The dangers of using Seasonal Adjustment and other filters in Econometrics

Some economic and environmental examples

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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?

2 Traditional approach

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

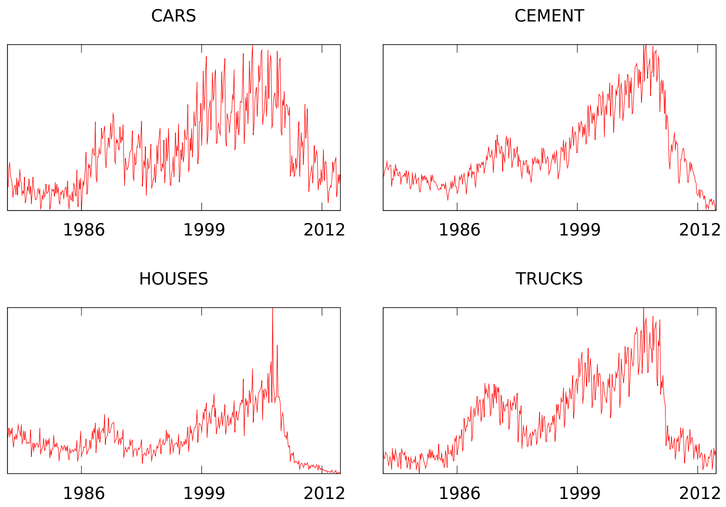
3 Small empirical exercise

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 $\boldsymbol{e} = \{e_t\}_{t\in\mathbb{Z}}$

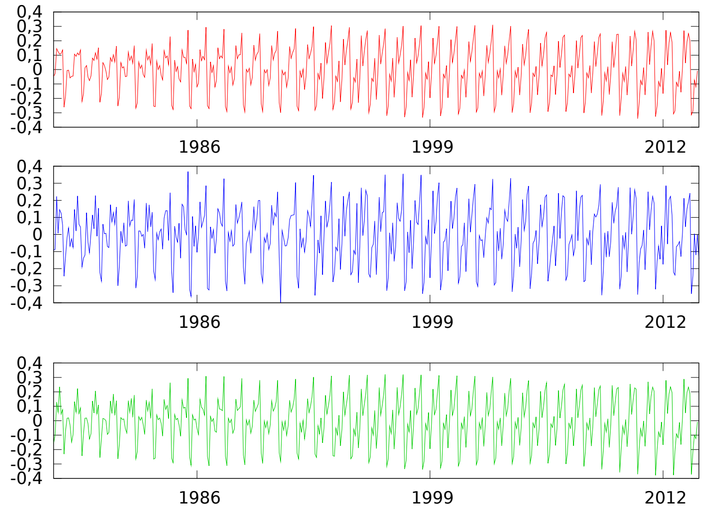
$$\boldsymbol{y} = \sum_{j=0}^{R} \boldsymbol{s}^j + \boldsymbol{e}. \tag{1}$$

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

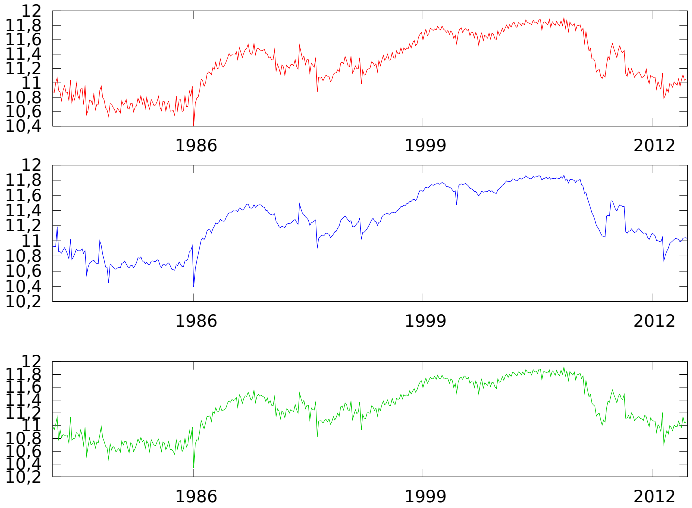
$$s_t^j = a_t^j \cos(\omega_j t) + b_t^j \sin(\omega_j t), \tag{2}$$

  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.

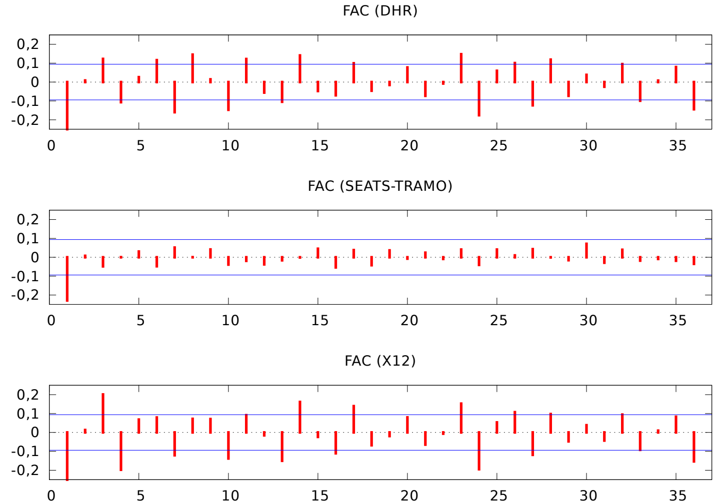
7 Car registrations Seasonal Factors: DHR, ST, X12



8 Seasonally adjusted Car registrations: DHR, ST, X12



9 FAC – First Difference of Seasonally adjusted Car registrations



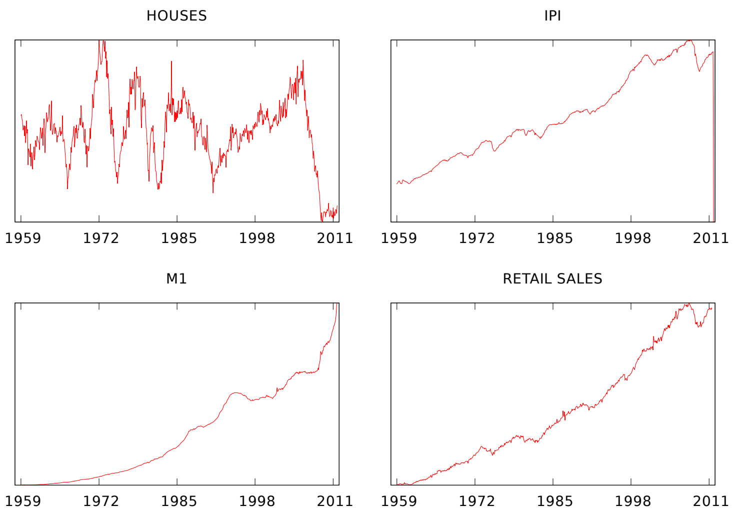
10 Summary of tentative results of the four series

- 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%

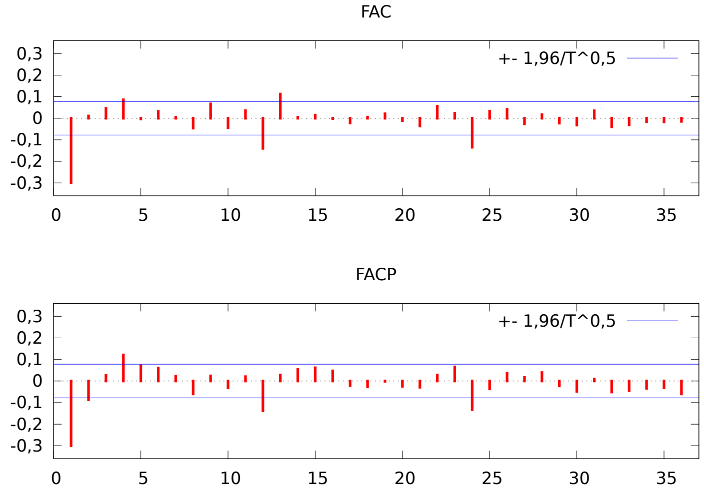
11 Results from a Stock & Watson data base

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

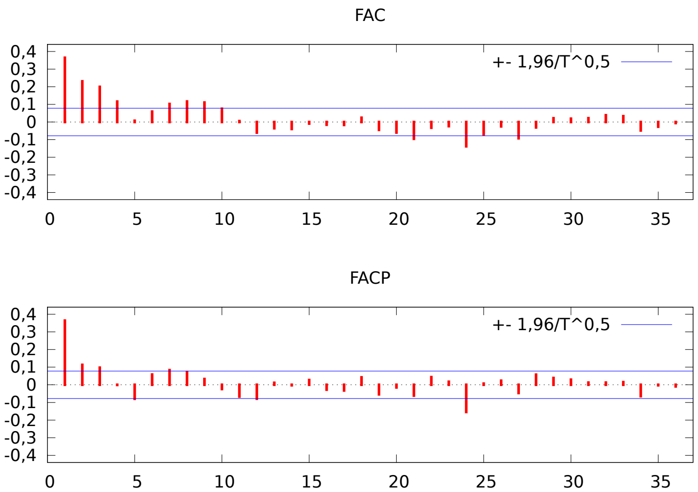
12 Results from a Stock & Watson data base



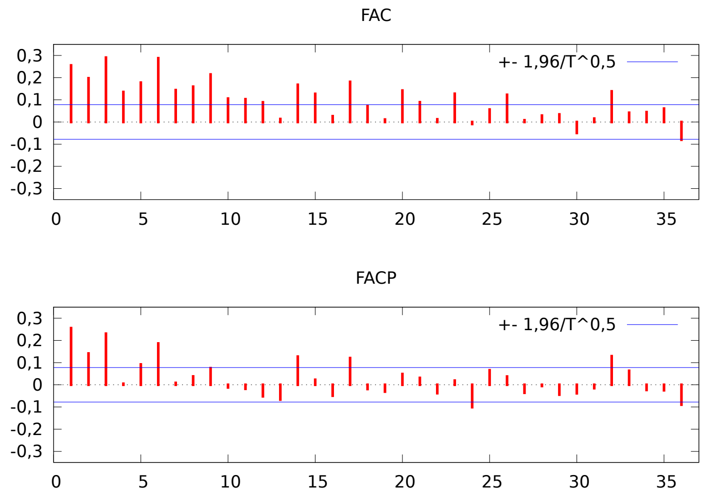
13 Results from a Stock & Watson data base: Housing starts



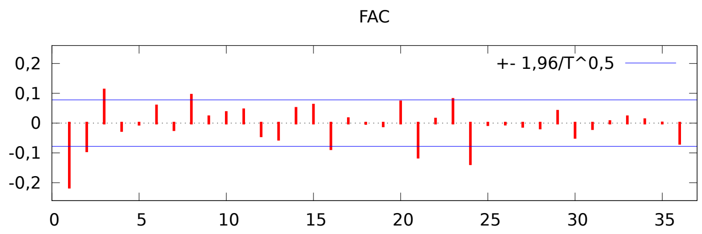
14 Results from a Stock & Watson data base: IPI

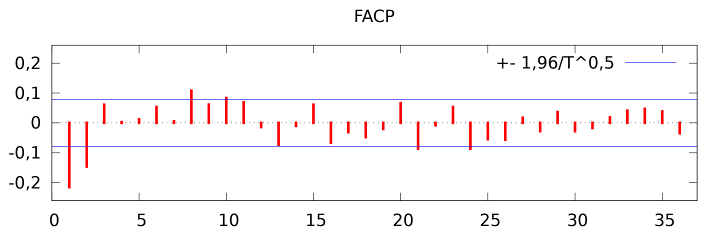


15 Results from a Stock & Watson data base: Money supply



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





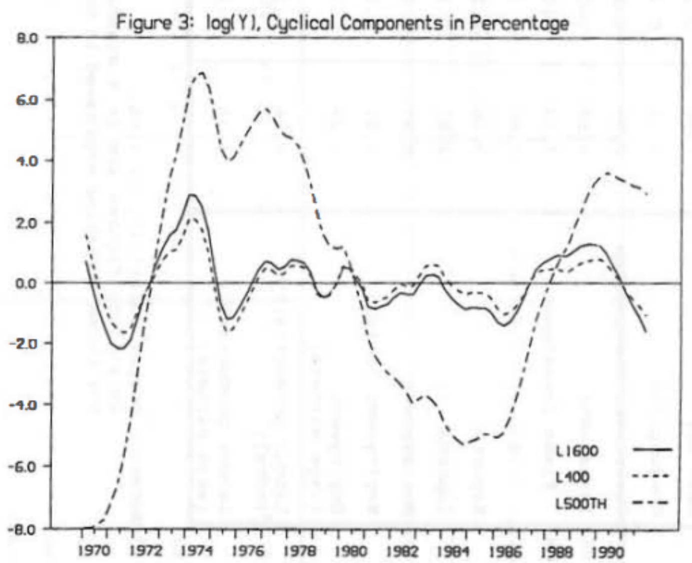
17 Hodrick–Prescott filter

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

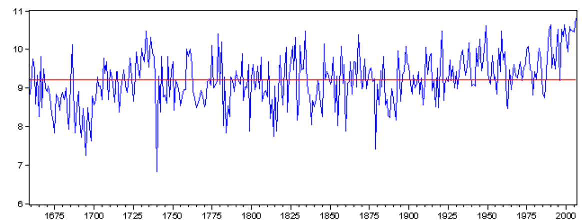
Given a positive λ, there is a trend component τ that solves

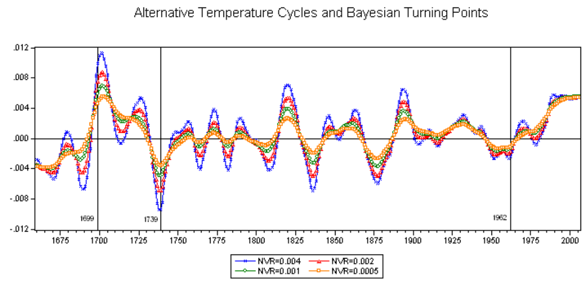
$$\min_{\tau} \left(\sum_{t=1}^{T} (y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 \right)$$

18 Hodrick–Prescott filter

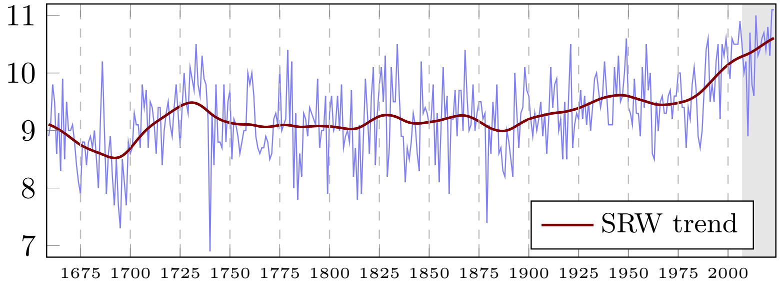


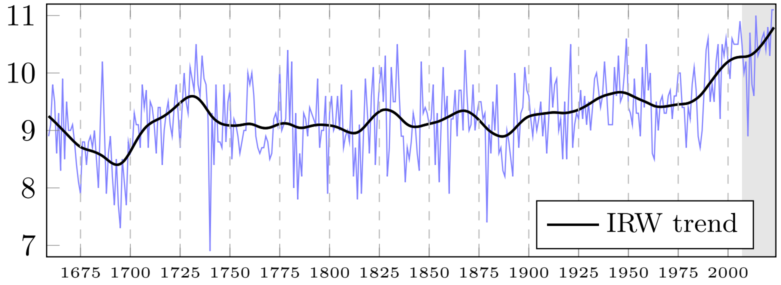
19 The Central England Temperature 1659–2007 (CET)



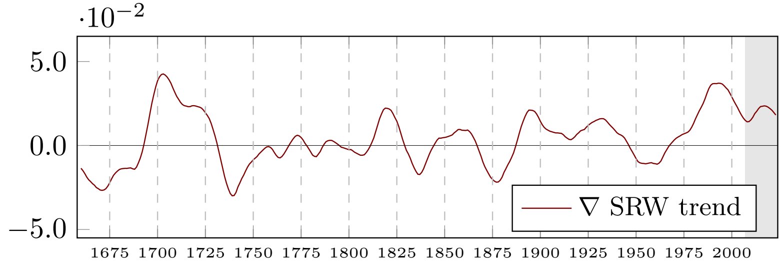


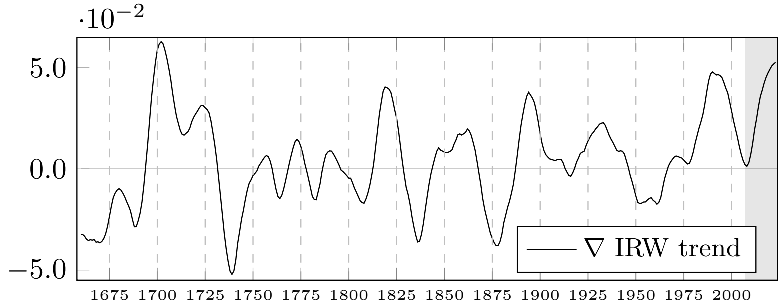
20 The Central England Temperature 1659–2023 (CET)





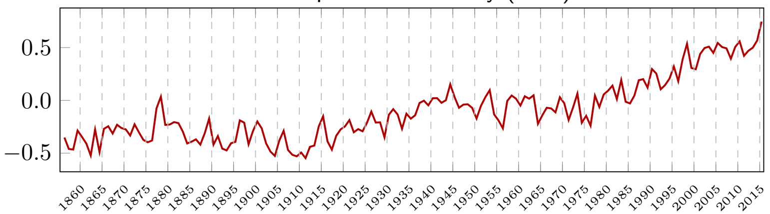
21 The Central England Temperature 1659–2023 (CET)



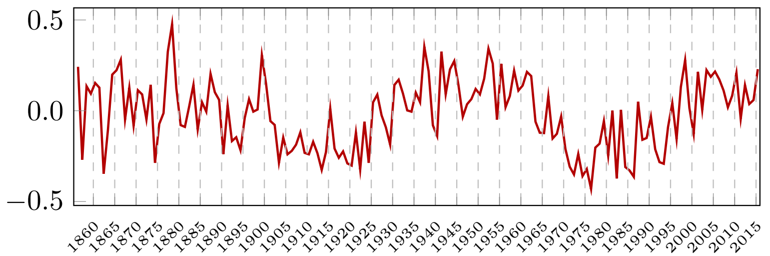


22 Modelling of Global Climate Change

Global Temperature Anomaly (GTA)

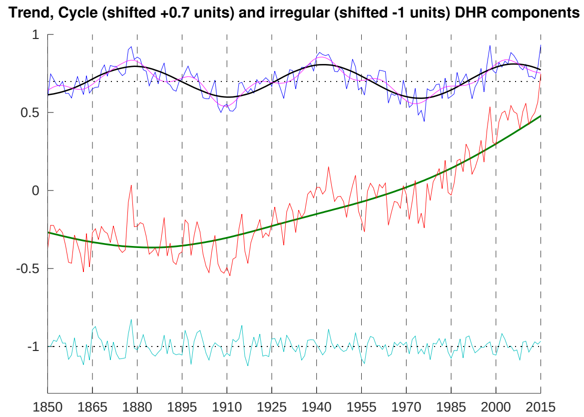


Atlantic Multidecadal Oscillation (AMO)



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

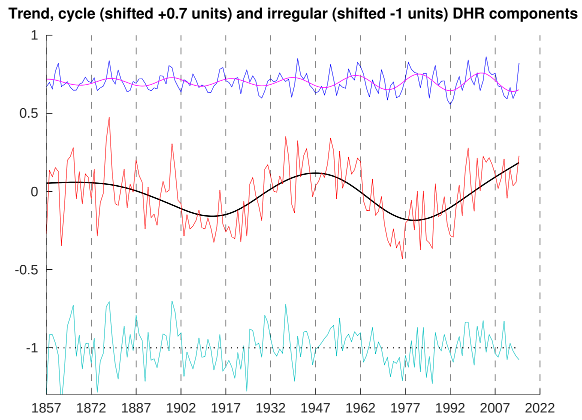
DHR components for GTA



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

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

DHR Trend-cycle component for AMO

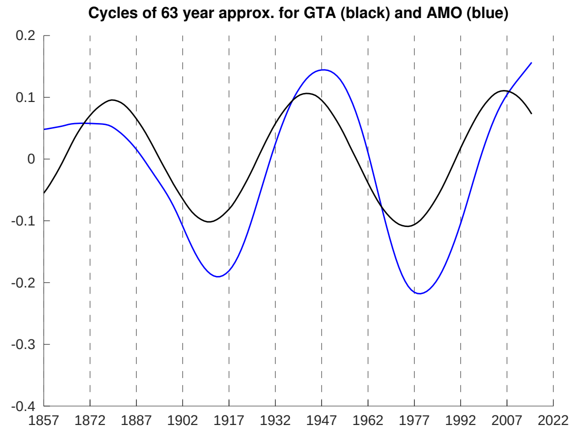


$$AMO = T + S^{21} + \sum(\text{other harmonics}) + Irreg$$

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

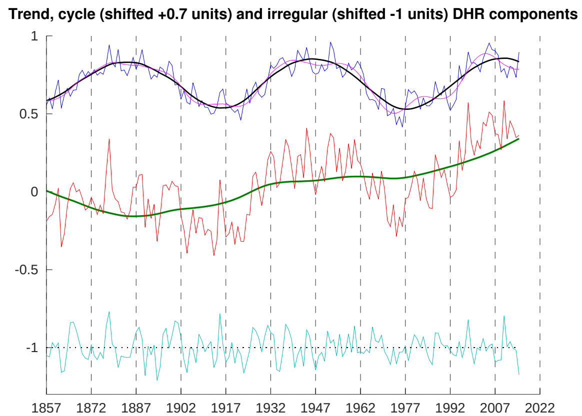
Not clear

GTA has a periodic cycle, but not AMO



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

DHR components for *"original"* AMO data

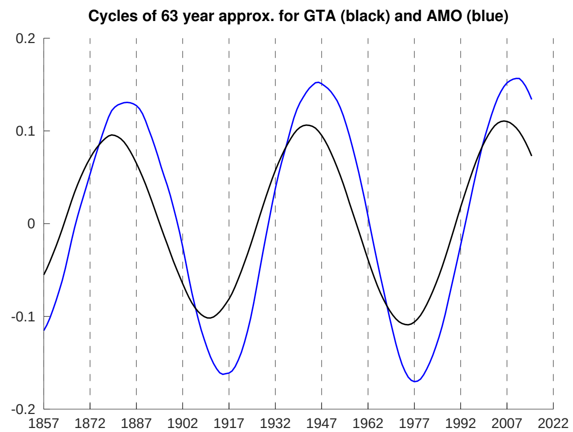


$$AMO_{\text{with trend}} = T + S^{63} + S^{21} + \sum(\text{other harmonics}) + Irreg$$

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

They seem to have a common cycle

(as suggested in Professor Young's article)



28 Number of confirmed cases at 3/22/2020

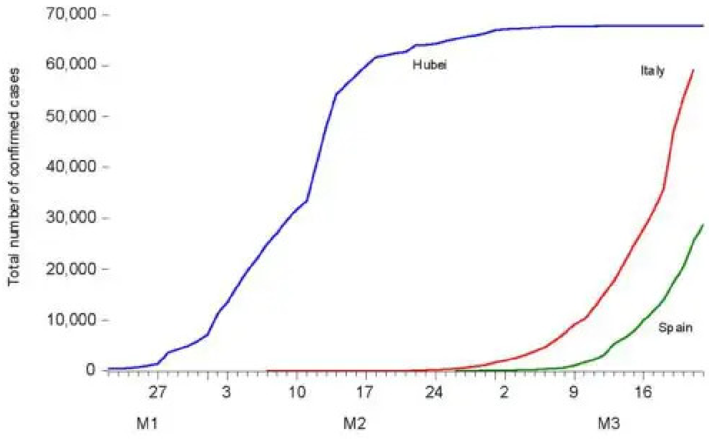


Figure 1: Number of confirmed cases at 3/22/2020

29 Observed contagions and forecasts in Spain

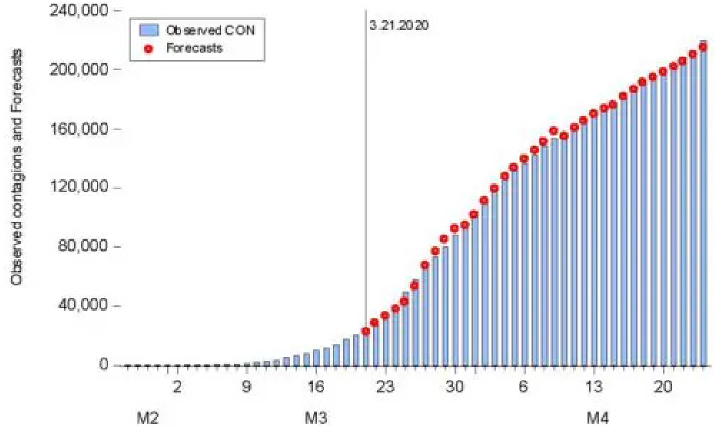


Figure 2: Observed contagions and Forecasts in Spain

30 Observed deaths and forecasts in Spain

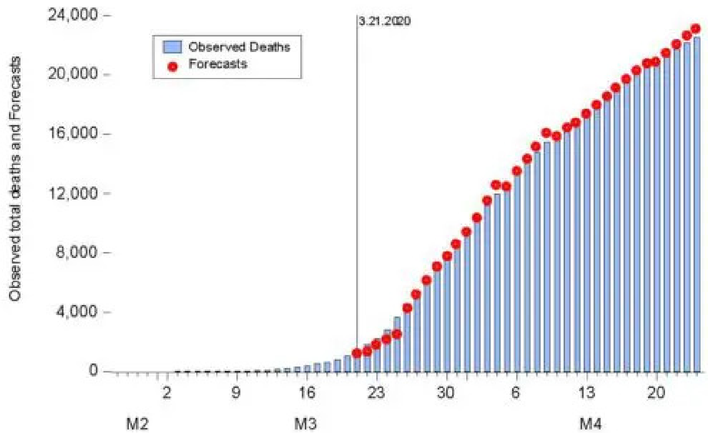


Figure 3: Observed Deaths and Forecasts in Spain

Bujosa, M., García-Ferrer, A., and Young, P. C. (2007). Linear dynamic harmonic regression. *Comput. Stat. Data Anal.*, **52**(2), 999–1024. ISSN 0167-9473.