

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

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## Main contributions

- Novel approach to **simultaneously** extract a short-term cycle and a medium-term cycle from a panel of macroeconomic and financial time series
- and **simultaneously** estimate co-cyclicalities of cycles
- and **simultaneously** mix time-series with monthly and quarterly frequencies

## Motivation

- Several papers document existence of medium-term macroeconomic cycles (e.g. Comin and Gertler, 2006 and Correa-López and de Blas, 2012);
- Since the Global Financial Crisis, the policy debate has increasingly paid attention to the concept of the financial cycle. (e.g. Borio, 2014 and Drehman et al., 2012)
- There has also been a fast growing literature exploring ways to estimate financial cycles and analyzing their properties.

- ① We find strong evidence for the existence of a separate short-term cycle and medium-term cycle in macroeconomic and financial variables in industrialized countries
- ② Co-movement between macroeconomic and financial variables limited to the medium-term
- ③ Strong concordance between the medium-term cycles of house prices and GDP. much less between credit and GDP
- ④ bulk of the estimated movements driven by domestic rather than global factors (see paper)

# Presentation Outline

- 1 Estimation method
- 2 Outcomes
- 3 Conclusion

# Unobserved Component (UC) models

- We apply the Kalman filter-smoother to an unobserved components time series model to extract multiple cycles, see Harvey (1989) and Durbin and Koopman (2012) for an overview.
- This approach has been applied to business cycle analysis, extracting **one** cycle, see e.g. Valle e Azevedo et al., 2006; Creal et al., 2010.
- Koopman and Lucas (2005) is one of the few papers extracting **two** cycles. They extract cycles from asset prices in the United States.

# Advantages of UC models and the Kalman filter

- Estimating an unobserved components model allows for **simultaneous extraction** of trend, short-term cycle, medium-term cycle and error term via the Kalman filter/smoothing algorithm.
- Since the Kalman filter/smoothing is based on a model, researchers have the possibility to use **diagnostics** to estimate the fit and validity of this model and hence the accuracy of their estimates.
- The **cycle frequency is also estimated instead of predetermined** as in non-parametric filters and turning point methods. This feature is especially convenient for estimating financial cycles, since there is no broad consensus yet on their characteristics.

# Multivariate Unobserved Component Model Framework

Model specification as in Koopman and Lucas (2005):

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

$y_t$ : time series in a panel with length  $N$ ,  $\mu_t$ : **long-term** trend,  $\gamma_t$ : **short-term** cycle,  $\psi_t$ : **medium-term** cycle,  $\varepsilon_t$ : noise.

Unobserved components  $\mu_t$ ,  $\gamma_t$  and  $\psi_t$  are assumed to represent unique dynamic processes and are **independent** of each other.

**Covariances between the disturbances are non-zero.** The loading matrices  $A$  and  $B$  reveal whether there is co-cyclicity between the time series in the panel. Trend is modeled as an integrated random walk process:

$$\begin{aligned} \mu_{t+1} &= \mu_t + \beta_t, \\ \beta_{t+1} &= \beta_t + \zeta_t, \quad \zeta_t \stackrel{i.i.d.}{\sim} \mathcal{N}(0, \Sigma_\zeta), \end{aligned} \quad (2)$$

# Modeling the cycles

The short-term cycle ( $\gamma_t$ ) and the medium-term cycle ( $\psi_t$ ) are specified as a restricted trigonometric processes as proposed by Harvey(1989). Consider  $\psi_t$ , i.e.:

$$\begin{pmatrix} \psi_{t+1} \\ \psi_{t+1}^* \end{pmatrix} = \phi_\psi \begin{bmatrix} \cos \lambda_\psi & \sin \lambda_\psi \\ -\sin \lambda_\psi & \cos \lambda_\psi \end{bmatrix} \begin{pmatrix} \psi_t \\ \psi_t^* \end{pmatrix} + \begin{pmatrix} \omega_t \\ \omega_t^* \end{pmatrix},$$
$$\begin{pmatrix} \omega_t \\ \omega_t^* \end{pmatrix} \overset{i.i.d.}{\sim} \mathcal{N}(0, \sigma_{i,\omega}^2), \quad (3)$$

where,  $\psi_t$  = (medium-term) cycle,  $\psi_t^*$  = 'first derivative' of the (medium-term) cycle,  $\lambda_\psi$  = cycle frequency,  $\phi_\psi$  = persistence parameter ( $0 < \phi_\psi < 1$ ),  $\omega_t$  = disturbance term. The length of  $\psi_t$  is given by  $p = 2\pi/\lambda_\psi$ .

For identification of the cycle disturbance variances,  $A$  and  $B$  in Eq.(1) are restricted to be lower triangular matrices with unity as diagonal elements.

► Details



We apply the multivariate UC model to extract trends and cycles from the following variables (all in real terms):

- Gross domestic product (GDP)
- House prices (HP)
- Bank credit to private sector (CRED)
- Industrial production index (IP)

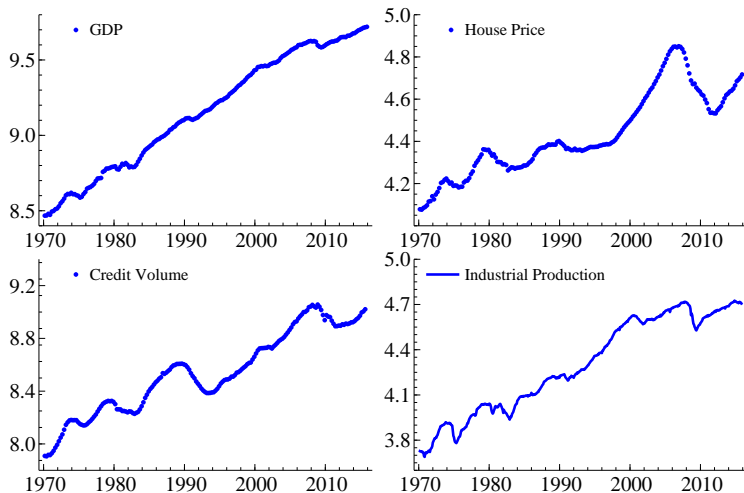
Countries analyzed:

- We consider the G7-countries (US, UK, JA, CA, DE, FR, IT) and NL

Period of analysis

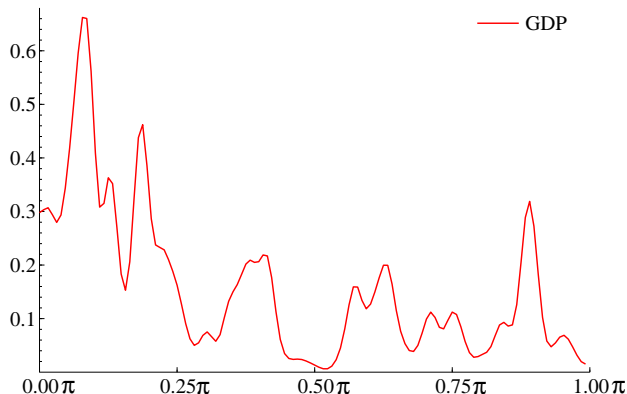
- 1970Q1–2015Q1 for GDP, HP & CRED;
- 1970M1–2015M12 for IP.

# Why two cycles in one model framework?



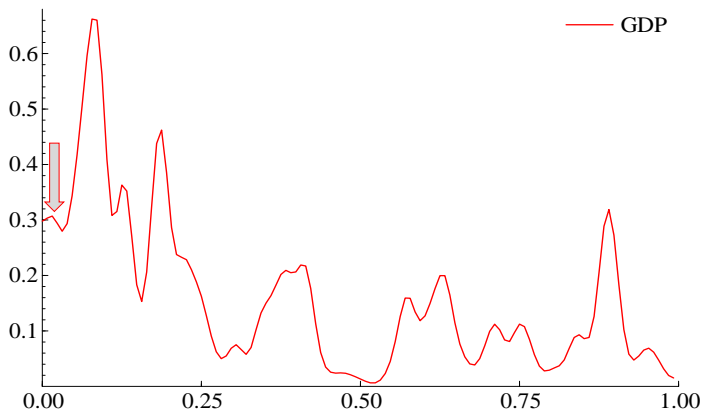
All US series are deflated, seasonally adjusted and in natural logs.

# Why two cycles in one model framework?



Estimated spectral densities (US data), series are in log-differences,  $0.25\pi$  translates into a cycle with period of  $\frac{2\pi}{0.25\pi} = 8$  quarters (2 years).  $0.50\pi$  translates into a cycle with period of  $\frac{2\pi}{0.50\pi} = 4$  quarters (1 year).

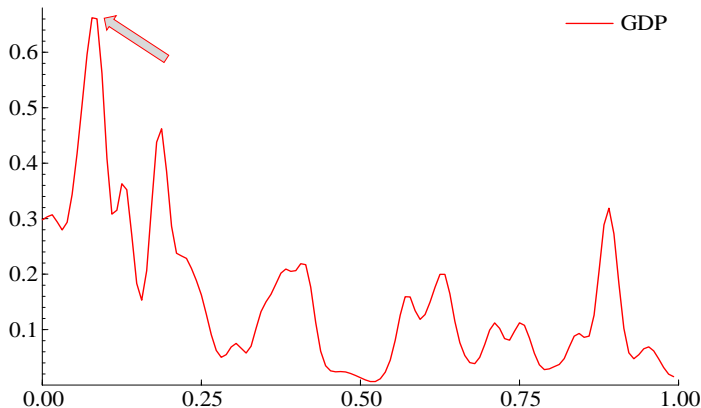
# Why two cycles in one model framework?



Estimated spectral densities (US data), series are in log-differences.

The **first** peak in the spectral density of GDP is estimated at approximately  $0.02\pi$ , which translates into a cycle with period of  $\frac{2\pi}{0.02\pi} = 100$  quarters, or 25 years.

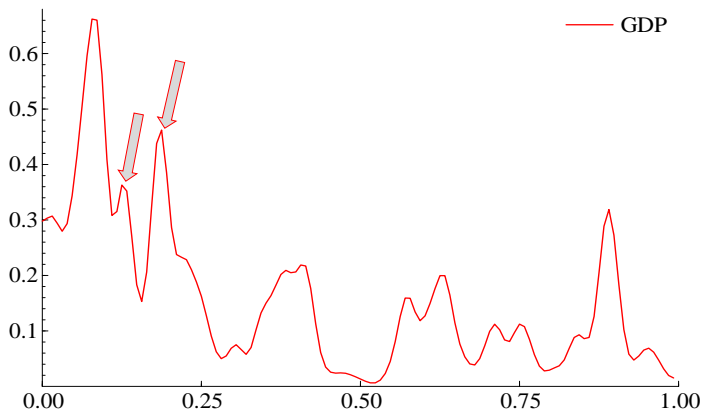
# Why two cycles in one model framework?



Estimated spectral densities (US data), series are in log-differences.

The **second** peak is at  $0.08\pi$ , which translates to a period of 25 quarters, or  $6\frac{1}{4}$  year. Seems to be related to the business cycle frequency.

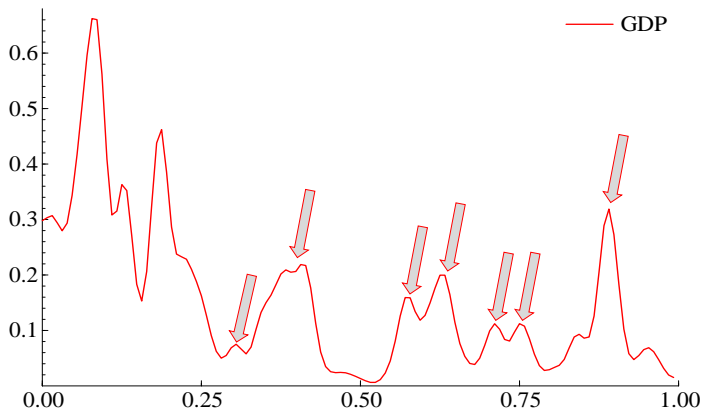
# Why two cycles in one model framework?



Estimated spectral densities (US data), series are in log-differences.

The **third** and **fourth** peak occur at  $0.13\pi$  (15 quarters; 3.8 years) and  $0.19\pi$  (10 quarters; 2.6 years). Most business cycle frequencies have period of  $6\frac{1}{4}$  years.

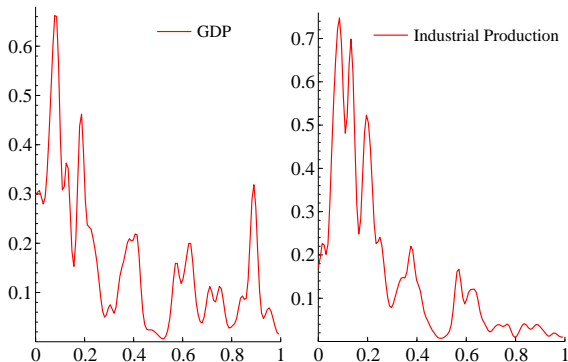
# Why two cycles in one model framework?



Estimated spectral densities (US data), series are in log-differences.

There are some local peaks in the spectral density above approximately  $0.25\pi$  (or 2 years). For our study these fluctuations are not so much of interest (noise).

# Why two cycles in one model framework?

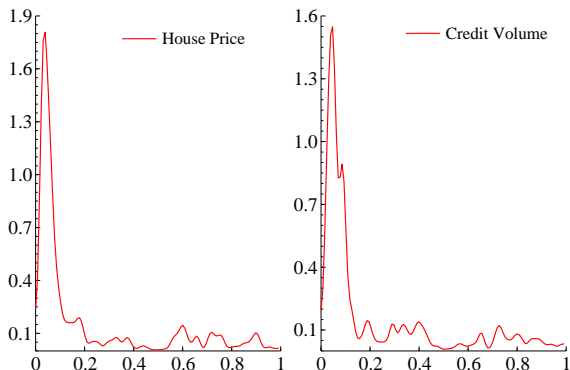


Estimated spectral densities (US data), series are in log-differences.

Spec. dens. IP very similar to the spec. dens. of GDP. Small peak at cycle-length of  $\pm 25$  years, and peaks at cycles of approximately 6, 4 and 3 years.



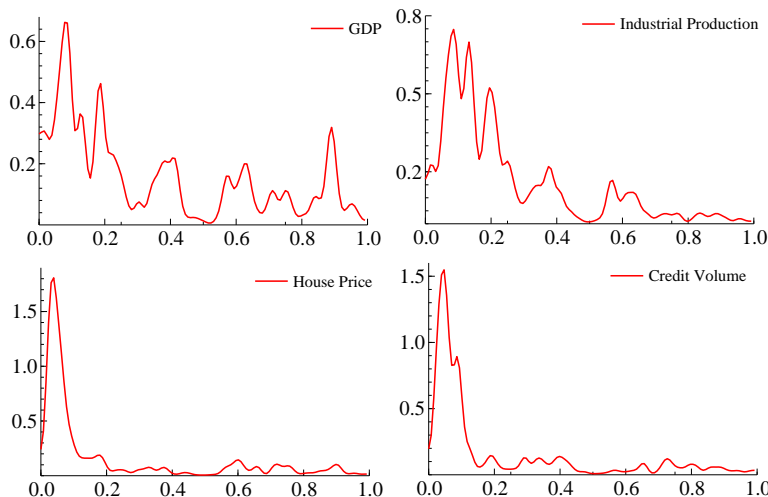
# Why two cycles in one model framework?



Estimated spectral densities (US data), series are in log-differences.

Spec. dens. HP and CRED **quite different** from GDP and IP. Former show large peaks at cycle-length of approximately 13 years. Not much cycl. movement at higher freq's.

# Why two cycles in one model framework?



Estimated spectral densities (US data), series are in log-differences.

# Why two cycles in one model framework?

- Besides spectral densities we perform statistical likelihood ratio (LR) test, following Rünstler and Vlekke (2018) and Galati et al. (2016).
- We conclude that in almost all countries and variables our four variables have two cycles (exceptions: GDP in NL and IP in UK)
- Our main conjecture from analyzing the spectral densities and formal testing:
  - **medium-term** frequencies are dominant in the house price & credit volume variables
  - **short-term** fluctuations are dominant for GDP & industrial production

# Model applied to our dataset

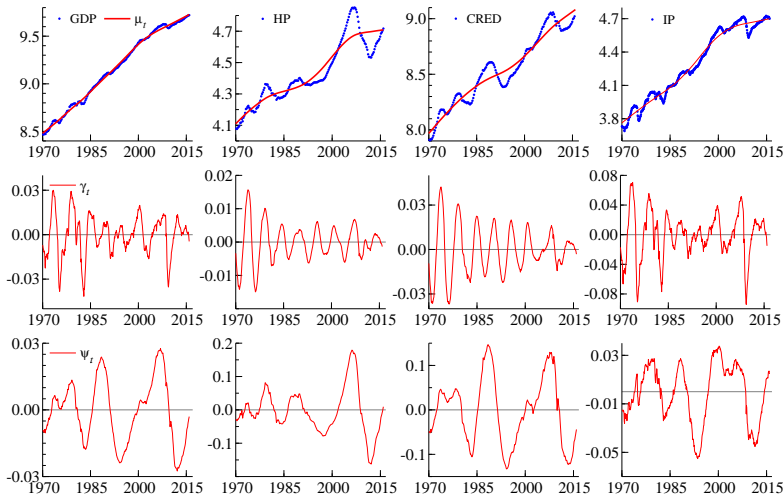
Our model once more:

$$y_t = \begin{bmatrix} y_t^{\text{GDP}} \\ y_t^{\text{HP}} \\ y_t^{\text{CRED}} \\ y_t^{\text{IP}} \end{bmatrix} = \begin{bmatrix} \text{real GDP (GDP)} \\ \text{real House Price (HP)} \\ \text{real Credit Volume (CRED)} \\ \text{real Industrial Production (IP)} \end{bmatrix},$$
$$= \mu_t + A\gamma_t + B\psi_t + \varepsilon_t, \quad \varepsilon_t \stackrel{i.i.d.}{\sim} \mathcal{N}(0, \Sigma_\varepsilon),$$

for  $t = 1, \dots, T$ , with  $\mu_t$  is the trend,  $\gamma_t$  is the short-term cycle and  $\psi_t$  is the medium-term cycle component. The model is cast in state space form and estimated using the maximum likelihood method.

► [Details state space model](#)

# Graphical representation outcomes for the United States



Estimated trend ( $\mu_t$ ), short-term cycle ( $\gamma_t$ ) and medium-term cycle ( $\psi_t$ ) for (US data) GDP, HP, CRED and IP. Series are in logs.

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# Properties and commonality of the short-term cycle $\lambda_\gamma$

Parameter estimates of multivariate UCTSM for short-term cycle

	US	UK	JA	CA	DE	FR	IT	NL
Properties cycles								
$p_\gamma$	5.4	6.7	3.3	7.1	4.5	3.6	3.8	7.9
$\phi_\gamma$	0.99	0.99	0.98	0.99	0.97	0.98	0.97	0.99
Loading matrix A								
<i>vs. GDP // 1st column loading matrices</i>								
HP	-0.02	1.79	0.48	-0.14	-0.09	0.52	-0.38	-0.06
CRED	0.25	0.20	0.01	0.94*	0.07	0.08	0.33	0.88*
IP	1.82***	1.11**	3.26***	1.97***	2.82***	3.14***	2.54***	1.45**
<i>vs. HP // 2nd column loading matrices</i>								
CRED	1.26	0.30	-0.04	0.25	-0.57	-0.13	0.00	-0.16
IP	1.51	0.11	0.43	0.02	0.34	0.86	-0.10	0.03
<i>vs. CRED // 3rd column loading matrices</i>								
IP	-0.07	0.27	-1.99	-0.19	-0.46	2.31	1.81	0.53

The table reports the estimates of persistence  $\phi_\gamma$  and the period  $p_\gamma$  in years ( $p = 2\pi/\lambda$ ), respectively. Significant estimates in these matrices are highlighted in grey. \*, \*\* and \*\*\* denote statistical significance at the 10%, 5% and 1% level, respectively.

# Properties and commonality of the medium-term cycle $\lambda_\psi$

Parameter estimates of multivariate UCTSM for medium-term cycle

	US	UK	JA	CA	DE	FR	IT	NL
Properties cycles								
$p_\psi$	13.6	18.4	9.2	22.3	9.3	16.2	14.7	23.7
$\phi_\psi$	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
Loading matrix B								
<i>vs. GDP // 1st column loading matrices</i>								
HP	2.77***	1.19	1.45	8.43	1.80	1.54	19.58	3.56
CRED	4.48	0.80	1.73	-1.98	1.10	1.58	2.78	0.45
IP	1.91	2.42	2.70	3.17	1.69	2.66	2.32	1.71
<i>vs. HP // 2nd column loading matrices</i>								
CRED	-0.25	0.16	0.42	1.28	6.56	-0.07	2.90	0.69
IP	-0.19	-0.36	-0.26	-0.80	-12.64	-0.17	-0.83	-0.48
<i>vs. CRED // 3rd column loading matrices</i>								
IP	-0.58	-0.03	0.06	0.24	0.29	-0.41	2.32	2.62

The table reports the estimates of persistence  $\phi_\psi$  and the period  $p_\psi$  in years ( $p = 2\pi/\lambda$ ), respectively. Significant estimates in these matrices are highlighted in grey. \*, \*\* and \*\*\* denote statistical significance at the 10%, 5% and 1% level, respectively.

- ① We find strong evidence for the existence of a separate short-term cycle and medium-term cycle in macroeconomic and financial variables in industrialized countries
- ② We present an elegant model to **simultaneously** extract these cycles and estimate their co-cyclicalilty
- ③ Co-movement between macroeconomic and financial variables limited to the medium-term
- ④ Strong concordance between the medium-term cycles of house prices and GDP. much less between credit and GDP



# Thank you for your attention!

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# Extra Slides

# Details of modeling the cycles (1/2)

Remember from Calculus:

- A deterministic cycle with amplitude  $a$  and frequency  $\lambda_\psi$  can be written as:

$$\psi_t = a \cos(\lambda_\psi t - b) \quad a, b, \lambda_\psi, t \in \mathbb{R} \quad a \neq 0, \lambda_\psi \neq 0$$

- The first partial derivative of  $\psi_t$  with respect to  $\lambda_\psi t$  equals:

$$\psi_t^* = -a \sin(\lambda_\psi t - b)$$

- The trigonometric identities:

$$\cos(x \pm y) = \cos x \cos y \pm \sin x \sin y$$

$$\sin(x \pm y) = \cos x \sin y \pm \sin x \cos y$$

## Details of modeling the cycles (2/2)

Using the formula's for the first partial derivative and the first trigonometric identity with  $x = \lambda_\psi t - b$  and  $y = \lambda_\psi$  it follows that,

$$\psi_{t+1} = a \cos(\lambda_\psi(t+1) - b)$$

$$\psi_{t+1} = a \cos(\lambda_\psi t - b + \lambda_\psi)$$

$$\psi_{t+1} = a \cos(\lambda_\psi t - b) \cos \lambda_\psi - a \sin(\lambda_\psi t - b) \sin \lambda_\psi$$

$$\psi_{t+1} = \psi_t \cos \lambda_\psi + \psi_t^* \sin \lambda_\psi$$

$$\psi_{t+1} = \cos \lambda_\psi \psi_t + \sin \lambda_\psi \psi_t^*$$

Or,

$$\begin{pmatrix} \psi_{t+1} \\ \psi_{t+1}^* \end{pmatrix} = \phi_\psi \begin{bmatrix} \cos \lambda_\psi & \sin \lambda_\psi \\ -\sin \lambda_\psi & \cos \lambda_\psi \end{bmatrix} \begin{pmatrix} \psi_t \\ \psi_t^* \end{pmatrix} + \begin{pmatrix} \omega_t \\ \omega_t^* \end{pmatrix},$$

Similarly, using the formula's for the first partial derivative and the second trigonometric identity it can be shown that  $\psi_{t+1}^*$  can be written as:

$$-\sin \lambda_\psi \psi_t + \cos \lambda_\psi \psi_t^*$$

# State Space Form

The multivariate components model equations (1) – (4) can be cast into the state space form. The measurement and transition equations are defined as:

$$\begin{aligned}y_t &= Z\alpha_t + \varepsilon_t, & \varepsilon_t &\sim N(0, H), \\ \alpha_{t+1} &= T\alpha_t + \nu_t, & \nu_t &\sim N(0, Q),\end{aligned}$$

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  $\alpha_t$  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.

# State Space Form

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:

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

# State Space Form

The state-disturbance vector  $\nu_t$  is given by

$$\nu_t = (0_{N \times 1}, \zeta_t, \kappa_t, \kappa_t^*, \omega_t, \omega_t^*)',$$

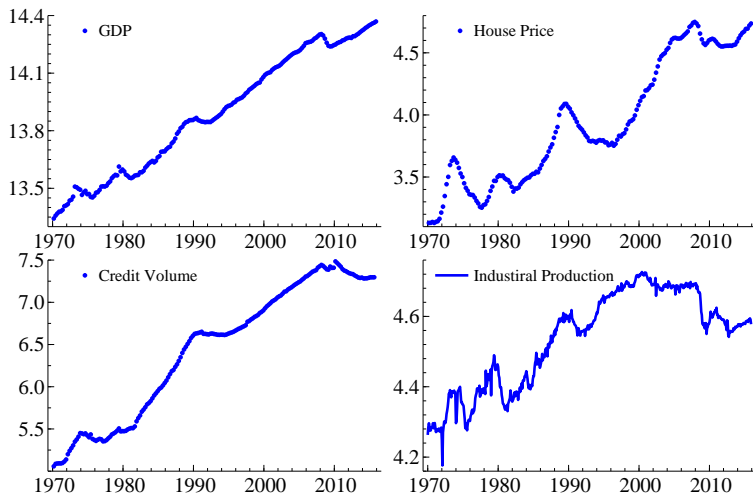
where  $\zeta_t = (\zeta_{1,t}, \dots, \zeta_{N,t})'$  are the slope-disturbances,  $(\kappa_t, \kappa_t^*)' = (\kappa_{1,t}, \dots, \kappa_{N,t}, \kappa_{1,t}^*, \dots, \kappa_{N,t}^*)'$  are the short-term cycle disturbances, and  $(\omega_t, \omega_t^*)' = (\omega_{1,t}, \dots, \omega_{N,t}, \omega_{1,t}^*,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

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

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

where  $\Sigma_\zeta$  is the variance matrix of the slope-disturbances,  $\Sigma_\kappa$  is the variance matrix of the short-term cycle disturbances, and  $\Sigma_\omega$  is the variance matrix of the medium-term cycle disturbances.  $\Sigma_\zeta$  is restricted to be diagonal, i.e.  $\Sigma_\zeta = \text{diag}(\sigma_{\zeta_1}^2, \dots, \sigma_{\zeta_N}^2)'$  and the signal-to-noise ratio  $(\sigma_{\zeta_i}^2 / \sigma_{\varepsilon_i}^2)$  is fixed for each  $i = 1, \dots, N$ .

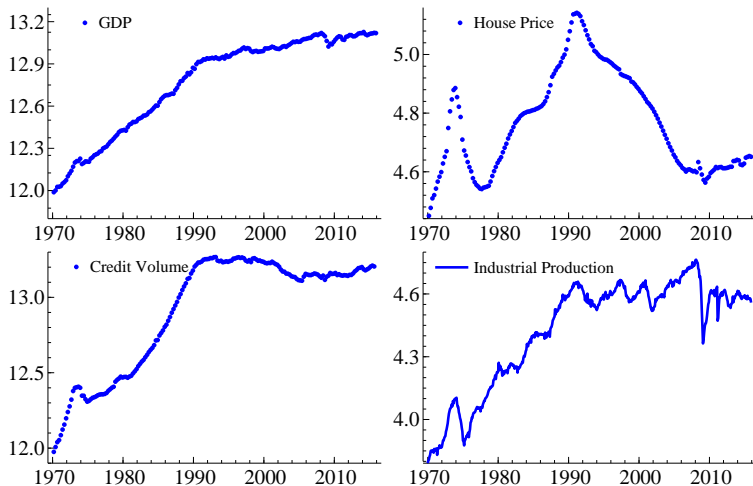
# Why two cycles in one model framework



All UK series are deflated, seasonally adjusted and in natural logs.

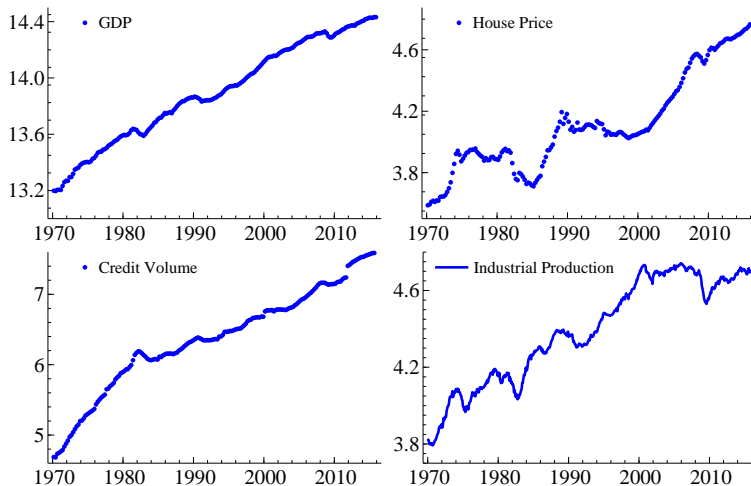


# Why two cycles in one model framework



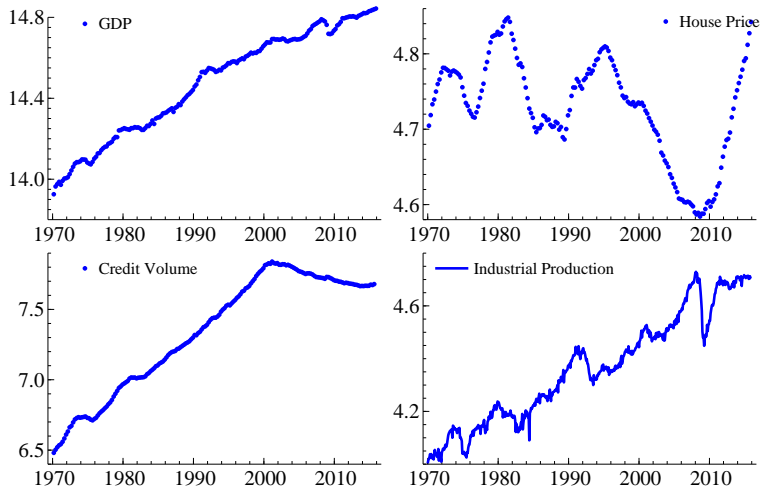
All JA series are deflated, seasonally adjusted and in natural logs.

# Why two cycles in one model framework



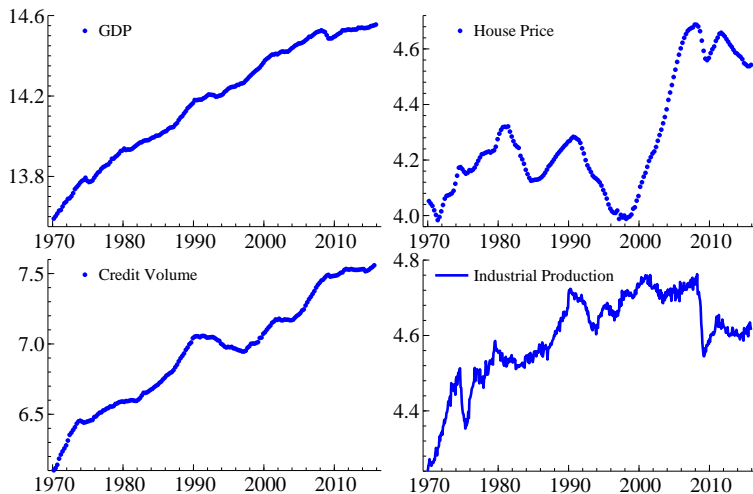
All CA series are deflated, seasonally adjusted and in natural logs.

# Why two cycles in one model framework



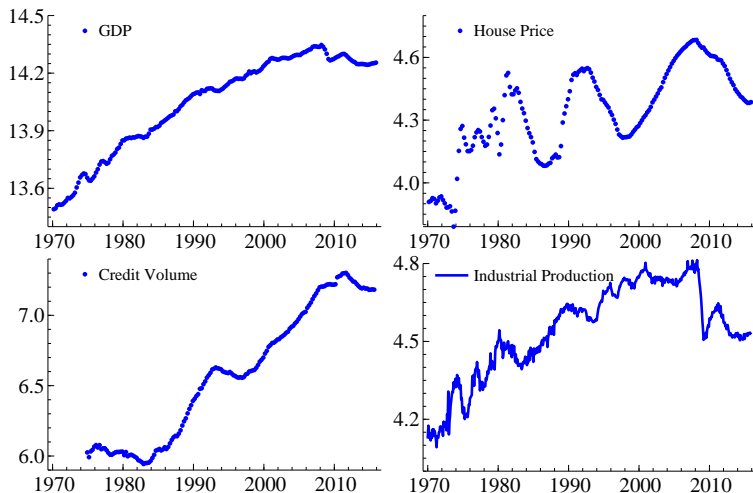
All DE series are deflated, seasonally adjusted and in natural logs.

# Why two cycles in one model framework



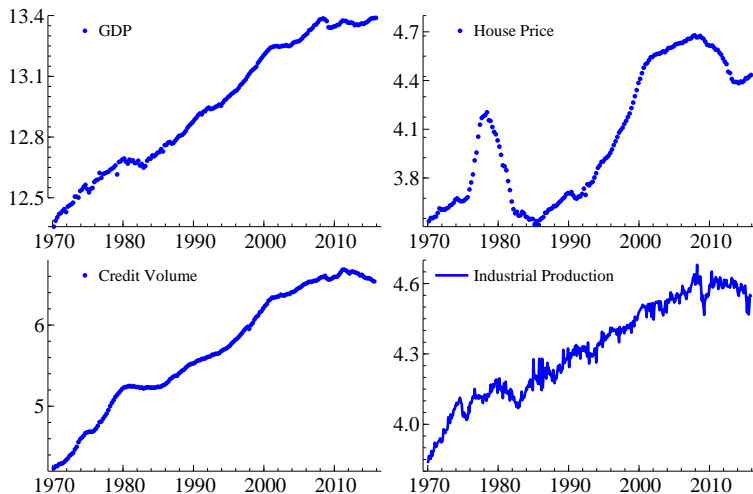
All FR series are deflated, seasonally adjusted and in natural logs.

# Why two cycles in one model framework



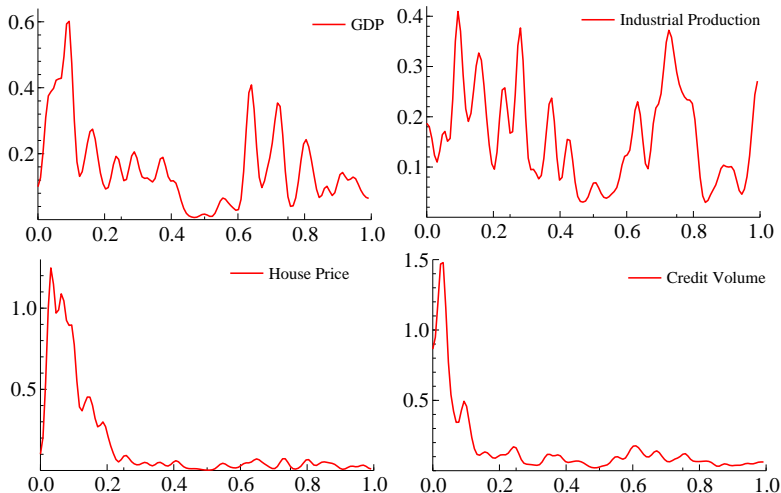
All IT series are deflated, seasonally adjusted and in natural logs.

# Why two cycles in one model framework



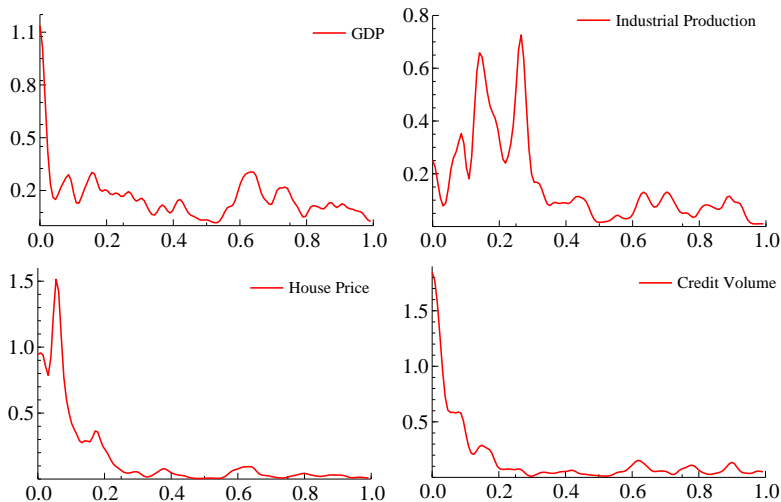
All NL series are deflated, seasonally adjusted and in natural logs.

# Why two cycles in one model framework



Estimated spectral densities (UK data), series are in log-differences.

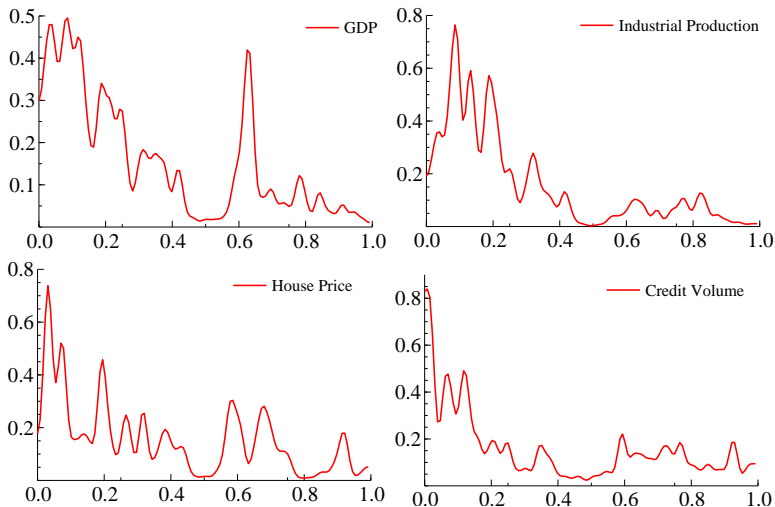
# Why two cycles in one model framework



Estimated spectral densities (JA data), series are in log-differences.

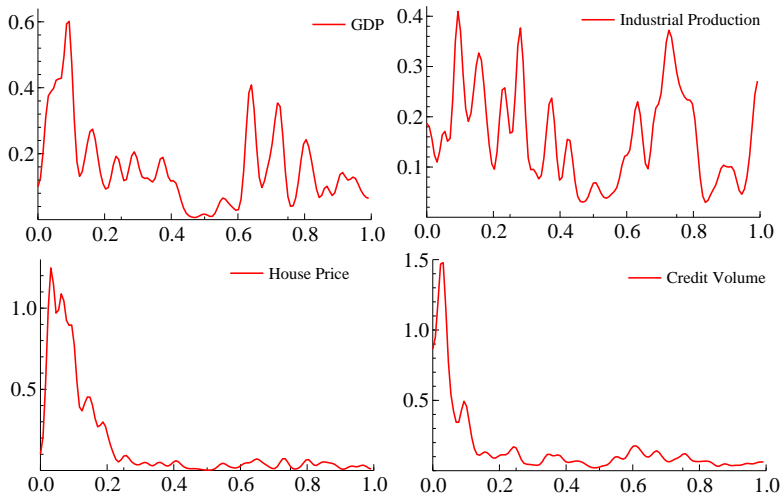


# Why two cycles in one model framework



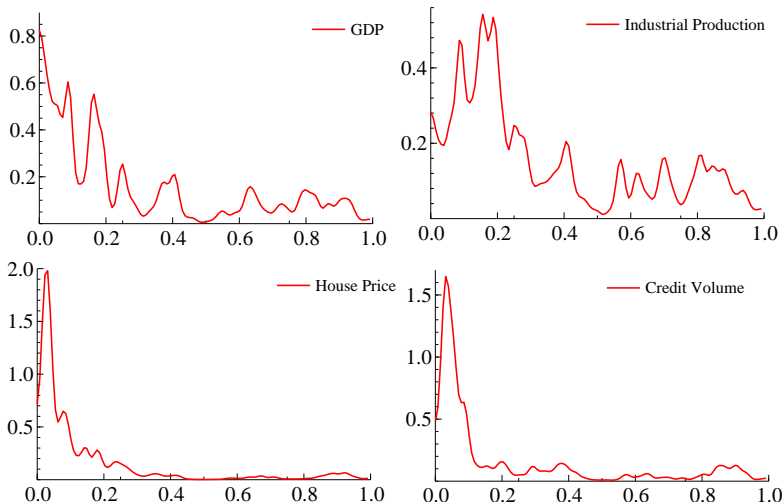
Estimated spectral densities (CA data), series are in log-differences.

# Why two cycles in one model framework



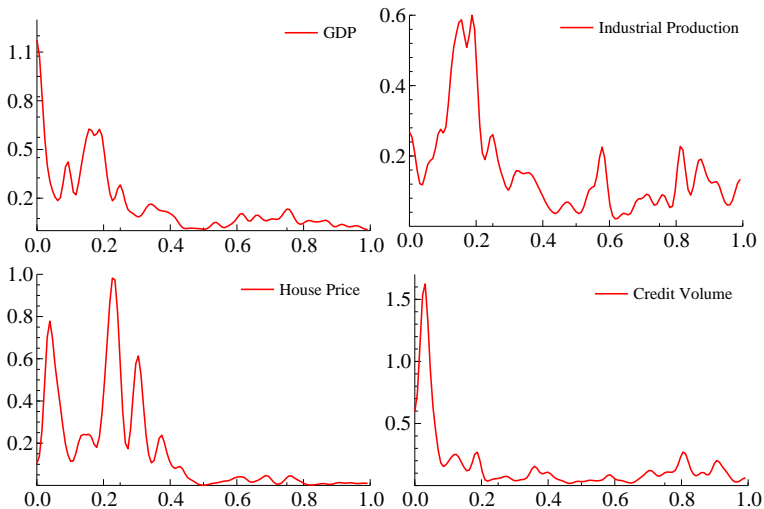
Estimated spectral densities (DE data), series are in log-differences.

# Why two cycles in one model framework



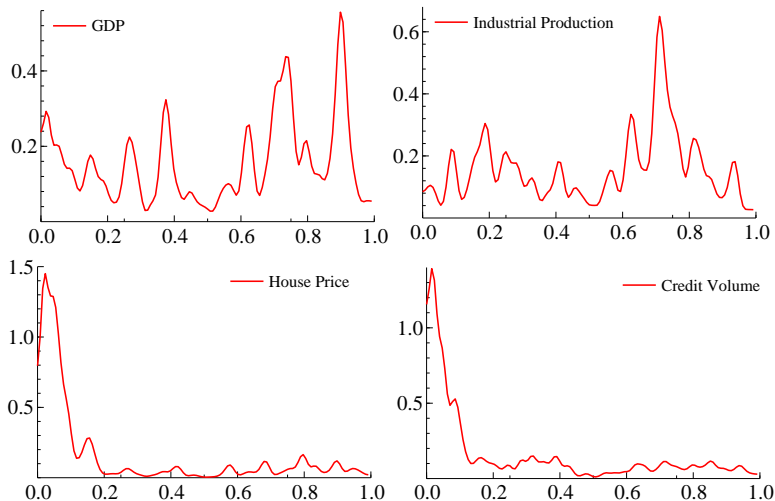
Estimated spectral densities (FR data), series are in log-differences.

# Why two cycles in one model framework



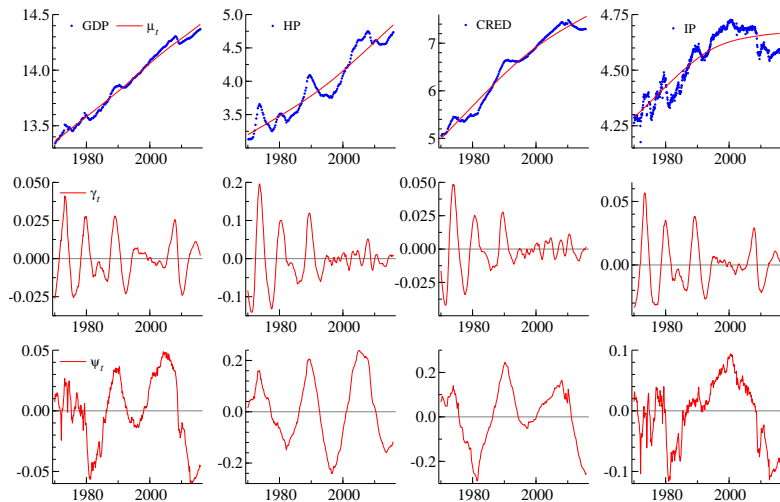
Estimated spectral densities (IT data), series are in log-differences.

# Why two cycles in one model framework



Estimated spectral densities (NL data), series are in log-differences.

# Graphical representation outcomes for the United Kingdom

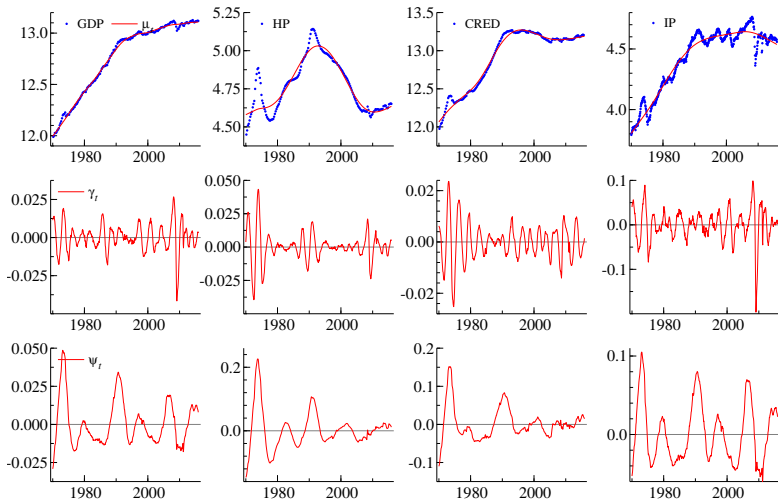


Estimated trend ( $\mu_t$ ), short-term cycle ( $\gamma_t$ ) and medium-term cycle ( $\psi_t$ ) for (UK data) GDP, HP, CRED and IP. Series are in logs.

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# Graphical representation outcomes for Japan



Estimated trend ( $\mu_t$ ), short-term cycle ( $\gamma_t$ ) and medium-term cycle ( $\psi_t$ ) for (JA data) GDP, HP, CRED and IP. Series are in logs.

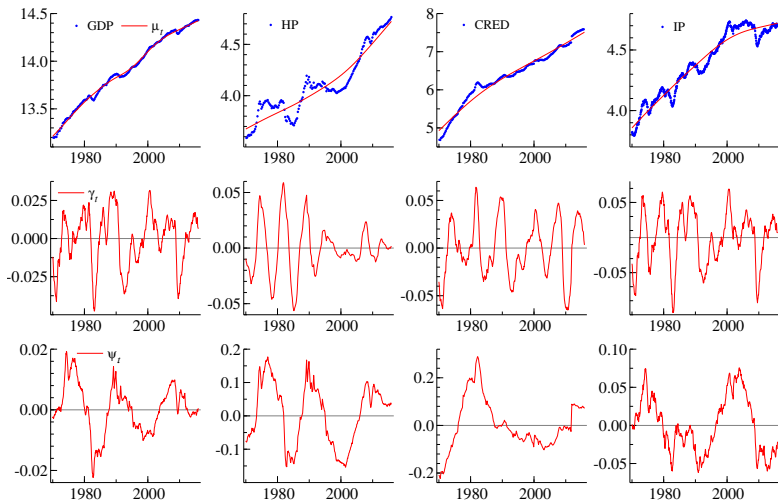
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▶ Results Canada

# Graphical representation outcomes for Canada



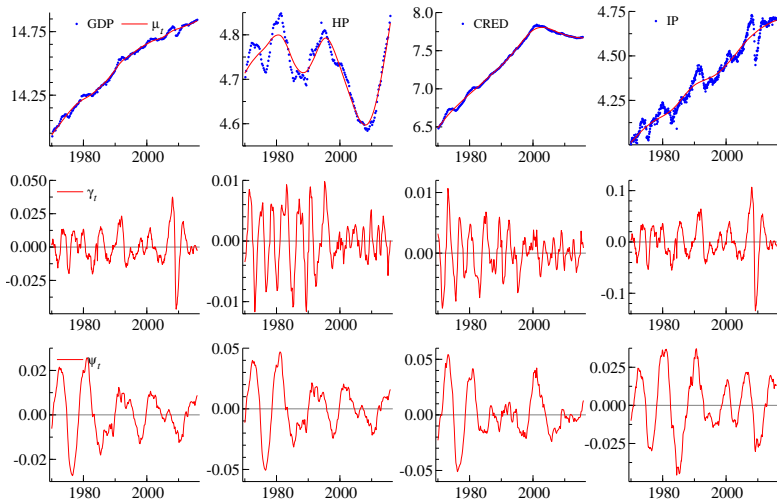
Estimated trend ( $\mu_t$ ), short-term cycle ( $\gamma_t$ ) and medium-term cycle ( $\psi_t$ ) for (CA data) GDP, HP, CRED and IP. Series are in logs.

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# Graphical representation outcomes for Germany



Estimated trend ( $\mu_t$ ), short-term cycle ( $\gamma_t$ ) and medium-term cycle ( $\psi_t$ ) for (DE data) GDP, HP, CRED and IP. Series are in logs.

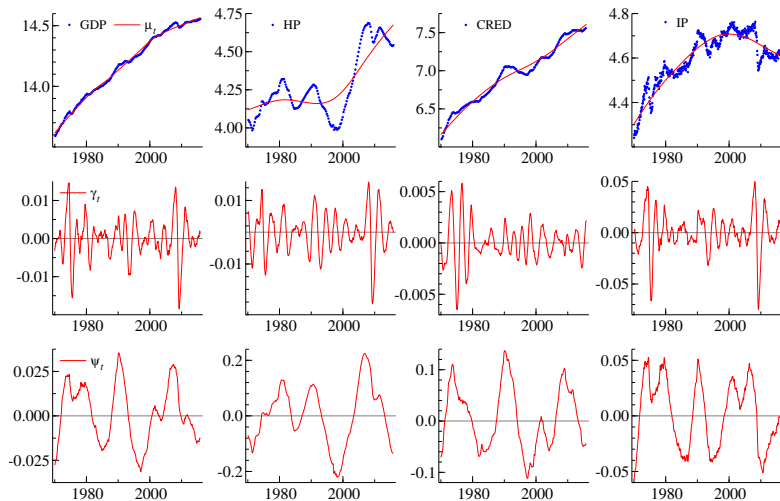
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▶ Results France

# Graphical representation outcomes for France

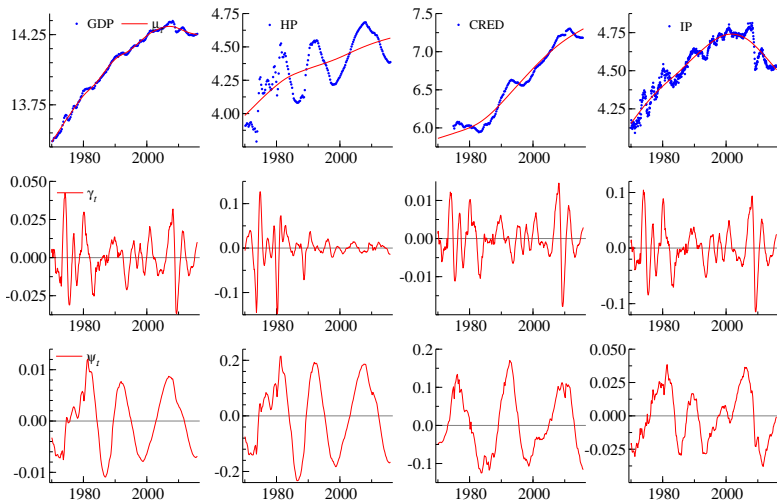


Estimated trend ( $\mu_t$ ), short-term cycle ( $\gamma_t$ ) and medium-term cycle ( $\psi_t$ ) for (FR data) GDP, HP, CRED and IP. Series are in logs.

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# Graphical representation outcomes for Italy

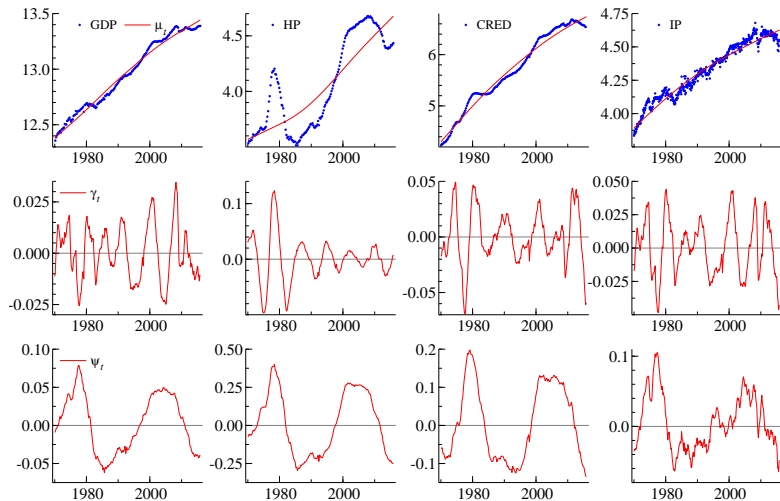


Estimated trend ( $\mu_t$ ), short-term cycle ( $\gamma_t$ ) and medium-term cycle ( $\psi_t$ ) for (IT data) GDP, HP, CRED and IP. Series are in logs.

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# Graphical representation outcomes for the Netherlands



Estimated trend ( $\mu_t$ ), short-term cycle ( $\gamma_t$ ) and medium-term cycle ( $\psi_t$ ) for (NL data) GDP, HP, CRED and IP. Series are in logs.

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