

# On the Sources of Business Cycles: “It’s the Demand...!”

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CEF 2014, Oslo

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The views expressed herein are those of the authors and should not be attributed to the International Monetary Fund, its Executive Board, or its management.

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## Motivation: a typical example

Shock / Series	Policy	Neutral	Govern.	Investment	Price mark-up	Wage	Preferences
Output	0.05	0.25	0.02	<b>0.50</b>	0.05	0.05	0.07
Consumpt.	0.02	0.26	0.02	<b>0.09</b>	0.01	0.07	<b>0.52</b>
Investment	0.03	0.06	0.00	<b>0.83</b>	0.04	0.01	0.02
Hours	0.07	0.10	0.02	<b>0.59</b>	0.06	0.07	0.08
Wages	0.00	<b>0.40</b>	0.00	0.04	0.31	0.23	0.00
Inflation	0.03	0.14	0.00	<b>0.06</b>	<b>0.39</b>	0.34	0.02
Int. Rates	0.17	0.09	0.01	<b>0.47</b>	0.05	0.04	0.16

Source: Justiniano, Primiceri, Tambalotti (2010)

# Note

The paper from which the table on the previous slide was taken was chosen since:

1. it is the **typical representative** of the literature;
  2. it is well known (among 10 most downloaded papers from the JME);
  3. it provides the table on the same frequencies we are interested in.
- 
- ▶ In fact, we could have chosen a table with *the similar message* from a *large set* of recent papers ...
  - ▶ .... similar conclusion for DSGE models with risk shocks and/or credit frictions.

# Our quest

Questions:

1. What are the sources of business cycle fluctuations?
2. How many are there?
3. And what are the implication for structural macroeconomic models?

In our research, we are trying to contribute to this agenda using an *empirical* approach:

- ▶ what are the facts? (if any)
- ▶ what are implications of such facts for structural modeling?

## Various answers proposed by our profession

- ▶ Various sources of cyclical fluctuations: the view implicitly (and tacitly) held by many DSGE model(er)s.

### VERSUS

- ▶ A single source of cyclical fluctuations (if 'cycles are all alike' as Cochrane 1994 puts it)
- ▶ And what is **the** source (if the latter view is assumed?):
  - ▶ productivity (RBC paradigm)
  - ▶ demand (old Keynesians)
  - ▶ or something else .....

# Real-nominal dichotomy?

We are especially interested in real-nominal dichotomy:

- ▶ Test of technology-driven fluctuations (Summers, 1986; Ohanian, 1991);
- ▶ Proper treatment of inflation needed:
  - ▶ It's about inflation, not price level;
  - ▶ Cyclical component of inflation is interesting for the purpose of the paper

We will call

- ▶ shocks that push inflations and output in the **same direction** as **demand** shocks,
- ▶ shocks that push inflations and output in the **opposite direction** as **supply** shocks

# Methods

We start with the **Dynamic Principal Component Analysis** (DPCA) of Brillinger (1981)

A series  $y_t$  can be decomposed in the common component  $\chi_t$  and (weakly) idiosyncratic component  $\xi_t$ :

$$y_t = \chi_t + \xi_t,$$

where the common component  $\chi_t$  is spanned by a *small number* of principal components (factors).

## Our premise

Since principal components are orthogonal, the number of principal components that span sufficiently well the dynamics of the series is revealing about the number of orthogonal (structural) shocks driving the series.



# DPCA in frequency domain

Dynamic Principal Component Analysis (DPCA):

- ▶ operates on the eigen-decomposition of the multivariate spectral density  $\Sigma^y(\omega)$  of the observation  $y_t$ ,
- ▶ tells on which frequency  $\omega$  the co-movement are strong (in the frequency domain).

A measure of co-movement (in frequency domain):

- ▶ Let  $\{\lambda_{(i)}(\omega)\}_{i=1}^N$  be order eigenvalues of  $\Sigma^y(\omega)$

$$\mathcal{C}^y(\omega|k) \equiv \frac{\sum_{i=1}^k \lambda_{(i)}(\omega)}{\sum_{i=1}^N \lambda_{(i)}(\omega)}$$

measures how much  $k$  first principal components explain the common dynamics at frequency  $\omega$ .

- ▶ This measure is invariant with respect to difference operators:  $\mathcal{C}^y(\omega|k) = \mathcal{C}^{\Delta y}(\omega|k)$ .

## DPCA in time domain

The spectral density of the common component  $\Sigma^x(\omega)$  can be inverted back to generate the time-domain filter:

$$\chi_t = \sum_{l=-L}^L \Lambda_l y_{t+l},$$

where  $\Lambda_l$  are filter weights.

The choice  $L > 0$  (i.e., two-sided filter)

- ▶ allows for lead-lag relationships among series,
- ▶ problems for real-time forecasting (but not the concern of our paper).

In time domain, we use the following measure of fit by  $k$  first principal components:

$$\mathfrak{R}^2(k) = 1 - \frac{\sum_{t=L+1}^{T-L} (x_{it} - \chi_{it}^k)^2}{\sum_{t=1}^T (x_{it} - \bar{x}_i)^2}.$$

# Data

The list of countries:

- ▶ Australia, Austria, Belgium, Canada, the Czech Republic, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Korea, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Spain, Sweden, Switzerland, Turkey, the U.K., the U.S.A.

The list of variables:

**Real:** GDP, Consumption, Investment, Exports, Imports, Unemployment.

**Nominal:** Trimmed mean inflation:

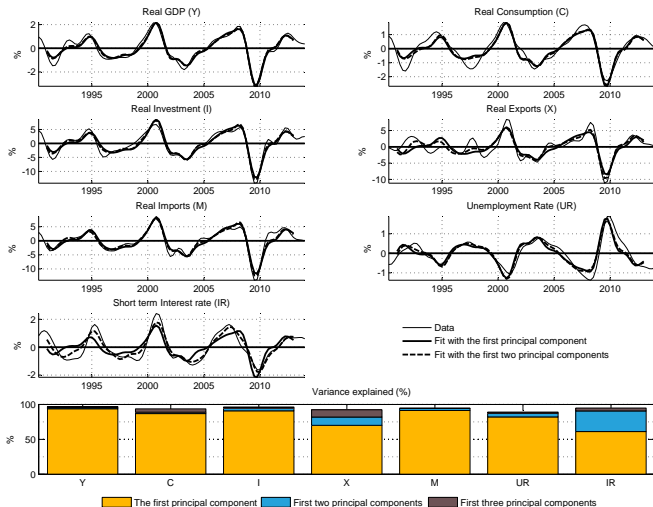
- ▶ It is robust to outliers.
- ▶ It exhibits the high comovement with output cycles (Andrle, Bruha and Solmaz, 2013; Meyer and Zaman, 2013).

# Analysis I: real variables

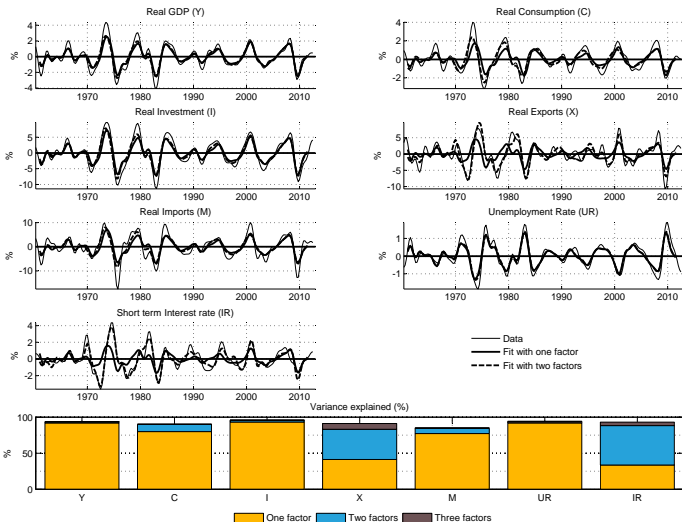
We have implemented the DPCA

- ▶ exactly as described by Forni, Hallin, Lippi and Reichlin (2000)
  - ▶ a non-parametric Bartlett approach to estimating the spectral density  $\Sigma(\omega)$ .
- ▶ In frequency domain, we report the summary statistics for first-differences in investigated series;
- ▶ in time domain, we measure the fit by the first two principal components for various data transformations.

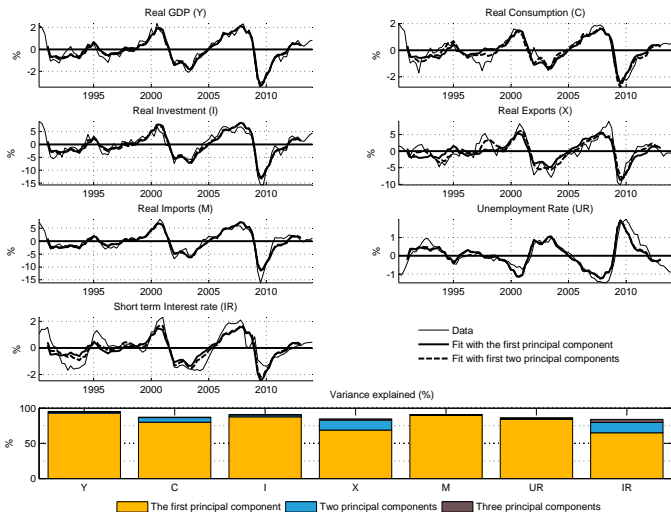
# Real variables in time domains – US cycles (band pass filter)



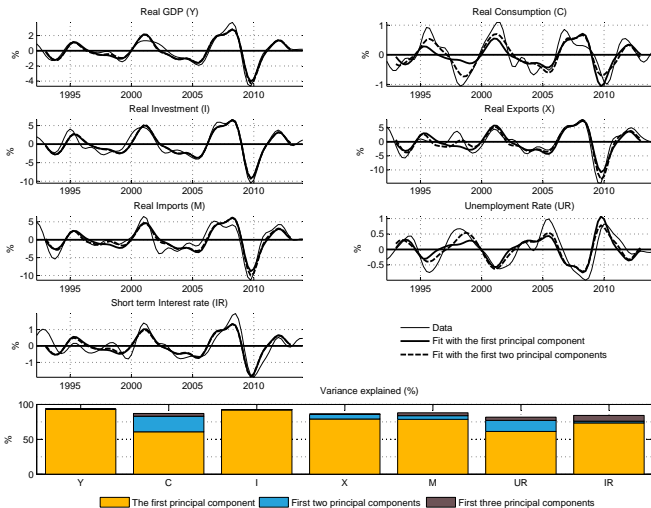
# Real variables in time domains – US cycles (band pass filter) – sample since the 50s'



# Real variables in time domains – US cycles (HP filter)

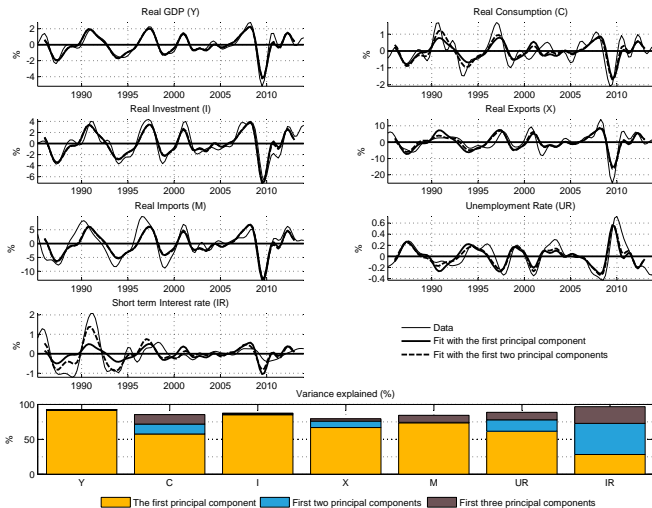


# Real variables in time domains – German cycles (band-pass filter)

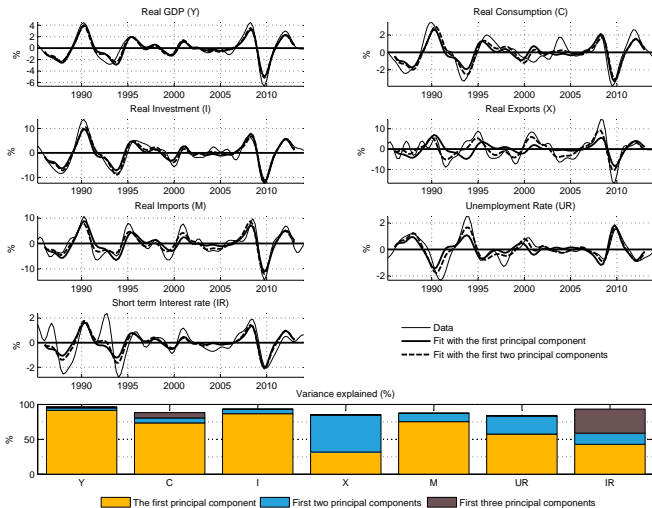




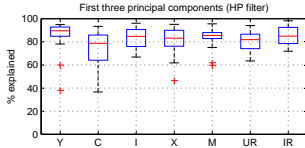
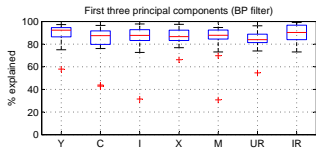
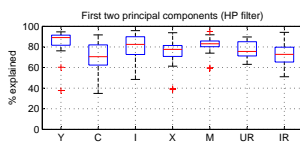
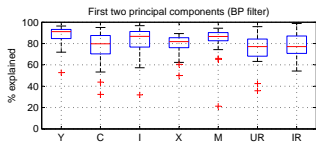
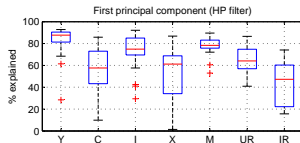
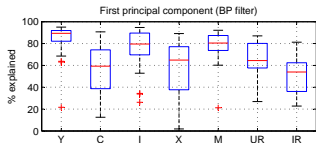
# Real variables in time domains – Japan cycles (band-pass filter)



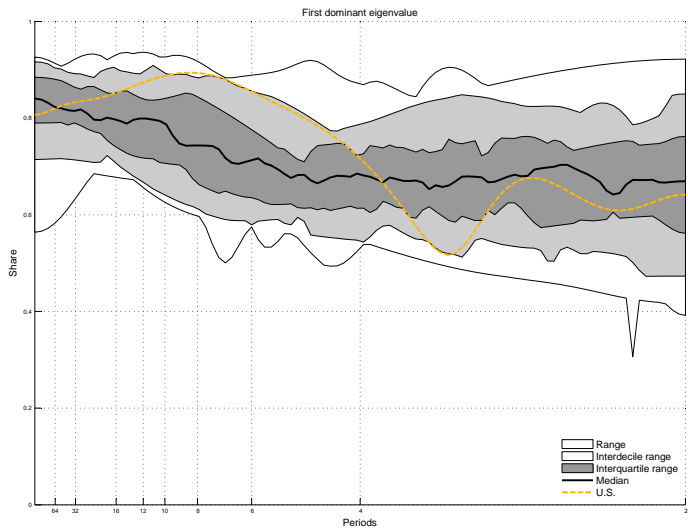
# Real variables in time domains – Finland cycles (band-pass filter)



# Real variables in time domains – summary statistics



# Real variables in frequency domain



# Real variables – implications

Our results suggest strong and predictable co-movements among cyclical components of real variables:

- ▶ One or two principal components span the dynamics in cyclical part of real variables.
- ▶ Data transformation crucial:
  - ▶ much worse fit for growth rates [▶ ... see here](#)
  - ▶ growth rates amplify high-frequency noise and contain some low-frequency movements.

# Real variables – robustness analysis

Our results are:

- ▶ robust to filter used to isolate statistical components (CF band pass filter [▶ versus](#) HP filter),
- ▶ robust to sample period,
- ▶ robust to dimension reduction technique:
  - ▶ also used one-sided DPCA and static PCA [▶ ... see here](#)
  - ▶ marginally lower fit due to the lack of lead-lag relationship

## Analysis II: real and nominal variables

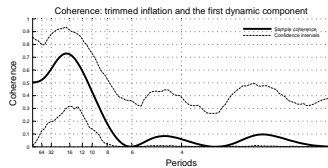
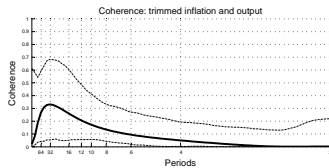
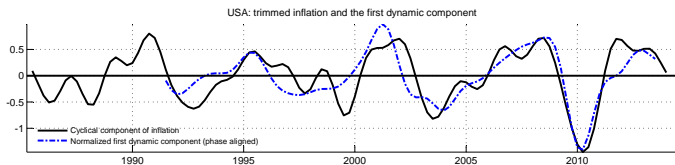
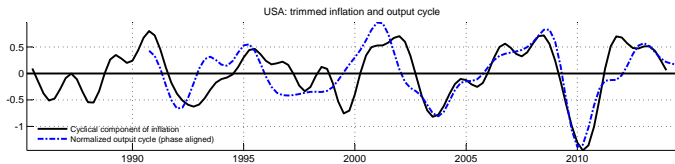
After isolating cycles from real variables, we investigate the comovement of the inflation with the output cycles and with the first 'real' principal component:

- ▶ coherence,
- ▶ correlation of cyclical parts.

Why do not we put the median inflation series directly to the first exercise?

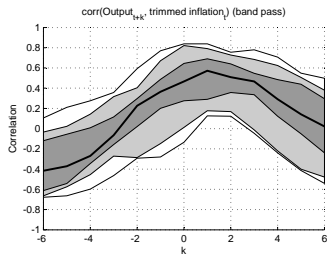
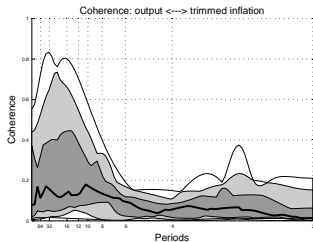
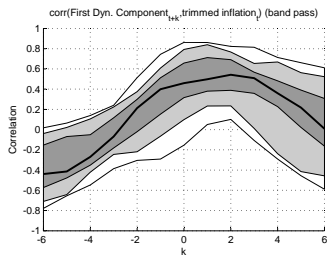
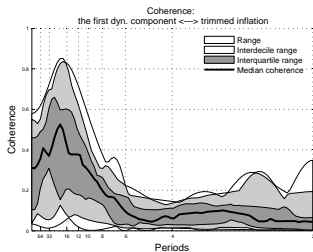
- ▶ much shorter time series for median inflation for most countries;
- ▶ why not using the CPI inflation?
  - ▶ strange results (CPI seems to lead real cycles in a bulk of countries);
  - ▶ artefact of recent crisis where the output drop was preceded by the fall in commodity prices.

# Real and nominal variables – the U.S.





# Real and nominal variables – summary picture



# Findings

## Findings 1

We demonstrate the strong and predictable co-movements among cyclical components of real variables.

## Findings 2

We show that this real comovement is aligned to the inflation cycle.

# Implications (1)

Implications of strong comovements of real variables for structural macroeconomic models:

- ▶ The number of primitive shocks that span the dynamics of cyclical variables should be controlled for.
  - ▶ Structural DSGE models in which each real variable has its own shock are **misspecified** in light of the strong comovement in real variables ...
  - ▶ ... if this is not controlled for, DSGE modeling will become 'a *degenerate research agenda*' [as Roger Farmer calls it].

## Implications (2)

Our interpretation of finding (2) – comovement of inflation and real dynamics:

This points toward the importance of demand shocks rather than to productivity-driven business cycles.

# Closing slides

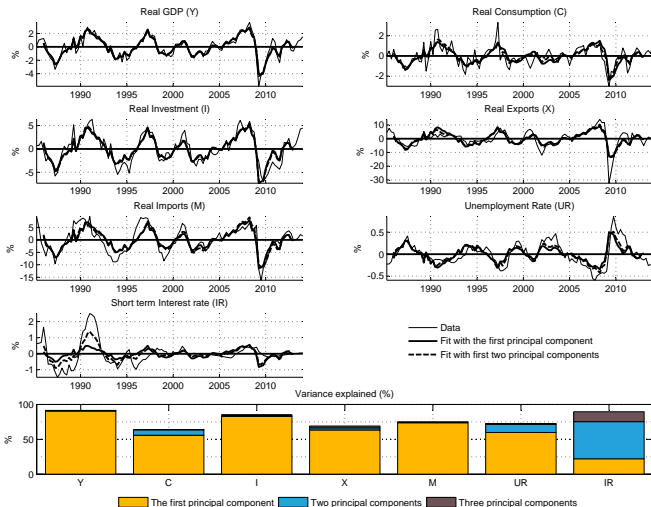
Thank you for your attention

[mandrle@imf.org](mailto:mandrle@imf.org)

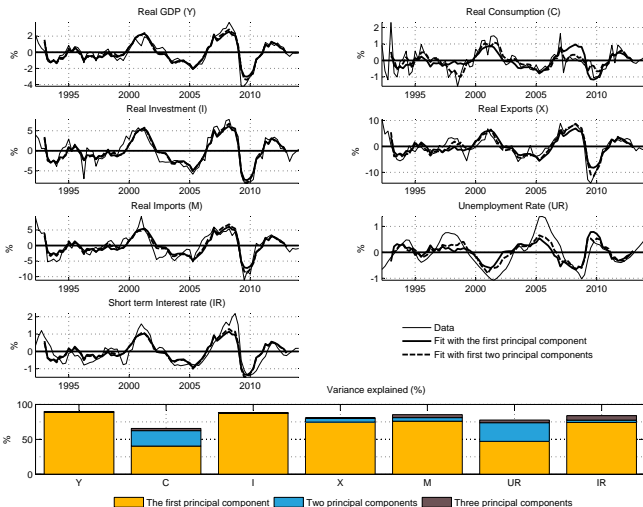
[Jan.bruha@cnb.cz](mailto:Jan.bruha@cnb.cz)

# BACK UP SLIDES

# Real variables in time domains – Japan cycles (HP filter)

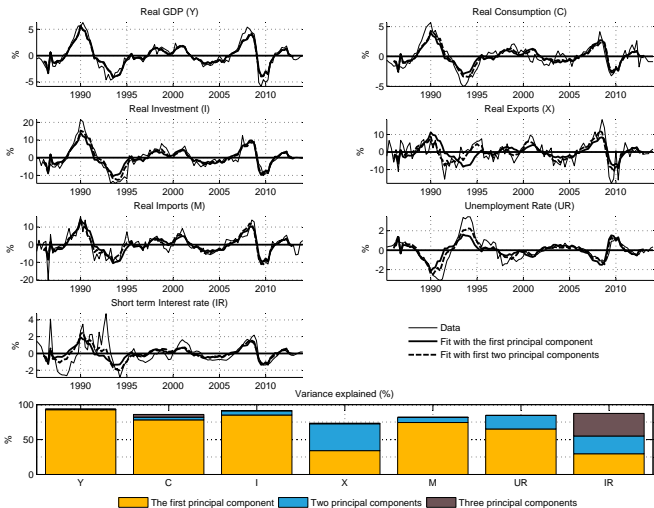


# Real variables in time domains – German cycles (HP filter)

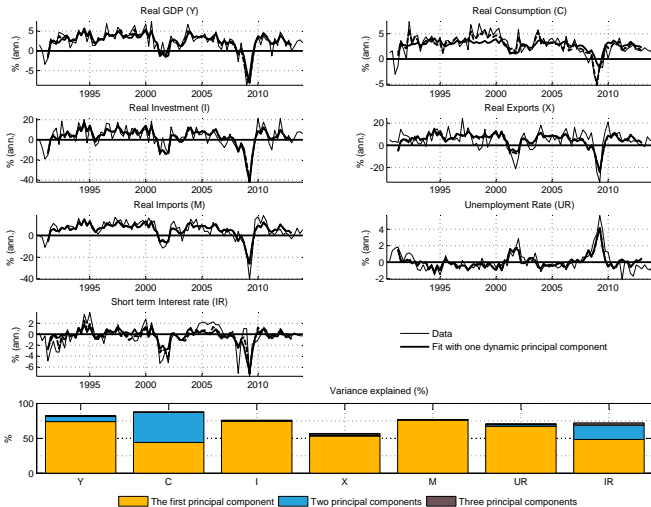




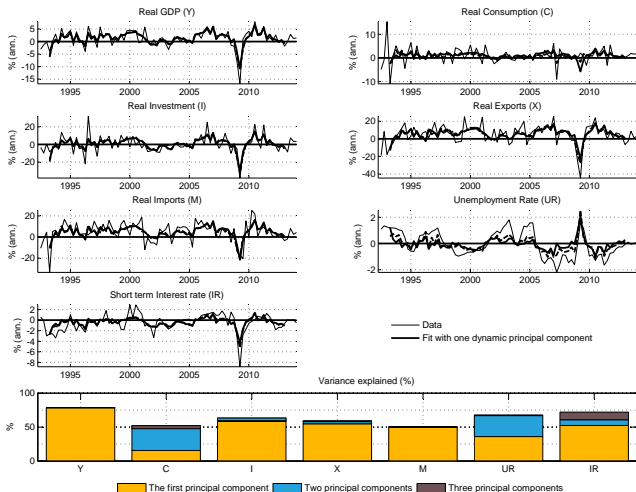
# Real variables in time domains – Finland (HP filter)



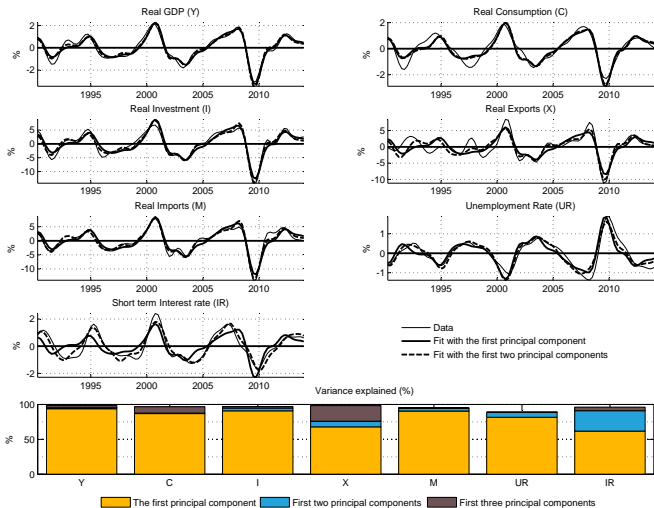
# Real variables in time domains – US growth rates



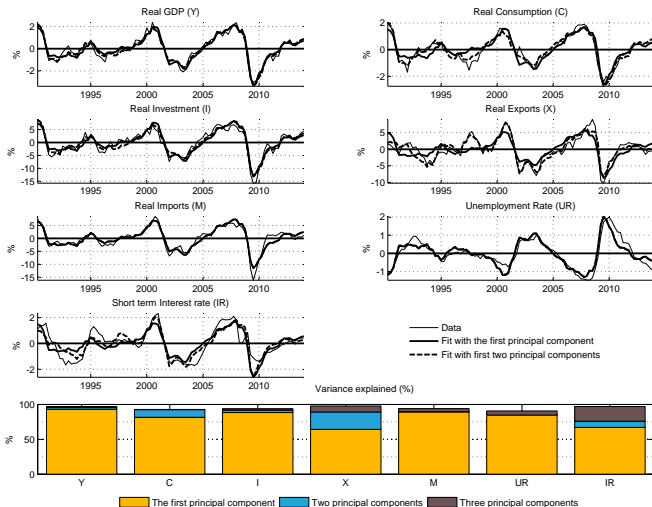
# Real variables in time domains – German growth rates



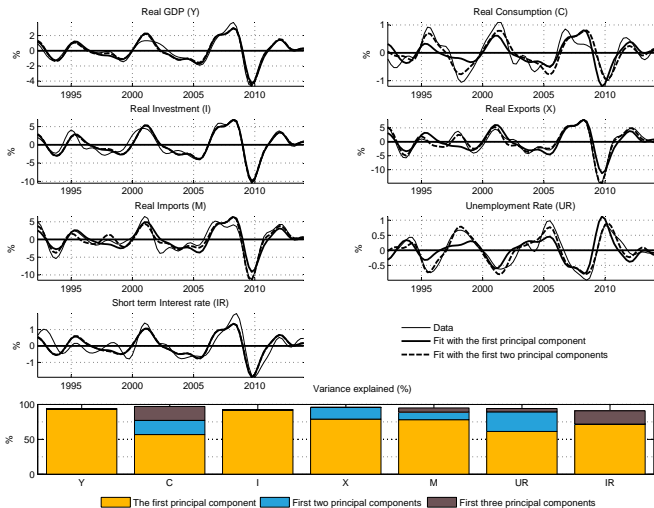
# Real variables in time domains – US cycles (band pass filter): static PCA



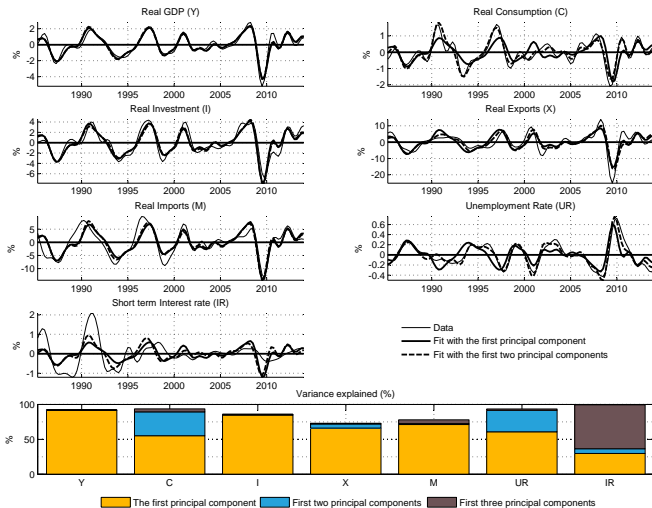
# Real variables in time domains – US cycles (HP filter): static PCA



# Real variables in time domains – German cycles (band-pass filter): static PCA



# Real variables in time domains – Japan cycles (band-pass filter): static PCA



# Real variables in time domains – Finland cycles (band-pass filter): static PCA

