

Unobserved Components Models: Applications in Post-COVID Analysis

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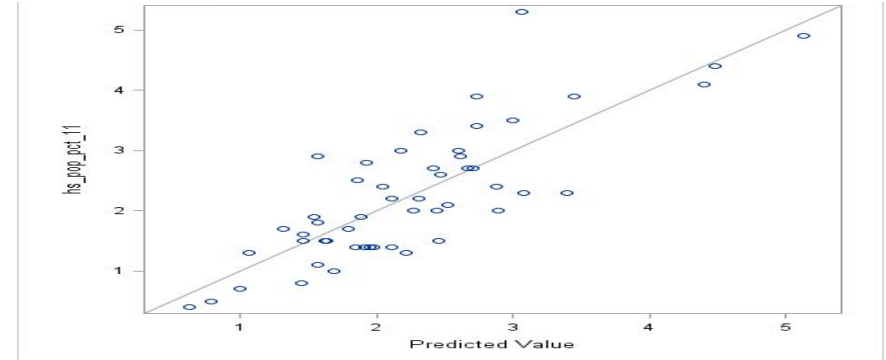
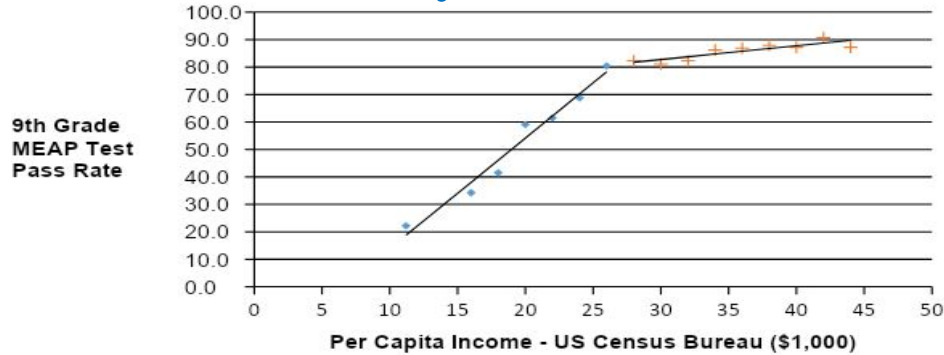
David J Corliss, Grafham Analytics

Modern Modeling Methods
University of Connecticut
June 27-28, 2023



Peace-Work: Statistical Volunteers For A Cause

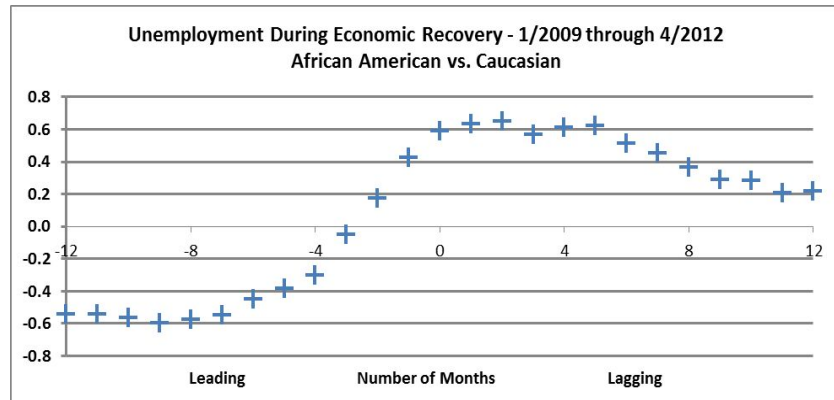
Poverty and Education



Homeless K-12 Students

	Riga	Blissfield
Population	1,439	3,340
% under 18	27.2%	34.2%
Population under 18	391	1,142
% in poverty	5.2%	8.4%
Population in poverty	75	281
% under 18 in poverty	3.3%	10.0%
# under 18 in poverty	13	114
% over 65	14.0%	15.5%
Population over 65	201	518
% over 65 in poverty	6.3%	9.4%
# over 65 in poverty	13	49

Impact of Racial Bias



Research and Fact-Checking



INTRODUCTION TO UNOBSERVED COMPONENTS MODELS

Unobserved Components Models

- **Model Type: State Space Time Series Model, A. Harvey 1989**
- **Decomposes a time series into unobserved components that together form the time series, including trends, periodic behavior, and irregular components**
- **Supports measurement of changes in long-term baseline values of the time series => good for modeling high-impact events**
- **SAS: PROC UCM, R Package: rucm, sm.tsa.UnobservedComponents**

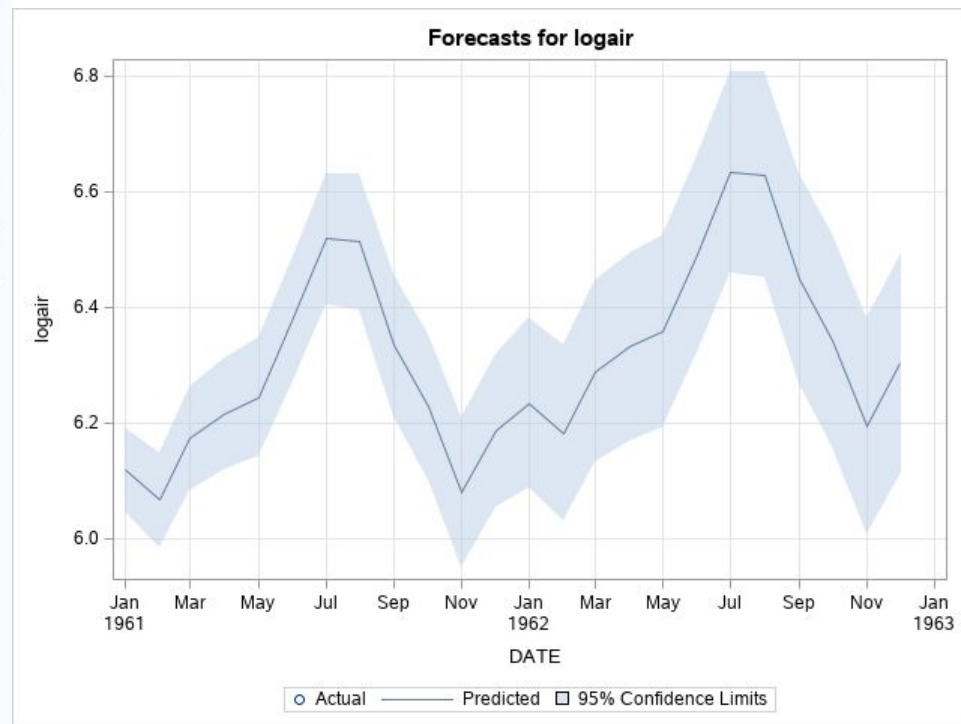
Python:



Unobserved Components Model Results, Output and Plots

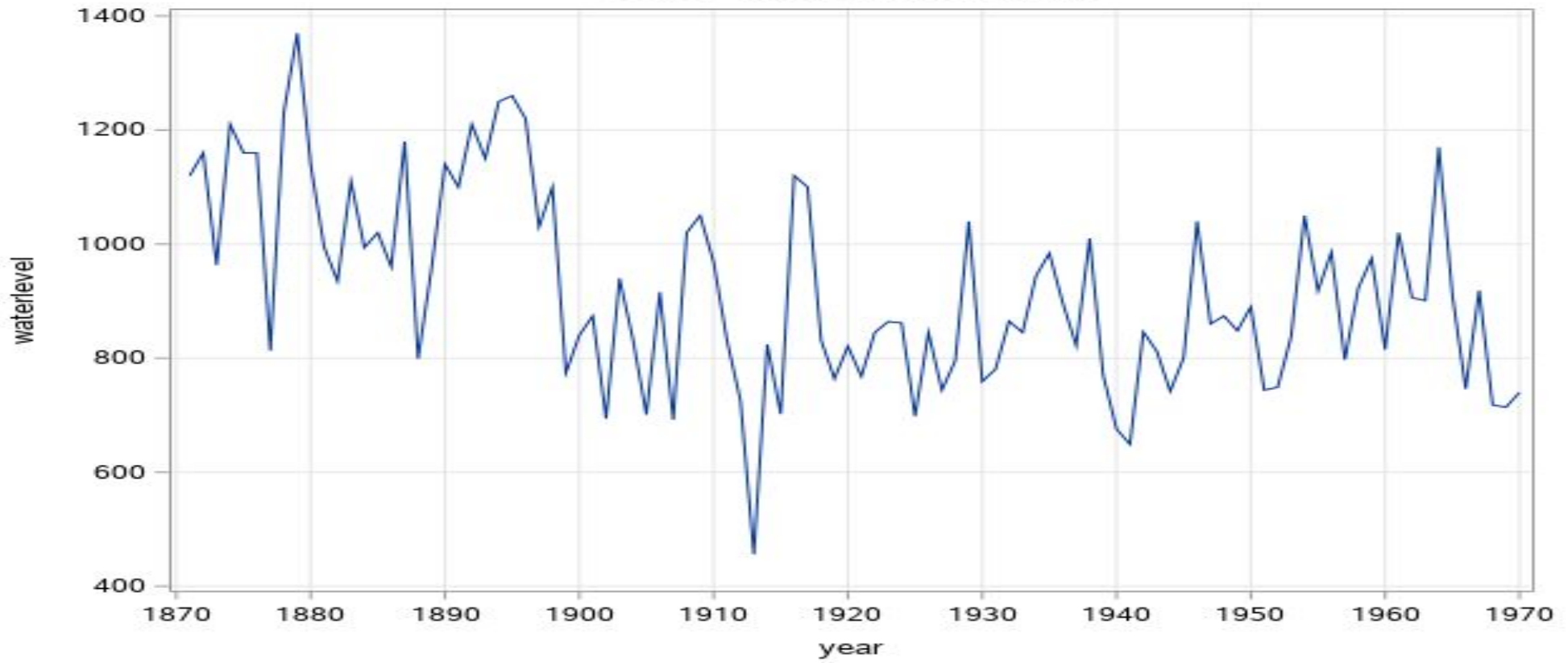
Final Estimates of the Free Parameters					
Component	Parameter	Estimate	Approx Std Error	t Value	Approx Pr > t
Irregular	Error Variance	0.00023436	0.0001079	2.17	0.0298
Level	Error Variance	0.00029828	0.0001057	2.82	0.0048
Slope	Error Variance	8.47922E-13	6.2271E-10	0.00	0.9989
Season	Error Variance	0.00000356	1.32347E-6	2.69	0.0072

Fit Statistics Based on Residuals	
Mean Squared Error	0.00147
Root Mean Squared Error	0.03830
Mean Absolute Percentage Error	0.54132
Maximum Percent Error	2.19097
R-Square	0.99061
Adjusted R-Square	0.99039
Random Walk R-Square	0.87288
Amemiya's Adjusted R-Square	0.99002
Number of non-missing residuals used for computing the fit statistics = 131	

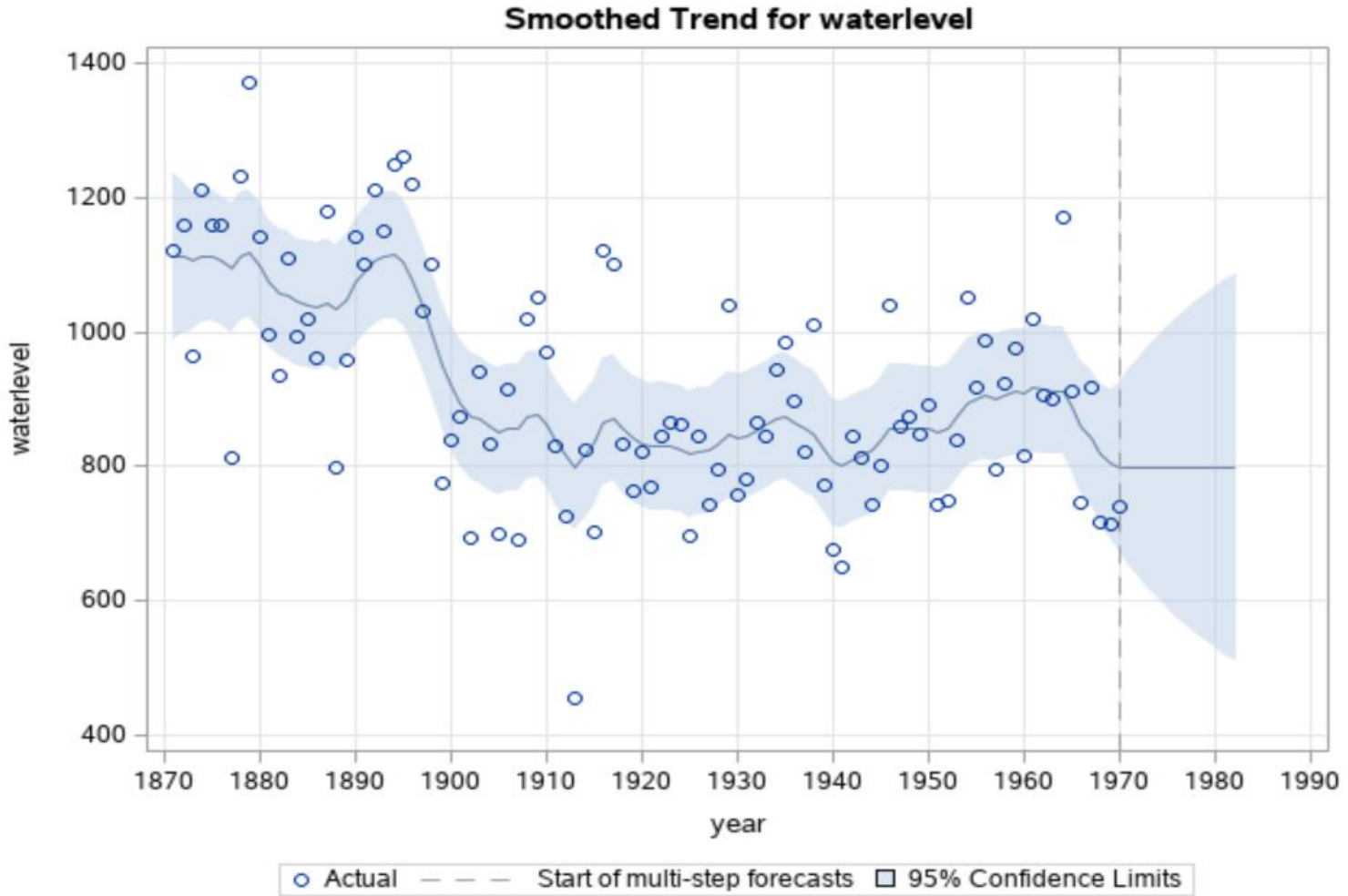


CHANGES IN BASELINE LEVELS WITH UCM

A UCM Classic Example: Depth of the Nile River



A UCM Classic Example: How has the Depth Changed?



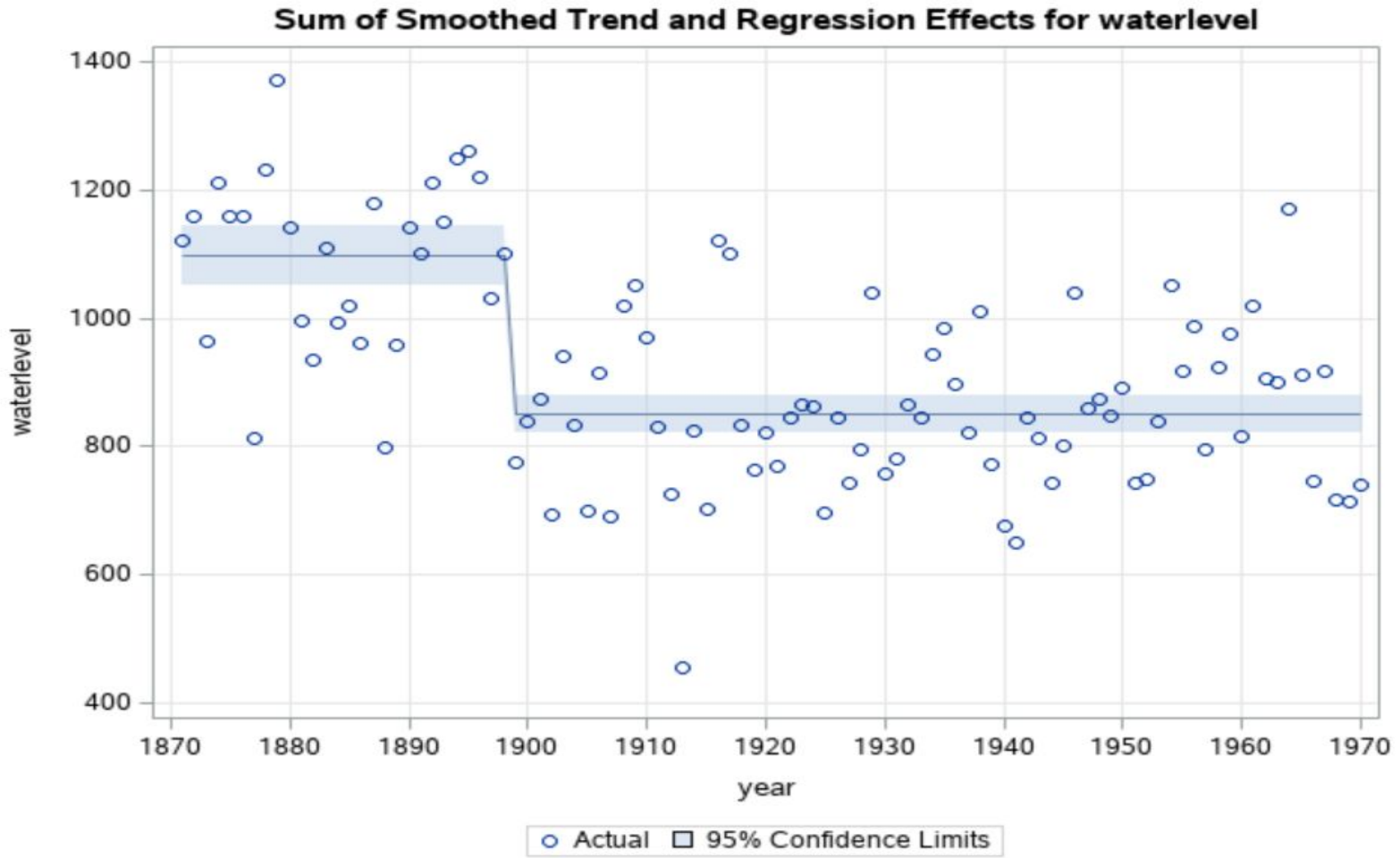
PEACE-WORK

A UCM Classic Example: Depth of the Nile River

```
data nile;  
  set nile;  
  shift1899 = ( year >= '1jan1899'd );  
run;
```

```
proc ucm data=nile;  
  id year interval=year;  
  model waterlevel = shift1899;  
  irregular;  
  level;  
  estimate;  
  forecast plot=decomp;  
run;
```

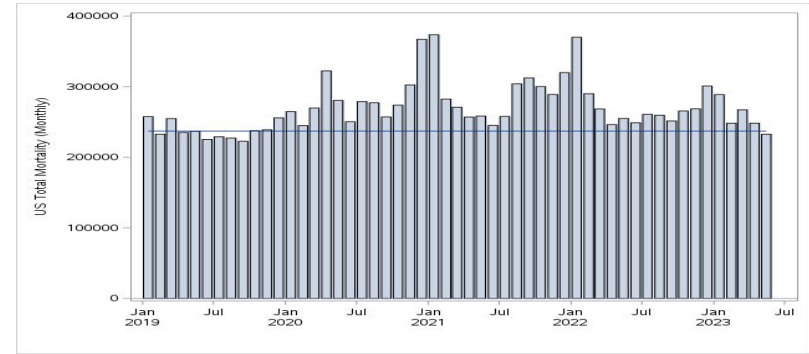
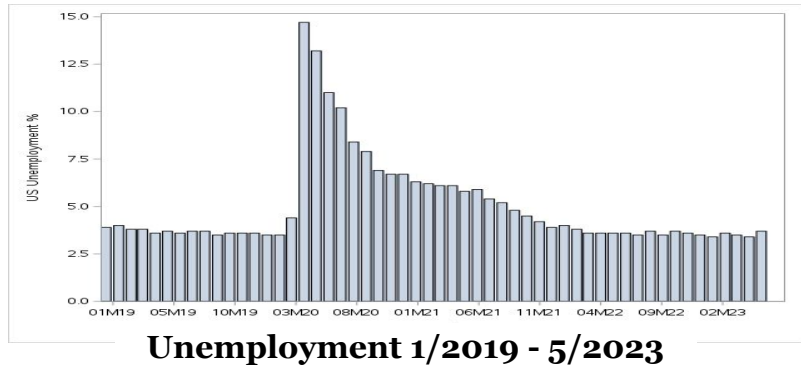
A UCM Classic Example: How has the Depth Changed?



COVID QUESTIONS

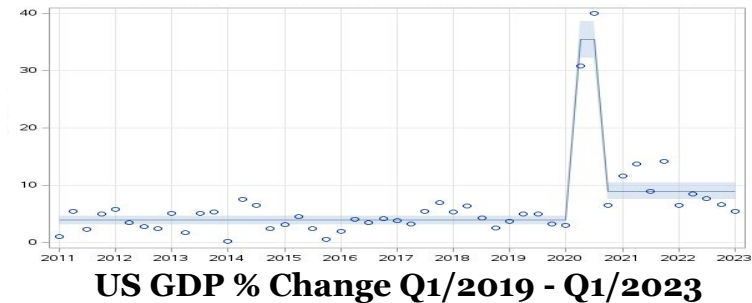
COVID Data: A Complex Time Series

Series of Waves



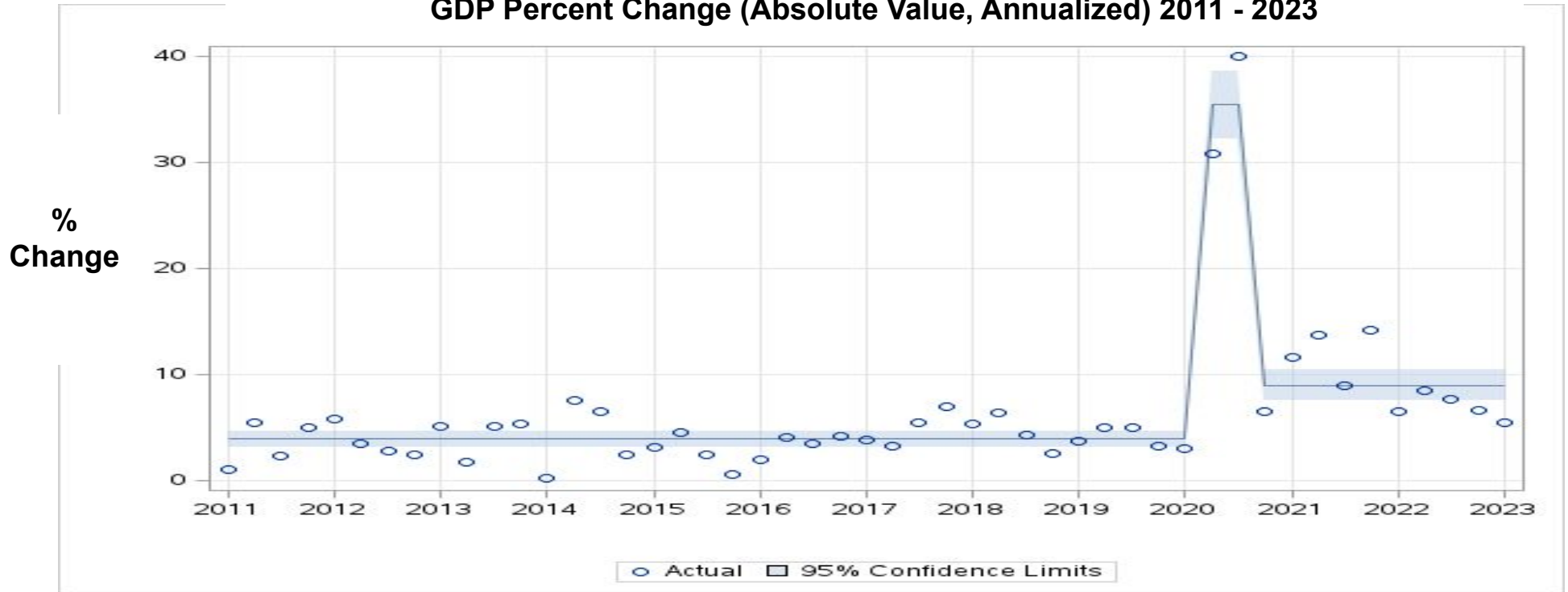
More than Medical

=> Unobserved Components



COVID-Era Changes: GDP Baseline Level

GDP Percent Change (Absolute Value, Annualized) 2011 - 2023



```
proc ucm data=tsa.gdp;  
  id qtr interval=qtr;  
  model GDP_ABS_Pct_Change = shift2020 shift2021;  
  irregular;  
  level;  
  estimate;  
  forecast plot=decomp;  
  where qtr ge mdy(1,1,2011) and qtr le mdy(3,31,2023);
```

COVID-Era Baseline Changes: Unemployment

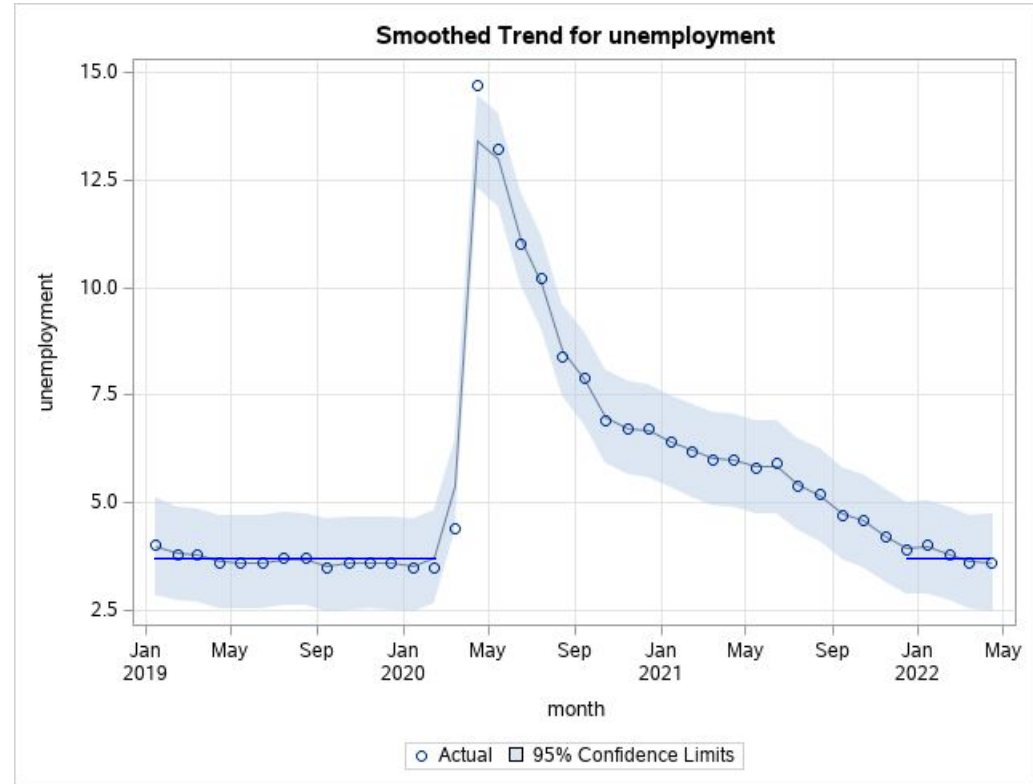
```
import statsmodels.api as sm
covid_ts['Date'] = pd.to_datetime(covid_ts['Date'])

# Unrestricted model, using string specification
unrestricted_model = {
    'level': 'local linear trend', 'cycle': True, 'damped_cycle':
    True, 'stochastic_cycle': True}

# The restricted model forces a smooth trend
restricted_model = {
    'level': 'smooth trend', 'cycle': True, 'damped_cycle':
    True, 'stochastic_cycle': True}

unemp_restricted_mod = sm.tsa.UnobservedComponents
(covid_ts['Unemployment_Pct'], **restricted_model)
unemp_restricted_res = unemp_restricted_mod.fit
(method='powell', disp=False)

unemployment_mod = sm.tsa.UnobservedComponents
(covid_ts['Unemployment_Pct'], **unrestricted_model)
unemployment_res = unemployment_mod.fit
(method='powell', disp=False)
```



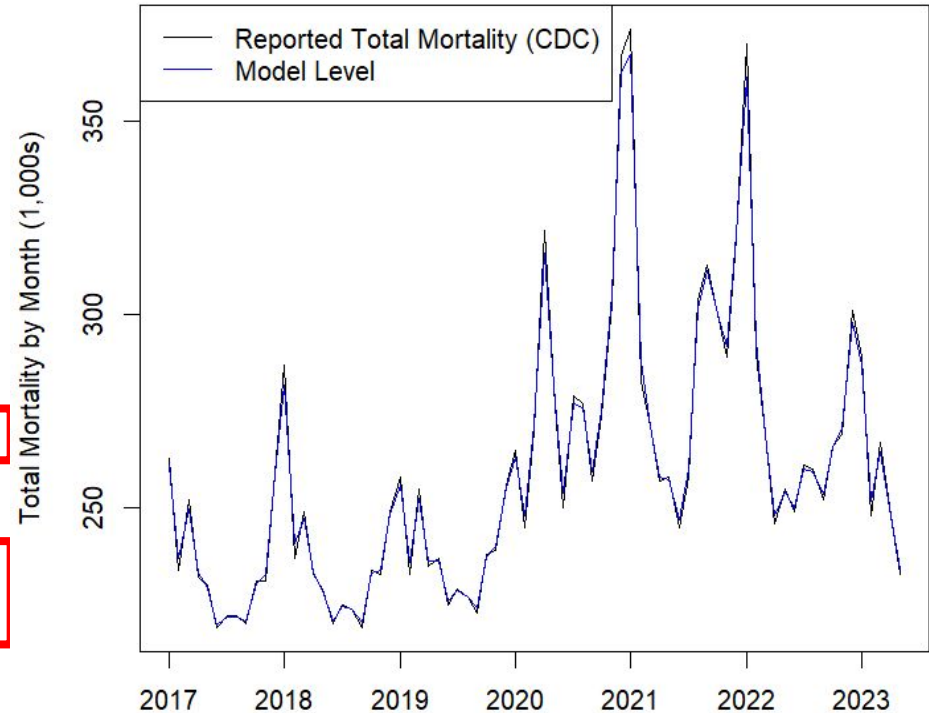
COVID-Era Changes: Deaths per Month

```
mortality <- c(
263,
234,
252,
.
.
.
267,
248,
233)
```

```
mortality_ts <- ts(mortality, start = c(2017, 1), frequency = 12)
```

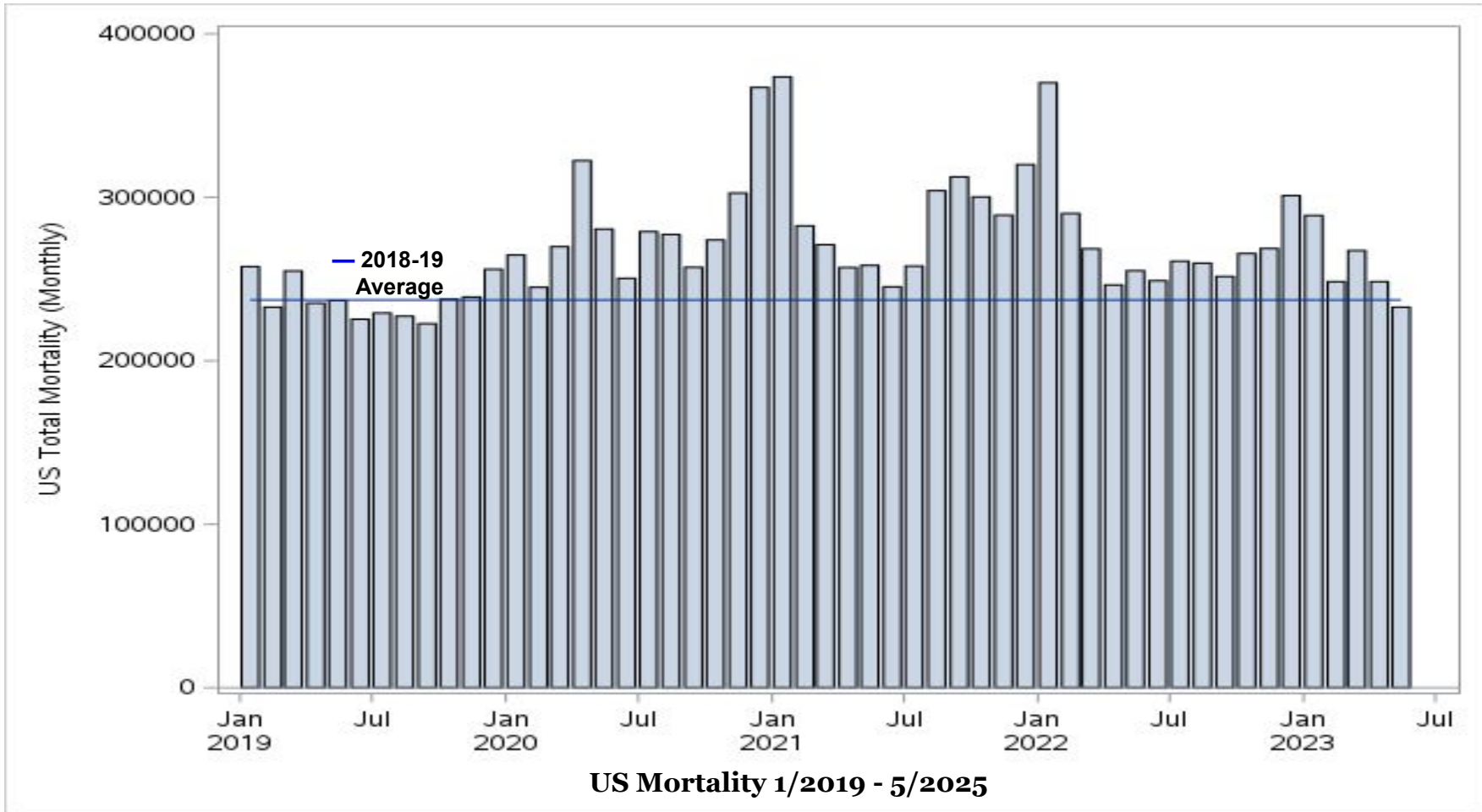
```
ucm_mortality <- ucm(formula = mortality_ts~0, data =
mortality_ts, level=TRUE, slope=TRUE, irregular=TRUE)
```

```
plot(mortality_ts, ylab = "Total Mortality by Month (1,000s)")
lines(ucm_mortality$s.level, col = "blue")
legend("topleft", legend = c("Reported Total Mortality
(CDC)", "Model Level"), col = c("black", "blue"), lty = 1)
```



LIMITATIONS OF UNOBSERVED COMPONENTS MODELS

Limitation of UCM: Rapidly Changing Non-Periodic Behavior



UCM Limitations

- **This method decomposes a time series into Baseline, Trend, and Periodic components, in addition to Irregular which is everything left. Where irregular dominates, the method isn't very informative => consider local regression**
- **Noisy or chaotic data often do not model well, as the components are difficult to distinguish**
- **Following a change to some underlying behavior, UCM needs sufficient data in the time series to accurately predict the new parameters - for example, a new baseline level**

CONCLUSIONS

Summary

- **Unobserved Components models decomposes time series data into level, slope, periodic, and irregular components**
- **Through the use of a binary dummy variable, Unobserved Components Models can estimate changes in baseline levels**
- **When changes in levels are numerous, large and irregular, UCM tends not to perform well – Local Regression is a better choice**
- **While the medical impacts have changed from pandemic to endemic, the non-medical effects of COVID continue to evolve**



References

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Questions

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