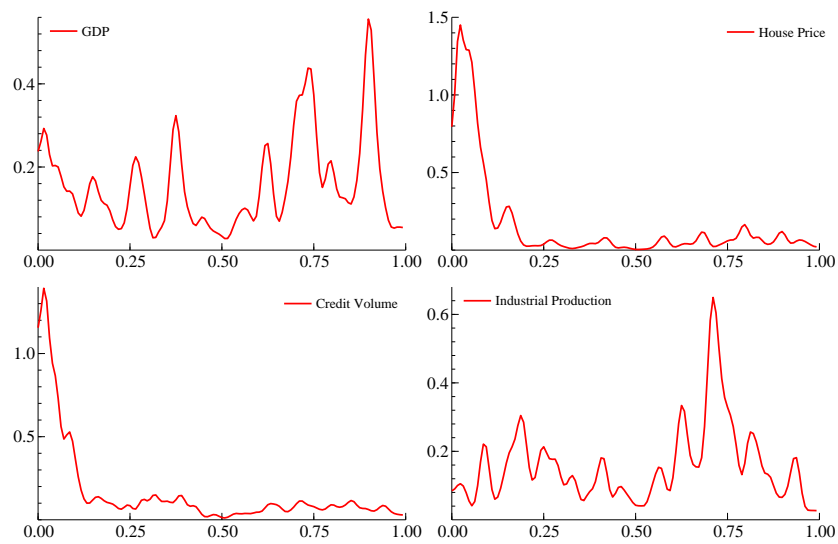


Figure A.14: Spectral densities the Netherlands for GDP, house prices, credit and industrial production. All series are deflated, seasonally adjusted and in log-differences



C State space representation UCTSM

The equations of our multivariate UCTSM, eqs. (2)–(4), 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 general terms and are respectively given by

$$y_t = Z\alpha_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, H), \quad (\text{A.1})$$

$$\alpha_{t+1} = T\alpha_t + \nu_t, \quad \nu_t \sim N(0, Q), \quad (\text{A.2})$$

where $y_t = (y_{1,t}, \dots, y_{N,t})'$, $\varepsilon_t = (\varepsilon_{1,t}, \dots, \varepsilon_{N,t})'$, and $H = \text{diag}(\sigma_{\varepsilon_1}^2, \dots, \sigma_{\varepsilon_N}^2)$. 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 $\mu_t = (\mu_{1,t}, \dots, \mu_{N,t})'$ is the long-term trend, $\beta_t = (\beta_{1,t}, \dots, \beta_{N,t})'$ is the slope, $(\gamma_t, \gamma_t^*)' = (\gamma_{1,t}, \dots, \gamma_{N,t}, \gamma_{1,t}^*, \dots, \gamma_{N,t}^*)'$ is the short-term cycle, and $(\psi_t, \psi_t^*)' = (\psi_{1,t}, \dots, \psi_{N,t}, \psi_{1,t}^*, \dots, \psi_{N,t}^*)'$ 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

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

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 $\zeta_t = (\zeta_{1,t}, \dots, \zeta_{N,t})'$ are the slope-disturbances, $(\kappa_t, \kappa_t^*)' = (\kappa_{1,t}, \dots, \kappa_{N,t}, \kappa_{1,t}^*, \dots, \kappa_{N,t}^*)'$ are the short-term cycle disturbances, and $(\omega_t, \omega_t^*)' = (\omega_{1,t}, \dots, \omega_{N,t}, \omega_{1,t}^*, \dots, \omega_{N,t}^*)'$ are the medium-term cycle disturbances.

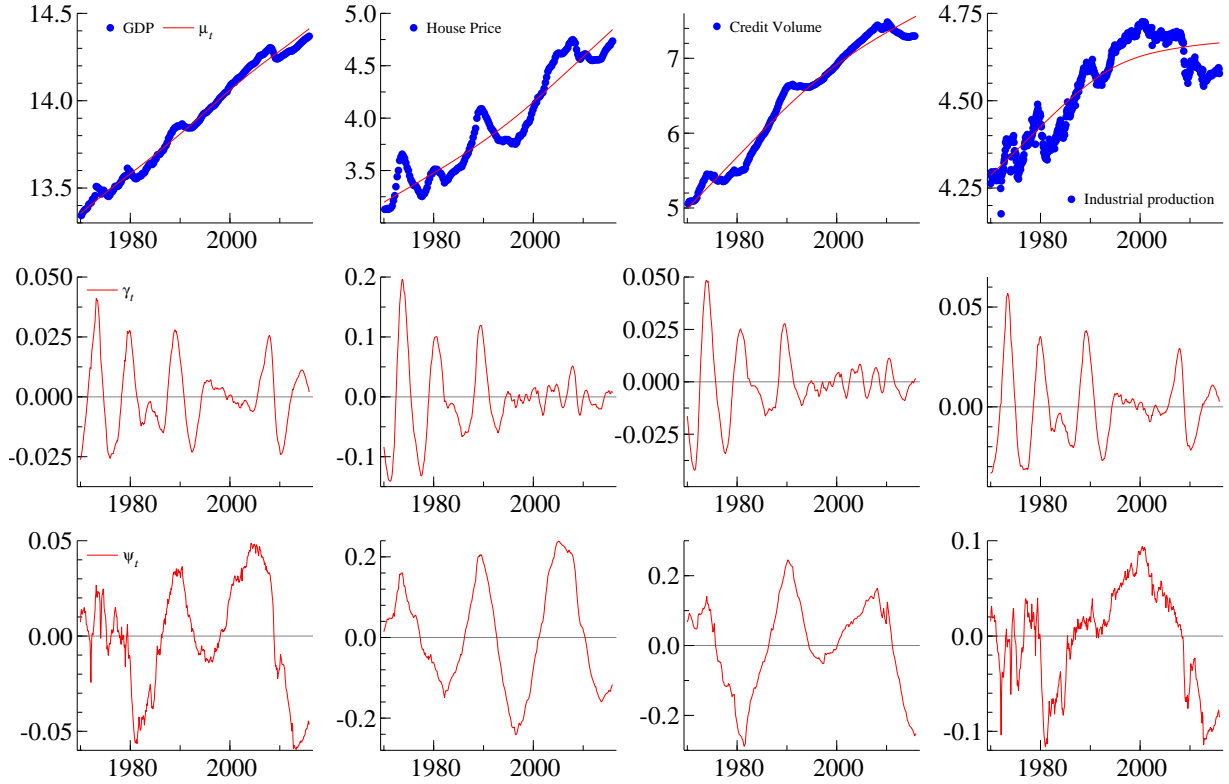
Lastly, the $(6N \times 6N)$ disturbance matrix Q in the transition equation is defined as:

$$Q = \text{diag} \begin{bmatrix} 0_{N \times N} & \Sigma_\zeta & I_2 \otimes \Sigma_\kappa & I_2 \otimes \Sigma_\omega \end{bmatrix},$$

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. $\Sigma_\zeta = \text{diag}(\sigma_{\zeta_1}^2, \dots, \sigma_{\zeta_N}^2)'$ and that the signal-to-noise ratio $(\sigma_{\zeta_i}^2 / \sigma_{\varepsilon_i}^2)$ is fixed to a certain number for each $i = 1, \dots, N$.

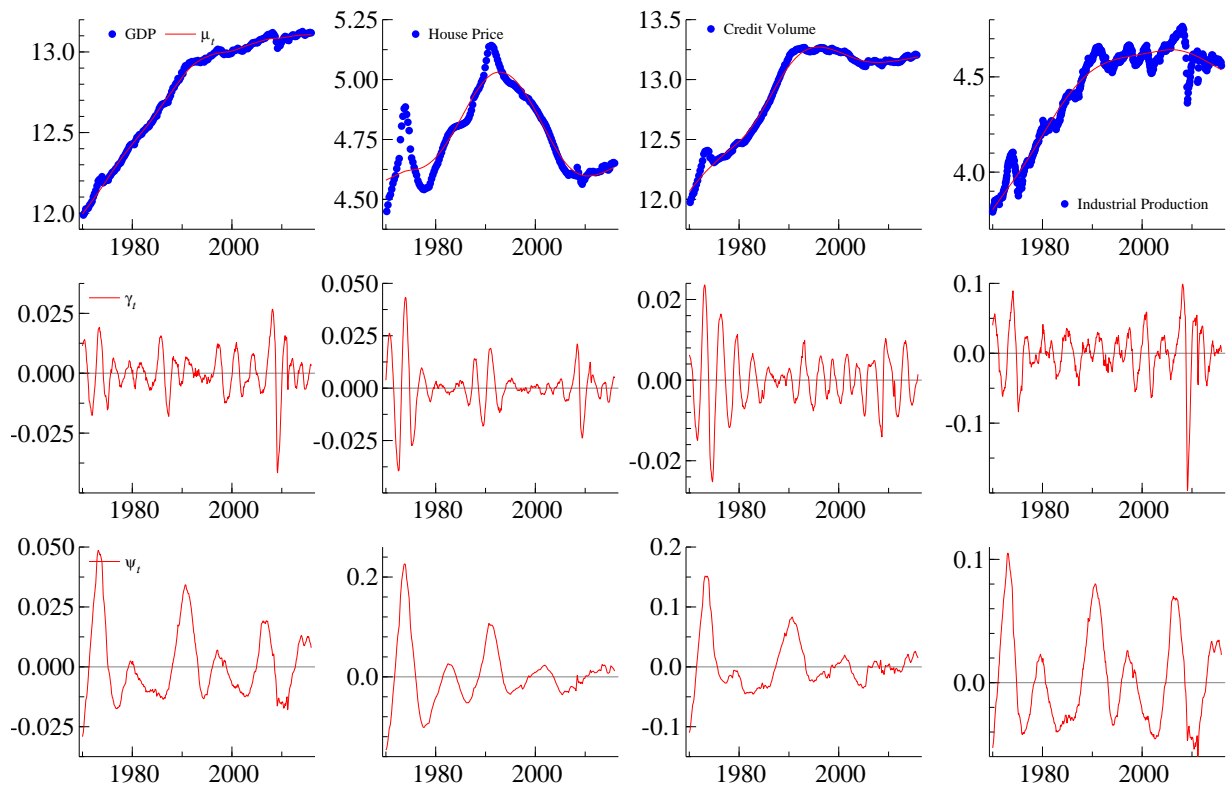
D Figures on UCTSM decomposition

Figure A.15: 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.



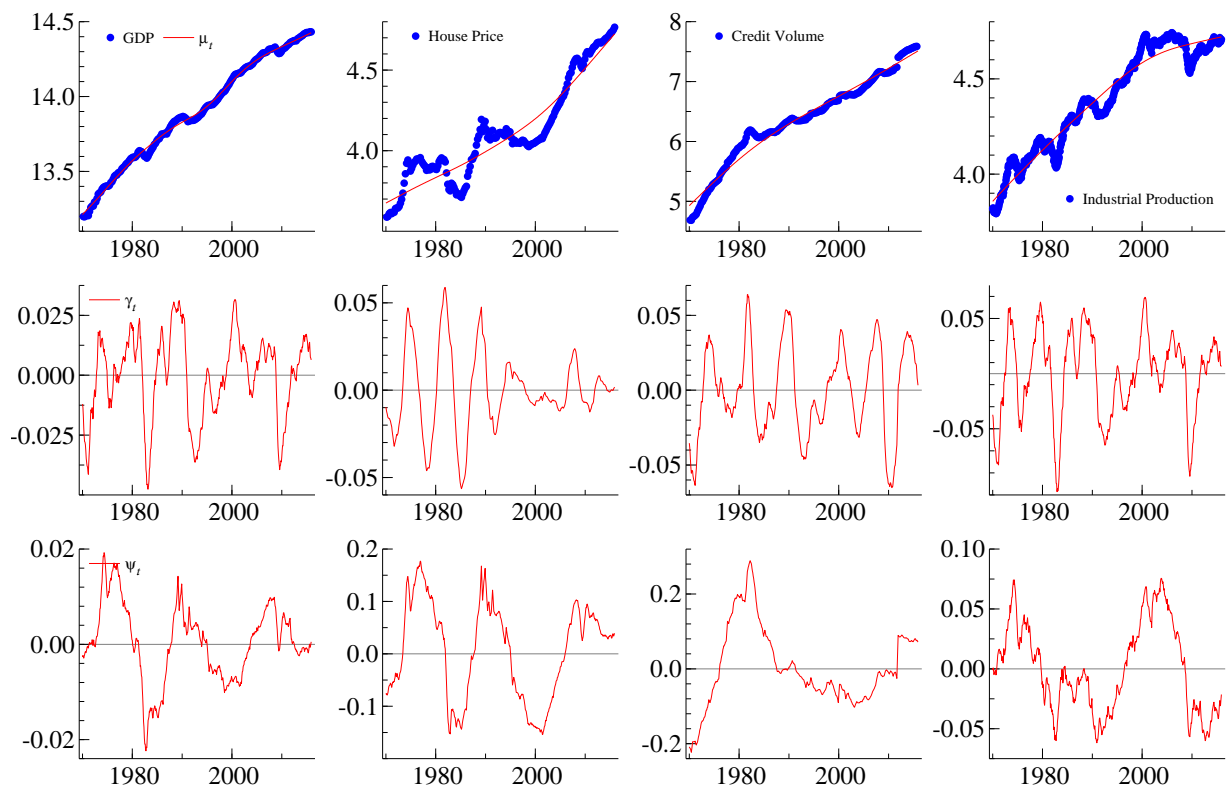
The figure presents the fit (smoothed estimates) of the model estimates in Table II and Table III. The top row shows the raw data (blue line) and trend (μ_t , red line) for GDP, house prices, credit and industrial production. The middle row presents the short-term cycle (γ_t) of the four series considered.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

Figure A.16: 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.



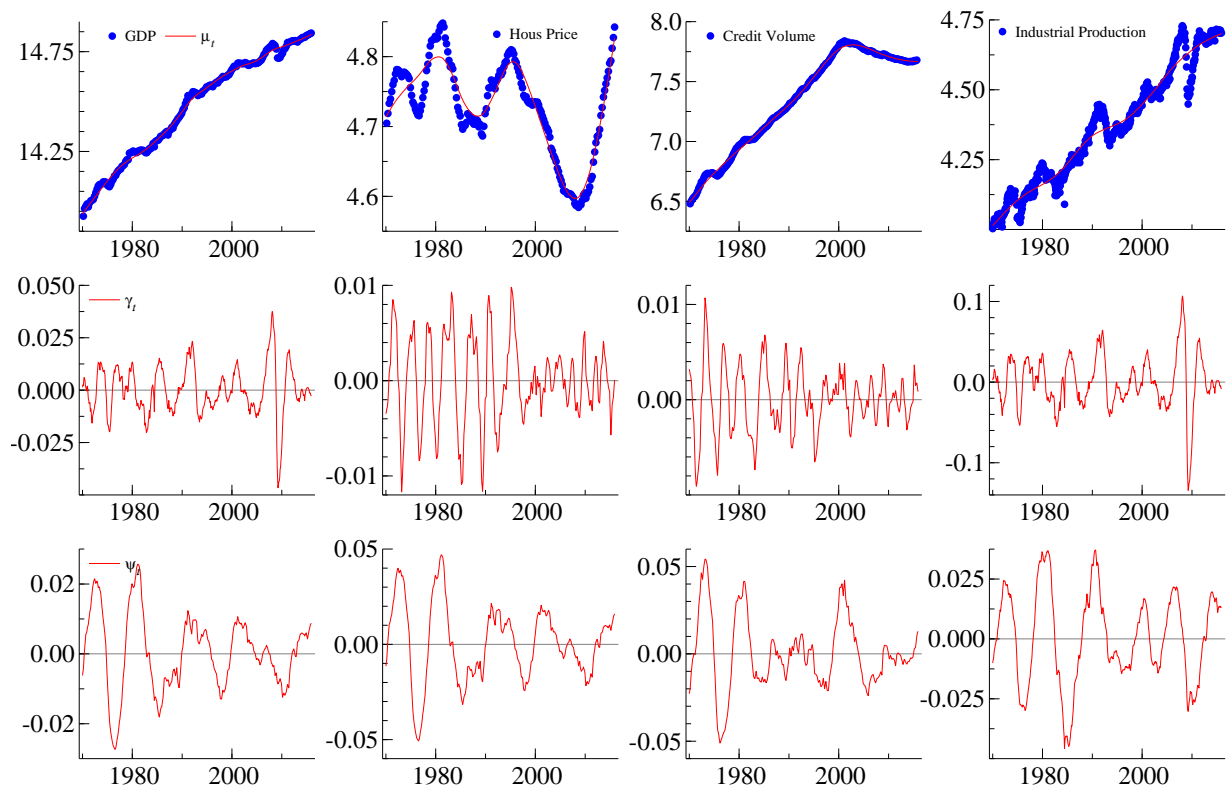
See notes on Figure A.15.

Figure A.17: 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.



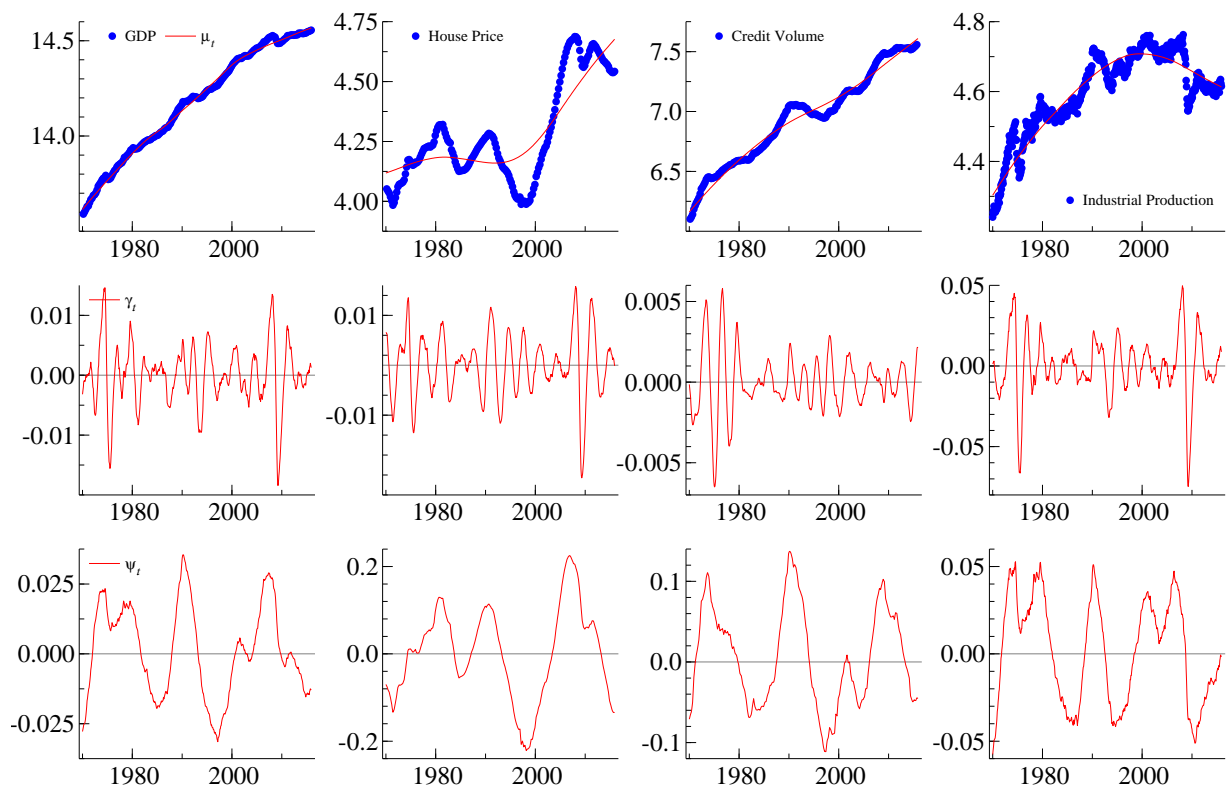
See notes on Figure A.15.

Figure A.18: 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.



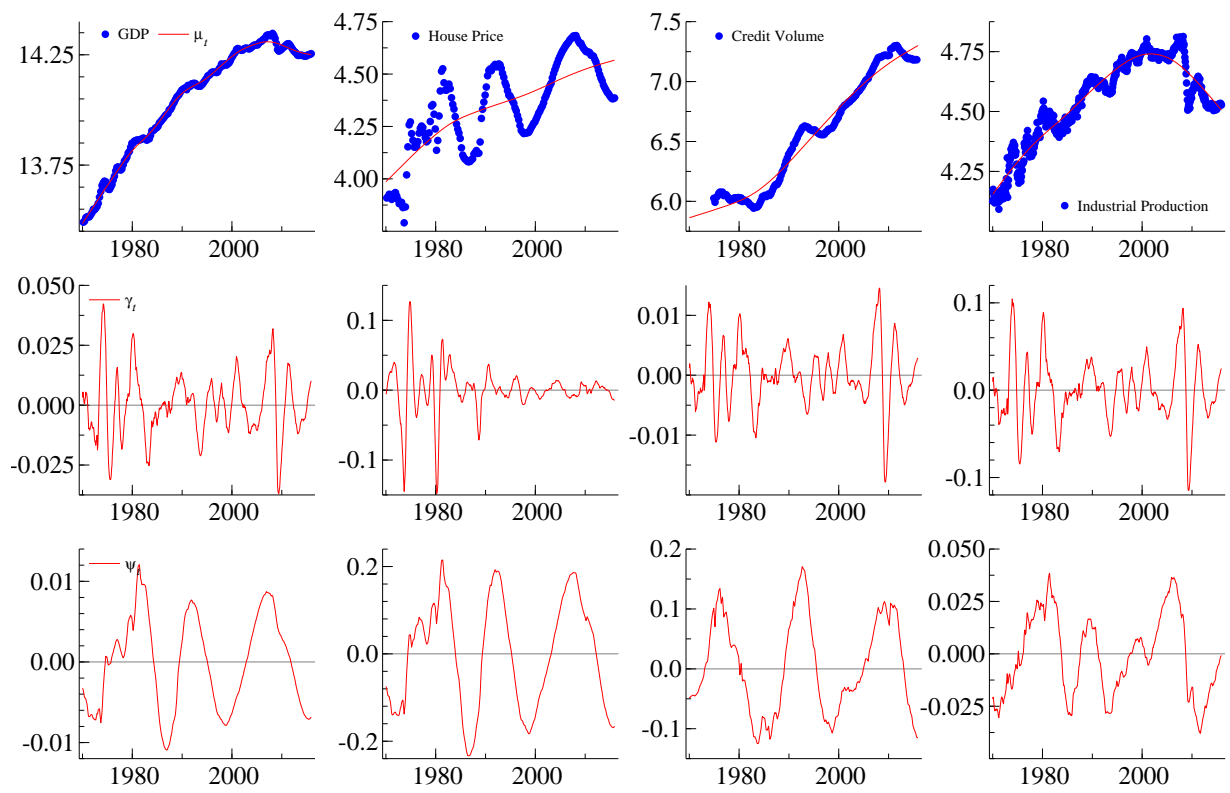
See notes on Figure A.15.

Figure A.19: 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.



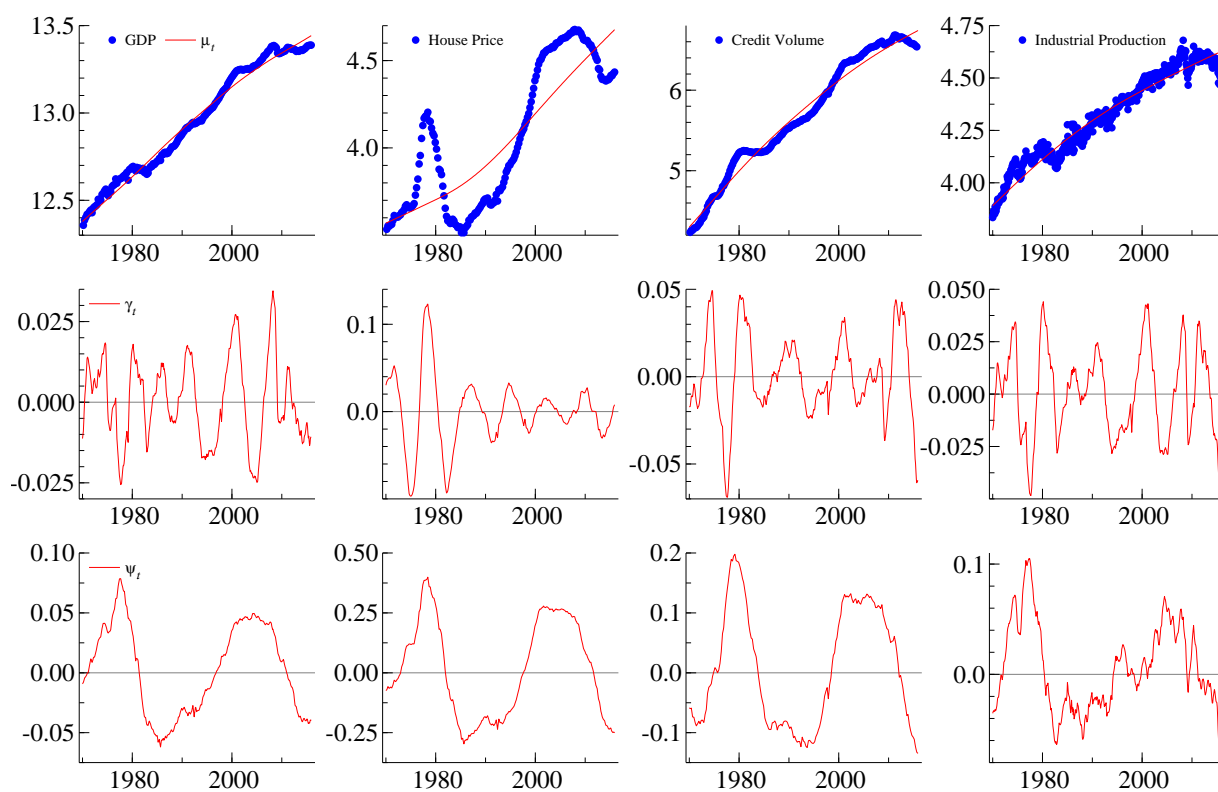
See notes on Figure A.15.

Figure A.20: 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 A.15.

Figure A.21: 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 A.15.

Table A.I: Variance residual expressed in terms of variance cycles

	GDP	HPIR	CRED
United States	1.29	1.21E-10	1.4E-11
United Kingdom	0.75	7.01E-13	3.8E-11
Japan	4.74	1.20E-10	0.04
Canada	0.52	4.18E-07	2.9E-06
Germany	4.85	1.15E-07	1.3E-09
France	0.64	1.62E-12	1.3E-10
Italy	1.42	4.95E-13	1.7E-04
Netherlands	1.20	2.97E-12	7.9E-11

The table reports (variance residual)/(variance sum of the short-term and medium-term cycle) $\times 100$ or respectively GDP, HPIR and CRED. Grey cells indicate that the variance of the residual > 0.01 percentage-point of the variance of the sum of the short-term & medium-term cycles.

E Residual diagnostics

Table A.I shows the size of the residuals of or UCTSMs for all countries considered. The table reports the relative size of the variance of the residuals.

Table A.II to Table A.XIX show residual diagnostics for all variables with a non-negligible size of the residuals, i.e. GDP for the G7 countries and the Netherlands and credit for Japan. The tables show the residual diagnostics for the whole sample (1970Q1–2015Q4), as well as the diagnostics for the less volatile second half of the sample (1992Q1–2015Q4). The tables shows the outcome of four tests for normality of the residual distribution, i.e. Bartlett’s test, kurtosis, skewness and joint kurtosis–skewness test by D’Agostino et al. (1990), the Shapiro–Wilk test and the Shapiro–Francia test. Besides the tables show the outcome of three tests for autocorrelation, i.e. the Durbin-Watson d statistic, Durbin’s alternative test for autocorrelation, a Breusch-Godfrey LM test for autocorrelation and a portmanteau (Q) test of autocorrelation by Ljung and Box. The table also shows the outcome of Engle’s LM test for ARCH (autoregressive conditional heteroskedasticity) effects.

Table A.II: Residual-diagnostics GDP United States; sample 1970Q1–2015Q4

Bartlett's test	0.0024	Shapiro-Wilk W test for normal data	0.3197
Kurtosis	0.9986	Shapiro-Francia W' test for normal data	0.3911
Skewness	0.2908	Durbin-Watson d-statistic	2.4813
Skewness & Kurtosis (joint)	0.5686		
LM test for autoregressive conditional heteroskedasticity (ARCH)		Breusch-Godfrey LM test for autocorrelation	
lag 1	0.2861	lag 1	0.0011
lag 2	0.3735	lag 2	0.0026
lag 3	0.2433	lag 3	0.0051
lag 4	0.3148	lag 4	0.0005
lag 5	0.3525	lag 5	0.0001
lag 6	0.3526	lag 6	0.0002
lag 7	0.2444	lag 7	0.0003
lag 8	0.2514	lag 8	0.0002
lag 9	0.2641	lag 9	0.0001
lag 10	0.2000	lag 10	0.0002
lag 11	0.2255	lag 11	0.0003
lag 12	0.2369	lag 12	0.0005
lag 13	0.2826	lag 13	0.0006
lag 14	0.4092	lag 14	0.0007
lag 15	0.4705	lag 15	0.0011
lag 16	0.4402	lag 16	0.0017
lag 17	0.4875	lag 17	0.0027
lag 18	0.4274	lag 18	0.0035
lag 19	0.3696	lag 19	0.0046
lag 20	0.4623	lag 20	0.0056
		Durbin's alternative test for autocorrelation	
		lag 1	0.0008
		lag 2	0.0019
		lag 3	0.0037
		lag 4	0.0002
		lag 5	0.0000
		lag 6	0.0001
		lag 7	0.0001
		lag 8	0.0000
		lag 9	0.0000
		lag 10	0.0000
		lag 11	0.0000
		lag 12	0.0001
		lag 13	0.0001
		lag 14	0.0001
		lag 15	0.0002
		lag 16	0.0003
		lag 17	0.0005
		lag 18	0.0007
		lag 19	0.0010
		lag 20	0.0012
		Ljung-Box Q-test	
		1 lag	0.0010
		2 lags	0.0042
		3 lags	0.0104
		4 lags	0.0030
		5 lags	0.0053
		6 lags	0.0103
		7 lags	0.0061
		8 lags	0.0034
		9 lags	0.0002
		10 lags	0.0005
		11 lags	0.0006
		12 lags	0.0009
		13 lags	0.0013
		14 lags	0.0008
		15 lags	0.0014
		16 lags	0.0019
		17 lags	0.0027
		18 lags	0.0042
		19 lags	0.0064
		20 lags	0.0090

Grey cells indicate significance at 1%-level.

Table A.III: Residual-diagnostics GDP United States; sample 1992Q1–2015Q4

Bartlett's test	0.3919	Shapiro-Wilk W test for normal data	0.7626		
Kurtosis	0.4620	Shapiro-Francia W' test for normal data	0.8899		
Skewness	0.8355	Durbin-Watson d -statistic	2.2240		
Skewness & Kurtosis (joint)	0.7431				
LM test for autoregressive conditional heteroskedasticity (ARCH)		Breusch-Godfrey LM test for autocorrelation		Durbin's alternative test for autocorrelation	
				Ljung-Box Q-test	
lag 1	0.8412	lag 1	0.2676	lag 1	0.2695
lag 2	0.9622	lag 2	0.5033	lag 2	0.5092
lag 3	0.9550	lag 3	0.5037	lag 3	0.5116
lag 4	0.9481	lag 4	0.0170	lag 4	0.0110
lag 5	0.4158	lag 5	0.0186	lag 5	0.0112
lag 6	0.4857	lag 6	0.0325	lag 6	0.0212
lag 7	0.4844	lag 7	0.0506	lag 7	0.0352
lag 8	0.4729	lag 8	0.0250	lag 8	0.0127
lag 9	0.5979	lag 9	0.0222	lag 9	0.0097
lag 10	0.6938	lag 10	0.0032	lag 10	0.0004
lag 11	0.7086	lag 11	0.0048	lag 11	0.0006
lag 12	0.8242	lag 12	0.0053	lag 12	0.0006
lag 13	0.8726	lag 13	0.0032	lag 13	0.0002
lag 14	0.9263	lag 14	0.0043	lag 14	0.0002
lag 15	0.9221	lag 15	0.0064	lag 15	0.0004
lag 16	0.9398	lag 16	0.0099	lag 16	0.0009
lag 17	0.9532	lag 17	0.0106	lag 17	0.0009
lag 18	0.9710	lag 18	0.0128	lag 18	0.0011
lag 19	0.9515	lag 19	0.0072	lag 19	0.0002
lag 20	0.9487	lag 20	0.0064	lag 20	0.0001

Grey cells indicate significance at 1%-level.

Table A.IV: Residual-diagnostics GDP United Kingdom; sample 1970Q1–2015Q4

Bartlett's test	0.0549	Shapiro-Wilk W test for normal data	0.1168
Kurtosis	0.4200	Shapiro-Francia W' test for normal data	0.2105
Skewness	0.5807	Durbin-Watson d-statistic	2.0113
Skewness & Kurtosis (joint)	0.6168		
LM test for autoregressive conditional heteroskedasticity (ARCH)		Breusch-Godfrey LM test for autocorrelation	
lag 1	0.5471	lag 1	0.9190
lag 2	0.3891	lag 2	0.1745
lag 3	0.2583	lag 3	0.0122
lag 4	0.3780	lag 4	0.0004
lag 5	0.4194	lag 5	0.0003
lag 6	0.5480	lag 6	0.0003
lag 7	0.4342	lag 7	0.0003
lag 8	0.5152	lag 8	0.0001
lag 9	0.5197	lag 9	0.0001
lag 10	0.5716	lag 10	0.0002
lag 11	0.6283	lag 11	0.0001
lag 12	0.7146	lag 12	0.0000
lag 13	0.8007	lag 13	0.0000
lag 14	0.8412	lag 14	0.0001
lag 15	0.7464	lag 15	0.0001
lag 16	0.6250	lag 16	0.0002
lag 17	0.5968	lag 17	0.0002
lag 18	0.5987	lag 18	0.0004
lag 19	0.7015	lag 19	0.0006
lag 20	0.5026	lag 20	0.0003
		Durbin's alternative test for autocorrelation	
		lag 1	0.9194
		lag 2	0.1737
		lag 3	0.0100
		lag 4	0.0002
		lag 5	0.0001
		lag 6	0.0001
		lag 7	0.0001
		lag 8	0.0000
		lag 9	0.0000
		lag 10	0.0000
		lag 11	0.0000
		lag 12	0.0000
		lag 13	0.0000
		lag 14	0.0000
		lag 15	0.0000
		lag 16	0.0000
		lag 17	0.0000
		lag 18	0.0000
		lag 19	0.0000
		lag 20	0.0000
		Ljung-Box Q-test	
		1 lag	0.9185
		2 lags	0.1709
		3 lags	0.0126
		4 lags	0.0012
		5 lags	0.0026
		6 lags	0.0052
		7 lags	0.0096
		8 lags	0.0165
		9 lags	0.0036
		10 lags	0.0047
		11 lags	0.0032
		12 lags	0.0001
		13 lags	0.0001
		14 lags	0.0003
		15 lags	0.0004
		16 lags	0.0008
		17 lags	0.0011
		18 lags	0.0017
		19 lags	0.0020
		20 lags	0.0029

Grey cells indicate significance at 1%-level.

Table A.V: Residual-diagnostics GDP United Kingdom; sample 1992Q1–2015Q4

Bartlett's test	0.8182	Shapiro-Wilk W test for normal data	0.3161				
Kurtosis	0.3000	Shapiro-Francia W' test for normal data	0.4950				
Skewness	0.4630	Durbin-Watson d-statistic	1.9869				
Skewness & Kurtosis (joint)	0.4375						
LM test for autoregressive conditional heteroskedasticity (ARCH)		Breusch-Godfrey LM test for autocorrelation		Durbin's alternative test for autocorrelation	Ljung-Box Q-test		
lag 1	0.4250	lag 1	0.9640	lag 1	0.9644	1 lag	0.9636
lag 2	0.6779	lag 2	0.9845	lag 2	0.9850	2 lags	0.9842
lag 3	0.7581	lag 3	0.1100	lag 3	0.1037	3 lags	0.1031
lag 4	0.9050	lag 4	0.0728	lag 4	0.0631	4 lags	0.0693
lag 5	0.7173	lag 5	0.1272	lag 5	0.1161	5 lags	0.1215
lag 6	0.0905	lag 6	0.1630	lag 6	0.1510	6 lags	0.1906
lag 7	0.1363	lag 7	0.2322	lag 7	0.2230	7 lags	0.2516
lag 8	0.2156	lag 8	0.3026	lag 8	0.2985	8 lags	0.3393
lag 9	0.2831	lag 9	0.3413	lag 9	0.3403	9 lags	0.3421
lag 10	0.3830	lag 10	0.4293	lag 10	0.4383	10 lags	0.4310
lag 11	0.4738	lag 11	0.2255	lag 11	0.2063	11 lags	0.2320
lag 12	0.3897	lag 12	0.0579	lag 12	0.0317	12 lags	0.0298
lag 13	0.4214	lag 13	0.0393	lag 13	0.0163	13 lags	0.0333
lag 14	0.4410	lag 14	0.0512	lag 14	0.0230	14 lags	0.0357
lag 15	0.5488	lag 15	0.0580	lag 15	0.0262	15 lags	0.0463
lag 16	0.5375	lag 16	0.0561	lag 16	0.0231	16 lags	0.0616
lag 17	0.6022	lag 17	0.0723	lag 17	0.0331	17 lags	0.0842
lag 18	0.5782	lag 18	0.0841	lag 18	0.0402	18 lags	0.1011
lag 19	0.6029	lag 19	0.1104	lag 19	0.0603	19 lags	0.1318
lag 20	0.6608	lag 20	0.1265	lag 20	0.0726	20 lags	0.1667

Grey cells indicate significance at 1%-level.

Table A.VI: Residual-diagnostics GDP Japan; sample 1970Q1–2015Q4

Bartlett's test	0.1046	Shapiro-Wilk W test for normal data	0.0070
Kurtosis	0.0131	Shapiro-Francia W' test for normal data	0.0235
Skewness	0.3128	Durbin-Watson d-statistic	2.1419
Skewness & Kurtosis (joint)	0.0337		
LM test for autoregressive conditional heteroskedasticity (ARCH)		Breusch-Godfrey LM test for autocorrelation	
lag 1	0.9605	lag 1	0.3350
lag 2	0.9671	lag 2	0.0004
lag 3	0.7382	lag 3	0.0004
lag 4	0.8403	lag 4	0.0002
lag 5	0.8417	lag 5	0.0002
lag 6	0.7947	lag 6	0.0004
lag 7	0.8522	lag 7	0.0002
lag 8	0.7849	lag 8	0.0000
lag 9	0.7806	lag 9	0.0000
lag 10	0.5755	lag 10	0.0000
lag 11	0.5481	lag 11	0.0001
lag 12	0.6440	lag 12	0.0000
lag 13	0.6687	lag 13	0.0000
lag 14	0.6744	lag 14	0.0000
lag 15	0.5933	lag 15	0.0000
lag 16	0.6944	lag 16	0.0000
lag 17	0.7786	lag 17	0.0000
lag 18	0.7880	lag 18	0.0000
lag 19	0.5820	lag 19	0.0000
lag 20	0.5303	lag 20	0.0000
		Durbin's alternative test for autocorrelation	
		lag 1	0.3364
		lag 2	0.0002
		lag 3	0.0002
		lag 4	0.0001
		lag 5	0.0001
		lag 6	0.0001
		lag 7	0.0000
		lag 8	0.0000
		lag 9	0.0000
		lag 10	0.0000
		lag 11	0.0000
		lag 12	0.0000
		lag 13	0.0000
		lag 14	0.0000
		lag 15	0.0000
		lag 16	0.0000
		lag 17	0.0000
		lag 18	0.0000
		lag 19	0.0000
		lag 20	0.0000
		Ljung-Box Q-test	
		1 lag	0.3311
		2 lags	0.0004
		3 lags	0.0002
		4 lags	0.0003
		5 lags	0.0007
		6 lags	0.0005
		7 lags	0.0009
		8 lags	0.0000
		9 lags	0.0001
		10 lags	0.0000
		11 lags	0.0000
		12 lags	0.0000
		13 lags	0.0000
		14 lags	0.0000
		15 lags	0.0000
		16 lags	0.0000
		17 lags	0.0000
		18 lags	0.0000
		19 lags	0.0000
		20 lags	0.0000

Grey cells indicate significance at 1%-level.

Table A.VII: Residual-diagnostics GDP Japan; sample 1992Q1–2015Q4

Bartlett's test	0.2440	Shapiro-Wilk W test for normal data	0.0325
Kurtosis	0.1037	Shapiro-Francia W' test for normal data	0.0892
Skewness	0.5253	Durbin-Watson d-statistic	2.1724
Skewness & Kurtosis (joint)	0.2082		
LM test for autoregressive conditional heteroskedasticity (ARCH)		Breusch-Godfrey LM test for autocorrelation	
lag 1	0.8811	lag 1	0.3982
lag 2	0.9787	lag 2	0.0068
lag 3	0.5726	lag 3	0.0087
lag 4	0.5797	lag 4	0.0127
lag 5	0.7135	lag 5	0.0114
lag 6	0.5937	lag 6	0.0171
lag 7	0.5545	lag 7	0.0190
lag 8	0.6463	lag 8	0.0020
lag 9	0.6532	lag 9	0.0030
lag 10	0.7333	lag 10	0.0040
lag 11	0.3490	lag 11	0.0056
lag 12	0.4075	lag 12	0.0060
lag 13	0.4206	lag 13	0.0089
lag 14	0.3324	lag 14	0.0126
lag 15	0.3782	lag 15	0.0157
lag 16	0.4499	lag 16	0.0234
lag 17	0.4585	lag 17	0.0242
lag 18	0.3754	lag 18	0.0329
lag 19	0.4492	lag 19	0.0458
lag 20	0.5111	lag 20	0.0578
		Durbin's alternative test for autocorrelation	
lag 1		lag 1	0.4014
lag 2		lag 2	0.0045
lag 3		lag 3	0.0054
lag 4		lag 4	0.0076
lag 5		lag 5	0.0059
lag 6		lag 6	0.0091
lag 7		lag 7	0.0095
lag 8		lag 8	0.0003
lag 9		lag 9	0.0004
lag 10		lag 10	0.0005
lag 11		lag 11	0.0008
lag 12		lag 12	0.0007
lag 13		lag 13	0.0013
lag 14		lag 14	0.0020
lag 15		lag 15	0.0027
lag 16		lag 16	0.0049
lag 17		lag 17	0.0046
lag 18		lag 18	0.0074
lag 19		lag 19	0.0126
lag 20		lag 20	0.0179
		Ljung-Box Q-test	
		1 lag	0.3909
		2 lags	0.0073
		3 lags	0.0041
		4 lags	0.0094
		5 lags	0.0182
		6 lags	0.0168
		7 lags	0.0302
		8 lags	0.0017
		9 lags	0.0029
		10 lags	0.0025
		11 lags	0.0028
		12 lags	0.0036
		13 lags	0.0053
		14 lags	0.0057
		15 lags	0.0090
		16 lags	0.0068
		17 lags	0.0042
		18 lags	0.0064
		19 lags	0.0053
		20 lags	0.0080

Grey cells indicate significance at 1%-level.

Table A.VIII: Residual-diagnostics Credit Japan; sample 1970Q1–2015Q4

Bartlett's test	0.0000	Shapiro-Wilk W test for normal data	0.2354
Kurtosis	0.9800	Shapiro-Francia W' test for normal data	0.3057
Skewness	0.6087	Durbin-Watson d-statistic	2.7943
Skewness & Kurtosis (joint)	0.8769		
LM test for autoregressive conditional heteroskedasticity (ARCH)		Breusch-Godfrey LM test for autocorrelation	
lag 1	0.0125	lag 1	0.0000
lag 2	0.0147	lag 2	0.0000
lag 3	0.0348	lag 3	0.0000
lag 4	0.0696	lag 4	0.0000
lag 5	0.0982	lag 5	0.0000
lag 6	0.1310	lag 6	0.0000
lag 7	0.1561	lag 7	0.0000
lag 8	0.2171	lag 8	0.0000
lag 9	0.2206	lag 9	0.0000
lag 10	0.2288	lag 10	0.0000
lag 11	0.2853	lag 11	0.0000
lag 12	0.2714	lag 12	0.0000
lag 13	0.2975	lag 13	0.0000
lag 14	0.1725	lag 14	0.0000
lag 15	0.2158	lag 15	0.0000
lag 16	0.2692	lag 16	0.0000
lag 17	0.1340	lag 17	0.0000
lag 18	0.1564	lag 18	0.0000
lag 19	0.2137	lag 19	0.0000
lag 20	0.2807	lag 20	0.0000
		Durbin's alternative test for autocorrelation	
		lag 1	0.0000
		lag 2	0.0000
		lag 3	0.0000
		lag 4	0.0000
		lag 5	0.0000
		lag 6	0.0000
		lag 7	0.0000
		lag 8	0.0000
		lag 9	0.0000
		lag 10	0.0000
		lag 11	0.0000
		lag 12	0.0000
		lag 13	0.0000
		lag 14	0.0000
		lag 15	0.0000
		lag 16	0.0000
		lag 17	0.0000
		lag 18	0.0000
		lag 19	0.0000
		lag 20	0.0000
		Ljung-Box Q-test	
		1 lag	0.0000
		2 lags	0.0000
		3 lags	0.0000
		4 lags	0.0000
		5 lags	0.0000
		6 lags	0.0000
		7 lags	0.0000
		8 lags	0.0000
		9 lags	0.0000
		10 lags	0.0000
		11 lags	0.0000
		12 lags	0.0000
		13 lags	0.0000
		14 lags	0.0000
		15 lags	0.0000
		16 lags	0.0000
		17 lags	0.0000
		18 lags	0.0000
		19 lags	0.0000
		20 lags	0.0000

Grey cells indicate significance at 1%-level.

Table A.IX: Residual-diagnostics Credit Japan; sample 1992Q1–2015Q4

Bartlett's test	0.0000	Shapiro-Wilk W test for normal data	0.7699
Kurtosis	0.8330	Shapiro-Francia W' test for normal data	0.8029
Skewness	0.5937	Durbin-Watson d-statistic	2.8264
Skewness & Kurtosis (joint)	0.8483		
LM test for autoregressive conditional heteroskedasticity (ARCH)		Breusch-Godfrey LM test for autocorrelation	
lag 1	0.2641	lag 1	0.0000
lag 2	0.5303	lag 2	0.0000
lag 3	0.7357	lag 3	0.0000
lag 4	0.6363	lag 4	0.0001
lag 5	0.5405	lag 5	0.0001
lag 6	0.6349	lag 6	0.0002
lag 7	0.6348	lag 7	0.0002
lag 8	0.5108	lag 8	0.0000
lag 9	0.5094	lag 9	0.0000
lag 10	0.4855	lag 10	0.0001
lag 11	0.5769	lag 11	0.0002
lag 12	0.4505	lag 12	0.0001
lag 13	0.4492	lag 13	0.0001
lag 14	0.3030	lag 14	0.0001
lag 15	0.3133	lag 15	0.0002
lag 16	0.3350	lag 16	0.0003
lag 17	0.3173	lag 17	0.0005
lag 18	0.3553	lag 18	0.0004
lag 19	0.4159	lag 19	0.0007
lag 20	0.4748	lag 20	0.0010
		Durbin's alternative test for autocorrelation	
		lag 1	0.0000
		lag 2	0.0000
		lag 3	0.0000
		lag 4	0.0000
		lag 5	0.0000
		lag 6	0.0000
		lag 7	0.0000
		lag 8	0.0000
		lag 9	0.0000
		lag 10	0.0000
		lag 11	0.0000
		lag 12	0.0000
		lag 13	0.0000
		lag 14	0.0000
		lag 15	0.0000
		lag 16	0.0000
		lag 17	0.0000
		lag 18	0.0000
		lag 19	0.0000
		lag 20	0.0000
		Ljung-Box Q-test	
		1 lag	0.0000
		2 lags	0.0001
		3 lags	0.0002
		4 lags	0.0002
		5 lags	0.0004
		6 lags	0.0010
		7 lags	0.0014
		8 lags	0.0001
		9 lags	0.0001
		10 lags	0.0002
		11 lags	0.0002
		12 lags	0.0004
		13 lags	0.0001
		14 lags	0.0000
		15 lags	0.0001
		16 lags	0.0001
		17 lags	0.0001
		18 lags	0.0002
		19 lags	0.0003
		20 lags	0.0003

Grey cells indicate significance at 1%-level.

Table A.X: Residual-diagnostics GDP Canada; sample 1970Q1–2015Q4

Bartlett's test	0.0170	Shapiro-Wilk W test for normal data	0.0380		
Kurtosis	0.0550	Shapiro-Francia W' test for normal dat	0.0946		
Skewness	0.7914	Durbin-Watson d-statistic	2.3714		
Skewness & Kurtosis (joint)	0.1497				
LM test for autoregressive conditional heteroskedasticity (ARCH)		Breusch-Godfrey LM test for autocorrelation		Durbin's alternative test for autocorrelation	
lag 1	0.6173	lag 1	0.0102	lag 1	0.0093
lag 2	0.6836	lag 2	0.0113	lag 2	0.0097
lag 3	0.2249	lag 3	0.0109	lag 3	0.0088
lag 4	0.1273	lag 4	0.0007	lag 4	0.0003
lag 5	0.1896	lag 5	0.0009	lag 5	0.0004
lag 6	0.1267	lag 6	0.0002	lag 6	0.0001
lag 7	0.2019	lag 7	0.0002	lag 7	0.0000
lag 8	0.2130	lag 8	0.0002	lag 8	0.0000
lag 9	0.2464	lag 9	0.0004	lag 9	0.0001
lag 10	0.2337	lag 10	0.0006	lag 10	0.0001
lag 11	0.2990	lag 11	0.0011	lag 11	0.0003
lag 12	0.3374	lag 12	0.0007	lag 12	0.0001
lag 13	0.4250	lag 13	0.0004	lag 13	0.0000
lag 14	0.5219	lag 14	0.0004	lag 14	0.0000
lag 15	0.5789	lag 15	0.0004	lag 15	0.0000
lag 16	0.6541	lag 16	0.0007	lag 16	0.0001
lag 17	0.7080	lag 17	0.0005	lag 17	0.0000
lag 18	0.7541	lag 18	0.0005	lag 18	0.0000
lag 19	0.8087	lag 19	0.0008	lag 19	0.0001
lag 20	0.8560	lag 20	0.0013	lag 20	0.0001
Ljung-Box Q-test					
		1 lag			0.0098
		2 lags			0.0208
		3 lags			0.0345
		4 lags			0.0103
		5 lags			0.0212
		6 lags			0.0007
		7 lags			0.0011
		8 lags			0.0005
		9 lags			0.0008
		10 lags			0.0013
		11 lags			0.0020
		12 lags			0.0035
		13 lags			0.0006
		14 lags			0.0010
		15 lags			0.0011
		16 lags			0.0017
		17 lags			0.0001
		18 lags			0.0001
		19 lags			0.0001
		20 lags			0.0002

Grey cells indicate significance at 1%-level.

Table A.XI: Residual-diagnostics GDP Canada; sample 1992Q1–2015Q4

Bartlett's test	0.2607	Shapiro-Wilk W test for normal data	0.0298		
Kurtosis	0.0304	Shapiro-Francia W' test for normal data	0.0814		
Skewness	0.4723	Durbin-Watson d -statistic	2.2569		
Skewness & Kurtosis (joint)	0.0771				
LM test for autoregressive conditional heteroskedasticity (ARCH)		Breusch-Godfrey LM test for autocorrelation		Durbin's alternative test for autocorrelation	
				Ljung-Box Q-test	
lag 1	0.4401	lag 1	0.1738	lag 1	0.1742
lag 2	0.6234	lag 2	0.2852	lag 2	0.2871
lag 3	0.7357	lag 3	0.4205	lag 3	0.4264
lag 4	0.5880	lag 4	0.0011	lag 4	0.0003
lag 5	0.5894	lag 5	0.0021	lag 5	0.0005
lag 6	0.6679	lag 6	0.0032	lag 6	0.0008
lag 7	0.7804	lag 7	0.0063	lag 7	0.0019
lag 8	0.8563	lag 8	0.0116	lag 8	0.0041
lag 9	0.4434	lag 9	0.0186	lag 9	0.0075
lag 10	0.5920	lag 10	0.0286	lag 10	0.0129
lag 11	0.5229	lag 11	0.0321	lag 11	0.0140
lag 12	0.6431	lag 12	0.0392	lag 12	0.0176
lag 13	0.6239	lag 13	0.0564	lag 13	0.0286
lag 14	0.6999	lag 14	0.0786	lag 14	0.0448
lag 15	0.7336	lag 15	0.1075	lag 15	0.0685
lag 16	0.7759	lag 16	0.1353	lag 16	0.0932
lag 17	0.8399	lag 17	0.1567	lag 17	0.1125
lag 18	0.8735	lag 18	0.1923	lag 18	0.1487
lag 19	0.8249	lag 19	0.1930	lag 19	0.1462
lag 20	0.9102	lag 20	0.2387	lag 20	0.1970

Grey cells indicate significance at 1%-level.

Table A.XII: Residual-diagnostics GDP Germany; sample 1970Q1–2015Q4

Bartlett's test	0.8214	Shapiro-Wilk W test for normal data	0.0001				
Kurtosis	0.5654	Shapiro-Francia W' test for normal data	0.0004				
Skewness	0.0015	Durbin-Watson d-statistic	1.9718				
Skewness & Kurtosis (joint)	0.0094						
LM test for autoregressive conditional heteroskedasticity (ARCH)		Breusch-Godfrey LM test for autocorrelation		Durbin's alternative test for autocorrelation		Ljung-Box Q-test	
lag 1	0.5577	lag 1	0.8534	lag 1	0.8542	1 lag	0.8523
lag 2	0.8248	lag 2	0.4968	lag 2	0.4998	2 lags	0.4911
lag 3	0.6944	lag 3	0.6054	lag 3	0.6102	3 lags	0.5889
lag 4	0.8012	lag 4	0.2873	lag 4	0.2873	4 lags	0.3029
lag 5	0.8791	lag 5	0.4132	lag 5	0.4166	5 lags	0.4339
lag 6	0.8898	lag 6	0.5070	lag 6	0.5133	6 lags	0.5590
lag 7	0.9391	lag 7	0.5086	lag 7	0.5155	7 lags	0.5958
lag 8	0.9428	lag 8	0.2924	lag 8	0.2899	8 lags	0.4426
lag 9	0.8666	lag 9	0.1547	lag 9	0.1443	9 lags	0.1841
lag 10	0.9873	lag 10	0.2129	lag 10	0.2039	10 lags	0.2229
lag 11	0.9904	lag 11	0.2737	lag 11	0.2674	11 lags	0.2836
lag 12	0.9878	lag 12	0.0485	lag 12	0.0355	12 lags	0.0697
lag 13	0.9943	lag 13	0.0665	lag 13	0.0509	13 lags	0.0691
lag 14	0.9931	lag 14	0.0659	lag 14	0.0492	14 lags	0.0866
lag 15	0.9888	lag 15	0.0900	lag 15	0.0707	15 lags	0.1178
lag 16	0.9084	lag 16	0.1083	lag 16	0.0873	16 lags	0.1507
lag 17	0.8693	lag 17	0.0298	lag 17	0.0161	17 lags	0.0645
lag 18	0.8847	lag 18	0.0358	lag 18	0.0199	18 lags	0.0514
lag 19	0.9207	lag 19	0.0376	lag 19	0.0205	19 lags	0.0582
lag 20	0.9456	lag 20	0.0502	lag 20	0.0295	20 lags	0.0752

Grey cells indicate significance at 1%-level.

Table A.XIII: Residual-diagnostics GDP Germany; sample 1992Q1–2015Q4

Bartlett's test	0.4215	Shapiro-Wilk W test for normal data	0.0011		
Kurtosis	0.6878	Shapiro-Francia W' test for normal data	0.0027		
Skewness	0.0117	Durbin-Watson d-statistic	1.9216		
Skewness & Kurtosis (joint)	0.0461				
LM test for autoregressive conditional heteroskedasticity (ARCH)		Breusch-Godfrey LM test for autocorrelation		Durbin's alternative test for autocorrelation	
				Ljung-Box Q-test	
lag 1	0.4828	lag 1	0.7298	lag 1	0.7324
lag 2	0.5166	lag 2	0.8847	lag 2	0.8878
lag 3	0.6002	lag 3	0.5896	lag 3	0.5986
lag 4	0.7460	lag 4	0.1088	lag 4	0.0998
lag 5	0.7151	lag 5	0.1618	lag 5	0.1524
lag 6	0.5285	lag 6	0.2045	lag 6	0.1954
lag 7	0.6423	lag 7	0.2031	lag 7	0.1915
lag 8	0.7133	lag 8	0.2237	lag 8	0.2115
lag 9	0.7659	lag 9	0.0675	lag 9	0.0463
lag 10	0.8935	lag 10	0.0919	lag 10	0.0668
lag 11	0.8828	lag 11	0.1146	lag 11	0.0866
lag 12	0.9394	lag 12	0.0196	lag 12	0.0058
lag 13	0.6710	lag 13	0.0293	lag 13	0.0102
lag 14	0.4614	lag 14	0.0340	lag 14	0.0118
lag 15	0.5705	lag 15	0.0441	lag 15	0.0167
lag 16	0.4266	lag 16	0.0503	lag 16	0.0193
lag 17	0.4916	lag 17	0.0695	lag 17	0.0310
lag 18	0.5741	lag 18	0.0929	lag 18	0.0475
lag 19	0.6349	lag 19	0.1194	lag 19	0.0687
lag 20	0.6595	lag 20	0.1463	lag 20	0.0923

Grey cells indicate significance at 1%-level.

Table A.XIV: Residual-diagnostics GDP France; sample 1970Q1–2015Q4

Bartlett's test	0.3789	Shapiro-Wilk W test for normal data	0.1523				
Kurtosis	0.6988	Shapiro-Francia W' test for normal data	0.2672				
Skewness	0.9721	Durbin-Watson d-statistic	2.0326				
Skewness & Kurtosis (joint)	0.9273						
LM test for autoregressive conditional heteroskedasticity (ARCH)		Breusch-Godfrey LM test for autocorrelation		Durbin's alternative test for autocorrelation		Ljung-Box Q-test	
lag 1	0.1985	lag 1	0.7448	lag 1	0.7461	1 lag	0.7428
lag 2	0.4743	lag 2	0.5682	lag 2	0.5715	2 lags	0.5689
lag 3	0.7163	lag 3	0.1570	lag 3	0.1547	3 lags	0.1672
lag 4	0.6810	lag 4	0.0187	lag 4	0.0153	4 lags	0.0307
lag 5	0.6811	lag 5	0.0337	lag 5	0.0285	5 lags	0.0585
lag 6	0.6979	lag 6	0.0591	lag 6	0.0519	6 lags	0.0903
lag 7	0.7158	lag 7	0.0931	lag 7	0.0842	7 lags	0.1312
lag 8	0.8210	lag 8	0.0215	lag 8	0.0152	8 lags	0.0665
lag 9	0.8552	lag 9	0.0105	lag 9	0.0061	9 lags	0.0234
lag 10	0.9100	lag 10	0.0018	lag 10	0.0006	10 lags	0.0043
lag 11	0.9194	lag 11	0.0033	lag 11	0.0012	11 lags	0.0074
lag 12	0.9477	lag 12	0.0002	lag 12	0.0000	12 lags	0.0005
lag 13	0.6623	lag 13	0.0004	lag 13	0.0000	13 lags	0.0005
lag 14	0.3449	lag 14	0.0007	lag 14	0.0001	14 lags	0.0006
lag 15	0.1651	lag 15	0.0007	lag 15	0.0001	15 lags	0.0010
lag 16	0.2928	lag 16	0.0009	lag 16	0.0001	16 lags	0.0009
lag 17	0.2916	lag 17	0.0014	lag 17	0.0002	17 lags	0.0014
lag 18	0.2994	lag 18	0.0009	lag 18	0.0001	18 lags	0.0008
lag 19	0.3585	lag 19	0.0014	lag 19	0.0001	19 lags	0.0011
lag 20	0.4151	lag 20	0.0014	lag 20	0.0001	20 lags	0.0017

Grey cells indicate significance at 1%-level.

Table A.XV: Residual-diagnostics GDP France; sample 1992Q1–2015Q4

Bartlett's test	0.5714	Shapiro-Wilk W test for normal data	0.4901				
Kurtosis	0.6218	Shapiro-Francia W' test for normal data	0.6761				
Skewness	0.9725	Durbin-Watson d-statistic	2.1078				
Skewness & Kurtosis (joint)	0.8849						
LM test for autoregressive conditional heteroskedasticity (ARCH)		Breusch-Godfrey LM test for autocorrelation		Durbin's alternative test for autocorrelation		Ljung-Box Q-test	
lag 1	0.6977	lag 1	0.5950	lag 1	0.5983	1 lag	0.5893
lag 2	0.8601	lag 2	0.7899	lag 2	0.7948	2 lags	0.7947
lag 3	0.9515	lag 3	0.4772	lag 3	0.4845	3 lags	0.4948
lag 4	0.8205	lag 4	0.1116	lag 4	0.1026	4 lags	0.1564
lag 5	0.9021	lag 5	0.1313	lag 5	0.1204	5 lags	0.1291
lag 6	0.9582	lag 6	0.2038	lag 6	0.1946	6 lags	0.1940
lag 7	0.9346	lag 7	0.2406	lag 7	0.2322	7 lags	0.2753
lag 8	0.9464	lag 8	0.3106	lag 8	0.3072	8 lags	0.3553
lag 9	0.9649	lag 9	0.1705	lag 9	0.1509	9 lags	0.3109
lag 10	0.9748	lag 10	0.2321	lag 10	0.2161	10 lags	0.3909
lag 11	0.8990	lag 11	0.2087	lag 11	0.1874	11 lags	0.4123
lag 12	0.4638	lag 12	0.0081	lag 12	0.0013	12 lags	0.0117
lag 13	0.4113	lag 13	0.0092	lag 13	0.0013	13 lags	0.0103
lag 14	0.5002	lag 14	0.0120	lag 14	0.0019	14 lags	0.0160
lag 15	0.4748	lag 15	0.0146	lag 15	0.0023	15 lags	0.0160
lag 16	0.5096	lag 16	0.0196	lag 16	0.0035	16 lags	0.0139
lag 17	0.3549	lag 17	0.0286	lag 17	0.0063	17 lags	0.0189
lag 18	0.4380	lag 18	0.0400	lag 18	0.0107	18 lags	0.0255
lag 19	0.5154	lag 19	0.0551	lag 19	0.0178	19 lags	0.0358
lag 20	0.5242	lag 20	0.0621	lag 20	0.0205	20 lags	0.0373

Grey cells indicate significance at 1%-level.

Table A.XVI: Residual-diagnostics GDP Italy; sample 1970Q1–2015Q4

Bartlett's test	0.0052	Shapiro-Wilk W test for normal data	0.0592
Kurtosis	0.1748	Shapiro-Francia W' test for normal data	0.1208
Skewness	0.6953	Durbin-Watson d-statistic	1.6286
Skewness & Kurtosis (joint)	0.3645		
LM test for autoregressive conditional heteroskedasticity (ARCH)		Breusch-Godfrey LM test for autocorrelation	
lag 1	0.8631	lag 1	0.0140
lag 2	0.3623	lag 2	0.0093
lag 3	0.3937	lag 3	0.0049
lag 4	0.5471	lag 4	0.0003
lag 5	0.5943	lag 5	0.0008
lag 6	0.6350	lag 6	0.0011
lag 7	0.6640	lag 7	0.0016
lag 8	0.5560	lag 8	0.0016
lag 9	0.5912	lag 9	0.0025
lag 10	0.6889	lag 10	0.0019
lag 11	0.7703	lag 11	0.0033
lag 12	0.8267	lag 12	0.0033
lag 13	0.8447	lag 13	0.0031
lag 14	0.7843	lag 14	0.0050
lag 15	0.8125	lag 15	0.0041
lag 16	0.5336	lag 16	0.0033
lag 17	0.6039	lag 17	0.0050
lag 18	0.5527	lag 18	0.0071
lag 19	0.3946	lag 19	0.0088
lag 20	0.4479	lag 20	0.0061
		Durbin's alternative test for autocorrelation	
		lag 1	0.0130
		lag 2	0.0079
		lag 3	0.0036
		lag 4	0.0001
		lag 5	0.0003
		lag 6	0.0004
		lag 7	0.0006
		lag 8	0.0006
		lag 9	0.0010
		lag 10	0.0006
		lag 11	0.0012
		lag 12	0.0011
		lag 13	0.0009
		lag 14	0.0016
		lag 15	0.0012
		lag 16	0.0008
		lag 17	0.0013
		lag 18	0.0020
		lag 19	0.0026
		lag 20	0.0014
		Ljung-Box Q-test	
		1 lag	0.0135
		2 lags	0.0190
		3 lags	0.0029
		4 lags	0.0000
		5 lags	0.0001
		6 lags	0.0000
		7 lags	0.0000
		8 lags	0.0000
		9 lags	0.0000
		10 lags	0.0000
		11 lags	0.0001
		12 lags	0.0001
		13 lags	0.0001
		14 lags	0.0002
		15 lags	0.0001
		16 lags	0.0000
		17 lags	0.0000
		18 lags	0.0001
		19 lags	0.0000
		20 lags	0.0001

Grey cells indicate significance at 1%-level.

Table A.XVII: Residual-diagnostics GDP Italy; sample 1992Q1–2015Q4

Bartlett's test	0.2149	Shapiro-Wilk W test for normal data	0.2217		
Kurtosis	0.6822	Shapiro-Francia W' test for normal data	0.3432		
Skewness	0.4684	Durbin-Watson d -statistic	1.8198		
Skewness & Kurtosis (joint)	0.7026				
LM test for autoregressive conditional heteroskedasticity (ARCH)		Breusch-Godfrey LM test for autocorrelation		Durbin's alternative test for autocorrelation	
				Ljung-Box Q-test	
lag 1	0.5683	lag 1	0.4248	lag 1	0.4281
lag 2	0.8417	lag 2	0.6006	lag 2	0.6070
lag 3	0.7031	lag 3	0.2126	lag 3	0.2104
lag 4	0.1415	lag 4	0.0058	lag 4	0.0027
lag 5	0.1855	lag 5	0.0125	lag 5	0.0067
lag 6	0.2692	lag 6	0.0241	lag 6	0.0144
lag 7	0.3648	lag 7	0.0329	lag 7	0.0200
lag 8	0.4873	lag 8	0.0218	lag 8	0.0104
lag 9	0.5912	lag 9	0.0327	lag 9	0.0170
lag 10	0.6559	lag 10	0.0504	lag 10	0.0293
lag 11	0.7058	lag 11	0.0695	lag 11	0.0436
lag 12	0.7590	lag 12	0.0519	lag 12	0.0270
lag 13	0.8074	lag 13	0.0723	lag 13	0.0416
lag 14	0.8168	lag 14	0.0435	lag 14	0.0177
lag 15	0.8507	lag 15	0.0539	lag 15	0.0233
lag 16	0.8934	lag 16	0.0743	lag 16	0.0368
lag 17	0.9107	lag 17	0.0971	lag 17	0.0537
lag 18	0.9448	lag 18	0.1186	lag 18	0.0708
lag 19	0.9201	lag 19	0.0830	lag 19	0.0371
lag 20	0.9378	lag 20	0.0757	lag 20	0.0296

Grey cells indicate significance at 1%-level.

Table A.XVIII: Residual-diagnostics GDP the Netherlands; sample 1970Q1–2015Q4

Bartlett's test	0.0553	Shapiro-Wilk W test for normal data	0.7952				
Kurtosis	0.7577	Shapiro-Francia W' test for normal data	0.8771				
Skewness	0.9934	Durbin-Watson d-statistic	1.8589				
Skewness & Kurtosis (joint)	0.9535						
LM test for autoregressive conditional heteroskedasticity (ARCH)		Breusch-Godfrey LM test for autocorrelation		Durbin's alternative test for autocorrelation		Ljung-Box Q-test	
lag 1	0.7764	lag 1	0.3784	lag 1	0.3800	1 lag	0.3775
lag 2	0.9059	lag 2	0.5596	lag 2	0.5629	2 lags	0.5810
lag 3	0.6667	lag 3	0.1210	lag 3	0.1179	3 lags	0.1159
lag 4	0.3371	lag 4	0.0218	lag 4	0.0182	4 lags	0.0137
lag 5	0.4882	lag 5	0.0090	lag 5	0.0063	5 lags	0.0076
lag 6	0.4948	lag 6	0.0156	lag 6	0.0113	6 lags	0.0090
lag 7	0.5868	lag 7	0.0152	lag 7	0.0105	7 lags	0.0153
lag 8	0.6395	lag 8	0.0058	lag 8	0.0031	8 lags	0.0050
lag 9	0.6622	lag 9	0.0069	lag 9	0.0036	9 lags	0.0089
lag 10	0.7331	lag 10	0.0111	lag 10	0.0062	10 lags	0.0148
lag 11	0.7155	lag 11	0.0071	lag 11	0.0033	11 lags	0.0019
lag 12	0.7019	lag 12	0.0071	lag 12	0.0030	12 lags	0.0031
lag 13	0.6566	lag 13	0.0113	lag 13	0.0053	13 lags	0.0035
lag 14	0.4042	lag 14	0.0175	lag 14	0.0090	14 lags	0.0051
lag 15	0.4354	lag 15	0.0225	lag 15	0.0120	15 lags	0.0080
lag 16	0.5157	lag 16	0.0318	lag 16	0.0183	16 lags	0.0048
lag 17	0.2475	lag 17	0.0408	lag 17	0.0245	17 lags	0.0057
lag 18	0.2288	lag 18	0.0561	lag 18	0.0362	18 lags	0.0085
lag 19	0.2440	lag 19	0.0468	lag 19	0.0276	19 lags	0.0125
lag 20	0.2799	lag 20	0.0571	lag 20	0.0351	20 lags	0.0170

Grey cells indicate significance at 1%-level.

Table A.XIX: Residual-diagnostics GDP the Netherlands; sample 1992Q1–2015Q4

Bartlett's test	0.0934	Shapiro-Wilk W test for normal data	0.1328		
Kurtosis	0.1615	Shapiro-Francia W' test for normal data	0.2820		
Skewness	0.5226	Durbin-Watson d -statistic	1.6910		
Skewness & Kurtosis (joint)	0.2962				
LM test for autoregressive conditional heteroskedasticity (ARCH)		Breusch-Godfrey LM test for autocorrelation		Durbin's alternative test for autocorrelation	
				Ljung-Box Q-test	
lag 1	0.7198	lag 1	0.2107	lag 1	0.2118
lag 2	0.9059	lag 2	0.2279	lag 2	0.2280
lag 3	0.9716	lag 3	0.0896	lag 3	0.0827
lag 4	0.9853	lag 4	0.1420	lag 4	0.1342
lag 5	0.9934	lag 5	0.1987	lag 5	0.1915
lag 6	0.9895	lag 6	0.2468	lag 6	0.2409
lag 7	0.6338	lag 7	0.2366	lag 7	0.2278
lag 8	0.7007	lag 8	0.1520	lag 8	0.1339
lag 9	0.4165	lag 9	0.1579	lag 9	0.1374
lag 10	0.4982	lag 10	0.1971	lag 10	0.1773
lag 11	0.2996	lag 11	0.2537	lag 11	0.2381
lag 12	0.3682	lag 12	0.3190	lag 12	0.3111
lag 13	0.4385	lag 13	0.3932	lag 13	0.3965
lag 14	0.3600	lag 14	0.4674	lag 14	0.4831
lag 15	0.3480	lag 15	0.5415	lag 15	0.5699
lag 16	0.4614	lag 16	0.5802	lag 16	0.6159
lag 17	0.4709	lag 17	0.6492	lag 17	0.6953
lag 18	0.4318	lag 18	0.7124	lag 18	0.7657
lag 19	0.3323	lag 19	0.4994	lag 19	0.5254
lag 20	0.4171	lag 20	0.4824	lag 20	0.5052

Grey cells indicate significance at 1%-level.

F Business Cycle Turning Points

Table A.XX: Turning points short-term cycle GDP G7 countries and the Netherlands

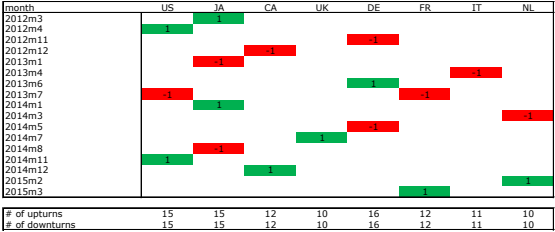
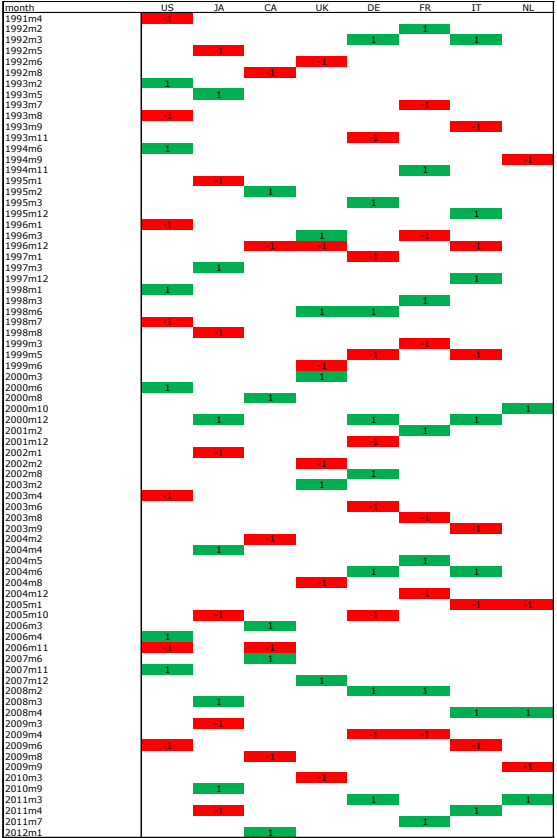
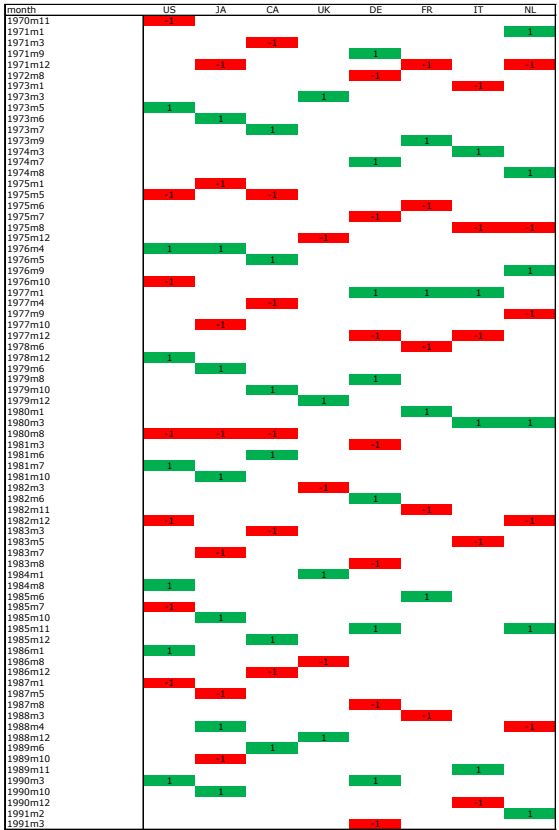


Table A.XXI: Turning points medium-term cycle GDP G7 countries and the Netherlands

month	US	JA	CA	UK	DE	FR	IT	NL
1970m10				1				
1970m11	-1							
1971m12								
1972m2				-1				
1972m6					1			
1972m8								
1972m9			-1					
1973m3		1		1			-1	
1973m11	1							
1974m2				-1				
1974m5								1
1974m6								
1974m8				1	1			
1974m9							1	
1975m1			-1					-1
1975m3							-1	
1975m4								-1
1975m8				-1	-1			
1975m9								
1975m11	-1							
1976m5			1					
1976m7								
1976m10		-1				-1		
1977m1				1				1
1977m8								
1978m3							-1	
1978m4					1			
1979m3	1							
1979m8		1						
1979m9							-1	
1980m3								
1980m5			-1					
1980m11			1					
1981m3				-1		1		
1981m5								
1981m6								1
1982m10			-1			-1		
1982m12								
1983m6	-1			1		1		
1984m1			1					
1984m7				-1				
1984m12			-1		-1			
1985m3				1				
1985m6						-1		
1985m9								-1
1985m12				-1				
1986m3		-1						
1986m8						1		
1987m1							-1	
1987m7								
1988m6	1						1	
1988m12								
1989m3			1					
1989m6						-1		
1990m4				1	1			1
1990m6								
1990m9		1						
1990m12			-1					
1991m3						1		-1
1991m6			1					
1991m12						-1	1	
1992m3								1
1992m8						1		
1993m6						-1		
1993m10				-1				
1994m3	-1							
1994m5		-1		1				
1994m9						1		
1995m10								
1996m12			-1	-1				
1997m2		1			-1			
1997m3				1				
1997m7								
1997m11						-1		
1998m7			-1					

month	US	JA	CA	UK	DE	FR	IT	NL
1998m10							-1	
2000m9	1	-1						
2000m10			1					
2001m1				1				-1
2001m2								
2001m3		1				1		
2001m7			-1					
2001m8					1			
2001m11				-1				
2002m3						-1		
2002m6	-1							
2002m8		-1						
2002m9						1		
2003m6								
2003m7								-1
2004m4				1				
2004m6						-1		1
2005m9								
2006m10								-1
2006m12	1	1				1	1	
2007m6					1			
2007m9								1
2008m7				1				
2009m6			-1					
2009m8				-1				
2010m3				1			-1	
2010m6								
2010m9			1			-1		
2011m3		-1						
2011m11								
2012m3	-1			-1				
2013m4								
2013m7			-1					
2013m12		1						
2014m1						1		
2014m5			1					
2014m7		-1						
2014m11					-1			
2015m3						-1		
2015m4		1						
2015m5			-1					
2015m6							-1	-1
# of upturns	5	8	12	11	6	12	6	7
# of downturns	-6	-7	-12	-11	-6	-12	-7	-7

Table A.XXII: Turning points short-term cycle industrial production G7 countries and the Netherlands

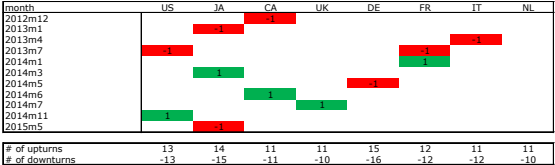
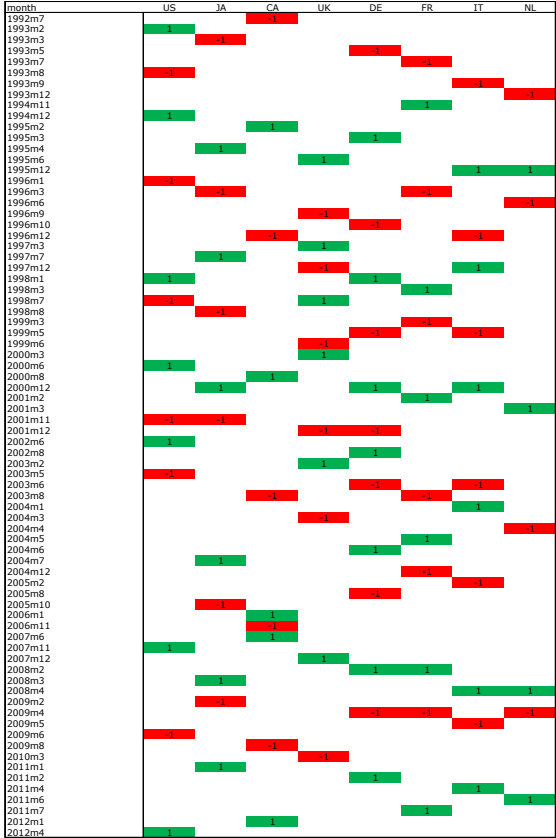
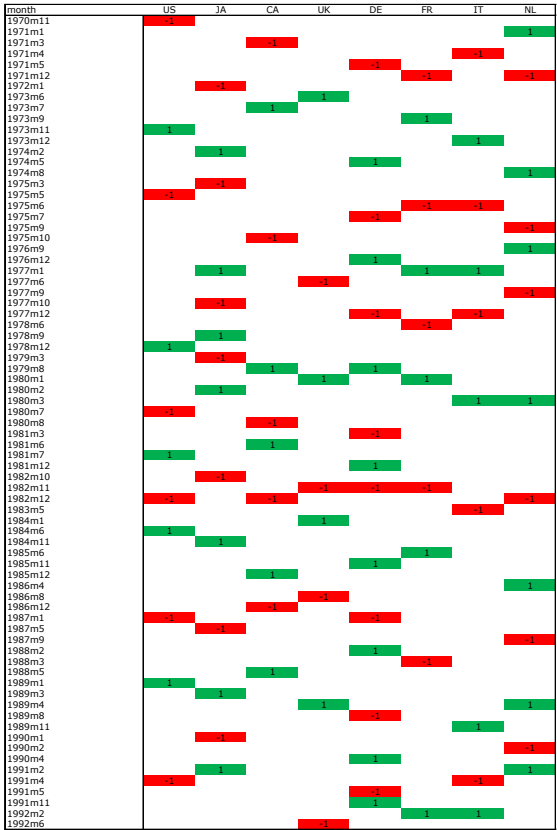


Table A.XXIII: Turning points medium-term cycle industrial production G7 countries and the Netherlands

month	US	JA	CA	UK	DE	FR	IT	NL
1970m9								
1970m11	-1							
1971m4								
1971m5			-1				-1	
1972m2			-1	-1				
1972m4								
1972m12								
1973m2		1						
1973m3								
1973m11								
1974m2				-1				
1974m5								
1974m7								
1974m8								
1975m5			-1					
1975m7								
1975m8				-1	-1			
1976m1		-1						
1976m5								
1976m7								
1977m6						-1		
1978m3								
1978m12								
1979m2								
1979m6								
1979m8								
1980m1								
1980m6								
1980m12								
1981m1								
1981m2								
1981m6								
1982m5								
1982m10								
1982m11								
1982m12								
1984m1								
1984m6								
1984m7								
1984m8								
1985m1								
1985m5								
1985m6								
1985m10								
1985m12								
1986m3								
1986m5								
1987m1								
1988m2								
1988m4								
1988m5								
1988m9								
1989m3								
1989m6								
1989m12								
1990m4								
1990m6								
1990m8								
1990m9								
1990m12								
1991m8								
1991m9								
1992m3								
1992m10								
1992m12								
1993m3								
1993m4								
1993m7								
1993m8								
1993m12								
1994m2								
1994m9								
1994m10								
1994m12								
1995m6								

month	US	JA	CA	UK	DE	FR	IT	NL
1995m12								
1996m3								
1997m2								
1997m3								
1997m12								
1998m4								
1998m11								
1998m12								
1999m9								
2000m4								
2000m5								
2000m6								
2000m9								
2000m10								
2001m2								
2001m3								
2001m12								
2002m2								
2002m8								
2002m10								
2003m2								
2003m3								
2003m4								
2003m6								
2003m8								
2003m11								
2004m3								
2004m7								
2005m6								
2005m12								
2006m4								
2006m6								
2006m10								
2006m12								
2007m11								
2008m7								
2008m4								
2009m6								
2009m8								
2010m1								
2010m5								
2010m6								
2010m9								
2011m1								
2011m3								
2011m6								
2011m9								
2012m9								
2012m10								
2013m4								
2013m11								
2014m1								
2014m5								
2014m6								
2014m7								
2015m3								
2015m4								
2015m6								

# of upturns	6	9	13	14	6	7	7	15
# of downturns	-7	-8	-14	-15	-6	-7	-8	-14

Table A.XXIV: Turning points short-term cycle house prices G7 countries and the Netherlands

month	US	JA	CA	UK	DE	FR	IT	NL
1970m10		1						
1971m3	-1							
1971m4								
1971m6				-1				
1971m9			-1		-1			
1972m7		-1						
1972m12					1			
1973m3						-1		
1973m9								-1
1973m11	1							
1973m12		1						
1974m6								
1974m7					1			
1974m11							1	
1975m1		-1						-1
1975m3								
1975m8					-1			
1975m9							-1	
1976m3								
1976m9	-1					-1		
1977m3		1					1	
1977m6								
1977m7				-1	1			
1978m3								
1978m5								
1978m6		-1					-1	1
1978m12		-1						
1979m3	1							
1979m4					-1		1	
1980m2								
1980m3						-1		
1980m4							-1	
1980m8								
1981m4	-1							
1981m6								
1981m9								
1981m12								
1982m1							-1	
1982m3								-1
1982m5								
1982m10		-1						
1982m11					-1	-1		1
1983m3								
1983m8								
1984m6	1							
1985m1								
1985m3								
1985m4							-1	
1985m5								
1985m9								
1986m5								
1986m8								
1986m9	-1	-1						
1987m3								
1987m9								
1987m10								
1988m9								
1989m3								
1989m6								
1989m7								
1989m8								
1989m12								
1990m9								
1991m1								
1991m2								
1991m3								
1991m12								
1992m3								
1992m6								
1992m11								
1992m12	-1	-1			-1			1
1993m9								
1994m3								
1994m7								
1994m8								

month	US	JA	CA	UK	DE	FR	IT	NL
1994m9								
1994m10								1
1994m12								
1995m3								
1995m4								
1995m8								
1996m2								
1996m4								
1996m6								
1997m3								
1997m4								
1997m8								
1997m9								
1997m12								
1998m1								
1998m8								
1998m9								
1999m3								
1999m4								
1999m5								
1999m12								
2000m4								
2000m5								
2000m9								
2000m12								
2001m3								
2001m11								
2001m12								
2002m3								
2002m6								
2002m9								
2002m10								
2003m3								
2003m4								
2003m8								
2004m2								
2004m3								
2004m9								
2004m12								
2005m3								
2005m12								
2006m2								
2006m5								
2006m6								
2006m12								
2007m4								
2007m6								
2007m9								
2007m10								
2007m12								
2008m2								
2008m3								
2008m4								
2008m6								
2008m11								
2009m4								
2009m5								
2009m6								
2009m12								
2010m6								
2010m9								
2010m12								
2011m1								
2011m5								
2011m6								
2011m12								
2012m3								
2012m7								
2012m10								
2012m12								
2013m1								
2013m2								
2013m6								
2013m8								
2013m9								
2014m1								

month	US	JA	CA	UK	DE	FR	IT	NL
2014m10								
2014m12								
2015m1								
2015m3								
# of upturns	9	15	7	14	14	16	15	7
# of downturns	-9	-15	-8	-14	-14	-16	-14	-7

Table A.XXV: Turning points medium-term cycle house prices G7 countries and the Netherlands

month	US	JA	CA	UK	DE	FR	IT	NL
1971m6			1		-1		1	
1971m12			1				1	
1972m6						1		
1972m8			-1					
1973m9				1			-1	
1973m10								
1973m11	1	1						
1974m6			1					
1974m12			-1		1			
1976m3	-1				-1			
1976m6						-1		
1976m7							1	
1976m9								
1976m12		-1	1					
1977m9							-1	
1978m3								1
1978m6								
1979m3	1						-1	
1979m9								
1980m3							-1	
1980m4			-1					
1980m9					1			
1980m10								
1981m3						1		
1981m5							1	
1982m3				-1				
1982m7		1						
1982m12			-1			-1		
1983m6						1		
1984m6	-1							
1984m9					-1			
1985m3			-1					
1985m6						-1		
1985m9								-1
1986m4		-1						
1986m8						1	-1	
1987m7						-1		
1988m6	1							
1988m12						1		
1989m3	-1		1					
1989m6				1		-1		
1989m12	1							1
1990m6		1			1			
1990m9								
1990m12		1	-1					
1991m3						1		
1991m6								
1991m12						-1	1	
1992m3			-1					
1992m6								-1
1992m8						1		
1992m9			1					
1993m6						-1		
1994m9						1		
1995m1		-1						
1996m7	-1			-1				
1997m3						-1		
1997m12					-1		-1	
1998m3								
1998m9						1		
2001m3								
2001m6			-1					
2001m9		1						1
2001m12								
2002m3						-1		
2002m9						1		-1
2003m9								
2004m3				1				-1
2005m2		-1						
2005m6								
2005m9						-1		
2005m12		1						
2006m3	1							
2006m9		-1						
2006m12					1			

month	US	JA	CA	UK	DE	FR	IT	NL
2007m8								1
2008m4		1	1					
2008m6		-1	-1					
2009m6					-1			
2009m12						-1		
2010m3							-1	
2010m6			1					
2010m12			-1					
2011m2		1						
2011m6					1			
2011m9								
2011m12		-1	1					
2012m3	-1							
2013m6		1						
2013m9				-1				
2014m2						1		
2014m8		-1	-1				-1	
2015m3								
# of upturns	5	9	11	3	5	12	6	4
# of downturns	-5	-8	-11	-3	-5	-12	-6	-3

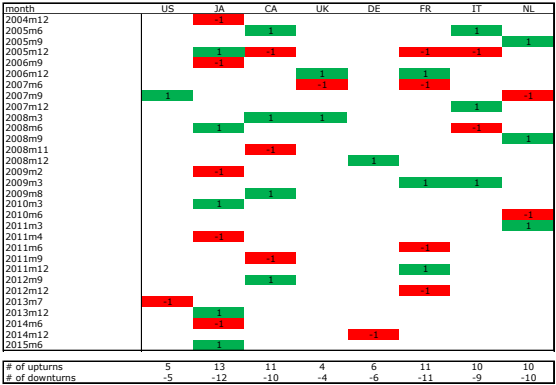
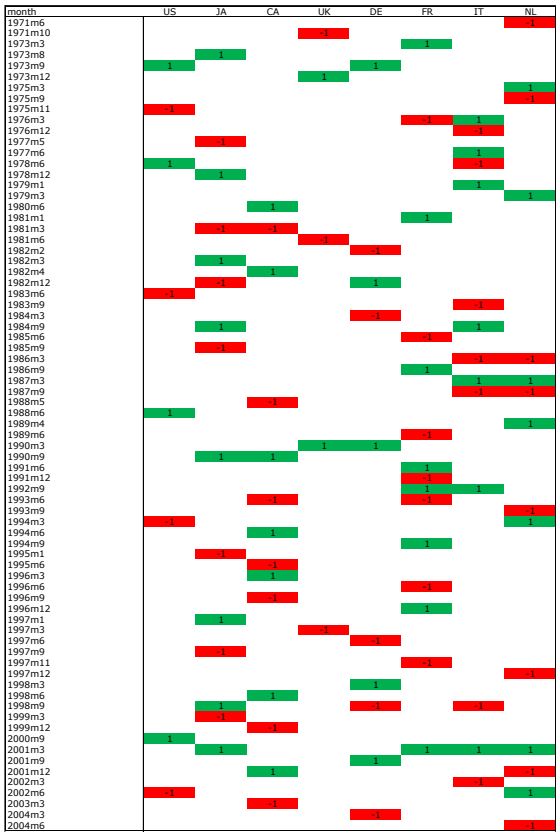
Table A.XXVI: Turning points short-term cycle credit G7 countries and the Netherlands

month	US	JA	CA	UK	DE	FR	IT	NL
1970m10					-1			1
1970m12	-1		-1					
1971m3								
1971m4	-1		-1				-1	
1971m6						-1		
1971m7				-1				
1971m9		-1						-1
1973m2		-1						
1973m3								
1973m6					1	1		
1973m11								
1973m12	1			1				
1974m1			1					
1974m8								
1974m9		-1						
1975m2					-1		-1	
1975m6								
1975m9		1				-1		
1976m5								
1976m6	-1							
1976m9					1			
1976m11						1		
1977m8				-1				-1
1977m9								
1977m12		-1			-1		-1	
1978m1								
1978m6						-1		
1978m8			-1					
1979m2	1							
1979m8					1			
1979m9						1	1	1
1980m3								
1980m9		-1		1				
1981m2								
1981m10			1					
1982m7					-1			
1982m10	-1							
1982m12								
1983m3						-1	-1	
1983m5								
1983m12								
1984m2		-1	-1		1			
1984m3								
1984m9		-1					1	
1984m10								-1
1984m11	1							
1984m12					-1			
1985m3						1		
1985m9				-1				
1985m11								
1985m12		1			1			
1986m1								
1986m6								
1986m12			-1	-1				
1987m1								
1987m6	-1	-1					-1	-1
1987m9								
1988m3						-1		
1988m10					-1			
1989m4			-1					1
1989m6								
1989m8								
1989m11							1	
1990m2								-1
1990m4	1				1			
1990m5								
1990m9						-1		
1991m3		-1						
1991m4							-1	
1992m1					-1			
1992m3							1	
1992m6								
1992m12					-1			
1993m1	-1		-1					
1993m2					1			

month	US	JA	CA	UK	DE	FR	IT	NL
1993m3		1					-1	-1
1993m9								
1993m12							-1	-1
1994m3								
1994m6								
1994m12		-1			1			
1995m2								
1995m3								
1995m8								
1995m12								1
1996m6								
1996m11								-1
1996m12		1	-1	-1				
1997m3								
1997m6								
1997m9		-1						
1997m12								
1998m3					1	-1		
1998m7								
1998m9	-1							
1998m10								
1998m12								
1999m3								
2000m3								
2000m6		-1	1	1				
2000m9								
2000m12								
2001m3								1
2001m9								
2001m12								
2002m3								
2002m6								
2002m9		-1					-1	
2003m3								
2003m5								
2003m7								
2003m8								
2003m9								-1
2003m12								
2004m1	-1							
2004m2			-1					
2004m5								
2004m9								
2004m12								
2005m3								
2006m1								
2006m5								
2006m6								1
2006m7								
2007m3								
2007m6								
2007m9								
2007m12								
2008m3								
2008m4								
2008m9		-1						
2008m12								
2009m2								
2009m3								
2009m4								-1
2009m5								
2009m12								
2010m7								
2010m9								
2011m4								
2011m5								
2011m6								
2011m7								
2011m10								
2012m3								
2012m8								
2012m10								
2013m2								
2013m4								

month	US	JA	CA	UK	DE	FR	IT	NL
2013m6		1						
2013m9								
2013m10								
2014m6								
2014m9								
2015m3								
# of upturns	9	15	8	12	13	15	12	11
# of downturns	-9	-16	-8	-13	-14	-15	-13	-10

Table A.XXVII: Turning points medium-term cycle credit G7 countries and the Netherlands



G Alternative measures of concordance and credit variables

Figure A.22: 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

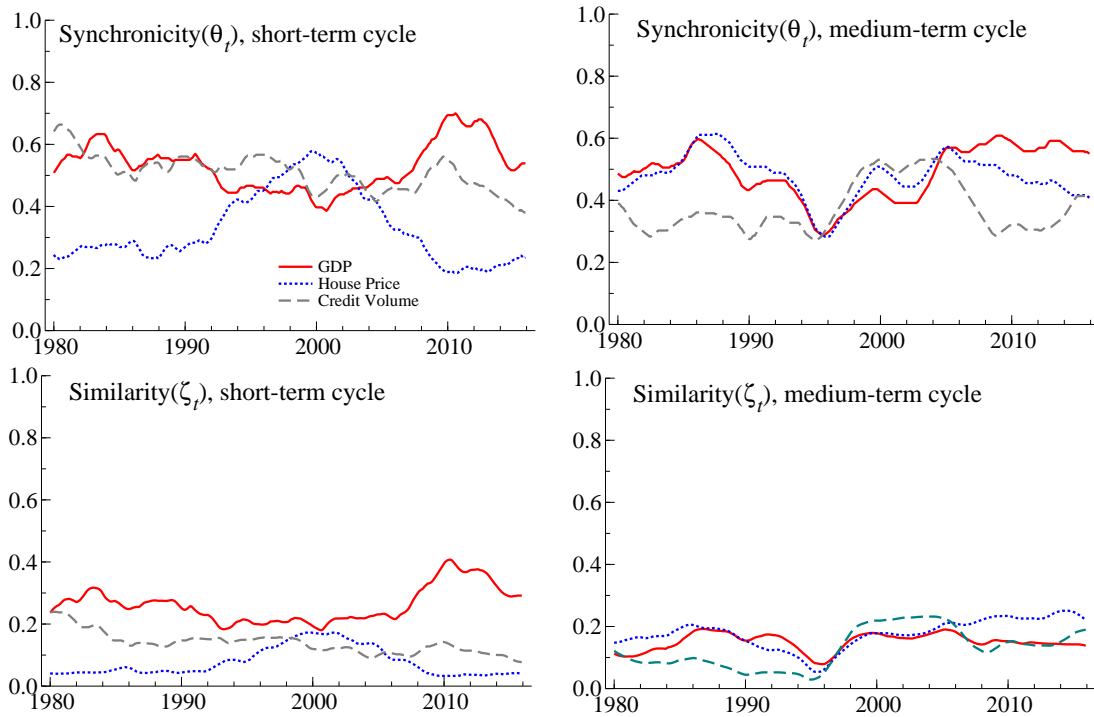


Figure A.23: Overall swing synchronicity (θ) and swing similarity (ζ) measures for the short-term and medium-term GDP, house price and credit cycle, G7 countries and the Netherlands

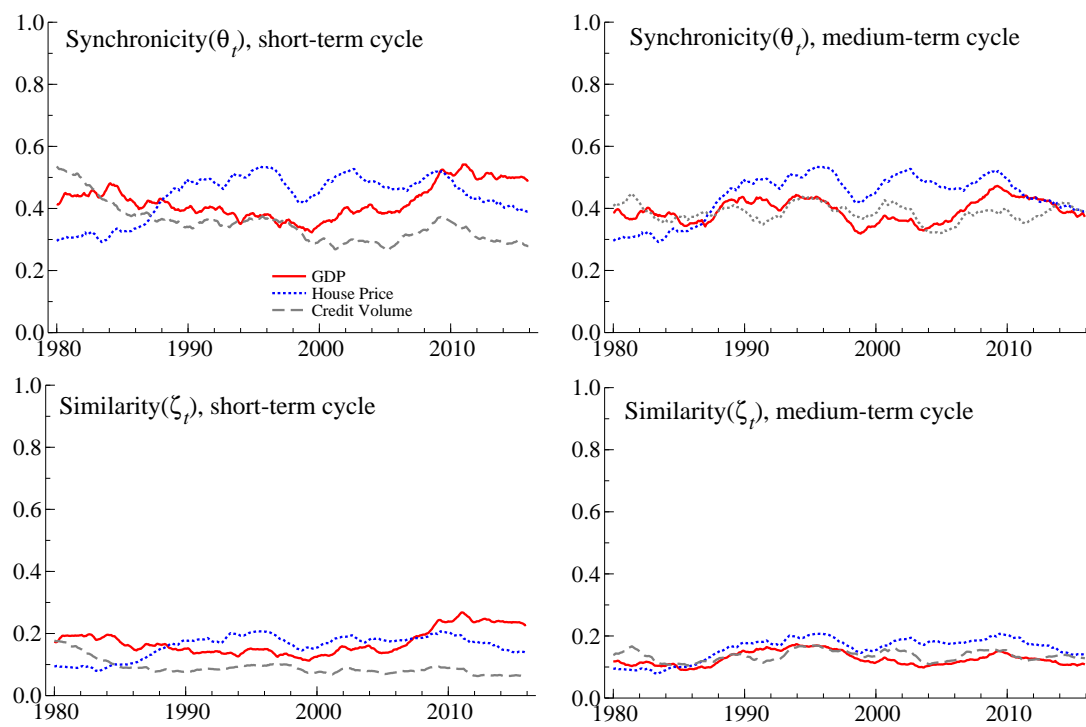


Table A.XXVIII: Parameter estimates of multivariate UCTSM for G7 countries and the Netherlands with alternative credit variable outstanding credit (all sectors) to non-financial corporations

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			
std. dev. D_γ	1.95	1.84	1.43	4.57	1.99	3.98	1.61	3.89	1.18	1.12	0.85	5.35	2.03	0.91	1.48	4.81	
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			
std. dev. D_γ	1.01	0.57	0.56	2.89	1.04	1.34	1.09	3.30	0.90	4.14	0.73	2.67	1.31	2.31	1.75	3.67	
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	
		Germany				France				Italy				Netherlands			
p_ψ		15.98				17.00				8.23				14.34			
ϕ_ψ		0.99				0.99				0.99				0.98			
std. dev. D_ψ	1.31	8.03	5.64	2.09	0.90	5.74	6.83	3.04	0.97	3.29	2.39	3.04	0.41	6.07	2.24	2.44	
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			
std. dev. D_ψ	1.17	1.59	1.45	2.86	0.50	4.07	2.75	2.20	1.54	7.43	4.63	4.01	1.29	5.94	2.97	1.90	
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 ($p = 2\pi/\lambda$), 100x the root of the diagonal of the variance-matrix (standard-deviation) 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. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table A.XXIX: 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			
std. dev. D_γ	0.06	0.56	0.36	71.94	3.29	7.89	2.71	5.90	1.03	0.97	0.81	4.27	0.00	0.00	0.00	0.00	
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			
std. dev. D_γ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.31	4.22	1.67	3.41	1.12	1.56	0.96	3.32	
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	
		Germany				France				Italy				Netherlands			
p_ψ		12.49				17.56				8.39				14.23			
ϕ_ψ		0.99				0.99				0.99				0.99			
std. dev. D_ψ	2.27	3.22	2.89	3.88	0.00	4.38	6.16	3.62	1.22	3.35	2.27	3.68	0.00	0.00	0.00	0.00	
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			
std. dev. D_ψ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.39	8.59	6.58	3.17	0.86	5.83	3.22	0.40	
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 ($p = 2\pi/\lambda$), 100x the root of the diagonal of the variance-matrix (standard-deviation) 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. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.