Asymmetric Linear Filters for Seasonal Adjustment Applications to the COVID-19

Alain Quartier-la-Tente (Lemna, Insee)
Ongoing research under supervision of:
Dominique Ladiray (Independent) and Olivier Darné (Lemna)
With the help of Jean Palate (NBB)

Introduction (1/2)

Ongoing research real-time detection of turning points with linear filters

- Under supervision of Dominique Ladiray and Olivier Darné
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In this presentation:

- First results comparing 4 methods for trend-cycle extraction:
    - Current X-13ARIMA algorithm (Henderson filter)
    - Local Polynomial filters (Proietti and Luati (2008))
    - Fidelity-Smoothness-Timeliness approach (Grun-Rehomme, Guggemos, and Ladiray (2018))
    - RKHS filters (Dagum and Bianconcini (2008))

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  - RKHS filters (Dagum and Bianconcini (2008))
- R package `rjdfilters` (https://github.com/palatej/rjdfilters, development version: https://github.com/AQLT/rjdfilters)

Introduction (2/2)

A raw time series can be decompose as (additive decomposition):

$$X_t = \underbrace{TC_t}_{\text{trend-cycle}} + \underbrace{S_t}_{\text{seasonality}} + \underbrace{I_t}_{\text{irregular}}$$

And TC_t generally estimated on a series *without* seasonality

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$$M_\theta(X_t) = \sum_{k=-p}^{+f} \theta_k X_{t+k}$$

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➔ Comparison of 3 methods that could be included in X-13-ARIMA

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➔ Comparison of 3 alternatives modern approaches that can reproduce Henderson filter

Local polynomials: R `rjdfilters::lp_filter()`

Assumption: $y_t = \mu_t + \varepsilon_t$ with $\varepsilon_t \overset{i.i.d}{\sim} \mathcal{N}(0, \sigma^2)$

μ_t locally approximated by polynomial of degree d:

$$\forall j \in [\![-h, h]\!] : y_{t+j} = m_{t+j} + \varepsilon_{t+j}, \quad m_{t+j} = \sum_{i=0}^{d} \beta_i j^i$$

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Estimation using WLS using *kernels*: $\hat{\beta} = (X'KX)^1 X'Ky$ and

$$\hat{m}_t = \hat{\beta}_0 = w'y = \sum_{j=-h}^{h} w_j y_{t-j}$$ ➔ equivalent to symmetric moving average

➔ Henderson filter using a specific kernel and $d = 3$.

Asymmetric filters: R `rjdfilters::lp_filter()`

Several solutions:

1. Same method with less data (DAF) $\iff$ Minimize revisions under same polynomial constraints (reproduce cubic trend)

➔ **no bias** but **lots of variance**

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2. Minimization of revisions filter under polynomial constraints:

   2.1 *Linear-Constant* (LC): y_t linear and v reproduce constant trends (*Musgrave* filter)

   2.2 *Quadratic-Linear* (QL): y_t quadratic and v reproduce linear trends

   2.3 *Cubic-Quadratic* (CQ): y_t cubic and v reproduce quadratic trends

   ➔ Asymmetric filters v depends on a ratio linked to "IC-Ratio"

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☺ simple models with easy interpretation

☹ Timeliness not controlled ➔ method extended in `rjdfilters::lp_filter()`

RKHS filters: R `rjdfilters::rkhs_filter()`

- RKHS theory used to approximate Henderson filter
- With K_p the **kernel function**, the symmetric filter:

$$\forall j \in [\![-h, h]\!] : w_j = \frac{K_p(j/b)}{\sum_{i=-h}^{h} K_p(i/b)}$$

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- For asymmetric filters:

$$\forall j \in \llbracket -h, q \rrbracket : w_{a,j} = \frac{K_p(j/b)}{\sum_{i=-h}^{q} K_p(i/b)}$$

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$$\forall j \in [\![-h, q]\!] : w_{a,j} = \frac{K_p(j/b)}{\sum_{i=-h}^{q} K_p(i/b)}$$

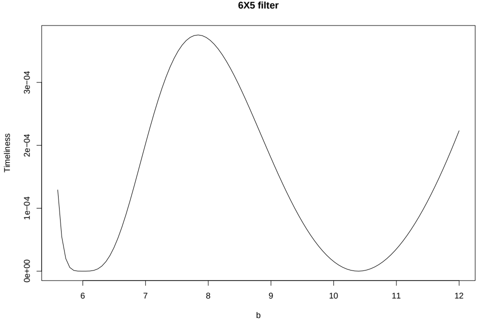
➔ b chosen by optimization, e.g. minimizing revisions linked to phase-shift:

$$b_{q,\varphi} = \min_{b_q} \int_0^{2\pi/12} \rho_s(\lambda)\rho_\theta(\lambda) \sin^2\left(\frac{\varphi_\theta(\omega)}{2}\right) \mathrm{d}\omega$$

Filtres asymétriques

several local extremum

```
fun <- rkhs_optimization_fun(horizon = 6,
            leads = 5, degree = 3,
            asymmetricCriterion = "Timeliness")
plot(fun, 5.6, 12, xlab = "b",
     ylab = "Timeliness", main = "6X5 filter")
```




```
rkhs_optimal_bw()
```

```
##     q=0    q=1    q=2    q=3    q=4    q=5
## 6.0000 6.0000 6.3875 8.1500 9.3500 6.0000
```

Generalizable to create filters that could be applied to irregular frequency series

FST approach: R `rjdfilters::fst_filter()`

Minimization of a weighted sum of 3 criteria under polynomial constraints:

$$\begin{cases}\min_{\theta} & J(\theta)=\alpha F_g(\theta)+\beta S_g(\theta)+\gamma T_g(\theta)\\ s.c. & C\theta=a\end{cases}$$

F_g: Fidelity (variance reduction ratio), S_g: Smoothness (Henderson criterion), T_g timeliness (phase-shift)

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- Unique solution
- Asymmetric filters independent of data and symmetric filter
- Non-normalized weights

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Methodology

2 404 calendar adjusted series (`sts_inpr_m`, industrial production indices of EU):

1. Seasonal adjustment with X-13ARIMA (`RJDemetra::x13`) for each date to extract: linearized component, length of trend and seasonal filters, decomposition mode and I-C ratio

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2. Seasonal adjustment using *fixed* linearized component (est. overall period) and same length/decomposition/I-C ratio with X-11 using custom trend-cycle filters (`rjdfilters::x11()`).

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3. For each estimate, downturns and upturns:
   - upturn: $y_{t-3} \geq \cdots \geq y_{t-1} < y_t \leq y_{t+1}$
   - downturn: $y_{t-3} \leq \cdots \leq y_{t-1} > y_t \geq y_{t+1}$

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Time-delay: time to detect the correct turning point without further revisions

Methods compared: RKHS minimizing phase-shift and local polynomial filters

Time delay to detect turning points in 2020

For series for which the optimal trend-cycle symmetric filter is of length 13 (900 series)

	X-13-ARIMA	RKHS	LC	QL	CQ	DAF
Min	2.0	2.00	2.00	2.00	2.00	2.00
D1	2.0	5.00	3.00	2.00	2.00	2.00
D2	3.0	5.00	3.00	3.00	2.00	2.00
D3	3.0	5.00	4.00	3.00	3.00	3.00
D4	3.0	5.00	4.00	3.00	5.00	3.00
Median	4.0	5.00	4.00	4.00	6.00	5.00
D6	4.0	7.00	4.00	5.00	6.00	6.00
D7	4.0	7.00	5.00	7.00	7.00	7.00
D8	5.0	7.00	5.00	7.00	7.00	7.00
D9	9.0	9.00	8.00	9.00	9.00	9.00
Max	14.0	14.00	14.00	14.00	14.00	14.00
Mean	4.4	6.29	4.69	4.97	5.32	5.09

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MAE in 2020

For series for which the optimal trend-cycle symmetric filter is of length 13

R_t: relative revision error between first and last estimates.

Distribution of $\frac{MAE(R_t)}{MAE(R_t^{X-13})}$

	RKHS	LC	QL	CQ	DAF
Min	0.4	0.5	0.5	0.5	0.5
D1	0.9	0.9	1.1	1.1	1.1
D2	1.0	1.0	1.3	1.4	1.3
D3	1.1	1.1	1.4	1.5	1.5
D4	1.1	1.2	1.6	1.7	1.6
Median	1.2	1.3	1.7	1.8	1.8
D6	1.3	1.4	1.9	2.0	1.9
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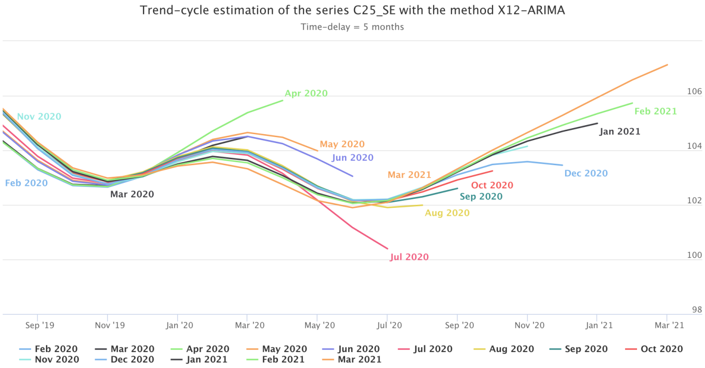
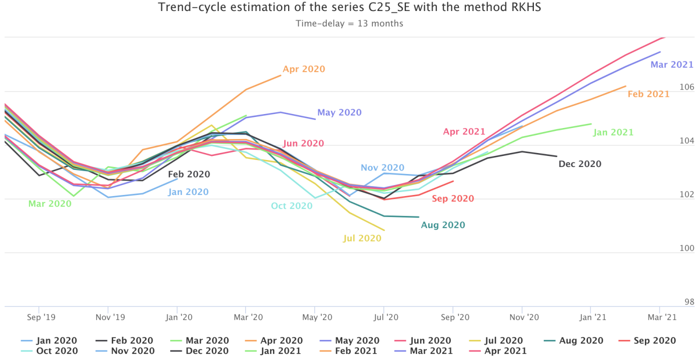
IPI in the manufacture of fabricated metal products, except machinery and equipment (C25) in Sweden (turning point in February 2020)




Trend-cycle estimation of the series C25_SE with the method RKHS
Time-delay = 13 months
Apr 2020
Mar 2021
106
Feb 2021
May 2020
Apr 2021
Jan 2021
Jun 2020
104
Dec 2020
Nov 2020
Feb 2020
Jan 2020
102
Sep 2020
Mar 2020
Oct 2020
Aug 2020
Jul 2020
100
98
Sep '19
Nov '19
Jan '20
Mar '20
May '20
Jul '20
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Nov '20
Jan '21
Mar '21
Jan 2020
Feb 2020
Mar 2020
Apr 2020
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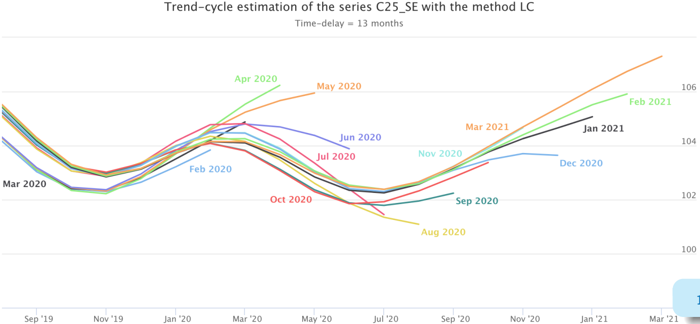
Trend-cycle estimation of the series C25_SE with the method LC
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106
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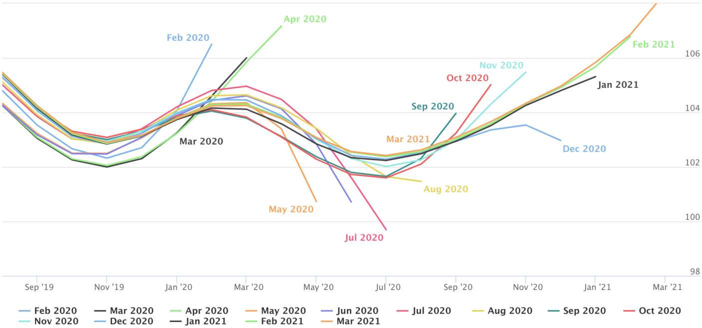
100
Sep '19
Nov '19
Jan '20
Mar '20
May '20
Jul '20
Sep '20
Nov '20
Jan '21
Mar '21

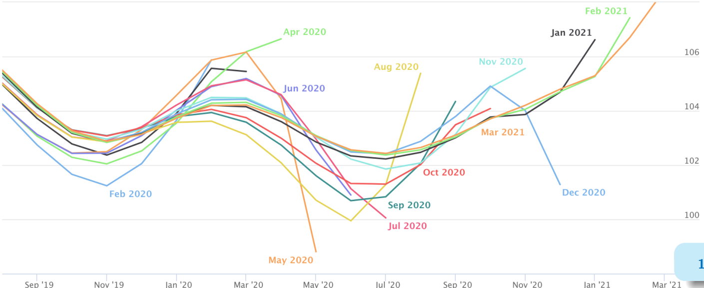
Trend-cycle estimation of the series C25_SE with the method QL

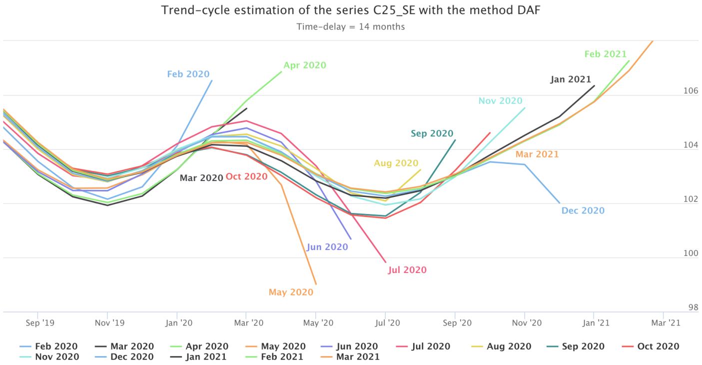
Time-delay = 14 months



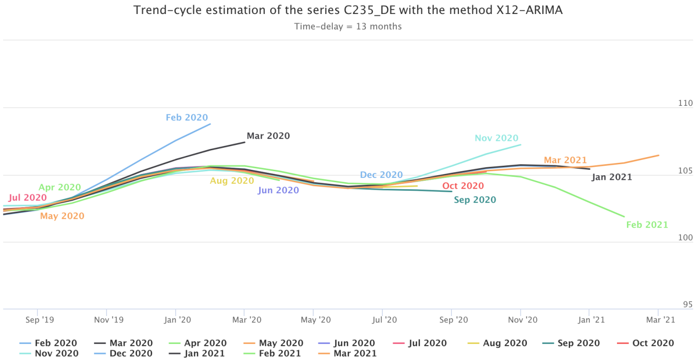
Trend-cycle estimation of the series C25_SE with the method CQ

Time-delay = 14 months



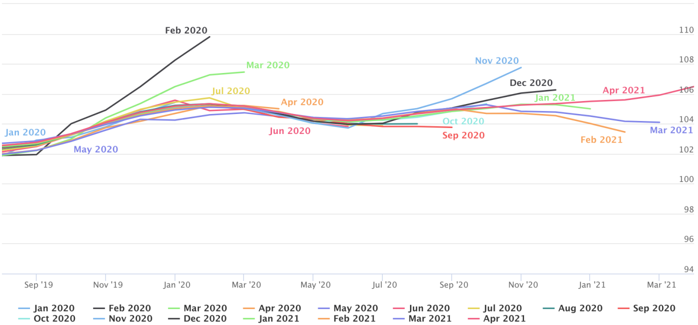

Trend-cycle estimation of the series C25_SE with the method DAF
Time-delay = 14 months
Feb 2020
Apr 2020
Feb 2021
Jan 2021
Nov 2020
Sep 2020
Mar 2021
Aug 2020
Mar 2020
Oct 2020
Dec 2020
Jun 2020
Jul 2020
May 2020
106
104
102
100
98
Sep '19
Nov '19
Jan '20
Mar '20
May '20
Jul '20
Sep '20
Nov '20
Jan '21
Mar '21
Feb 2020
Mar 2020
Apr 2020
May 2020
Jun 2020
Jul 2020
Aug 2020
Sep 2020
Oct 2020
Nov 2020
Dec 2020
Jan 2021
Feb 2021
Mar 2021

IPI in the manufacture of cement, lime and plaster (C235) in Germany (turning point in February 2020)



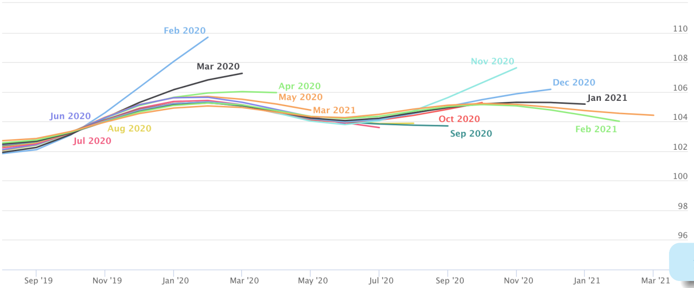
Trend-cycle estimation of the series C235_DE with the method RKHS

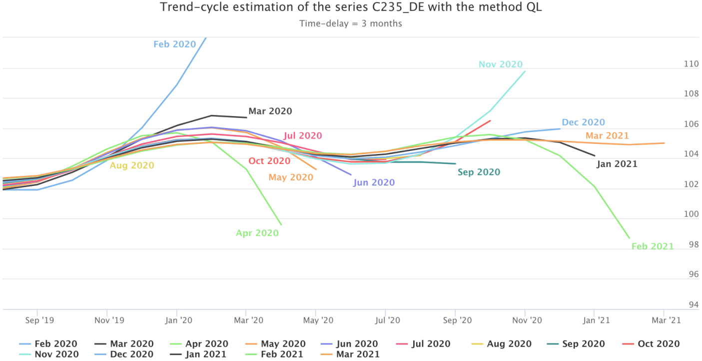
Time-delay = 5 months

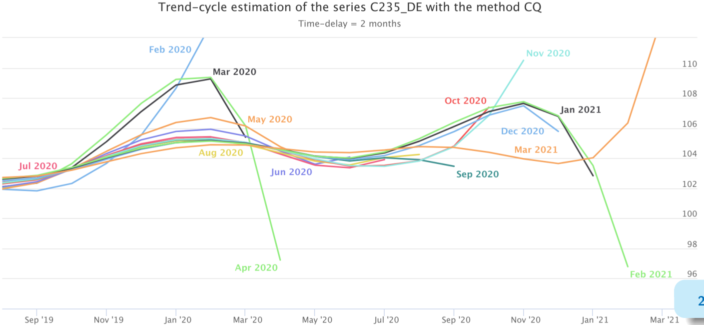


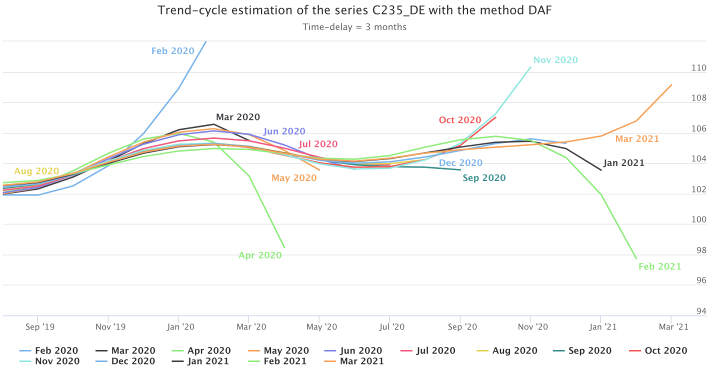
Trend-cycle estimation of the series C235_DE with the method LC

Time-delay = 3 months




Trend-cycle estimation of the series C235_DE with the method QL
Time-delay = 3 months
Feb 2020
Mar 2020
Apr 2020
May 2020
Jun 2020
Jul 2020
Aug 2020
Sep 2020
Oct 2020
Nov 2020
Dec 2020
Jan 2021
Feb 2021
Mar 2021
110
108
106
104
102
100
98
96
94
Sep '19
Nov '19
Jan '20
Mar '20
May '20
Jul '20
Sep '20
Nov '20
Jan '21
Mar '21


Trend-cycle estimation of the series C235_DE with the method CQ
Time-delay = 2 months
Feb 2020
Mar 2020
Apr 2020
May 2020
Jun 2020
Jul 2020
Aug 2020
Sep 2020
Oct 2020
Nov 2020
Dec 2020
Jan 2021
Feb 2021
Mar 2021
110
108
106
104
102
100
98
96
Sep '19
Nov '19
Jan '20
Mar '20
May '20
Jul '20
Sep '20
Nov '20
Jan '21
Mar '21


Trend-cycle estimation of the series C235_DE with the method DAF
Time-delay = 3 months
Feb 2020
Mar 2020
Apr 2020
May 2020
Jun 2020
Jul 2020
Aug 2020
Sep 2020
Oct 2020
Nov 2020
Dec 2020
Jan 2021
Feb 2021
Mar 2021
110
108
106
104
102
100
98
96
94
Sep '19
Nov '19
Jan '20
Mar '20
May '20
Jul '20
Sep '20
Nov '20
Jan '21
Mar '21
Feb 2020 Mar 2020 Apr 2020 May 2020 Jun 2020 Jul 2020 Aug 2020 Sep 2020 Oct 2020
Nov 2020 Dec 2020 Jan 2021 Feb 2021 Mar 2021

Conclusion

- To build asymmetric filters, we can focus on the ones that reproduces at most linear trend (excluding QL, CQ and DAF filters)

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- In some cases, we could prefer others trend-cycle filters ➔ `rjdfilters` can help

What next?

- More investigations to understand why and when a method performs better

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- FST can lead to filters that performs better in terms of Fidelity, Smoothness, Timeliness than:
  - RKHS filters with same polynomial constraints
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➔ Study of those moving averages?

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- Direct Filter Approach (Wildi and McElroy (2019)), Cascade Linear Filter (Dagum and Luati (2008)), etc.
- Impact of outliers? Study of robust methods?

Thanks for your attention

R package: palatej/rjdfilters About me: AQLT

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