Business cycles in the EU: an ultimate, comprehensive comparison across methods

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The conclusions expressed in the presentation are those of the authors and do not necessarily represent the official views of the Bank of Lithuania (LB), the ECB , the ESCB or any other institutions the authors are affiliated with.

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PROJECT "EURO4EUROPE"

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

Study the impact of European integration on business cycle asymmetries (BCA) and provide empirical evidence on the long-standing dispute among proponents of endogenous optimal currency area (OCA) theories, on whether integration increases BCA (as argued by Frankel and Rose, 1998) or decreases it (Krugman, 1993).

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.

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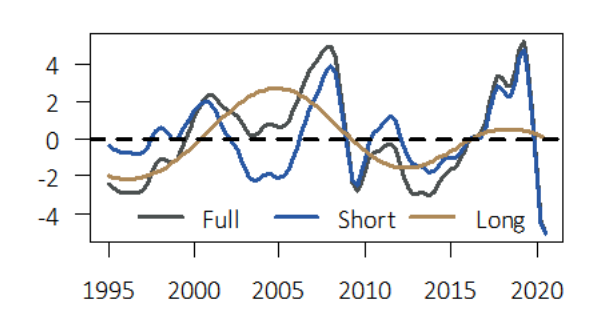
C. **The impact of integration on regional BC synchronization.** The third part will analyse the effect of several integration events on **BCS at the regional** (**NUTS2** and NUTS3) level which will allow to identify the causal effects of joining EMU on BC synchronisation using various identification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

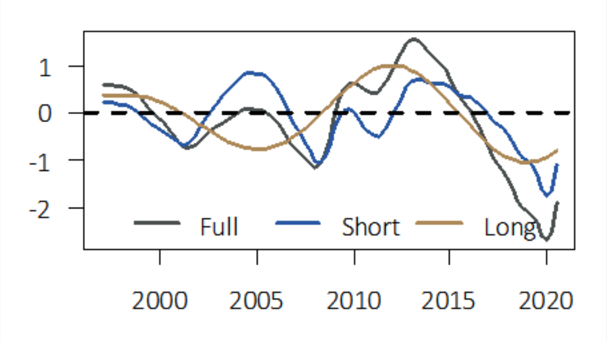
CONTRIBUTION AND INTRODUCTION

Research question and brief summary

EA19, real GDP, CF filter: relative importance, short 59.9%, long 40.1%



EA unemployment rate, CF filter: relative importance, short 48.7%, long 51.3%



RESEARCH QUESTION

What?/Why? And How?

WHAT?/WHY?

- Great interest in star variables (potential output, natural rate of interest, NAIRU, etc.) and in the post-crisis nature of cyclical fluctuations (see Canova, 2020).
- Estimates of cyclical components provide an important input for the conduct of monetary policy (see ECB, 2018) and fiscal policy (see EU IFIs, 2018). **Very important also after COVID19 outbreak, for policy purposes!**
- 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 (2020) tried to compare the main ones for US BCs, Celov et al. (2018) overviewed the trend-cycle decomposition methods used within EU IFIs network.
- The original idea presented in 2019-12-17 was too broad and splits into 2 papers:
  1. “Business cycles in the EU: an ultimate, comprehensive comparison of across methods” ← TODAY
  2. “Decomposing business cycles in a regional and sectoral perspective: a study on EU”

RESEARCH QUESTION

What?/Why? And How?

WHAT?/WHY?

- In this paper we FIRSTLY conduct a Monte Carlo experiment using a broad spectrum of univariate trend-cycle decomposition methods initially done and documented at Danske bank
- Then we calculate the BCs in the growth cycles sense for real GDP and unemployment data
- We focus on **EU27 (+ other countries in Europe)**. We compare euro area to non-euro area countries.
- **Data: 1995Q1 to 2020Q3 for unemployment and GDP to 2020Q4.**
- Compare EU results with Canova findings (methods) and ECB (results)

HOW?

We apply 10 different methodologies + alternatives, when parameters are uncertain. All inspired by Celov et al. (2018) and Canova (2020), namely:

1. Polynomial trend (PT)
2. First differences (FD)
3. Hodrick-Prescott filters (HP)
4. Butterworth-Whittaker filter (BWF)
5. Hamilton filter (HF)
6. Beveridge-Nelson filter (BN)
7. Christiano-Fitzgerald filter (CF)
8. Wavelet (WAVE)
9. Trend-cycle-seasonal filter by Mohr (TCS)
10. Unobserved components model (UCM)
11. Suite of models (Suite)

MONTE CARLO SIMULATION

Observing the cycles

The Monte Carlo Method allows predicting performance without conducting hundreds of real experiments or building thousands of samples. Having time constraint – this is a powerful argument for giving the Monte Carlo method a try

SETTING THE STAGE:

The model

Monte-Carlo simulations aim to justify our decisions on:

1. The structure of the suite of trend-cycle decomposition methods used to retrieve the cycles from the data
2. The approach to evaluate the upper limit for the length of the stochastic cycle

Simulation design (Rünstler, G., & Vlekke, M. (2016)):

Signal: $y_t - y_t^* - \alpha \cdot C_t = \nu_t, \nu_t \sim NID(0, \sigma^2),$

A. Stochastic trend:

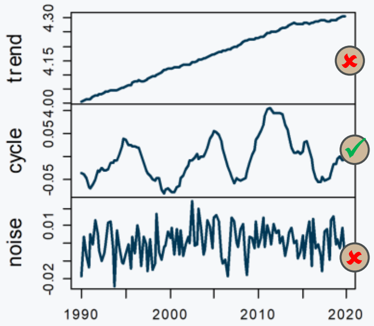
State: $y_t^* = y_{t-1}^* + \mu_{t-1} + \varepsilon_{l,t}, \varepsilon_{l,t} \sim NID(0, \sigma_l^2),$

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

B. Stochastic cycle:

State: $C_t = c_{t-1} + \rho_c \cdot C_{t-1},$

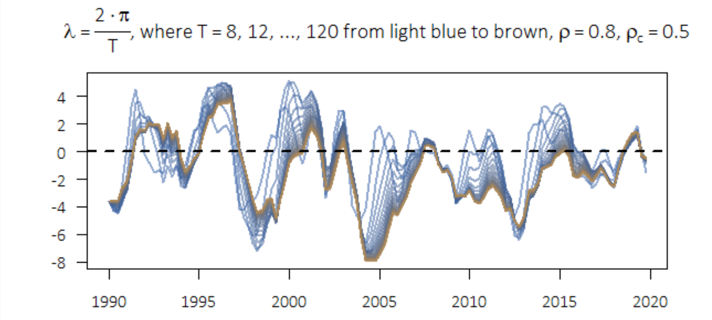
State: $(1 - 2 \cdot \rho \cdot \cos(\lambda) L + \rho^2 L^2) c_t = (1 - \rho \cos(\lambda) L) \varepsilon_{1,t}, \varepsilon_{1,t} \sim NID(0, 1),$



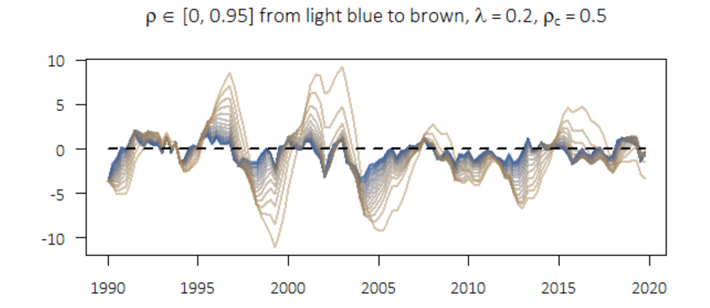
Monte Carlo randomization in $\nu_t, \varepsilon_{l,t}, \varepsilon_{\mu,t}$ and $\varepsilon_{1,t}$ as mutually and serially uncorrelated normally distributed zero-mean random variables with the chosen variances, 500 simulations

SETTING THE STAGE:

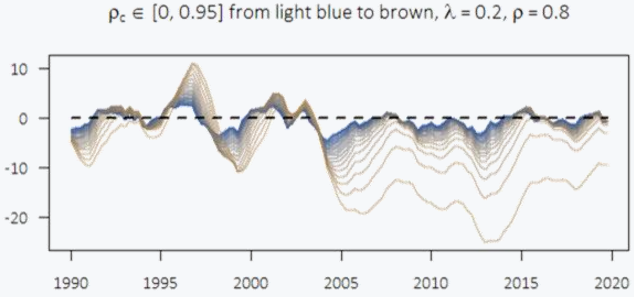
The impact of stochastic cycle parameters on the form of the cycle



Increasing the length of the cycle makes waves to last longer. Adding an extra year to the long-wave makes smaller change than to the shorter cycles → the impact is proportional to the relative increase in length



The inner dampening factor proportionally changes the amplitude of the generated cycle, keeping the placement of local peaks and troughs almost unchanged. High values of ρ are likely for medium and long cycles.



The second dampening parameter adds a very long wave to the original cycle and expands the amplitude of the cycle, resembling the behaviour of the financial data. High values of ρ_c are unlikely though for the most of the macroeconomic data.

SETTING THE STAGE

Setting parameters

Monte-Carlo simulation experiments uses the **5,000** independent replicas generated using the structural model with parameters:

Scenario A: $\alpha = 0.008, \sigma = 0.0001, \sigma_l = 0.00004, \sigma_\mu = 0.0002, \rho_c = 0.55, \rho = 0.7, y_0^* = 14.5,$
$$\mu_0 = 0.003, C_0 = c_0 = -2, \lambda = 2\pi/29$$

Scenario B: $\alpha = 0.004, \sigma = 0.00001, \sigma_l = 0.000002, \sigma_\mu = 0.000002, \rho_c = 0.8, \rho = 0.8, y_0^* = 6.8,$
$$\mu_0 = -0.0002, C_0 = c_0 = 1, \lambda = 2\pi/46$$

Why such parameters?

- Inspired by the behaviour of EA real GDP and unemployment, estimated applying the Bayes MCMC approach, using 22,228 simulations with 2,020 used as a burn-in.
- All disturbances are independent normally distributed random variables.
- Time series are 100 quarters long, 25 years of data for the EU countries
- Data simulated without structural breaks in the trend but starting the cycle at -2% recession (1% gap for unemployment) to reflect the end-of-sample problem
- The variance of slope follows the double exponential smoothing restriction: $\sigma_\mu = \sigma_l^2/2\sigma$, which results in smoother trends consistently with our prior beliefs

WHAT IS IN THE MENU?

From simple to more sophisticated dishes

The simulation aims to analyse the ability of different trend-cycle decomposition methods to find the observed simulated cycle with structural properties similar to actual macroeconomic data guiding the composition of the suite of models

Notation	Description	Trend	Cycle
A. Polynomial trends			
POLY1	Linear trend, optimal HP noise reduction	Deterministic, allows structural breaks	Smoothed residual
POLY2	Quadratic trend, optimal HP noise reduction	Deterministic, allows structural breaks	Smoothed residual
POLY3	Cubic trend, optimal HP noise reduction	Deterministic, allows structural breaks	Smoothed residual
B. First differences			
SFD	First quarterly difference	Random walk	Acceleration
AFD	First annual (4 quarters) difference	Random walk	Acceleration
LFD	First 4 years (16 quarters) difference	Random walk	Acceleration
C. One-sided filters			
BNF	Beveridge Nelson filter, rolling window mean adjustment (40 quarters window), p = 12	Deterministic, random walk	Beveridge-Nelson decomposition
HPnever	Hamilton filter, h = 8, p =4	I(1) with drift	Smoothed residual
HPnever_a	Hamilton filter, h =16, p = 4	I(1) with drift	Smoothed residual
D. Asymmetric two-sided filters			
CFs	Christiano-Fitzgerald, short, 6-44 quarters	IMA(1, q) with drift	Band-pass
CFl	Christiano-Fitzgerald, long, 44-120 quarters	IMA(1, q) with drift	Band-pass
CFf	Christiano-Fitzgerald, full, 6-120 quarters	IMA(1, q) with drift	Band-pass
CFo	Christiano-Fitzgerald, optimal, 6-implied upper limit	IMA(1, q) with drift	Band-pass

WHAT IS IN THE MENU?

Bring me more food…

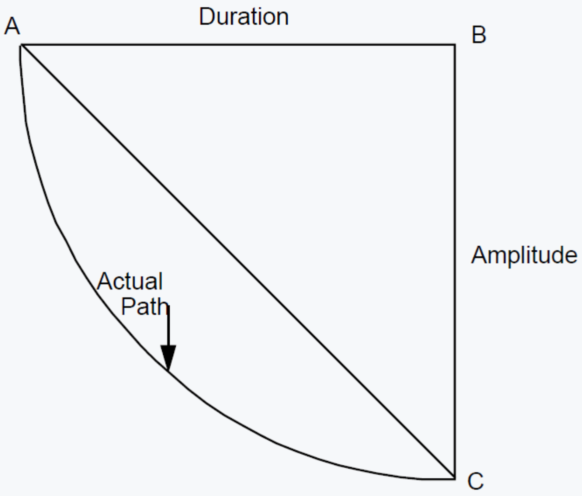
Notation	Description	Trend	Cycle
D. Asymmetric two-sided filters			
BWF	3rd order Butterworth-Whittaker filter, optimal HP noise reduction	I(3)	Smoothed residual
HPo	Hodrick Prescott, optimal penalty	I(2)	Smoothed residual
HPof	Hodrick Prescott, optimal penalty for the fixed 120Q upper limit	I(2)	Smoothed residual
HPob	Hodrick Prescott, optimal penalty boosted	I(2)	Smoothed residual
WAVE	Discrete wavelet transformation	I(1) with drift	Band-pass
E. Structural models			
TCS	Trend-cycle-seasonal filter	I(d) with drift, allows structural breaks	Generalized stochastic cycle
TCSf	Trend-cycle-seasonal filter, optimized for the fixed 120Q upper limit	I(d) with drift, allows structural breaks	Generalized stochastic cycle
UCM	Unobserved components model (1)-(5), maximum likelihood estimated parameters	Local linear trend	Doubly persistent stochastic cycle
F. Suite of models			
SUITEs	Suite of CFo, HPo, TCS	-	Mid-range statistic of smooth cycles
SUITEsa	Suite of CFf, HPo, TCS	-	
SUITEsf	Suite of CFf, HPof, TCSf	-	
SUITEsfa	Suite of CFf, HPof, TCSf, POLY2	-	
SUITEf	Suite of A, C, D, E models, excluding CFs, CFl, HPof, TCSf	-	

BEAUTY CONTEST CRITERIA

How to pick the fairest of them all?

The results have several statistics averaged over the simulated cases and used for exploratory data analysis:

1. The correlation coefficient between the simulated observed cycle and the cycle extracted by the TCD methods.
   Higher values → good, small (below 0.5) or negative → bad
2. BBQ dating algorithm. The outcomes of setting the dates and structuring the expansion and contraction phases of the cycle:
   a) Triangular dissection of expansion and contraction phases to get the average amplitude and average duration of the phases
   b) Cycle length is the sum of average durations of the phases
   c) Overlap is the average alignment of the phase dummies of the estimated cycles overlapping with the similar indicator functions of the simulated cycle.
   Smaller than 0.5 → bad
   d) Dissimilarity measure computes the (Euclidean) distance between the simulated cycle features a)-c) and the same features of the cycles obtained by trend-cycle decomposition methods.
   Closer to zero → good
3. End-of-sample points precision measured as RMSE
4. NA column denotes the number of observations lost at the beginning of the sample applying the method → unwanted feature, the best is 0



SIMULATED TIME SERIES OF REAL GDP RELATED SCENARIO A

Method	Corre-lation	Amplitude		Duration		Cycle length	Overlap	Dissi-milarity	Ends of sample		NA
		Exp.	Contr.	Exp.	Contr.				m0	mT	
Cycle	1.00	5.09	4.88	9.64	9.46	19.10	1.00	0.00	0.00	0.00	0.00
POLY1	0.94	3.97	3.91	8.67	8.71	17.38	0.89	4.50	1.04	1.03	0.00
POLY2	0.90	3.94	3.88	8.63	8.68	17.31	0.89	4.57	1.62	1.44	0.00
POLY3	0.86	3.85	3.88	8.52	8.65	17.16	0.88	4.70	2.21	1.79	0.00
SFD	0.18	1.45	1.48	7.58	7.71	15.29	0.54	8.28	2.89	1.89	1.00
AFD	0.57	5.55	5.68	7.28	7.38	14.66	0.67	6.91	3.82	2.36	4.00
LFD	0.70	5.96	6.19	9.12	9.31	18.43	0.60	6.78	7.71	5.43	16.00
BNF	0.55	2.38	2.42	7.66	7.73	15.39	0.70	7.20	2.50	1.64	1.00
HPnever	0.73	5.40	5.18	9.48	9.15	18.63	0.70	5.12	1.39	2.13	11.00
HPnever_a	0.73	4.93	4.60	9.75	9.24	18.99	0.61	6.56	1.52	2.15	19.00
CFf	0.90	4.15	4.15	8.23	8.33	16.55	0.85	5.03	1.57	1.39	0.00
CFo	0.82	3.99	3.99	8.02	8.06	16.08	0.83	5.42	1.89	1.55	0.00
CFs	0.83	4.01	4.00	8.05	8.07	16.12	0.84	5.41	1.86	1.54	0.00
CFl	0.40	1.74	1.90	27.65	29.34	55.72	0.59	45.07	2.21	1.93	0.00
HPo	0.86	3.57	3.57	8.21	8.29	16.50	0.87	5.21	2.12	1.57	0.00
HPob	0.85	3.52	3.52	8.13	8.20	16.33	0.86	5.35	2.18	1.62	0.00
HPof	0.94	3.94	3.89	8.64	8.67	17.31	0.89	4.53	1.18	1.07	0.00
HPs	0.84	3.43	3.44	8.02	8.05	16.07	0.86	5.55	2.44	1.99	0.00
HPl	0.92	3.88	3.84	8.56	8.61	17.17	0.89	4.63	2.44	1.98	0.00
BWF	0.84	3.67	3.69	8.27	8.35	16.62	0.86	5.07	2.49	1.84	0.00
WAVE	0.86	3.48	3.67	8.07	8.53	16.60	0.85	5.35	1.55	1.66	0.00
TCS	0.79	3.31	3.26	8.08	8.06	16.15	0.84	5.85	1.71	1.52	0.00
TCSf	0.83	3.44	3.37	8.57	8.51	17.08	0.86	5.37	1.54	1.44	0.00
UCM	0.87	4.44	4.62	9.04	9.44	18.48	0.93	2.93	2.45	1.33	0.00
SUITEs	0.84	3.53	3.51	8.00	8.00	16.00	0.85	5.60	1.84	1.47	0.00
SUITEsa	0.89	3.61	3.60	8.06	8.09	16.15	0.86	5.42	1.71	1.37	0.00
SUITEf	0.87	3.70	3.68	8.66	8.69	17.35	0.85	5.11	1.63	1.29	0.00
SUITEsf	0.92	3.72	3.68	8.35	8.39	16.74	0.87	5.05	1.34	1.18	0.00
SUITEsfa	0.91	3.71	3.67	8.38	8.40	16.78	0.87	5.00	1.40	1.21	0.00

SIMULATED TIME SERIES OF U RELATED SCENARIO B

Method	Corre-lation	Amplitude		Duration		Cycle length	Overlap	Dissi-milarity	Ends of sample		NA
		Exp.	Contr.	Exp.	Contr.				m0	mT	
Cycle	1.00	4.05	4.21	10.81	11.08	21.89	1.00	0.00	0.00	0.00	0.00
POLY1	0.93	3.69	3.70	10.53	10.54	21.07	0.93	3.75	1.50	1.58	0.00
POLY2	0.87	3.63	3.63	10.43	10.40	20.84	0.92	4.15	1.90	2.19	0.00
POLY3	0.81	3.56	3.55	10.31	10.30	20.61	0.90	4.49	2.07	2.63	0.00
SFD	0.15	1.06	1.06	8.35	8.24	16.59	0.54	9.13	0.77	2.25	1.00
AFD	0.44	3.95	3.90	8.25	8.14	16.39	0.65	7.99	0.83	2.28	4.00
LFD	0.75	6.34	6.17	12.00	11.79	23.80	0.64	8.53	1.09	2.35	16.00
BNF	0.50	1.80	1.79	8.96	8.94	17.90	0.74	7.55	0.89	2.11	1.00
HPnever	0.87	3.37	3.59	8.51	8.88	17.39	0.72	7.24	1.22	1.59	11.00
HPnever_a	0.90	3.27	3.62	9.66	10.39	20.05	0.68	6.58	1.45	1.51	19.00
CFf	0.90	3.70	3.75	10.10	10.23	20.33	0.90	4.52	1.17	1.87	0.00
CFo	0.80	3.54	3.56	9.81	9.89	19.70	0.88	5.07	1.19	2.01	0.00
CFs	0.73	3.34	3.35	9.49	9.50	18.99	0.86	5.71	1.18	2.09	0.00
CFl	0.59	2.66	2.64	28.44	29.00	56.98	0.62	43.16	0.86	2.06	0.00
HPo	0.85	3.40	3.40	10.07	10.04	20.11	0.91	4.50	1.56	2.06	0.00
HPob	0.79	3.08	3.08	9.50	9.47	18.97	0.88	5.49	1.61	2.22	0.00
HPof	0.92	3.65	3.65	10.47	10.47	20.94	0.93	3.80	1.46	1.62	0.00
HPs	0.75	2.78	2.76	9.11	9.09	18.20	0.87	6.20	0.72	2.28	0.00
HPl	0.89	3.52	3.51	10.23	10.23	20.46	0.92	4.21	0.72	2.27	0.00
BWF	0.77	3.25	3.23	9.76	9.73	19.49	0.88	5.05	1.71	2.54	0.00
WAVE	0.94	3.52	3.54	10.27	10.29	20.56	0.90	4.32	1.28	1.50	0.00
TCS	0.75	3.11	3.14	10.67	10.70	21.38	0.88	5.48	1.45	1.94	0.00
TCSf	0.82	3.27	3.33	11.21	11.33	22.54	0.90	5.51	1.46	1.86	0.00
UCM	0.96	4.12	4.07	10.98	10.83	21.81	0.98	1.34	0.72	1.49	0.00
SUITEs	0.82	3.28	3.30	10.13	10.18	20.31	0.89	4.83	1.32	1.93	0.00
SUITEsa	0.88	3.33	3.36	10.16	10.24	20.39	0.90	4.66	1.23	1.83	0.00
SUITEf	0.93	2.95	3.00	9.73	9.83	19.56	0.89	5.09	1.22	1.61	0.00
SUITEsf	0.90	3.44	3.48	10.50	10.59	21.09	0.92	4.35	1.25	1.66	0.00
SUITEsfa	0.90	3.45	3.48	10.52	10.59	21.11	0.92	4.34	1.40	1.77	0.00

TAKEAWAYS

Five conclusions emerge from the MC beauty-contest of trend-cycle decomposition methods:

1. The Christiano-Fitzgerald, Hodrick-Prescott and trend-cycle-seasonal filters perform better with the upper limit fixed to 100 quarters for cycles longer than five years. The suite of models based on these three approaches is judged the fairest in MC beauty contest.
2. The inclusion of quadratic polynomial only marginally improves the accuracy of the suite of models in the middle of the sample, yet at the cost of poor fits at the ends-of sample. In line with Canova (2020), it is a well performing method though. May be considered for the inclusion as the improvement region fits the purpose of, for example, wavelet analysis application.
3. The suite of models is stable and robust to the inclusion of weaker performing methods into the suite at the level of point estimates but at the cost of increased uncertainty.
4. Boosted Hodrick-Prescott filter does not improve the accuracy of the Hodrick-Prescott filter with the optimal penalty and tends to select shorter cycles than are simulated → suggest starting from larger cut-off frequency.
5. The acceleration cycles and one-sided filters have the worst accuracy and lose the observations at the beginning of the sample hence do not fit the purpose of the long historical BCs data assessment to be used for the application of wavelet analysis methods.

APPLICATION TO EU/EA DATA

Is COVID-19 wagging the cat’s tail?

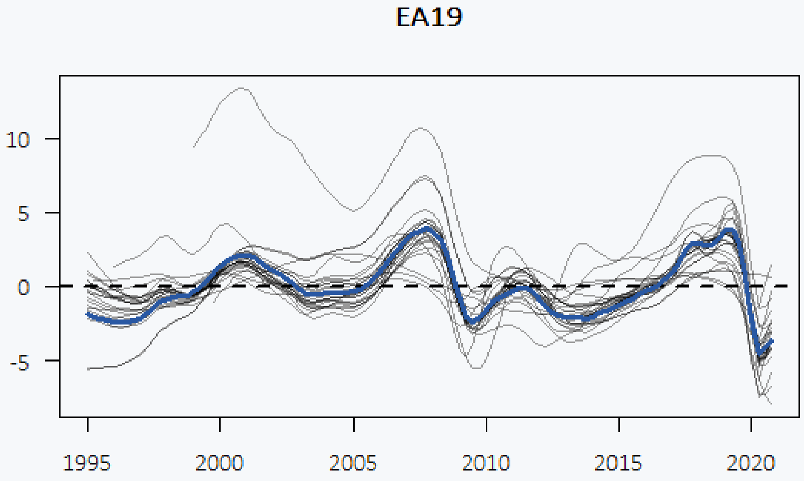
REAL GDP AND UNEMPLOYMENT

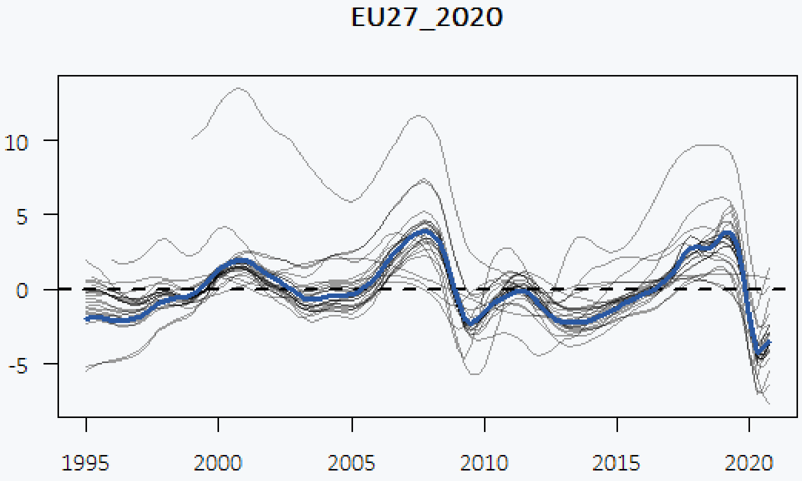
The setup

- Eurostat quarterly seasonally and calendar adjusted data for Real GDP and Unemployment are used – 1995Q1 to 2020Q3 for unemployment and to 2020Q4 for real GDP.
- 28 different estimates for each geographic location are produced
- The highlighted method is the MC simulations suggested suite of 3 models' approach (SUITEsf) = band-pass full Christiano-Fitzgerald with 6-100 quarters (CFf), the HP filter with the optimal penalty for the fixed 100 quarters upper limit (HPof), and the stochastic cycle trend-cycle-seasonal filter, optimized for the fixed 100 quarters upper limit (TCSf).
- The highlited method is the reference cycle.
- We apply criteria as in MC simulation through which we assess the validity of one possible cycle over the reference one.
- The correlation coefficient between the simulated observed cycle and the reference cycle, and the overlap of expansion and contraction phases with high values are preferred.
- We look at the overlap as the average alignment of the phase dummies of the estimated cycles overlapping with the similar indicator functions of the simulated cycle. Higher values than 0.5 are positive.
- And lastly, we assess the dissimilarity measure that computes the (Euclidean) distance between the simulated cycle and the same features of the cycles. The closest to zero are the better.

REAL GDP

In total: EA19 vs post-Brexit EU





COMPARISON – REAL GDP

Comparison of trend-cycle decomposition methods: **Business cycle for the EURO AREA**

WHERE TO LOOK:

- The correlation coefficient between the reference suite of 3 models cycle and the cycle extracted by other TCD methods. Higher values → good
- Overlap is the average alignment of the phase dummies of the estimated cycles overlapping with the similar indicator functions of the simulated cycle. Smaller than 0.5 → bad
- Dissimilarity measure computes the (Euclidean) distance between the simulated cycle features a)-c) and the same features of the cycles obtained by trend-cycle decomposition methods. Closer to zero → good
- End-of-sample values compared to reference cycle end-of-sample values in RMSE sense. Closer to zero → good

Method	Corre-lation	Amplitude		Duration		Cycle length	Over-lap	Dissi-milarity	Ends of sample		NA
		Exp.	Contr.	Exp.	Contr.				m0	mT	
SUITEsf	1.00	4.31	4.84	16.75	7.50	24.25	1.00	0.00	0.00	0.00	0.00
POLY1	0.79	3.61	4.13	15.00	8.67	23.67	0.87	2.41	-3.68	-3.09	0.00
POLY2	0.93	4.64	4.91	16.00	7.50	23.50	0.93	1.11	1.53	2.01	0.00
POLY3	0.88	4.13	5.03	14.00	7.50	21.50	0.86	3.90	4.21	-0.49	0.00
SFD	0.09	0.95	1.27	11.75	8.60	20.35	0.58	8.10	2.45	5.14	1.00
AFD	0.54	4.11	5.47	11.00	9.00	20.00	0.69	7.34	3.77	-2.14	4.00
LFD	0.77	5.83	8.08	10.00	12.00	22.00	0.56	9.16	9.81	2.86	16.00
BNF	0.37	1.52	2.19	10.80	8.60	19.40	0.69	8.66	2.00	3.33	1.00
HPnever	0.85	5.95	5.15	14.67	8.67	23.33	0.76	3.06	-0.28	-1.07	11.00
HPnever_a	0.85	5.47	3.82	14.00	10.00	24.00	0.63	4.05	-1.93	1.24	19.00
CFf	0.98	5.20	4.24	16.25	8.33	24.58	0.94	1.49	0.11	0.61	0.00
CFo	0.93	4.80	4.27	16.00	8.67	24.67	0.93	1.63	1.66	0.08	0.00
CFs	0.87	4.75	4.52	16.00	8.67	24.67	0.93	1.55	1.52	-0.01	0.00
CFl	0.51	3.32	4.04	30.00	30.00	60.00	0.59	44.29	0.48	4.34	0.00
HPo	0.95	4.03	4.90	16.00	7.50	23.50	0.93	1.10	2.29	-0.07	0.00
HPob	0.95	4.03	4.90	16.00	7.50	23.50	0.93	1.10	2.29	-0.07	0.00
HPof	0.96	4.47	5.04	16.50	7.50	24.00	0.95	0.44	-0.30	-0.61	0.00
HPs	0.88	3.45	4.26	14.00	9.25	23.25	0.86	3.57	2.75	0.84	0.00
HPl	0.98	4.34	5.04	16.00	7.50	23.50	0.93	1.08	0.97	-0.07	0.00
BWF	0.87	3.67	4.43	15.50	7.75	23.25	0.91	1.79	2.94	1.35	0.00
WAVE	0.79	3.87	4.28	14.67	8.67	23.33	0.86	2.66	-3.63	-4.26	0.00
TCS	0.82	3.06	4.47	12.25	11.00	23.25	0.83	5.94	1.89	-0.47	0.00
TCSf	0.94	3.46	4.22	15.00	9.25	24.25	0.89	2.69	0.30	0.60	0.00
UCM	0.96	3.86	4.59	15.75	7.50	23.25	0.92	1.51	1.90	1.20	0.00
SUITEs	0.92	3.76	4.87	16.00	7.25	23.25	0.93	1.39	1.97	-0.20	0.00
SUITEsa	0.98	4.00	4.89	15.75	7.75	23.50	0.96	1.32	1.19	0.07	0.00
SUITEf	0.96	3.89	4.45	15.75	8.25	24.00	0.90	1.40	0.19	-0.54	0.00
SUITEsfa	0.99	4.29	4.74	16.50	7.25	23.75	0.95	0.62	0.61	0.69	0.00

COMPARISON - GDP

Comparison of trend-cycle decomposition methods: **Business cycle for the EURO AREA**

- **Apart from other suite of models, the polynomial method (POLY2) with quadratic trend and optimal HP noise reduction seems to be one of the closest to the reference cycle.**
- Plotting the two together, the major differences arise indeed after the GFC, with the polynomial-based cycle signaling a much lower GDP than the reference.

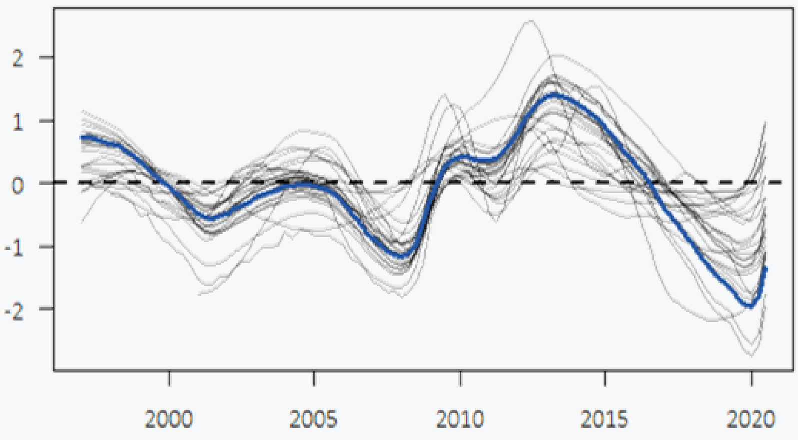
- **Interestingly, very simple filtering methods based on Hodrick Prescott**, e.g. with long penalty 51200 (HPl) and with the optimal penalty for the fixed 100 quarters upper limit (HPof) **are also promising**.
- If the reference cycle and the HPl cycle are plotted together the differences are very small indeed, with a slight difference during the pre-GFC periods and just before 2020. The Hamilton filters perform much worse.

- **We confirm that taking first-differences (i.e. SFD, AFD and LFD) are among the worst compared to the reference suite,** with the acceleration cycle based on the first 4 years (16 quarters) difference (LFD) are the latest desirable cycle for the aggregate EA19. The former seems to fail catching the lower frequency fluctuations at the 6-44 quarters level.

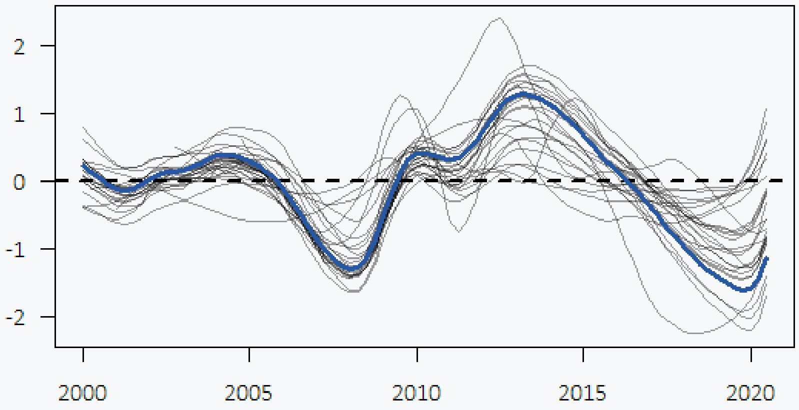
UNEMPLOYMENT

In total: EA19 vs post-Brexit EU

EA19



EU27_2020



COMPARISON – UNEMPLOYMENT

Comparison of trend-cycle decomposition methods: **Business cycle for the EURO AREA**

WHERE TO LOOK:

- **The correlation** coefficient between the reference suite of 3 models cycle and the cycle extracted by other TCD methods. Higher values → good
- **Overlap** is the average alignment of the phase dummies of the estimated cycles overlapping with the similar indicator functions of the simulated cycle. Smaller than 0.5 → bad
- **Dissimilarity** measure computes the (Euclidean) distance between the simulated cycle features a)-c) and the same features of the cycles obtained by trend-cycle decomposition methods. Closer to zero → good
- **End-of-sample** values compared to reference cycle end-of-sample values in RMSE sense. Closer to zero → good

Method	Corre-lation	Amplitude		Duration		Cycle length	Over-lap	Dissi-milarity	Ends of sample		NA
		Exp.	Contr.	Exp.	Contr.				m0	mT	
SUITEsf	1.00	1.55	2.25	16.50	20.50	37.00	1.00	0.00	0.00	0.00	0.00
POLY1	0.95	1.27	1.44	9.67	14.67	24.33	0.95	15.55	0.29	0.47	0.00
POLY2	0.94	1.26	1.40	9.67	14.67	24.33	0.95	15.56	0.41	0.58	0.00
POLY3	0.55	1.05	0.97	9.33	12.00	21.33	0.75	19.26	-1.34	2.33	0.00
SFD	0.10	0.34	0.34	7.33	14.33	21.67	0.60	19.04	-0.75	1.77	1.00
AFD	0.38	1.26	1.28	8.00	13.67	21.67	0.62	18.85	-0.81	1.77	4.00
LFD	0.86	3.65	3.20	18.00	18.00	36.00	0.68	3.86	-1.26	0.18	16.00
BNF	0.37	0.46	0.52	8.33	13.67	22.00	0.69	18.51	-0.71	1.43	1.00
HPnever	0.73	1.78	1.82	8.00	16.67	24.67	0.72	15.47	-0.30	1.45	11.00
HPnever_a	0.76	1.23	1.10	6.00	11.50	17.50	0.64	23.94	0.01	1.12	19.00
CFf	0.97	1.26	1.92	9.33	15.33	24.67	0.95	15.18	-0.22	-0.62	0.00
CFo	0.98	1.22	1.88	9.33	15.33	24.67	0.95	15.18	-0.15	-0.42	0.00
CFs	0.76	1.28	1.64	9.00	16.00	25.00	0.92	14.86	-0.50	0.24	0.00
CFl	0.78	1.80	1.60	28.00	28.00	56.00	0.60	23.46	-0.45	0.49	0.00
HPo	0.94	1.21	1.30	9.67	14.67	24.33	0.95	15.56	0.01	0.93	0.00
HPob	0.39	0.82	0.70	9.33	13.00	22.33	0.77	18.05	-0.85	2.00	0.00
HPof	0.95	1.25	1.39	9.67	14.67	24.33	0.95	15.56	0.22	0.62	0.00
HPs	0.58	0.93	0.81	9.67	12.75	22.42	0.78	17.94	-0.75	1.94	0.00
HPl	0.94	1.20	1.29	9.67	14.67	24.33	0.95	15.56	-0.03	0.98	0.00
BWF	0.53	1.03	0.91	9.67	12.50	22.17	0.77	18.24	-0.89	2.26	0.00
WAVE	0.73	2.15	1.76	17.50	18.50	36.00	0.96	2.57	-0.54	1.10	0.00
TCS	0.98	1.30	1.82	17.00	19.50	36.50	0.97	1.32	-0.04	0.36	0.00
TCSf	0.99	1.28	1.84	16.50	19.50	36.00	0.98	1.50	0.04	0.27	0.00
UCM	0.79	2.14	1.90	17.50	19.00	36.50	0.96	1.99	-0.73	0.87	0.00
SUITEs	1.00	1.04	1.44	9.67	15.00	24.67	0.96	15.16	-0.07	0.25	0.00
SUITEsa	1.00	1.07	1.50	9.67	15.00	24.67	0.96	15.16	-0.11	0.16	0.00
SUITEf	0.95	1.17	1.32	10.00	14.50	24.50	0.87	15.35	-0.47	0.86	0.00
SUITEsfa	1.00	1.57	2.26	16.50	20.50	37.00	1.00	0.02	0.09	0.00	0.00

COMPARISON - UNEMPLOYMENT

Comparison of trend-cycle decomposition methods: **Business cycle for the EURO AREA**

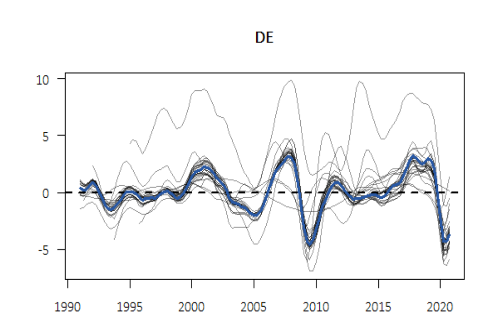
- **For the aggregate EA19, the polynomial method (POLY2) and HP filtered cycles do not show the best assessment compared to the preferred suite.**

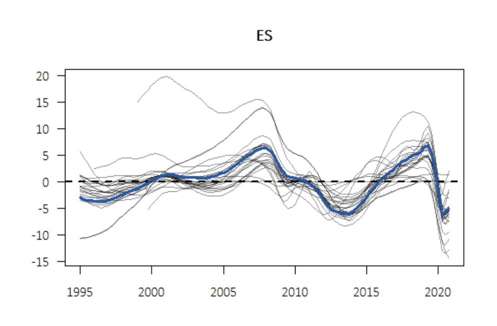
- **Instead, structural models and especially trend-cycle-seasonal filters are among the best choices for unemployment cycles.**
- They are indeed the closest to target but capturing the drop in 2020 in a smaller magnitude.
- On the contrary, for EU27 polynomials models and some Hodrick Prescott filters perform relatively good again. This makes the analysis of extra EA countries even more to the point for unemployment rates.

- This conclusion is likely due to the fact that there is only **a small and a very smooth negative trend in the unemployment data**. The structural models having an explicit description of the stochastic cycle are more successful in catching the same expansion and contraction phases compared to the reference suite of models.

WE DID CAPTURE THE CYCLE! - GDP

Core vs. Periphery



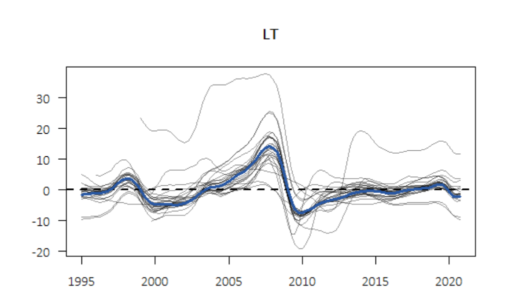


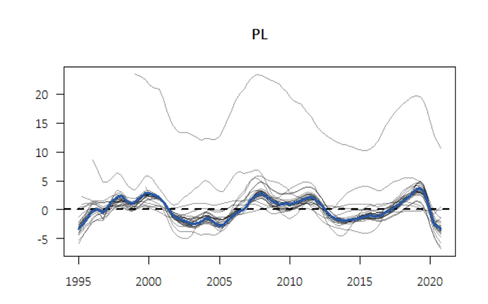
- For Germany as well for other core countries (Austria and Finland, for instance), is easier to find cycles comparable to the reference if assessed via our criteria.
- The main outliers are again the Christiano-Fitzgerald filter with 44-100 quarters (CFI) and the acceleration cycles, especially the LFD.

- The cycles overall are less comparable with the reference suite. The polynomial method (POLY2) still performs decently.
- In general, it is especially tricky to find cycles with low dissimilarity. Spain was especially affected by large financial cycles (bigger magnitude and length) rather than fluctuations at the business cycle level.
- **When swings are more limited it is easier to pick a good method to capture the business cycle based on real GDP.**

WE DID CAPTURE THE CYCLE! - GDP

New-EA vs new-EU (non-EA)



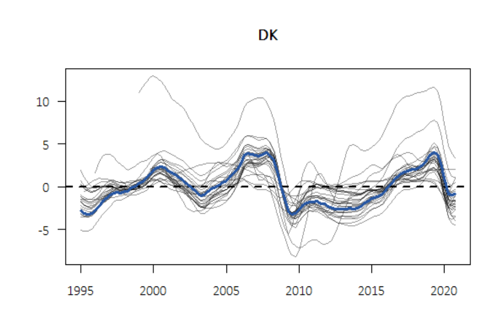


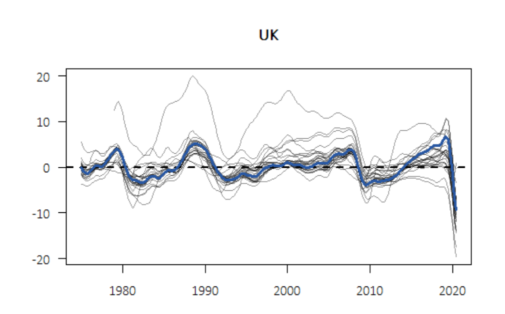
- Lithuania, as well as its Baltic peers, suffered large swings after joining the EU mostly due to increase income and financial inflows making them like some of the periphery.
- Lithuania is closer to the periphery cycles, some few types of HP filtered cycles and CF based cycles being more correlated and less dissimilar compared to the suite.

- Poland suffered a much smaller dip in the business cycle in the aftermath of the GFC compared to Lithuania. This was likely due to independent monetary policy and bigger size of its economy.
- Both the polynomial method (POLY2) and HP filtered cycles (but not Hamilton filters) perform quite well.
- **When swings are more limited it is easier to pick a good method to capture the business cycle based on real GDP.**

WE DID CAPTURE THE CYCLE! - GDP

Non-EU





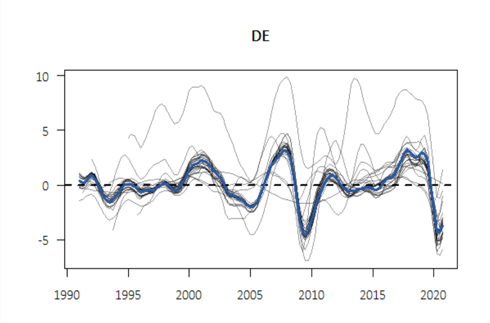
✓ Both countries look similar in their cycle's magnitude or length.

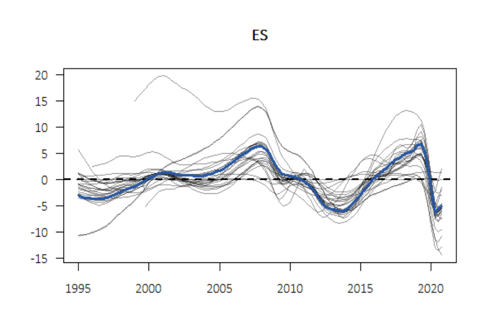
- For Denmark is easier to get closer to the reference as the economy is mature.
- The best possible choices are a Hodrick Prescott filter with long penalty and the trend-cycle-seasonal filter, optimized for the fixed 100 quarters upper limit.

- For the UK it is hard to pick one method that shows good scores for all the criteria.

WE DID CAPTURE THE CYCLE! - UNEMPLOYMENT

Core vs Periphery



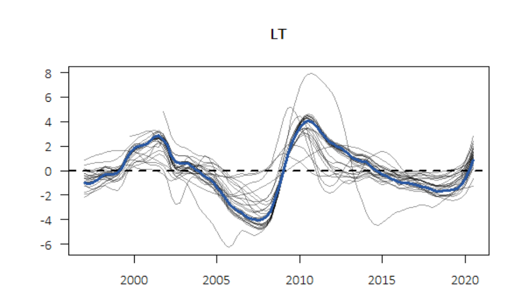


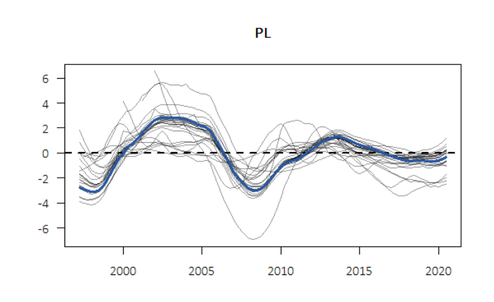
- Fluctuations in unemployment rates are much less sizable after the labour markets reforms in 2005 and nowadays the rates are very close to potential. Increase at the very end of sample (2020Q3) due to the first wave of the COVID19 outbreak.
- **Many approaches delivering similar cycles as the reference suite for the core countries**, with acceleration cycles and UCM models excluded.

- Spanish unemployment cycle has increased its magnitude and length since the GFC.
- For Spain is easier to capture similar cycles as done in the suite now for unemployment compared to real GDP, with again polynomials and some CF based cycles preferred. These outcomes are confirmed also in other periphery countries.
- Interestingly, wavelets perform also well for the unemployment rate.

WE DID CAPTURE THE CYCLE! - UNEMPLOYMENT

New-EA vs new-EU (non-EA)





- Lithuania experienced bigger swings over time, and we can already see the unemployment rate cycle going into positive territories following the COVID19 outbreaks.

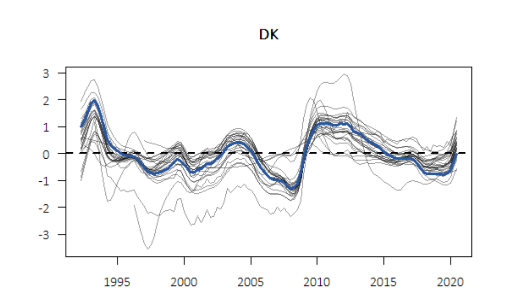
- Instead, Poland is almost in line with potential in the aftermath of the GFC.
- For Poland also some Christiano-Fitzgerald based cycles can be preferred.

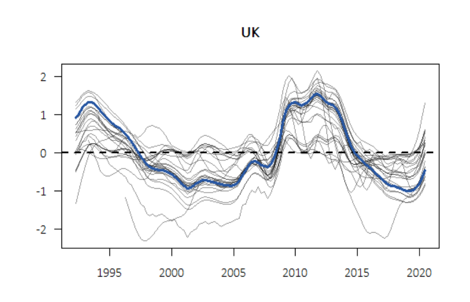
✓ In general, for new EU member states the unemployment cycles are of bigger magnitude compared to the core euro area, for instance.

✓ We confirm the intuition we had for the previous groups: the polynomials (especially for Lithuania), trend-cycle-seasonal filters and the wavelets really perform quite nicely in case of unemployment gaps.

WE DID CAPTURE THE CYCLE! - UNEMPLOYMENT

Non-EU





- ✓ In both cases, the swings are relatively comparable to the ones of the core and they already show an increase in unemployment rates in the last quarter of our sample.
- ✓ Once again, we see that the polynomials (especially for the UK), trend-cycle-seasonal filters and the wavelets are possible options if we assess them in terms of our reference cycle.
- ✓ The reason for this is that the trends are very smooth and slowly varying.

SYNCHRONIZATION!

✓ **In this section we perform a synchronization exercise for the aggregate euro area cycle (as the best ones from Monte Carlo, i.e., the suite of models (SUITEsf)), by using different methods:**

1) simple correlations,
2) synchronicity/similarity/coherence as in Mink et al. (2012) and Samarina et al. (2017) and
3) the cyclical convergence as introduced in Crespo Cuaresma and Fernández Amador (2013a, 2013b).

- We focus on the comparison with the euro area, as the business cycle coherence is key for the smooth definition and transmission of monetary policy (ECB, 2018).
- When possible, we draw comparison to this cycle also for non-EA and non-EU countries, as in some cases their exchange rate regimes, and therefore monetary policy, or external sector can be very much driven by the euro area.

SYNCHRONIZATION!

- ✓ We start computing the simple correlation, for completeness. However, this approach is criticised in the literature (Mink et al., 2012) as the correlation does not properly consider that cycles can have a different sign and/or have a different amplitude.

- ✓ Then following Mink et al. (2012) we rather include synchronicity/similarity measures. The synchronicity between two cycles is based on binary indicators: in each period, a value of one indicates that two cycles have the same sign. The similarity measure is based on the average absolute differences between the levels of the two cycles (ECB, 2018). The terms coherence in the narrative is when both aspects are considered. We use here in the baseline the EA19 aggregate cycle, for the sake of clarity and easier narrative towards monetary policy.

- ✓ Crespo Cuaresma and Fernández Amador (2013a, 2013b) instead measure business cycle synchronization using the dispersion of business cycles. This measure compares the standard deviation the cycle with all euro area countries included with the one excluding the country of interest. If the country is a non-EA we artificially add it to the club and then measure club-synchronization against hypothetical inclusion/exclusion of that country.

SYNCHRONIZATION!

Following Mink et al. (2012)

- ✓ **The business cycles of the euro area members are quite coherent with the aggregate EA19**. This is mostly true in case of real GDP, while there *are some exceptions when unemployment rate cycles* are considered.

- ✓ **The less synchronized or similar country compared to EA19 for unemployment cycles is Germany,** as we have seen after mid-2000 is basically at potential, while this is not the case for other groups or the aggregate. The coherence level of Germany when real GDP cycles are considered is also smaller than other core countries. This is in line with the literature as in ECB (2018). Other core countries, such as Austria and Luxembourg, perform in a similar way for the unemployment cycles.

- ✓ **Some new member states (Estonia, Slovakia, Lithuania) periods are also less synchronised** and like the aggregate EA19 both in GDP and unemployment cycles; this mainly because joined the EU later and went through transition, boom and (sometimes) harder bust.

- ✓ **In general, other countries not in EU do not seem to show high coherence either, e.g., Turkey, Norway and Switzerland especially**. Turkey has a very different economy and larger swings are also due to its openness to trade and financial flows and to changes in its own independent monetary policy. Norway can be affected more by changes in energy prices and lastly, Switzerland is seen as a safe haven and has had different exchange rate regimes in the last year in order to curb possible larger capital flows.

SYNCHRONIZATION!

Following Crespo Cuaresma and Fernández Amador (2013a, 2013b).

- ✓ Here we look at business cycle synchronization using **the dispersion of business cycles**. We do not look at time variation – using averages.

- ✓ This measure compares a) the standard deviation the cycle with all euro area countries included (st) with b) the one excluding the country of interest (st_{it}). A lower standard deviation is better.
- ✓ synchit = log(st_{it}) − log(st)
- ✓ **If the sign is (-) it means that we are better off without the inclusion of the country; if sign (+) the situation is worse without the country in the euro area.**

- ✓ For real GDP, we can see (-) sign and big magnitudes in some countries with larger swings (Ireland and Greece) and some few new EU member states (Latvia, Bulgaria, Romania – only Latvia is in EA).

- ✓ In the case of unemployment, also Spain has a (-) sign for this measure, while among the new EU member states this is only the case of Lithuania, Poland and Slovakia.

- ✓ **Based on this measure, the business cycles of the euro area members are quite synchronized with the aggregate EA19.**

SYNCHRONIZATION!

Real GDP

Code	Correlation	Amplitude Exp.	Amplitude Contr.	Duration Exp.	Duration Contr.	Cycle length	Implied upper limit Quart.	Implied upper limit Norm.	Implied upper limit Group	Mean Synchr.	Mean Similar.	Mean S.D.
AT	0.93	4.20	2.88	13.75	9.50	23.25	48.09	0.13	Short	0.81	0.60	2.03
BE	0.91	2.81	3.50	12.40	6.80	19.20	51.11	0.16	Short	0.63	0.19	1.85
BG	-0.02	14.06	23.31	27.50	19.00	46.50	67.43	0.55	Medium	0.21	0.06	-5.57
CH	0.81	3.81	3.88	14.50	10.00	24.50	63.22	0.41	Medium	0.62	0.18	1.52
CY	0.61	8.14	7.08	15.75	8.67	24.42	74.34	0.62	Medium	0.38	0.19	-0.50
CZ	0.58	7.49	7.38	16.67	11.33	28.00	68.53	0.59	Medium	0.36	0.20	0.83
DE	0.82	3.77	3.29	13.00	7.60	20.60	47.37	0.25	Short	0.69	0.32	1.38
DK	0.88	4.67	3.80	17.75	8.00	25.75	65.74	0.54	Medium	0.81	0.58	2.32
EA	0.98	4.24	4.86	14.75	8.75	23.50	57.56	0.37	Medium	0.88	0.83	2.23
EA12	1.00	4.31	4.83	16.75	7.50	24.25	57.34	0.34	Medium	1.00	0.98	2.29
EA19	1.00	4.31	4.84	16.75	7.50	24.25	57.36	0.34	Medium	1.00	1.00	2.30
EE	0.63	14.24	16.46	25.67	8.50	34.17	64.26	0.55	Medium	0.40	0.18	0.59
EL	0.54	20.83	27.29	36.00	22.00	58.00	88.01	0.81	Medium	0.29	0.07	-7.59
ES	0.88	7.82	8.68	20.00	12.00	32.00	69.67	0.52	Medium	0.60	0.39	2.33
EU15	0.94	3.47	3.24	16.75	8.00	24.75	71.25	0.61	Medium	0.78	0.69	2.24
EU27_2020	1.00	4.19	4.74	16.25	7.75	24.00	57.51	0.34	Medium	1.00	0.94	2.29
EU28	0.94	3.44	3.26	16.75	8.00	24.75	71.37	0.61	Medium	0.76	0.67	2.26
FI	0.81	7.25	5.36	18.00	8.75	26.75	83.58	0.66	Medium	0.60	0.34	2.04
FR	0.93	2.91	3.76	12.14	10.29	22.43	56.02	0.38	Medium	0.77	0.56	1.98
HR	0.63	12.88	11.00	23.50	20.00	43.50	71.65	0.57	Medium	0.27	0.18	1.52
HU	0.66	13.49	11.13	32.50	14.50	47.00	78.83	0.81	Medium	0.54	0.23	1.24
IE	0.64	27.03	26.72	25.00	24.00	49.00	85.32	0.81	Medium	0.60	0.15	-14.34
IT	0.97	4.87	5.48	17.00	7.75	24.75	57.31	0.40	Medium	0.69	0.75	2.49
LT	0.47	9.68	10.28	19.00	9.33	28.33	63.71	0.45	Medium	0.35	0.01	-0.07
LU	0.84	5.02	5.82	10.33	12.00	22.33	62.03	0.46	Medium	0.73	0.41	1.69
LV	0.60	16.65	15.61	24.67	7.33	32.00	68.01	0.57	Medium	0.38	0.10	-5.17
MT	0.70	8.31	6.24	21.50	16.00	37.50	75.96	0.60	Medium	0.57	0.24	-0.50
NL	0.88	4.10	4.68	14.33	8.75	23.08	61.63	0.29	Short	0.84	0.52	1.99
NO	0.47	3.93	4.13	13.29	10.43	23.71	62.47	0.41	Medium	0.25	-0.26	0.93
PL	0.55	3.30	3.09	11.25	8.25	19.50	61.81	0.23	Short	0.23	0.03	0.97
PT	0.83	5.62	5.83	16.00	7.50	23.50	70.78	0.46	Medium	0.56	0.38	1.88
RO	0.24	16.12	17.67	27.50	18.00	45.50	68.99	0.68	Medium	0.29	0.08	-3.03
RS	0.14	10.81	13.98	21.67	15.00	36.67	64.02	0.66	Medium	0.06	-0.08	-1.24
SE	0.85	4.53	4.10	13.75	8.75	22.50	50.77	0.24	Short	0.56	0.42	1.77
SI	0.81	6.66	6.41	16.50	7.75	24.25	70.89	0.56	Medium	0.58	0.32	2.46
SK	0.37	4.77	5.95	11.00	9.40	20.40	67.18	0.45	Medium	0.04	0.00	-1.56
TR	0.26	8.37	9.45	12.50	8.25	20.75	62.79	0.19	Short	-0.02	0.02	-2.22
UK	0.79	5.45	4.95	20.50	10.20	30.70	67.92	0.49	Medium	0.44	0.31	1.25

Unemployment rate

Code	Correlation	Amplitude Exp.	Amplitude Contr.	Duration Exp.	Duration Contr.	Cycle length	Implied upper limit Quart.	Implied upper limit Norm.	Implied upper limit Group	Mean Synchr.	Mean Similar.	Mean S.D.
AT	0.49	0.91	0.96	14.33	12.50	26.83	55.84	0.09	Short	0.28	-1.22	1.77
BE	0.73	1.04	1.15	12.67	15.75	28.42	68.05	0.37	Medium	0.41	-0.19	1.99
BG	0.63	5.17	4.81	20.00	25.50	45.50	73.58	0.64	Medium	0.49	0.30	0.34
CH	0.13	0.37	0.36	7.00	9.50	16.50	57.91	0.06	Short	0.02	-6.29	0.47
CY	0.86	2.22	3.56	12.33	16.00	28.33	75.06	0.62	Medium	0.60	0.36	-0.10
CZ	0.54	1.05	1.31	7.33	12.75	20.08	49.58	0.46	Medium	0.28	0.01	1.65
DE	0.03	1.06	0.91	10.50	11.00	21.50	61.31	0.33	Short	-0.05	-1.07	0.62
DK	0.64	1.02	1.37	8.50	14.20	22.70	64.11	0.43	Medium	0.43	0.15	2.10
EA19	1.00	1.55	2.25	16.50	20.50	37.00	71.64	0.52	Medium	1.00	1.00	2.53
EE	0.28	4.36	4.47	7.33	21.00	28.33	55.87	0.33	Short	0.03	-0.05	-0.89
EL	0.78	8.73	5.26	20.00	36.00	56.00	82.02	0.80	Medium	0.52	0.09	-4.01
ES	0.89	5.05	5.77	14.00	24.33	38.33	88.56	0.83	Medium	0.94	0.24	-8.61
EU15	0.95	1.40	0.77	16.50	14.00	30.50	80.07	0.73	Medium	0.98	0.71	2.35
EU27_2020	0.96	1.55	2.30	16.50	20.50	37.00	71.29	0.51	Medium	0.49	0.68	2.16
EU28	0.96	1.56	1.50	16.50	15.00	31.50	73.26	0.64	Medium	0.78	0.66	2.18
FI	0.59	0.98	1.03	11.00	13.33	24.33	59.85	0.43	Medium	0.47	-0.33	1.98
FR	0.86	0.99	1.12	11.00	11.67	22.67	66.62	0.52	Medium	0.41	-0.35	1.54
FX	0.82	0.74	0.91	10.50	12.40	22.90	76.34	0.64	Medium	0.89	0.17	1.95
HR	0.81	5.34	4.73	23.00	26.00	49.00	75.21	0.68	Medium	0.33	0.34	0.68
HU	0.71	2.92	3.30	40.00	28.00	68.00	88.56	0.87	Medium	0.73	0.26	1.26
IE	0.74	3.24	3.98	18.00	22.67	40.67	86.58	0.82	Medium	0.73	0.26	-3.64
IS	0.54	3.94	3.92	12.00	30.00	42.00	65.82	0.60	Medium	0.63	0.16	0.58
IT	0.65	1.55	1.28	12.50	19.50	32.00	91.26	0.85	Medium	0.39	0.10	1.46
LT	0.45	8.10	6.32	12.00	28.00	40.00	63.82	0.48	Medium	0.26	0.09	-2.11
LU	0.37	0.98	1.02	12.67	15.50	28.17	61.54	0.26	Short	0.03	-1.20	1.69
LV	0.47	2.50	2.41	5.75	12.60	18.35	60.23	0.38	Medium	0.45	0.07	0.16
ME	0.67	0.58	0.89	4.00	9.50	13.50	59.28	0.38	Medium	0.59	-1.42	0.70
MK	0.89	0.29	0.98	5.00	6.67	11.67	39.08	0.63	Medium	0.76	0.31	1.29
MT	0.58	0.48	0.57	13.00	14.00	27.00	60.10	0.34	Medium	0.24	-2.01	1.91
NL	0.74	2.21	2.32	18.50	20.67	39.17	72.74	0.43	Medium	0.35	0.23	1.79
NO	0.19	0.93	0.86	16.33	10.33	26.67	54.22	0.23	Short	-0.09	-1.43	1.50
PL	0.15	5.12	3.91	19.50	23.50	43.00	71.52	0.55	Medium	0.00	0.01	-4.32
PT	0.91	2.90	3.33	17.00	20.67	37.67	79.91	0.67	Medium	0.79	0.42	0.84
RO	0.59	0.73	0.78	11.25	10.25	21.50	54.95	0.39	Medium	0.40	-0.94	1.99
SE	0.62	1.28	1.69	9.67	14.00	23.67	69.18	0.59	Medium	0.64	0.13	1.19
SI	0.87	1.73	1.69	11.50	20.00	31.50	79.87	0.73	Medium	0.77	0.42	2.58
SK	0.40	3.21	2.94	13.33	15.33	28.67	68.57	0.52	Medium	0.18	0.24	-3.22
TR	-0.27	1.51	1.52	8.00	12.50	20.50	43.37	0.16	Short	-0.08	-1.35	0.12
UK	0.63	0.92	1.27	10.00	18.25	28.25	89.75	0.83	Medium	0.58	0.14	1.67

TAKEAWAYS

Summing up!

1. High level of model uncertainty comparing 28 cycle estimates.
2. Growth rate (acceleration) cycles are often off the road, very, yet could be useful early warning predictors of the turning points in the growth and business cycle.
3. **Best performing MC approaches provide reasonable combination as the suite of models**, in line with Canova findings for a longer US cycles. The paper suggests that the suite of models, approach should be used for the NUTS2 regions and sectoral data.
4. Drawing comparisons for the EA19 and our countries of interest, **we find that some HP filtered cycles as well as the polynomial method** with quadratic trend and optimal HP noise reduction seem to be very close to the reference cycle (suite of models).
5. It is generally harder to find comparable cycles for the periphery of the euro area or new euro area countries compared to the core. **When swings last less and/or are smaller it is easier to pick a good method alternative to the suite to capture the business cycle in the case of real GDP.**
6. **The business cycles of the euro area members are quite coherent (Mink et al., 2012) and synchronized (Crespo Cuaresma and Fernández Amador (2013a, 2013b) with the aggregate EA19**. German cycles show among the least coherent cyclical movements.

THANK YOU FOR YOUR ATTENTION!

GRAZIE! AČIŪ! DANKE!

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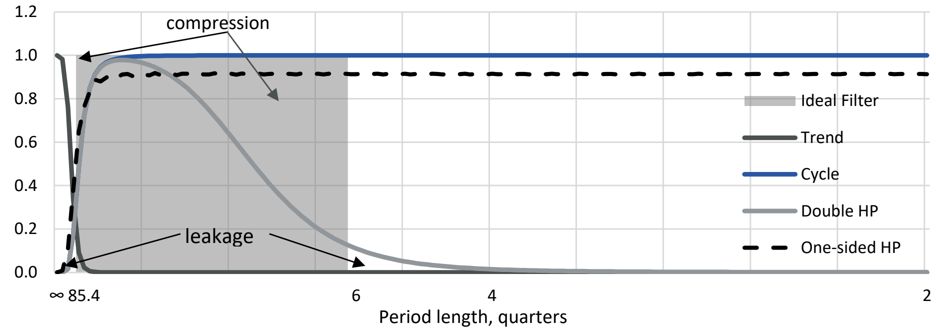
RESERVE SLIDES

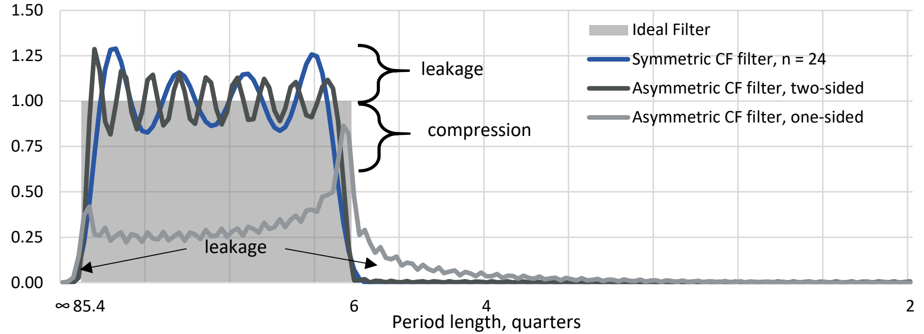
ANOTHER LOOK INTO THE WINNING METHODS

Power transfer functions in the frequency domain

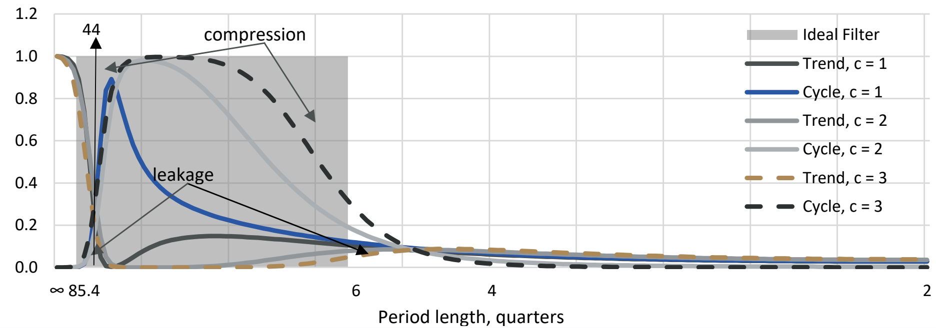
HP filter



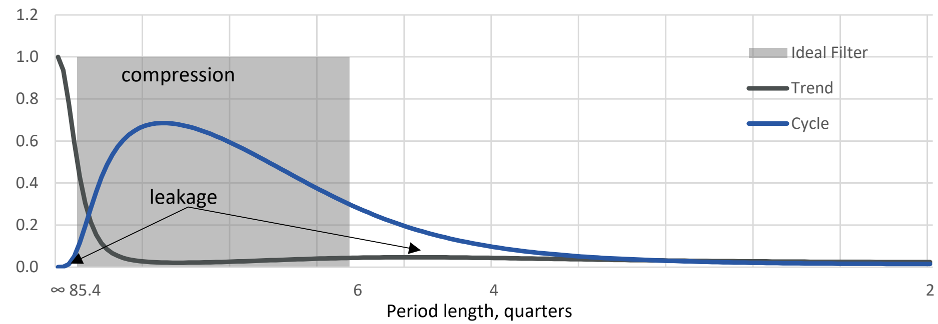
CF filter



TCS filter



UCM filter



COMPARISON OF SELECTED APPROACHES

Beauty contest criteria for the prettiest

	CF filter	HP filter	TCS filter	UCM	Suite of models
Approach	Matrix algebra	Matrix algebra	Matrix algebra	Bayesian, Kalman filter and smoother	Averaging statistic
Model based cycle	No	No	Yes	Yes	No
Decision parameters	Frequency band	Smoothness penalty	Trend, cycle length and persistency	Trend, initial cycle state, length and persistency, MCMC	Averaging statistic
Allows for structural breaks	No	No	Yes	Yes	Partially
Trend	I(1) with drift or I(0)	Integrated random walk, I(2)	I(d) with drift, prior consistent	I(d) with drift, prior consistent	Imposed statistically
Complexity	Low	Low	Medium	High	Medium
Stability	Low	Low	Low	Low	Medium
Robustness to data pre-processing	Medium	Medium	High	High	High
Economic rationale	Low	Low	Low	Low	Low

MINDING THE GAP

Business, growth and acceleration cycles revisited

	Business cycle	Growth cycle	Acceleration cycle
Definition	Aperiodic, recurrent sequence of expansions and contractions in the levels of macroeconomic data	Difference between the actual macroeconomic data and its trend expressed as per cent of the trend	A growth rate of the macroeconomic data experiencing a sequence of decelerations and accelerations
Reference	Burns and Mitchel (1946)	Mintz (1969)	Mintz (1969)
Trend impact	Strong	Weak	Weak
Noise impact	Weak	Weak	Strong
Model	Changes in the levels	Trend-cycle decomposition	Changes in the growth rates, first differences
Amplitude	Low	Moderate	Low
Phase asymmetry	High	Moderate	Low
Model uncertainty	No	Yes	No\Yes when de-noising
Data uncertainty	Yes	Yes	Yes
Number of full cycles	Small	Medium	High
	Conclusions:		
Pros	Systematic analysis of changes in the levels.	More visible and symmetric medium-term fluctuations, with small distortions by trend and noise.	Systematic analysis of changes in the growth rates, early warning signals, symmetric cycles.
Cons	Asymmetric phases with more rapid and shorter recessions. The high levels of mature EU economies result in a small number of full cycles. Depends on data revisions.	Depends on the trend-cycle decomposition method and data revisions.	Dominated by the noise that requires smoothing introducing model uncertainty. Depends on data revisions. The frequent changes in the cycle lead to many false downturn and upturn signals. Lose observations at the start.