The dangers of using Seasonal Adjustment and other filters in Econometrics

Some economic and environmental examples

44th International Symposium on Forecasting, Dijon

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OCGtools: processing OCG's ...

1 Introduction

- When using seasonally unadjusted data, how can we decide what is the optimal seasonal adjustment to use?
  - Not theoretical point of view
- Do we have sensible statistical tools to discriminate among the different available alternatives?
- Knowing that the *estimated* components are not *observable*, is it enough to pay attention to just the component of interest and forget about the remaining ones?
- Is the ideal property of *orthogonality* among the different component reasonably fulfilled?
- How potential *outliers* and other variants of *intervention* analysis affect final estimated components?

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2 Traditional approach

$$y_t = T_t + C_t + S_t + e_t$$

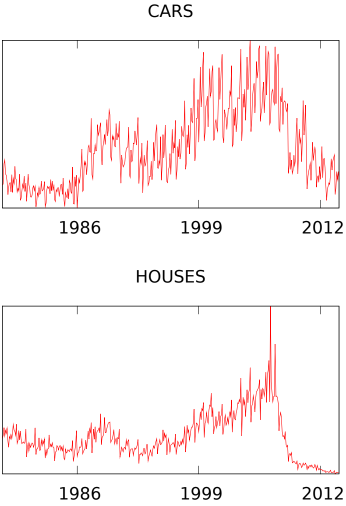
3 Small empirical exercise

Four monthly time series pertaining to the Spanish economic CLI used in: `http://uam-ucm-economic-indicators.es/`

- CAR REGISTRATIONS
- HOUSING STARTS
- CEMENT CONSUMPTION
- TRUCKS

From 1978M01 to 2013M12

4 Small empirical exercise



5 Several signal extraction methodologies

Using several model-based signal extraction methodologies, namely

- SEATS-TRAMO
- X-12 ARIMA
- Linear Dynamic Harmonic Regression (Bujosa et al., 2007)

Disclaimer and explanation of the posterior empirical results

6 Dynamic Harmonic Regression Model

The DHR model consists of several unobserved components plus an irregular stationary zero mean component $\boldsymbol{e} = \{e_t\}_{t\in\mathbb{Z}}$

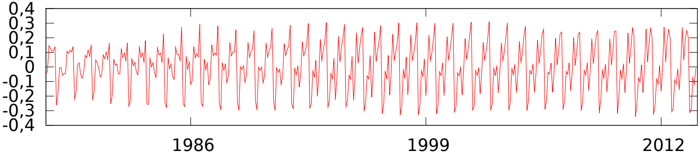
$$\boldsymbol{y} = \sum_{j=0}^{R} \boldsymbol{s}^j + \boldsymbol{e}. \qquad (1)$$

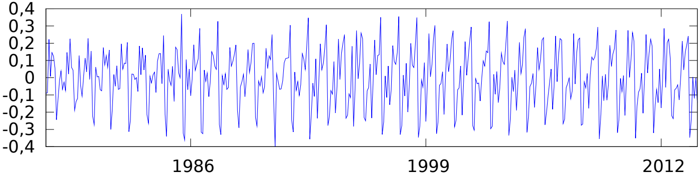
- DHR components $\boldsymbol{s}^j = \{s_t^j\}_{t\in\mathbb{Z}}$ are oscillatory

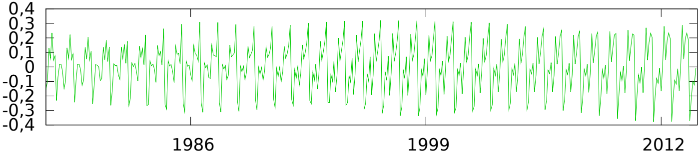
  $$s_t^j = a_t^j \cos(\omega_j t) + b_t^j \sin(\omega_j t), \qquad (2)$$

  where frequency ω_j is associated to the j-th component.
- Oscillations are modulated by two GRW processes $\boldsymbol{a}^j = \{a_t^j\}_{t\in\mathbb{Z}}$ and $\boldsymbol{b}^j = \{b_t^j\}_{t\in\mathbb{Z}}$.
- $\omega_0 = 0$ corresponds to the trend (or zero frequency term).
- The model is fitted in the frequency domain.

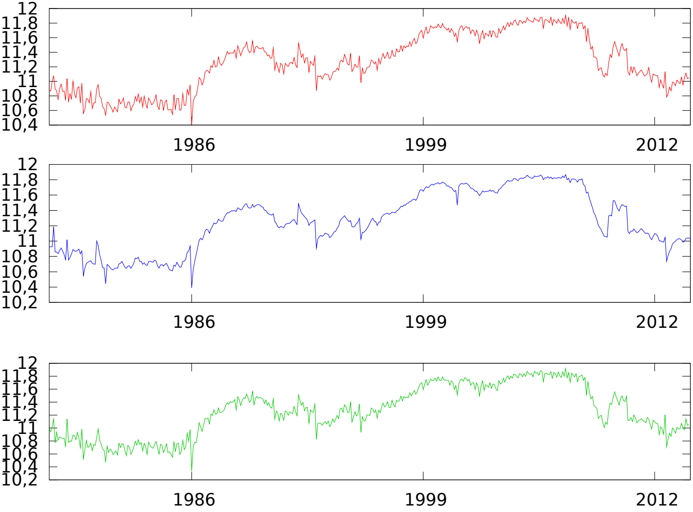
7 Car registrations Seasonal Factors: DHR, ST, X12



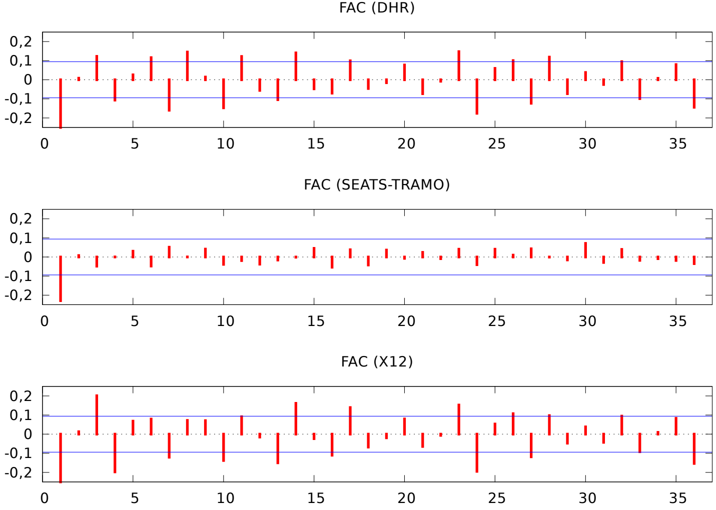




8 Seasonally adjusted Car registrations: DHR, ST, X12



9 FAC – First Difference of Seasonally adjusted Car registrations



10 Summary of tentative results of the four series

- Outlier detection plus other interventions as easter effects and calendar effects are crucial in the estimation of unobserved components models

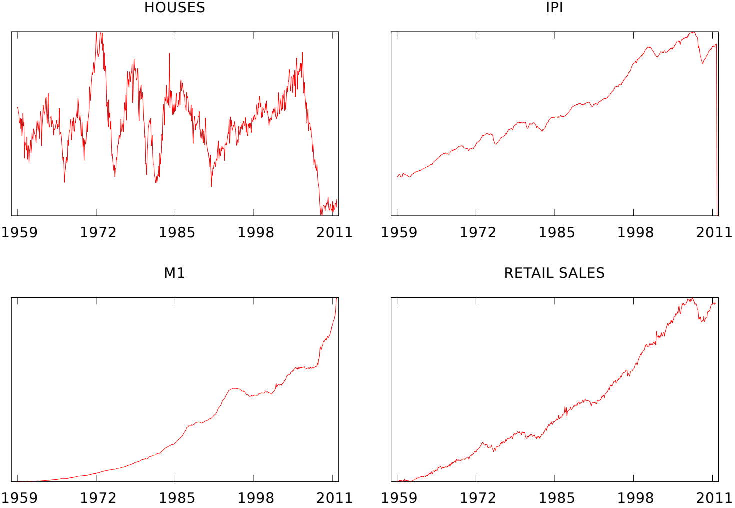
- As a matter of fact when you don't use this option in SEATS-TRAMO there is evidence of seasonality in the SA series

- Using outlier detection plus easter and calendar effects produce considerable reduction in the estimated residual variances ranging from 21% to 31%

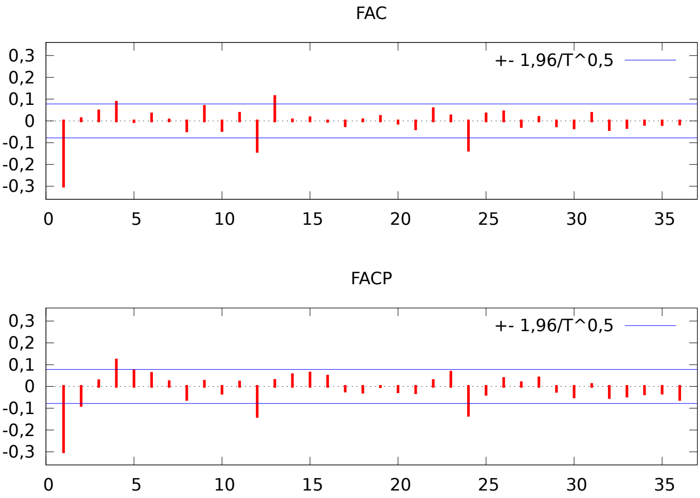
11 Results from a Stock & Watson data base

- Housing starts
- IPI
- Money supply – M1
- Retail sales

12 Results from a Stock & Watson data base

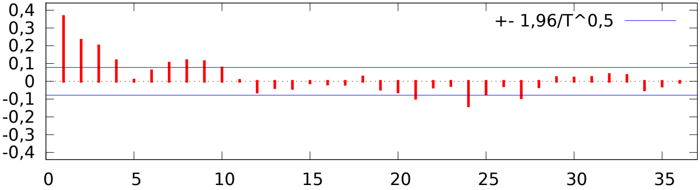


13 Results from a Stock & Watson data base: Housing starts

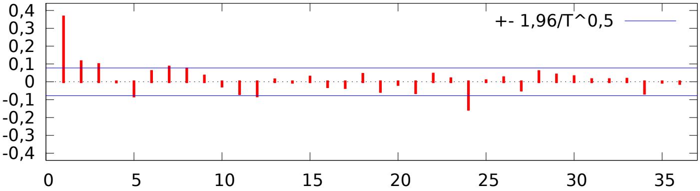


14 Results from a Stock & Watson data base: IPI

FAC

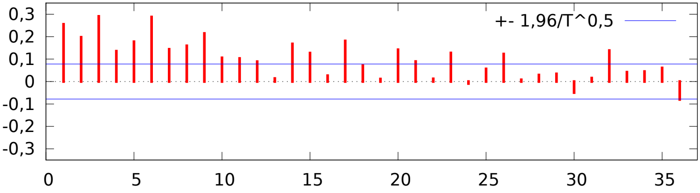


FACP



15 Results from a Stock & Watson data base: Money supply

FAC



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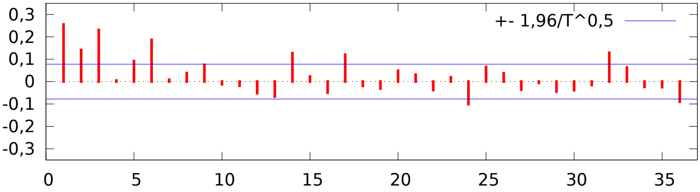
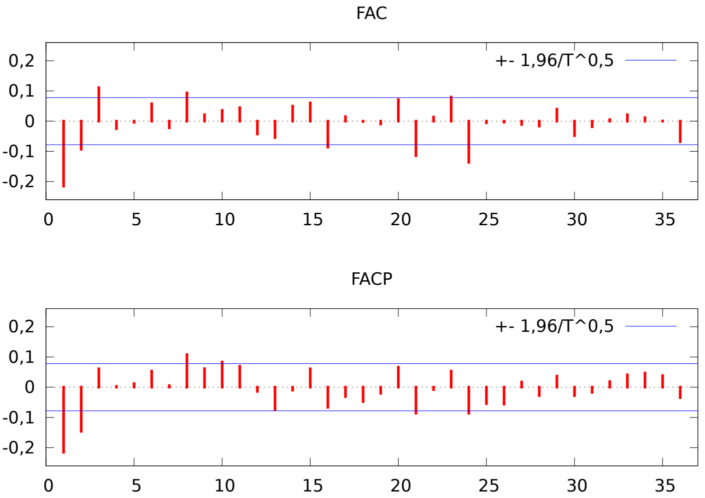


16 Results from a Stock & Watson data base: Retail sales



17 Hodrick–Prescott filter

Hodrick and Prescott (1981, 1997); Whittaker (1922)

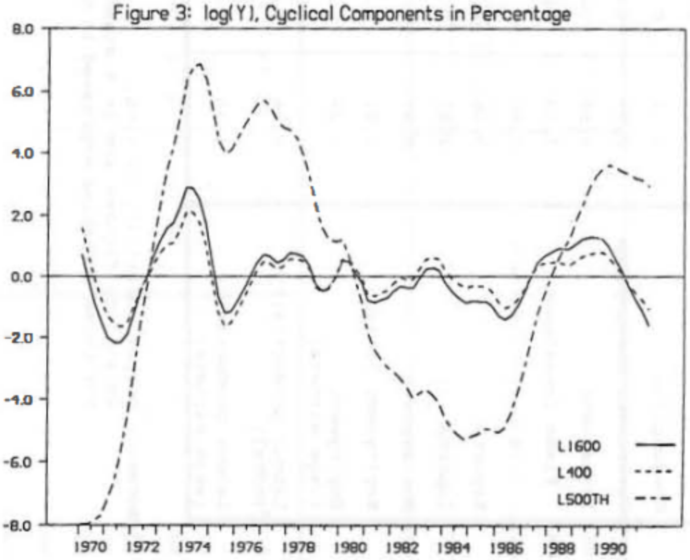
$$y_t = \tau_t + c_t + \epsilon_t$$

Given a positive λ, there is a trend component τ that solves

$$\min_{\tau} \left(\sum_{t=1}^{T} (y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 \right)$$

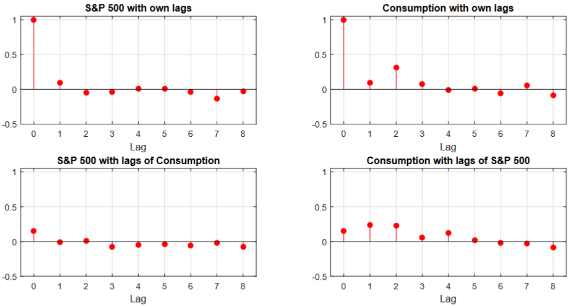
Why $\lambda = 1600$?

18 Hodrick–Prescott filter



19 Why You Should Never Use the Hodrick-Prescott Filter (Hamilton, 2018)

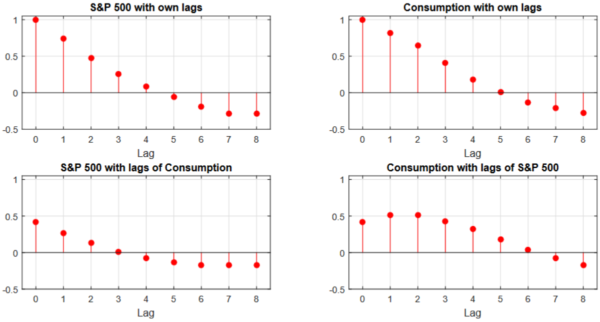
Figure 2. Autocorrelations and cross-correlations for first-difference of stock prices and real consumption spending.



Notes to Figure 2. Upper left: autocorrelations of log growth rate of end-of-quarter value for S&P 500. Upper right: autocorrelations of log growth rate of real consumption spending. Lower panels: cross correlations.

20 Why You Should Never Use the Hodrick-Prescott Filter (Hamilton, 2018)

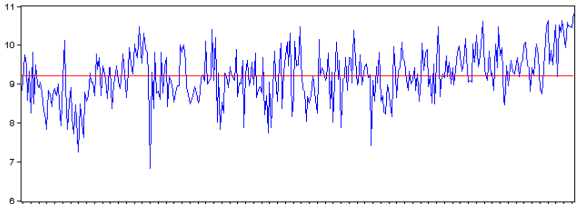
Figure 3. Autocorrelations and cross-correlations for HP cyclical component of stock prices and real consumption spending.

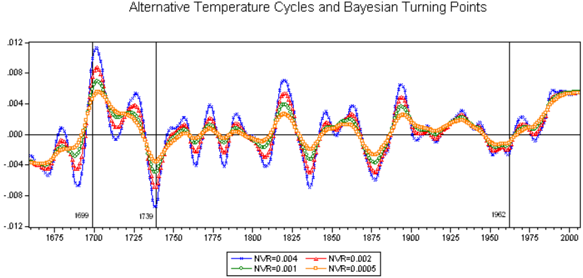


Notes to Figure 3. Upper left: autocorrelations of HP cycle for log of end-of-quarter value for S&P 500. Upper right: autocorrelations of HP cycle for log of real consumption spending. Lower panels: cross correlations.

42

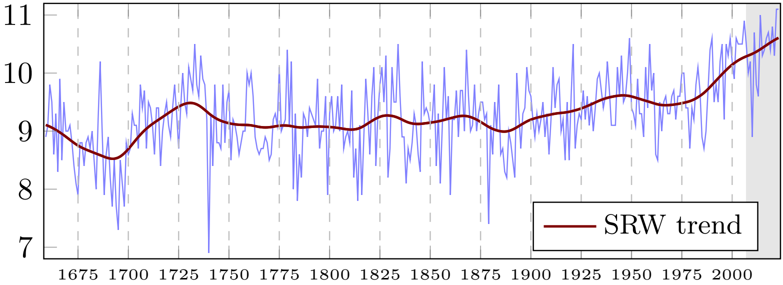
21 The Central England Temperature 1659–2007 (CET)

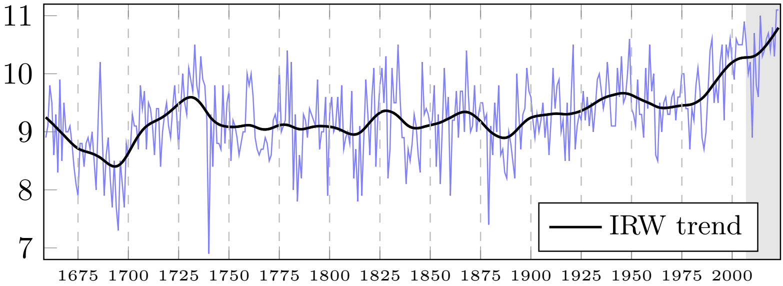




(Moreno et al., 2013; García-Ferrer et al., 2008)

22 The Central England Temperature 1659–2023 (CET)





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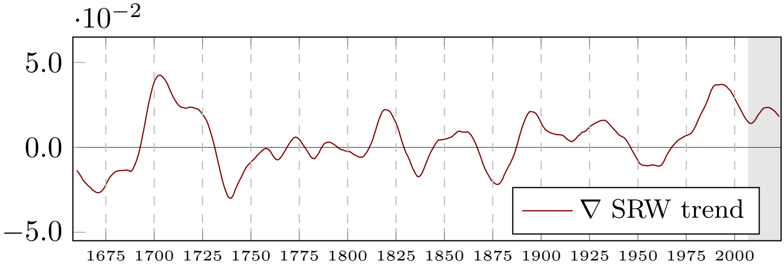
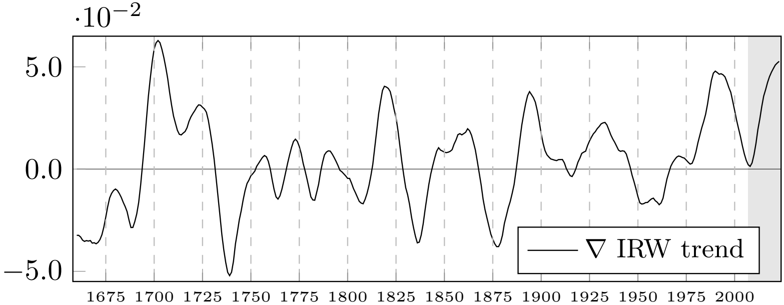
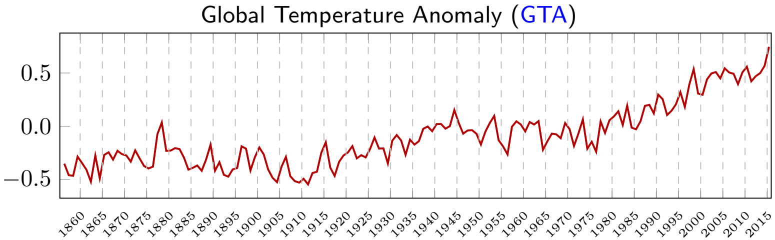
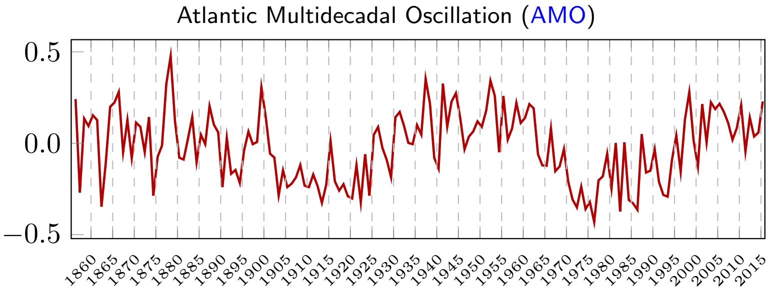




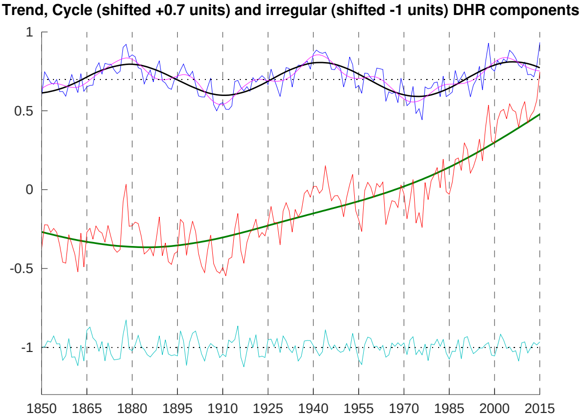
24 Modelling of Global Climate Change (Young et al., 2021)





25 Have AMO and GTA a common 63-years cycle?

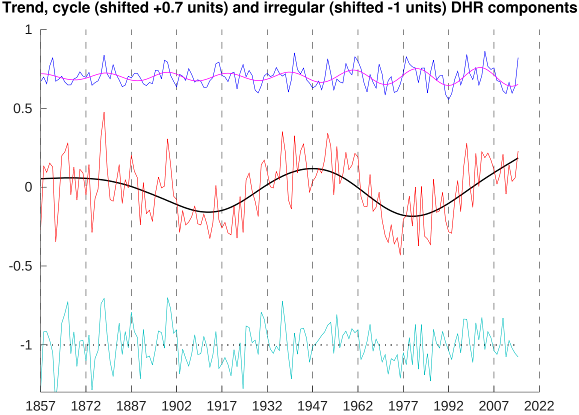
DHR components for GTA



$$GTA = T + S^{63} + S^{21} + \sum(\text{other harmonics}) + Irreg$$

26 Have AMO and GTA a common 63-years cycle?

DHR Trend-cycle component for AMO

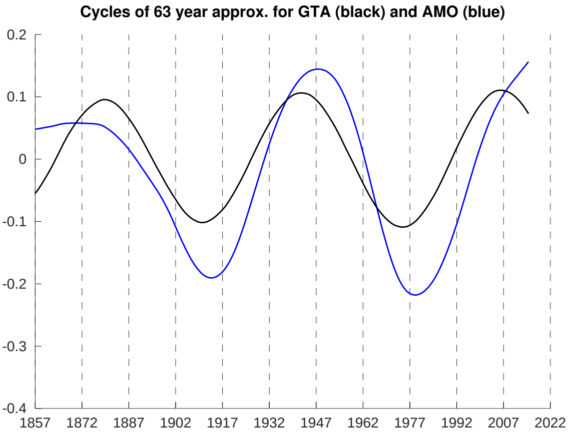


$$AMO = T + S^{21} + \sum(\text{other harmonics}) + Irreg$$

27 Have AMO and GTA a common 63-years cycle?

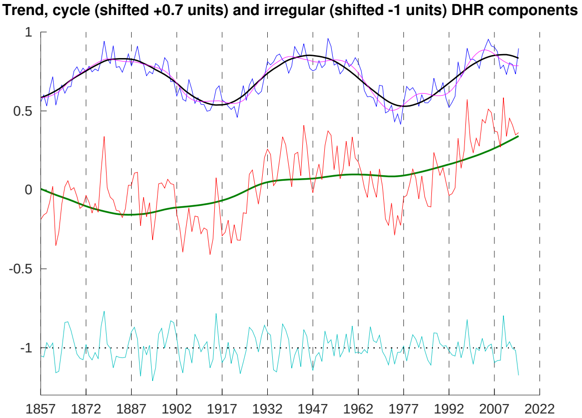
Not clear

GTA has a periodic cycle, but not AMO



28 Have original AMO and GTA a common 63-years cycle?

DHR components for *"original"* AMO data

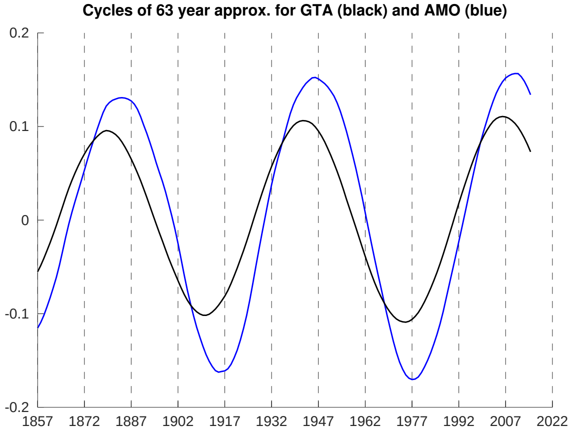


$$AMO_{\text{with trend}} = T + S^{63} + S^{21} + \sum(\text{other harmonics}) + Irreg$$

29 Have the *"original"* AMO and GTA a common cycle?

They seem to have a common cycle

(as suggested in Professor Young's article)



30 Number of confirmed cases at 3/22/2020

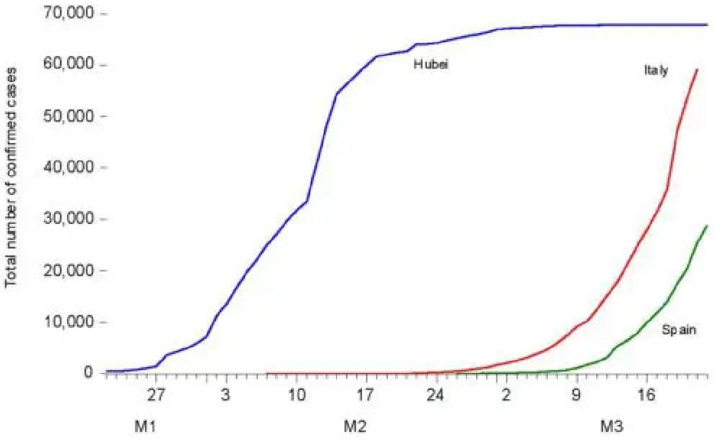


Figure 1: Number of confirmed cases at 3/22/2020

31 Observed contagions and forecasts in Spain

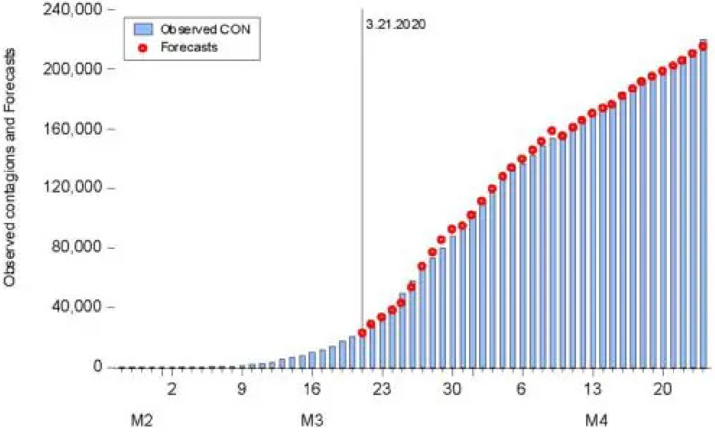


Figure 2: Observed contagions and Forecasts in Spain

32 Observed deaths and forecasts in Spain

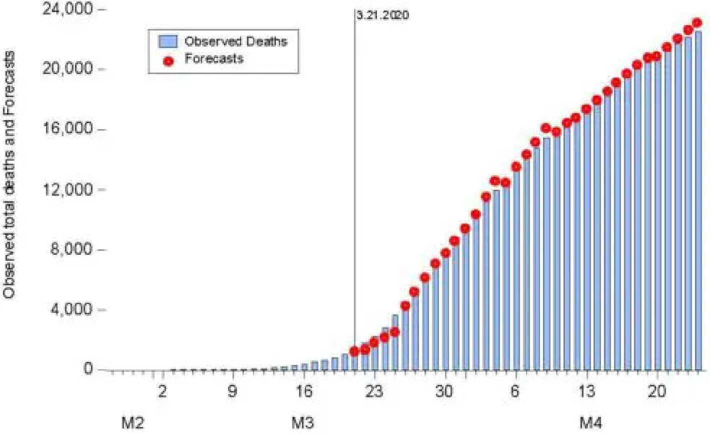
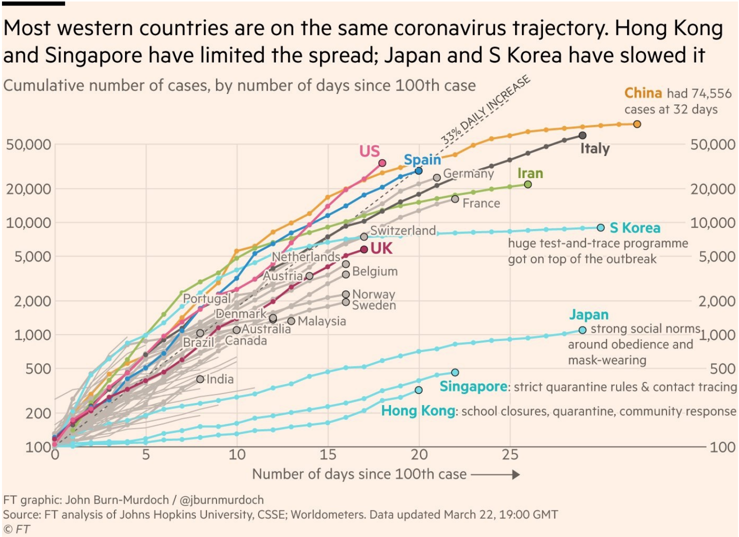


Figure 3: Observed Deaths and Forecasts in Spain

33 Coronavirus trajectories



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URL https://dx.doi.org/10.1088/1748-9326/abfa50