

Capturing sectorial and regional cycles in Europe: Who is the Fairest of Them All?

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PROJECT "EURO4EUROPE"

Aim – to reassess business cycle synchronization (BCS) using an integrated approach.



A. Analysis of national BCS First, a univariate and multivariate analyses at the country level will be conducted using alternative identification strategies in time-frequency domain. The directions of causal relationships will be identified by phase shift.

B. Economic Integration and the Transmission of Macroeconomic Shocks. Here we will focus on transmission mechanisms on the BC. It will employ a GVAR framework to assess the transmission of macroeconomic demand and supply shocks across European countries. The comparison of shock transmission across countries within the euro area and in other world regions will also provide evidence the effects of integration on BC symmetry.

C. The impact of integration on regional BC synchronization. The third part will analyse the effect of several integration events on BCS at the regional (NUTS2 and NUTS3) level which will allow to identify the causal effects of joining EMU on BC synchronisation using various identification strategies. It will also allow for an assessment of potentially heterogeneous and non-linear treatment effects.



CONTRIBUTION AND INTRODUCTION

Research question and brief summary

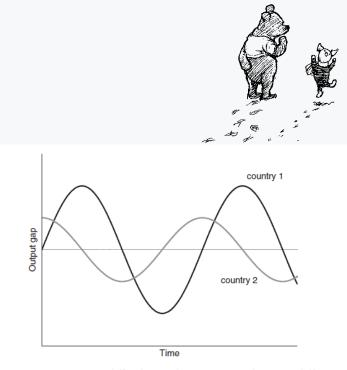


Fig. 1 Output gaps can differ due to the output gaps having a different sign or different amplitude.

Source: Mink et al. (2012)

RESEARCH QUESTION

What?/Why? And How?



WHAT?/WHY?

- Great interest in star variables (potential output, natural rate of interest, NAIRU, etc.) and in the postcrisis nature of cyclical fluctuations (see Canova, 2019).
- Estimates of cyclical components provide an important input for the conduct of monetary policy (see ECB, 2018) and fiscal policy (see EU IFIs, 2018).
- If output gaps (as BCs in the sense of Mintz (1969)) are not sufficiently coherent in the euro area, the common monetary policy will not be optimal for all countries or regions in the union (see Mink et al., 2012 Oxford Econ. Papers) and even worse in the absence of a common fiscal policy.
- Different methods to assess BCs lead to different cyclical facts.
- Many methods are available: Canova (2019) tried to compare the main ones for US BCs, Celov et al. (2018) overviewed the trend-cycle decomposition methods used within EU IFIs network.
- This paper aims to shed some light on the sectorial and regional BCs in Europe, the best method to capture them and their co-movements in a better way than via simple correlations.
- So... who is the fairest of them all? For sectors and for regions, in Europe.

RESEARCH QUESTION

What?/Why? And How?

WHAT?/WHY?

- In this paper we will FIRSTLY calculate the business cycles (BCs) at the country level for different sectors (NACE v.2) and the overall business cycle for each region (NUTS 2).
- We focus on wide range of European countries (EU28 + Norway and Switzerland). We compare euro area to non-euro area countries
- The data are annual/quarterly (max) 1975-2019.
- GVA and employment
- Different methods are applied to a) pick the "fairest of them all" among the considered methods (following criteria) and b) we will create an *ad hoc* cycle as combination of them all (PCA or average).

HOW?

We apply 6 different methodologies following the approach by Canova (2019). Namely:

- 1. Hodrick-Prescott filter (HP)
- 2. Hamilton filter (never-HP)
- 3. Beveridge-Nelson filter (BN)
- 4. Christiano-Fitzgerald filter (CF)
- 5. Trend-cycle-seasonal filter by Mohr (TCS)
- 6. Unobserved components model (UCM)

(4.-6.) are common practices applied within the ECB

(1.-6.) could be combined into the suite of models

RESEARCH QUESTION

What?/Why? And How?



WHAT?/WHY?

- THEN we will look at the synchronicity/similarity (= coherence) of:
- i) different sectorial cycles within a country;
- ii) different regional cycles within a country (if the country has more than 1 region) also compared to the aggregate country BC;
- iii) across countries for each sector w.r.t. the EU aggregate cycle.
- \rightarrow Synchronicity = cycles have the same sign
- → Similarity = cycles have same amplitudes

HOW?

We apply different methodologies following the approach by ECB (2018). Namely:

- Synchronicity index as in Comunale (2019, IJFE) within a country;

- Synchronicity and similarity (= coherence) indices a la Mink et al. (2012, Oxford Econ. Papers) or Samarina et al. (2017, JIMF) in the cross country perspective;

- Wavelets as in Kunovac et al. (2018, BuBa WP).

CONTRIBUTION

What?/Why? And How?



WHAT?/WHY?

- First paper (to the best of our knowledge) comparing different methodologies to capture BCs at regional and sectorial level at best.
- First paper to analyze fully the co-movement of cycles also w.r.t. the aggregates, with measures of coherence.

 \rightarrow Correlations do not accurately reflect to what extent cycles have the same sign and they also do not consider whether they have the same amplitude.

HOW?

The paper is structured in 2 parts:

- Fairest picking of the cycle (and pros/cons of trend-cycle decomposition methods);
- Co-movements;
- Policy recommendations, for monetary and fiscal policy.



TREND-CYCLE DECOMPOSTION

Finding Yeti





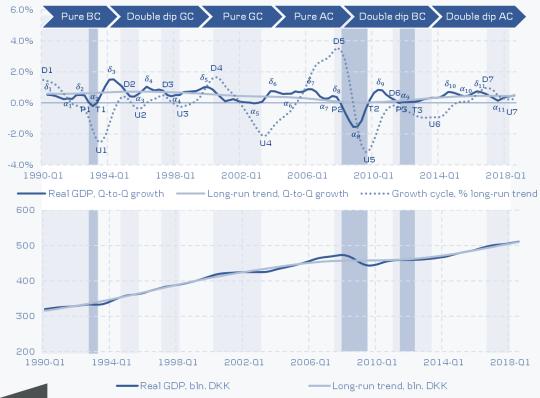


- There is no one-size-fits-all method and none of the methods takes priority other the rest in all aspects: economic and statistical soundness, transparency, stability of real time estimates, plausibility with hindsight, etc.
- It is prudent to consider various methods and assess the robustness of inferences to the chosen detrending method on a sector and region specific basis
- The credibility of the decisions gains in solidity as different measures confirm the same message ⇒ complementarity of statistical approaches achieved in the suite of models
- Long-run trends mean keeping imbalances in-balance: external, internal or financial
- Uncertainty sources: model within a method and between methods, statistical data revisions and changes in definitions, end-of-sample (real-time)



MINDING THE GAP

Business, growth and acceleration cycles in Denmark





- 1. Business or classical cycle (BC) a sequence of aperiodic, recurrent expansions and contractions in the levels of a large set of aggregate macro-variables (Burns and Mitchel 1946)
- 2. Growth cycle (GC) due to Mintz (1969) is the difference between actual realization of the variable and its long-run trend expressed as a percent of the trend, which is assumed to keep domestic and global imbalances to be in balance

3. Acceleration or growth rate cycle (AC) is a

growth rate of the dependent variable experiencing a sequence of decelerating and accelerating phases. The acceleration cycle is crucial for the short-term economic analysis not led by recessions or as an early warning system (e.g. building a heat-map).



PROSPECTING THE FUTURE

Short versus medium-to-long run view or who cares?

- In the academic literature and public discussions, economic slack is often viewed as short-run concept ignoring a bunch of external disturbances especially on the credit side
- Inflation-targeting CBs concerned with the short-term measure of economic slack
- Fiscal authorities assessing general government finances care more about sustainability, hence they rather focus on the medium to the long-term concept of fiscal space



I used to believe in forever, but forever's

too good to be true

Ο.

ACCOMMODATING UNCERTAINTY

Model, data and real-time



The growth cycle is the difference between two variables: actual and trend values

⇒ the growth cycle is surrounded by a considerable uncertainty stemming from the observed data revisions and unobserved data – long-run trend estimates

MODEL UNCERTAINTY

Within uncertainty from estimated and calibrated parameters and residuals

Between uncertainty from the range of trend-cycle decomposition methods and theories

DATA UNCERTAINTY

Statistical real-time data is not a final vintage and data definitions (capital input) can change

Keep an eye on small open catching-up economies + structural changes, tiny regions and sectors

END-OF-SAMPLE

Regulatory policy decisions require cyclical estimates in real-time

Incomplete data, misspecified models, one-sided filters ⇒ end-ofsample (forecasting) bias

FINDING YETI

Trend-cycle decomposition in the nutshell



 $y_t = y_t^* + c_t + \varepsilon_t, \quad \forall t = 1, \dots, T,$

where y_t^* is a trend, c_t is a growth cycle and ε_t irregular shocks including one-offs (additive outliers)

- Trend-cycle decomposition methods could be grouped into several overlapping categories highlighting their particular properties:
 - a) Estimation: parametric, semi-parametric and non-parametric
 - b) Data requirements: univariate and multivariate
 - c) Theoretical/empirical adequacy: *statistical*, semi-structural and structural
 - d) Linearity: *linear* and non-linear
- Objective to determine the growth cycle by isolating the patterns in duration varying from more than one year to ten or twelve (X?) years, but not divisible into shorter cycles



CAPTURING THE CYCLE

Mirror, mirror on the wall who is the fairest of them all?

HOW?

We apply 6+ different methodologies following the approach by Canova (2019) among others. Namely:

- 1. Hodrick-Prescott filter (HP)
- 2. Hamilton filter (never-HP)
- 3. Beveridge-Nelson filter (BN)
- 4. Christiano-Fitzgerald filter (CF)
- 5. Trend-cycle-seasonal filter by Mohr (TCS)
- 6. Unobserved components model (UCM)

Uncertainty table for a given year tModel, j

		1	2		J	Mean	Std.dev.
Alternative inputs, f	1	0G _{1,1}	0G _{1,2}		0G _{1,J}	$\overline{OG}_{1,\cdot}$	$\sigma(OG_{1,\cdot})$
	2	0G _{2,1}	0G _{2,2}		0G _{2,J}	$\overline{OG}_{2,\cdot}$	$\sigma(OG_{2,\cdot})$
	F	$OG_{F,1}$	$OG_{F,2}$		$OG_{F,J}$	$\overline{OG}_{F,\cdot}$	$\sigma(OG_{F,\cdot})$
	Mean	$\overline{OG}_{\cdot,1}$	$\overline{OG}_{\cdot,2}$	•••	$\overline{OG}_{\cdot,J}$	$\overline{OG}_{\cdot,\cdot}$	
	Std.dev.	$\sigma(OG_{\cdot,1})$	$\sigma(OG_{\cdot,2})$	•••	$\sigma(OG_{\cdot,J})$		$\sigma(OG_{\cdot,\cdot})$

(4.-6.) are common practices applied within the ECB among others (Mohr (2005), GEM ECB (2018))

(1.-6.) could be combined into the suite of models, where mixed OG estimate is a statistic: arithmetic mean, weighted average, a robust to overuse of a particular method mid-range





HODRICK-PRESCOTT FILTER

General formulation and state-space representation

Rests on two assumptions:

- 1. The output gap is not too big
- 2. The potential output is not too volatile

 $\min_{\{y_t^*\}_{t=1}^T} \underbrace{\sum_{t=1}^T (y_t - y_t^*)^2}_{\text{goodness-of-fit}} + \underbrace{\lambda \sum_{t=2}^{T-1} [(y_{t+1}^* - y_t^*) - (y_t^* - y_{t-1}^*)]^2}_{\text{degrees-of-smoothness}}, \underbrace{\lambda = \frac{\sigma_1^2}{\sigma_2^2} > 0}_{\text{penalty}}$

- A particular case of Butterworth family of filters and unobserved components models
- Simple and tractable, easy to program in MS Excel
- Arbitrary choice of the penalty λ





State-space representation:

- Signal: $y_t y_t^* c_t = 0$,State: $y_{t+1}^* = 2y_t^* y_{t-1}^* + \varepsilon_{2,t}, \varepsilon_{2,t} \sim NID(0, \sigma_1^2/\lambda)$,State: $c_t = \varepsilon_{1,t}, \varepsilon_{1,t} \sim NID(0, \sigma_1^2)$.Implicit assumptions and judgements:
- Trend is the second order random walk
- There is no irregular shocks $arepsilon_t$
- $\varepsilon_{1,t}$ is defined as a zero-mean WN process
- Shocks to demand $\varepsilon_{1,t}$ and to supply $\varepsilon_{2,t}$ are assumed to be uncorrelated

Criticism of the method led to never-HP proposal by Hamilton (2018) – TBA

BEVERIDGE-NELSON DECOMPOSITION

Unjustly forgotten parametric approach

- The actual output growth is a stationary ARIMA(p, 1, q) process: $a(L)\Delta y_t = \mu + \Delta f_t + b(L)\varepsilon_t$, $\varepsilon_t \sim NID(0, \sigma^2)$
- The trend mean growth rate adjusted limiting forecast:

$$y_t^* = \lim_{h \to \infty} [E(y_{t+h} | \Omega_t) - h\tau]$$

• Trend and cycle are affected by a common shock, negative correlated:

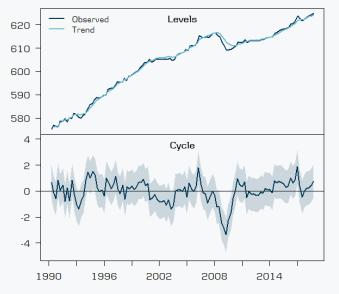
$$y_t = \underbrace{y_0 + \mu \cdot t + f_t}_{\text{deterministic trend}} + \underbrace{c(1)\sum_{j=1}^t \varepsilon_j}_{\text{stochastic trend}} + \underbrace{c^*(L)\varepsilon_t}_{\text{cycle}}, \varepsilon_t \sim NID(0, \sigma^2)$$

- Unrestricted estimation for any AR(p) model implies signal-to-noise ratio $\hat{\delta} = 1/a(1) > 1 \Rightarrow$ trend more volatile than GDP, while restricted estimation gives for AR(12) in DK case gives $\hat{\delta} \approx 0.16$
- The state-space representation of BN filter ~ univariate UC model









PASSING THROUGH THE BAND

Non-parametric approximation of ideal filters





- The ideal band-pass (IBP) filter is the difference of two ideal low-pas filters $h_i^{bp}=h_i^1-h_i^2$
- The ideal low-pass filter is an infinite dimensional linear time invariant filter (Koopmans (1974)):

$$y_t^f = \sum_{i=-\infty}^{\infty} h_i^f y_{t-i}, \ \sum_{i=-\infty}^{\infty} |h_i^f| < \infty, \ h_0^f = \frac{\omega_f}{\pi}, h_i^f = \sin(i\omega_f)/i\pi, f \in \{1, 2\}$$

- Infinitely many parameters could not be estimated within a finite sample finite sample approximations are used
- An asymmetric time-varying Christiano-Fitzgerald (CF) filter (also known as a random walk filter) which solves the following optimization problem:

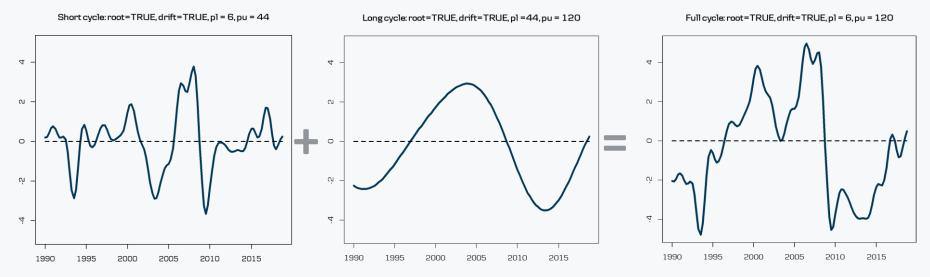
$$\hat{y}_{t}^{CF} = \sum_{i=-n_{t,1}}^{n_{t,2}} \hat{h}_{t,i}^{CF} y_{t-i}, \quad \min_{\{\hat{h}_{j}^{CF}\}_{j=-n_{t,1}}^{n_{t,2}}} \frac{1}{2\pi} \int_{-\pi}^{\pi} \left(h(\omega) - \hat{h}^{CF}(\omega)\right)^{2} f_{y}(\omega) d\omega,$$

where $f_y(\omega)$ is the spectral density of the actual data y_t – the first order with probably deterministic drift and MA(q) errors

The approximation window depends on the choice of time-varying $n_{t,1}$ and $n_{t,2}$

Denmark's real GDP: CF filter with short, long and full band widths





- Applicable in real-time at the cost of phase shifts, exclude noise produce smoother cycles
- The estimated cycles change with extended sample introducing end-points problem
- Used for peak-trough detection, short-long cycles relative contribution to the full cycle analysis



UNIVARIATE UC AND TCS FILTERS

A generic state-space representation by Harvey (1985) and Mohr (2005)

Signal: $y_t - y_t^* - c_t = \varepsilon_t, \, \varepsilon_t \sim NID(0, \sigma^2),$ $y_t^* = y_{t-1}^* + \mu + \varepsilon_{2t}, \varepsilon_{2t} \sim NID(0, \sigma_2^2),$ State: c_t is stationary and ergodic, $\varepsilon_{1,t} \sim NID(0, \sigma_1^2)$. State:

General model of stochastic trend:

 $\Delta^{d-1}(\Delta y_t^* - \mu) = \varepsilon_{2,t}, \, \varepsilon_{2,t} \sim NID(0, \sigma_2^2).$ State:

- d = 1 with $\mu = 0$ is exponential smoothing ٠
- d = 2 with $\mu = 0$ is second order stochastic trend (HP) •
- d > 2 corresponds to Butterworth class of filters •
- If μ_t is time varying (e.g., AR(1)) we can get U shaped ٠ patterns

 $\mu_t = \rho_\mu \mu_{t-1} + \varepsilon_{\mu,t}, \, \varepsilon_{\mu,t} \sim NID(0, \sigma_\mu^2), \, \rho_\mu \in [0, 1]$ State:

General model of stochastic cycle:

 $(1 - 2\rho\cos(\omega_c)L + \rho^2 L^2)^c c_t =$ = $(1 - \rho\cos(\omega_c)L)^c \varepsilon_{1,t}, \varepsilon_{1,t} \sim NID(0, \sigma_1^2).$ State:

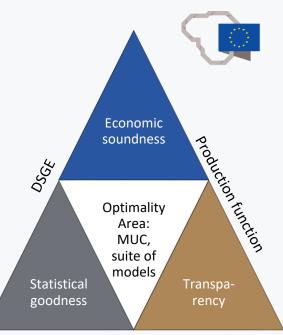
- ARMA(2c, c) representation of the cycle •
- $\rho \in (0, 1)$ determines a damping factor ~ 1 •
- ω_c is a frequency in radians $\omega_c = 2\pi/T_c$
- We can assume or estimate cycle length T_c
- Conventional restriction of order c = 1•
- ٠ Often restricted AR(2) is estimated
- TC filter was translated from Matlab to R •



ASSESSING PERFORMANCE

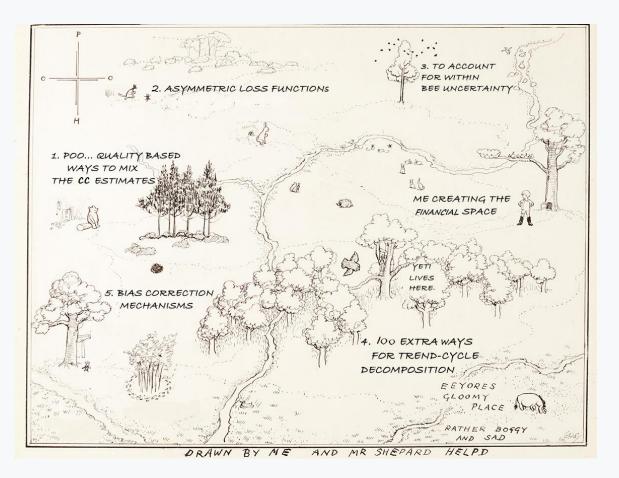
Stability and plausibility, fit-theory-transparency trilemma

- Long-run trend is unobserved ⇒ there is no benchmark data
- Necessary conditions of fit-theory-transparency trilemma →
- A sufficient condition for the final estimate of the cycle is given by the smell test or a plausibility with a hindsight done by IFIs
- Trade-offs every cycle is different keeping analysis simple and with a clear narrative is problematic
- Stability based on:
 - a. Mean Absolute Revision
 - b. Maximal Revision
 - c. the number of sign changes observed with focus on the end-of-sample
- Comparisons make sense within the same class of methods (high vs low-pass filters)



Univariate filters





THANK YOU FOR YOUR ATTENTION!

GRAZIE! AČIŪ! DANKE!

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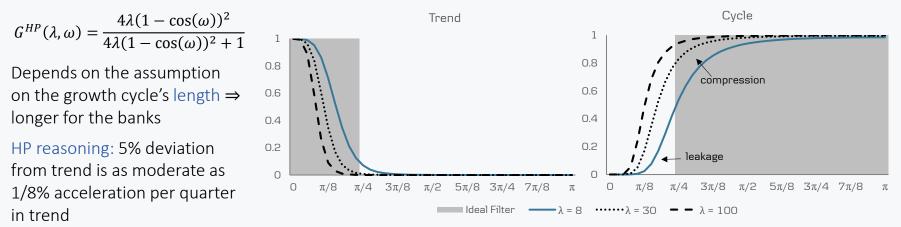
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PENALIZING HODRICK-PRESCOTT

The value of penalty λ

The frequency response (gain) function:



 $\lambda = \sigma_1^2/\sigma_2^2 = 5^2/(1/8)^2 = 1600$ for quarterly data and 100 for annual; from frequency-domain: Ravn and Uhlig (2002) 6.25–8.25; Pedersen (2002) ~4, Bouthevillain, et al. (2001) ~30

Distortions: compression when a part of high frequency goes to the trend, and leakage when a part of low-frequency data goes to the cycle – trade-off is to balance the distortions, weights are uncertain