Interrupted Time-Series Designs for Policy and Intervention Analysis

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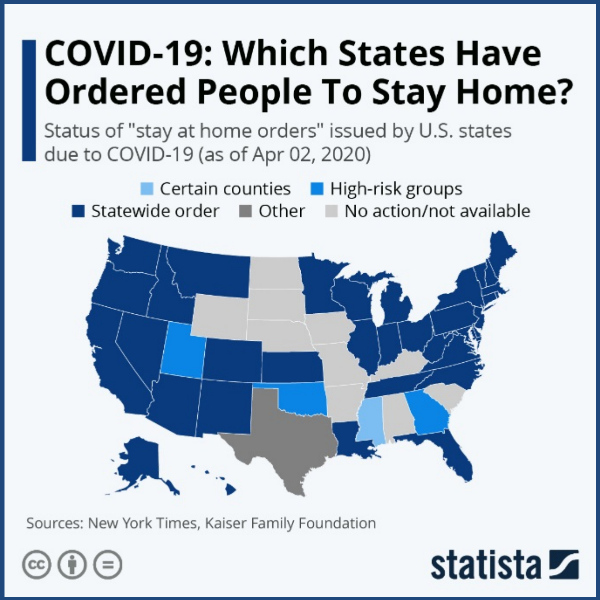
Overview

- why ITS?
- when to use
- logic of test
- practical considerations
- one example
- extensions
- resources

Why ITS?



MENTAL HEALTH SERVICES ACT
PROPOSITION 63
CALIFORNIA
WELLNESS • RECOVERY • RESILIENCE

ACOG
The American College of Obstetricians and Gynecologists

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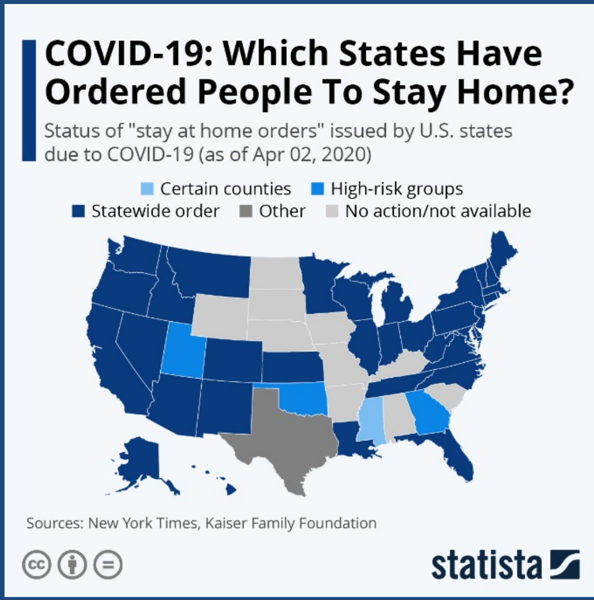

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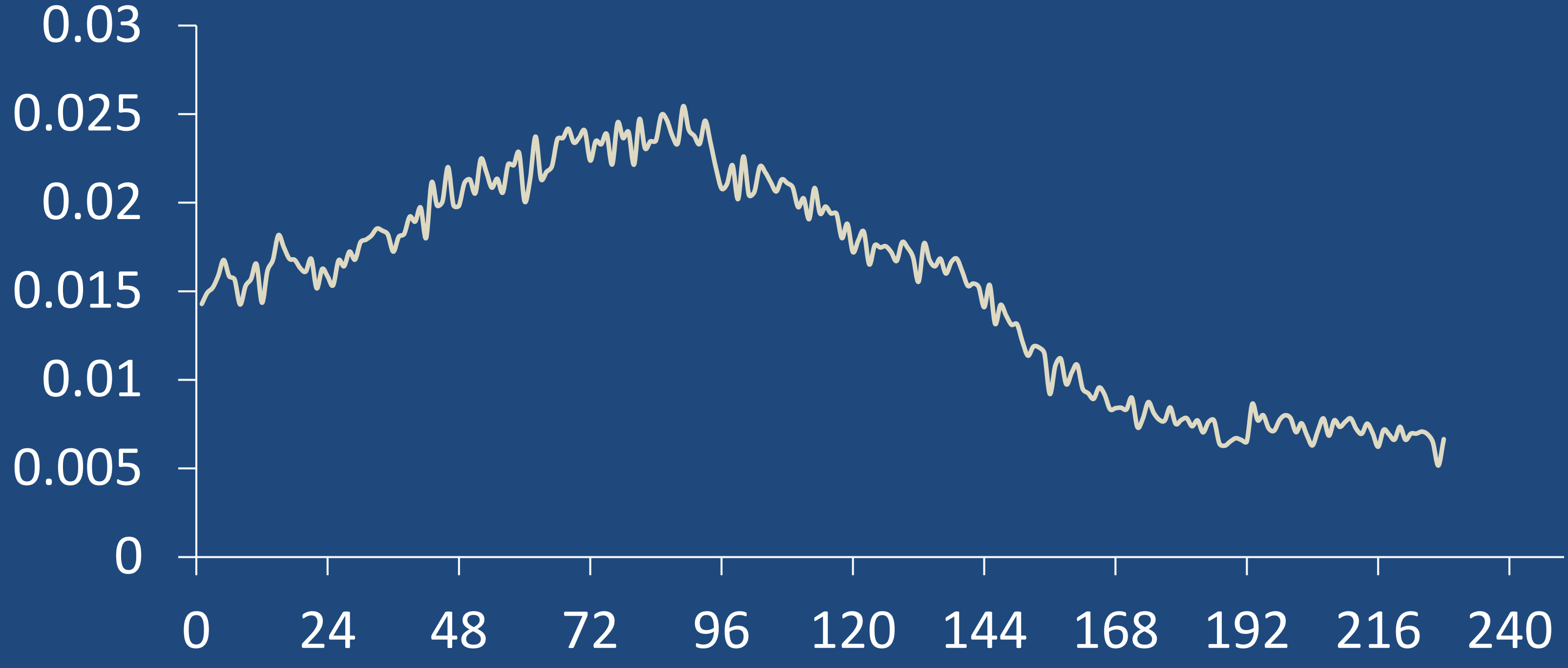
Why ITS

- Population is unit of interest
- Interruption has well-defined time of onset
- Exchangeability principle

When to use

When to use: phenomenon is complex

Incidence of vaginal births after C-section, 1989 to 2007



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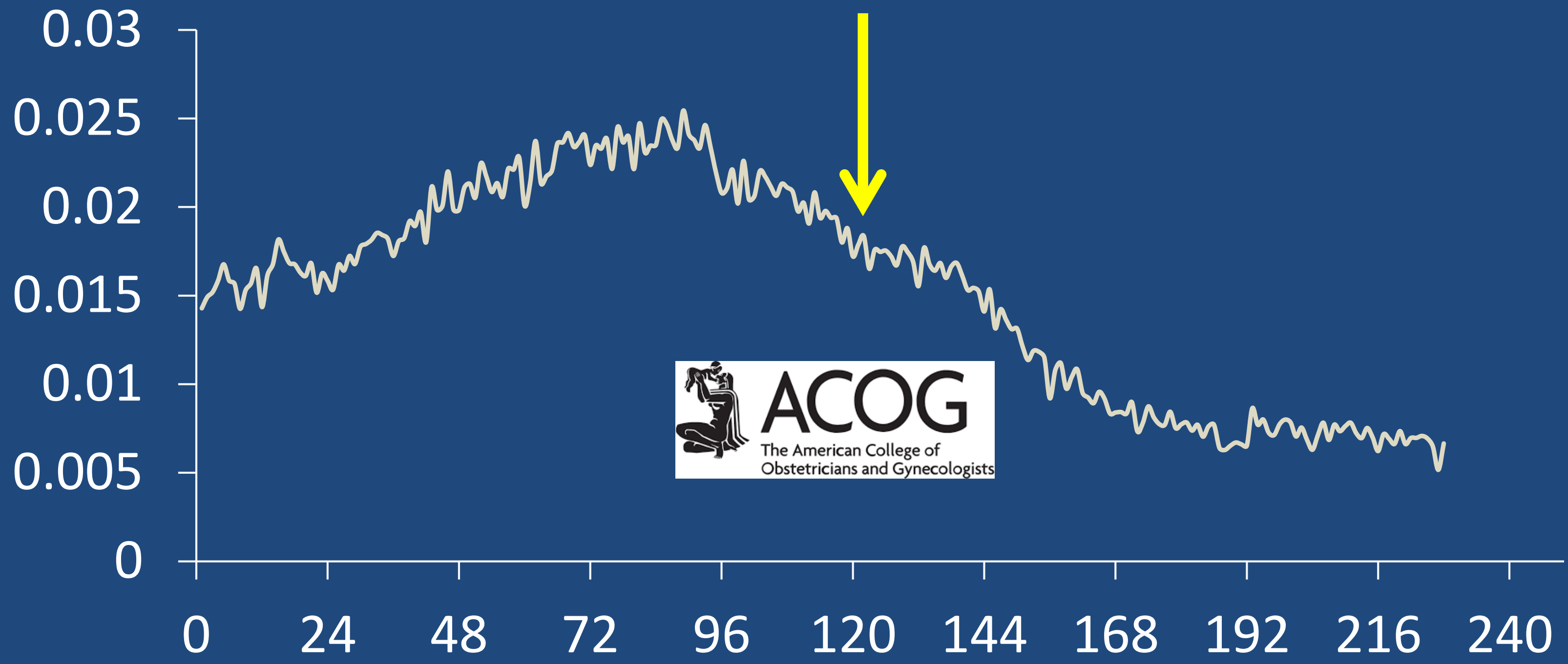

When to use: phenomenon is complex*

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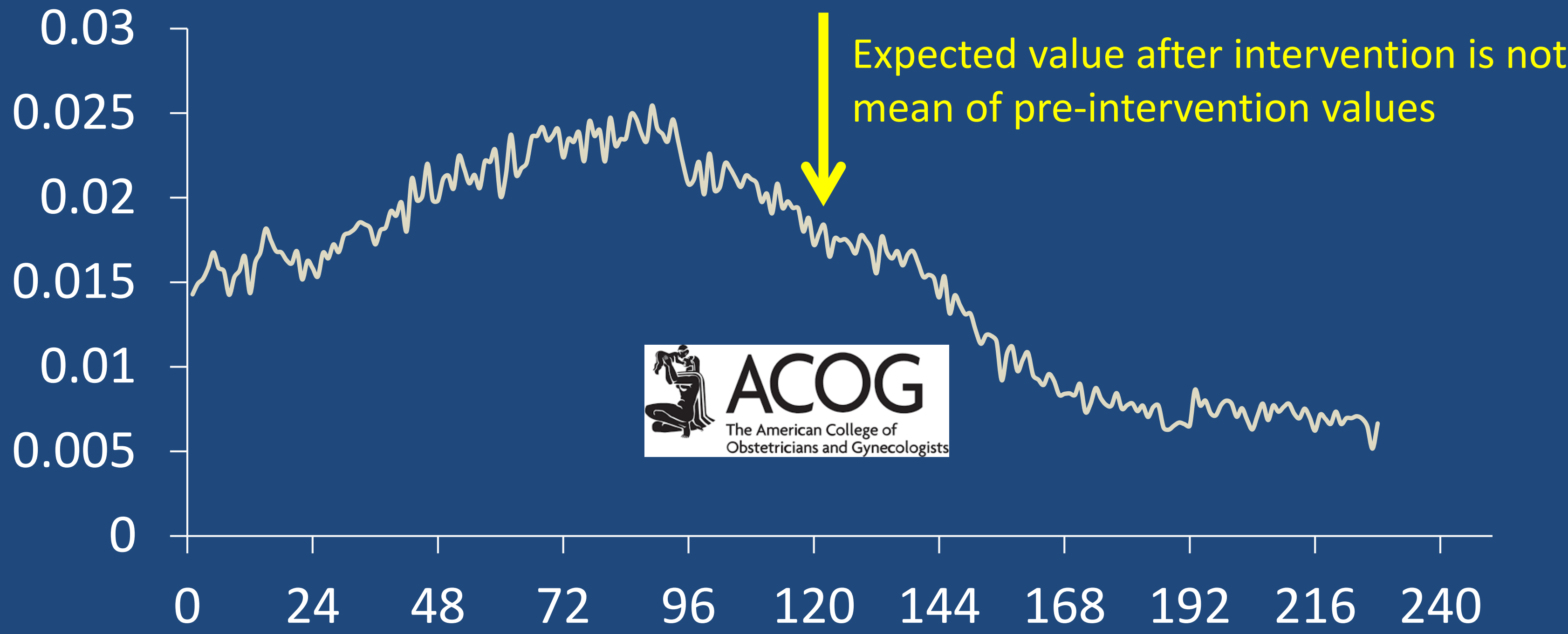

*** Most population health outcomes are complex**

When to use

- Patterns in outcome variable may include trend, seasonality and other autocorrelation “signatures”
- Failure to identify and control for autocorrelation in the pre-intervention often leads to falsely attributing an “effect” to the intervention itself
  - or, leads to artificially precise standard errors
- “But . . . my outcome has no patterns”
  - did you check?

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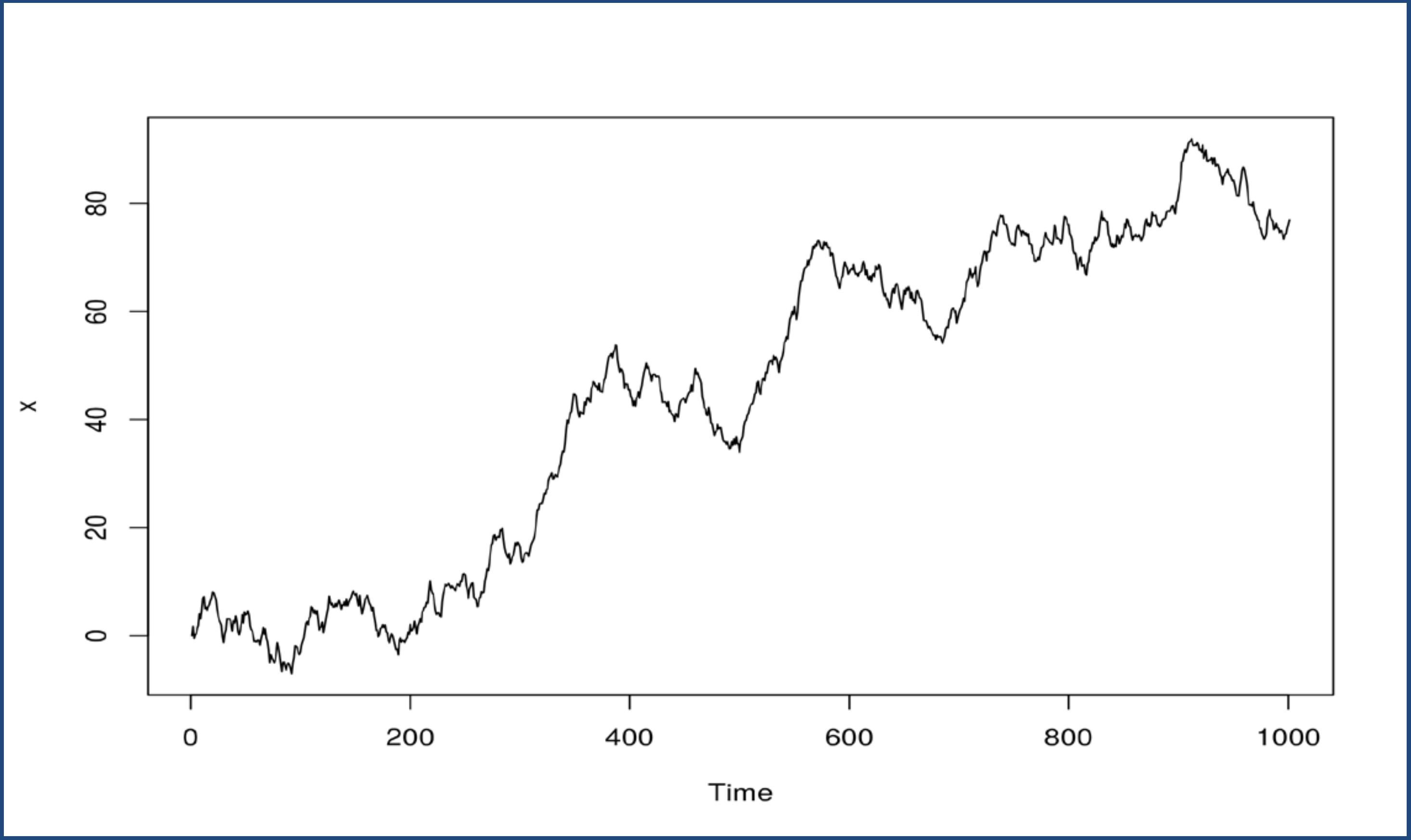
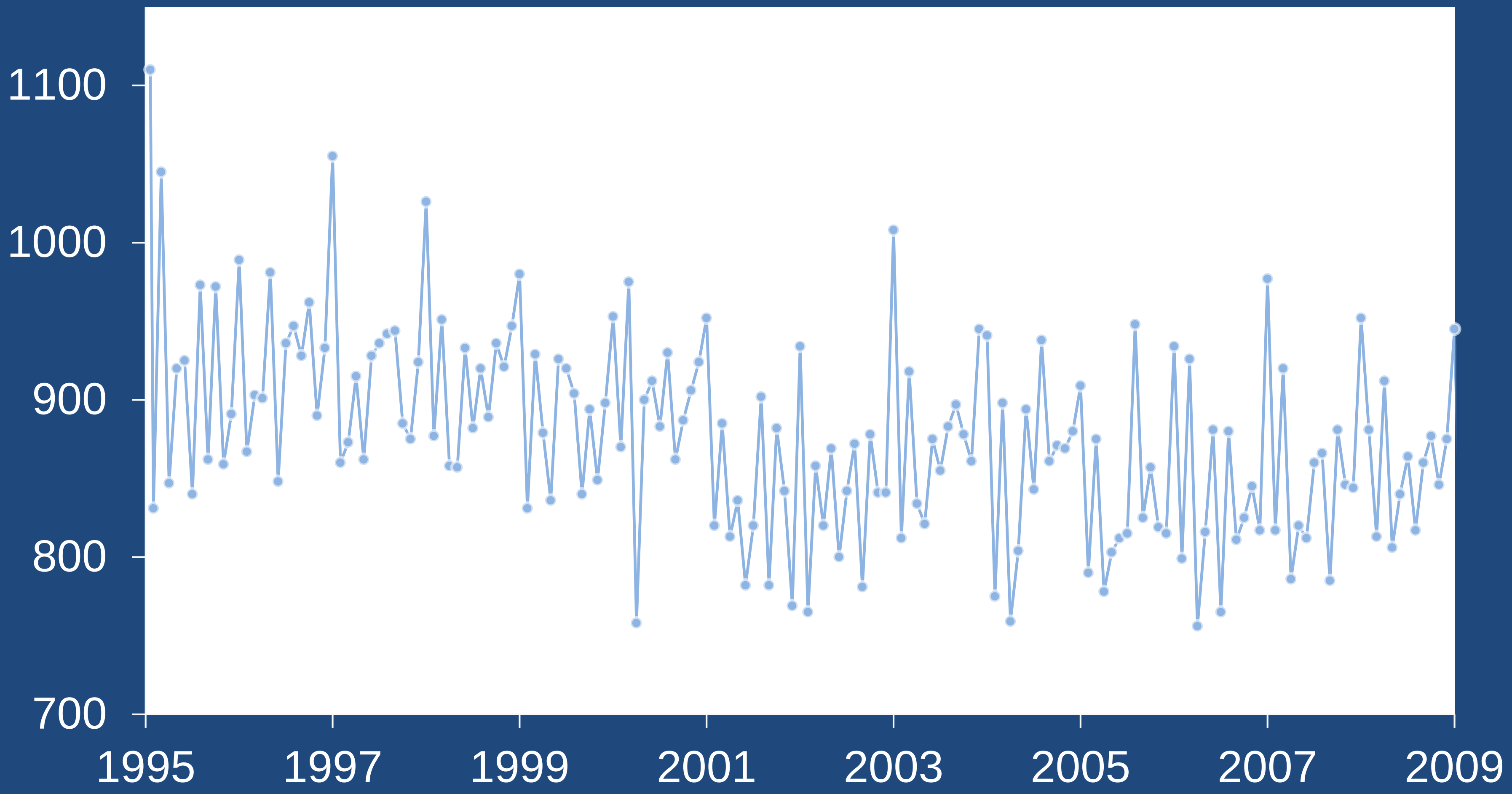
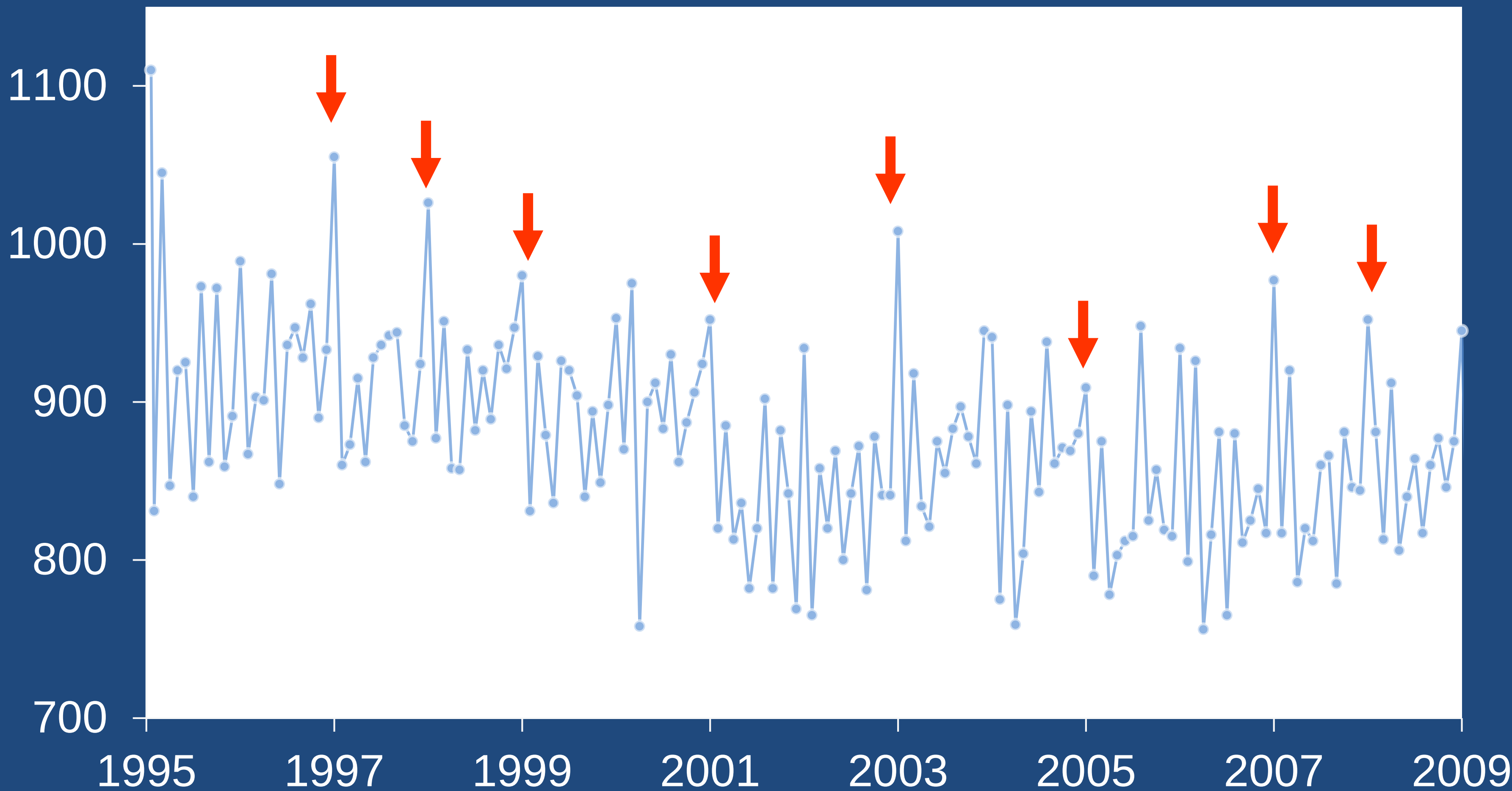
Trend



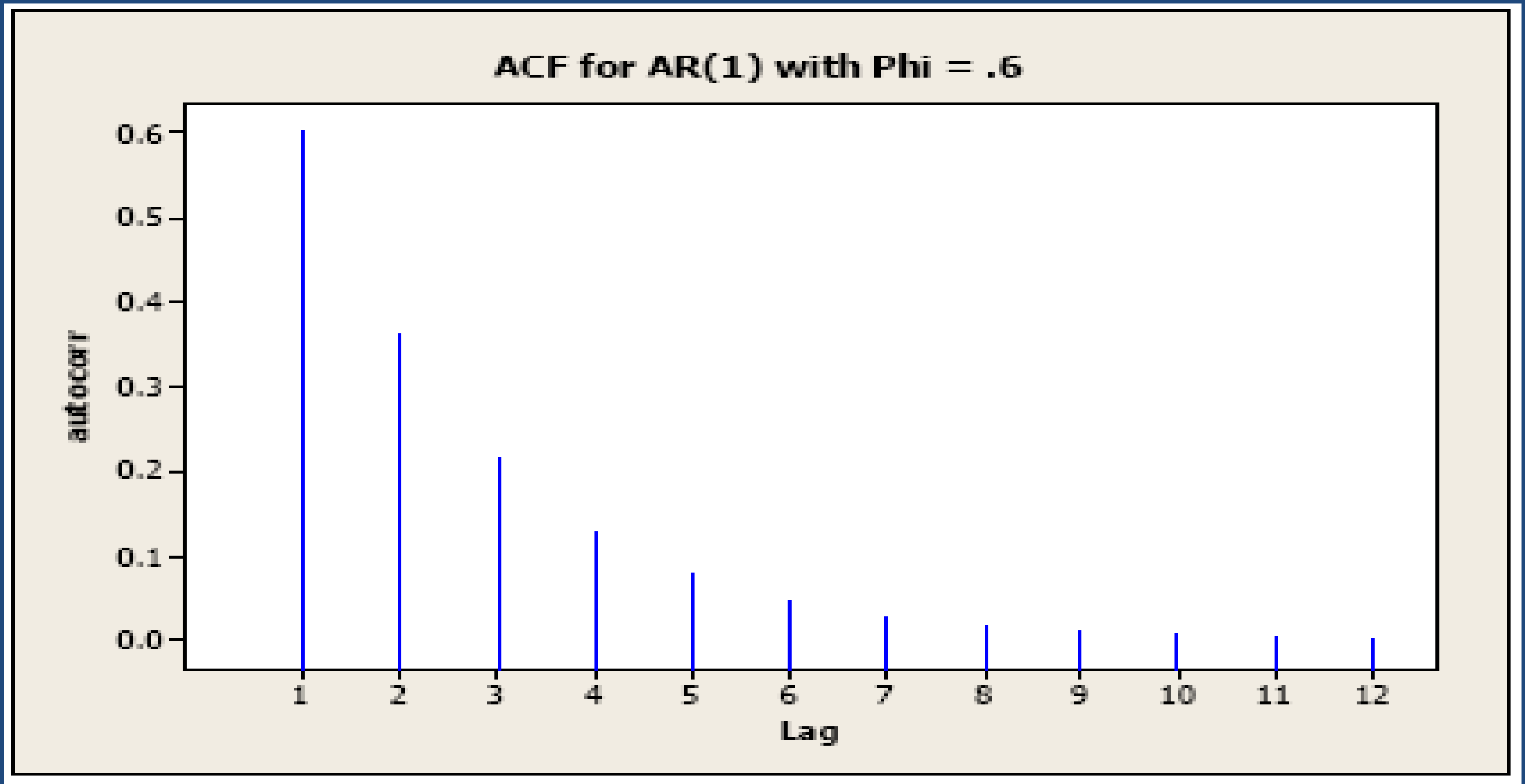
Seasonality



Seasonality



“Memory”



ACF for AR(1) with Phi = .6
autocorr
0.6
0.5
0.4
0.3
0.2
0.1
0.0
1
2
3
4
5
6
7
8
9
10
11
12
Lag

Logic of ITS

- Identify autocorrelation of outcome (Y) *before* intervention to derive statistically expected values of Y after intervention
  - Counterfactual (comparison) is derived from history of Y

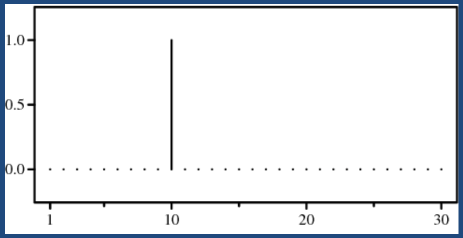
- earlier values of Y are used to remove patterns, so that expected value of residuals = 0

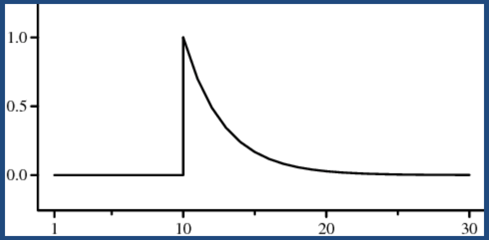
- Intervention (X) may cause Y only if it predicts Y better than history of Y itself
  - Granger-cause; conservative

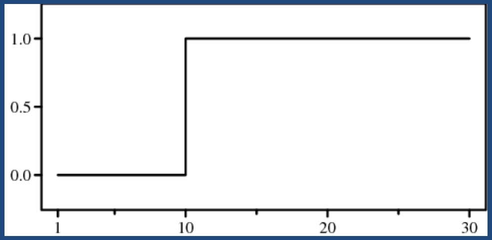
Practical considerations

- >50 time points pre-intervention provides adequate power
- consistent spacing (e.g., monthly)
- know exact timing of intervention/policy
- theory leads to an *a priori* expectation of induction period
  - Mental health, birth outcomes, health behaviors, stroke (vs. diabetes)

- Bonus: have an expectation about shape of response







Practical Considerations

- Time series vs. other approaches
  - One observation per time point
  - Sample size is duration of the series
- Crucial that data quality and collection methods are consistent throughout series
  - also, assumes constant variance of "segments"

Example

Mental Health Services Act, CA

Tax on 40,000 millionaires in CA

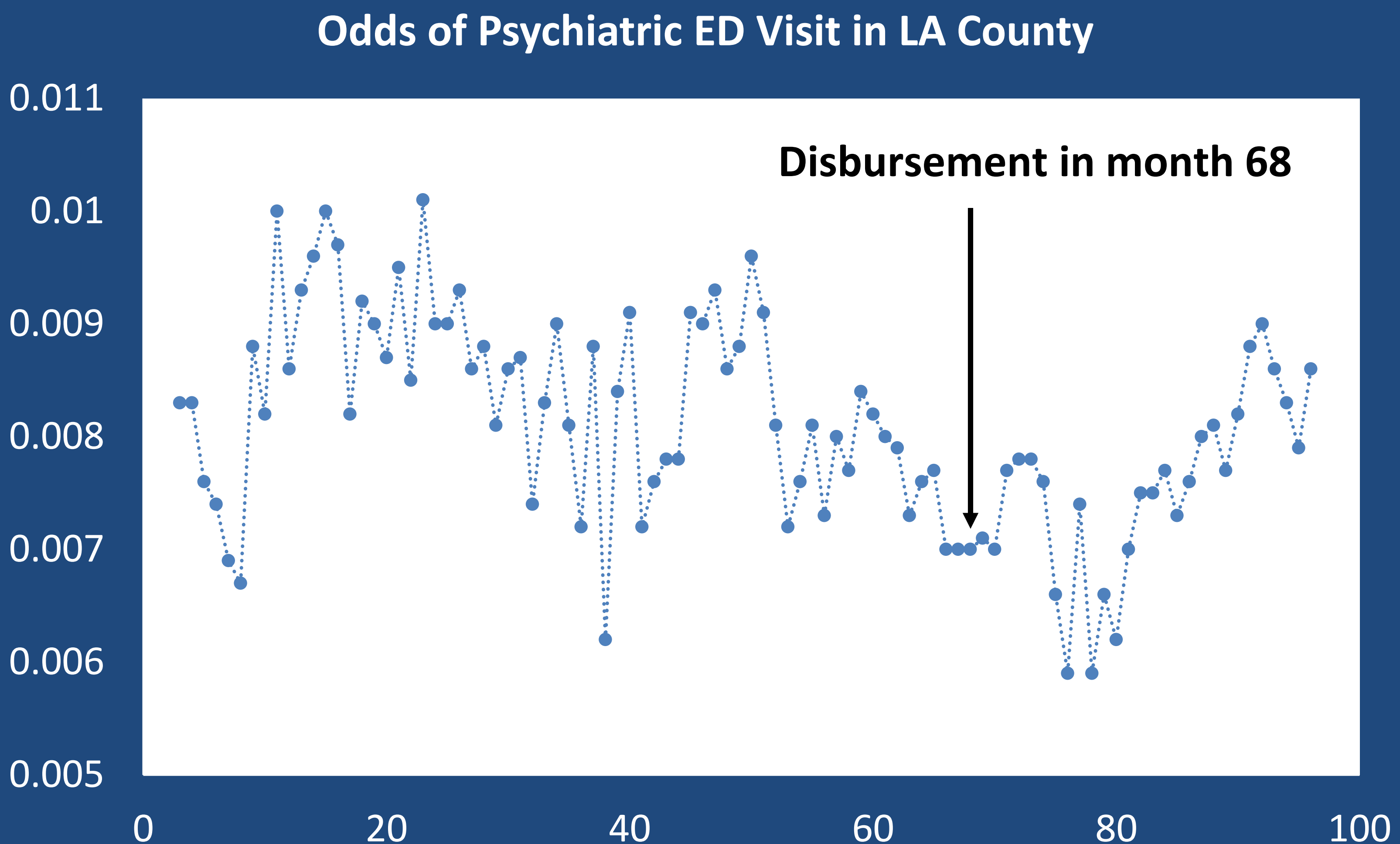
Redistributed $$ to county mental health dep'ts

Targets persons with SMI

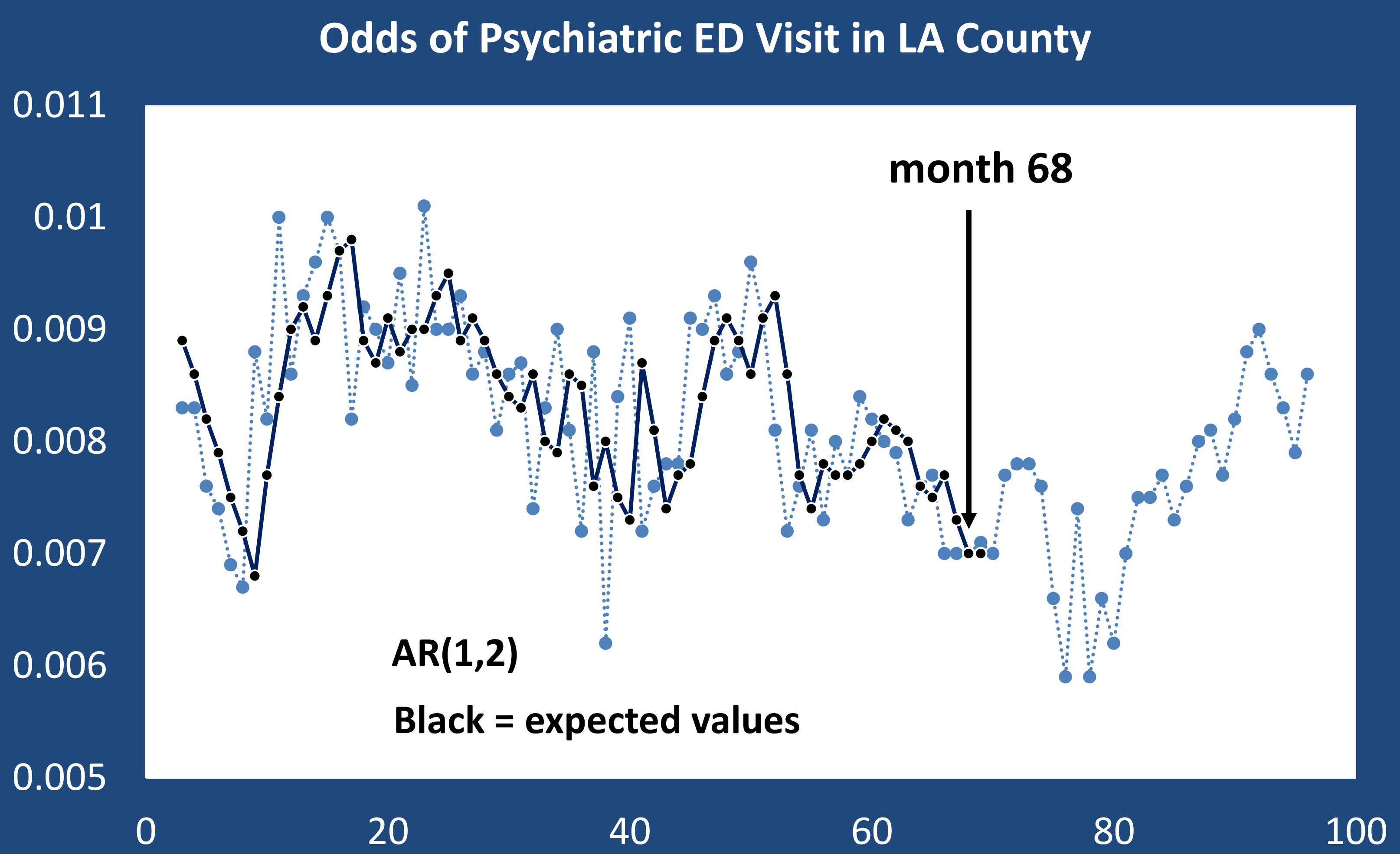
$27 Billion since 2005

Counties had to apply for funds

Did MHSA reduce psychiatric ED visits?



1. ID patterns; derive expected values



2. Insert controls (confounders)

- Unemployment Rate
- Precipitation
- Hospitals with emergency stations

3. Specify induction period

- Start with 5 to 12 months post-MHSA funds
  - based on discussions with LA County
  - Ideally, specify before you peek at data
- Then, examine change in mean

4. Insert MHSA variable

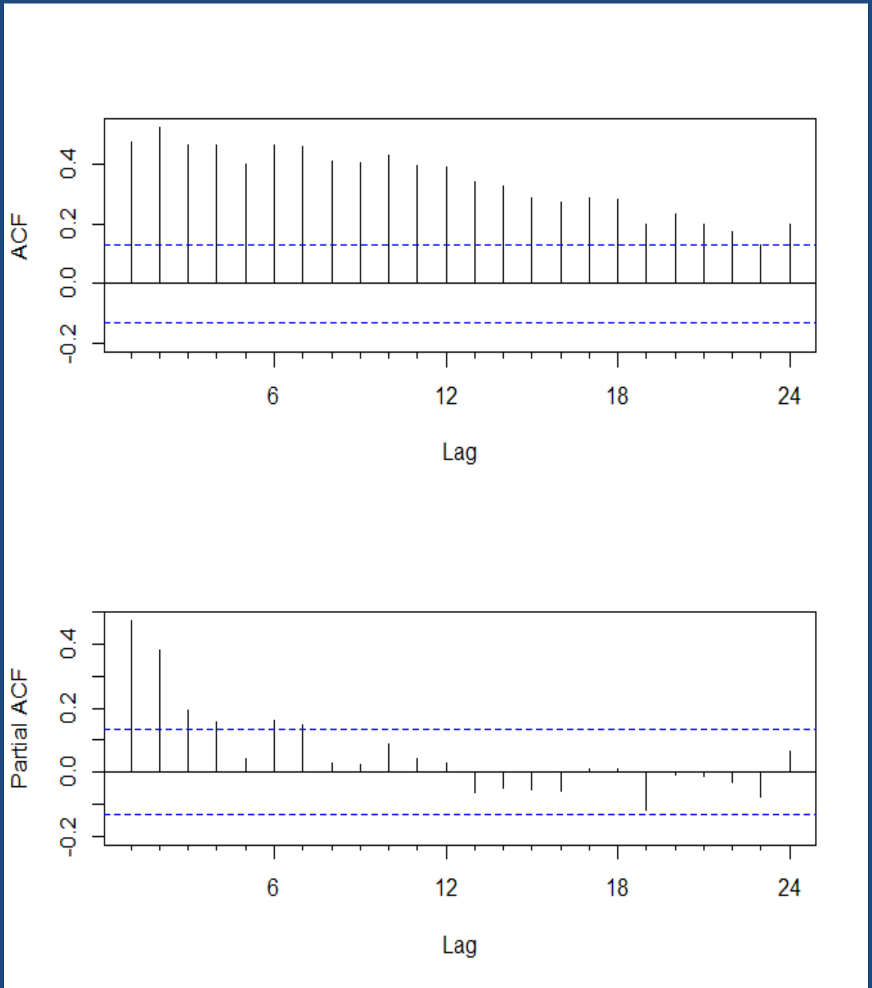
- Binary (1/0) at time 68; lags of 5 through 12 months
- Estimate its association with psychiatric ED visits
  - ARIMA regression framework

5. Inspect residuals for patterns

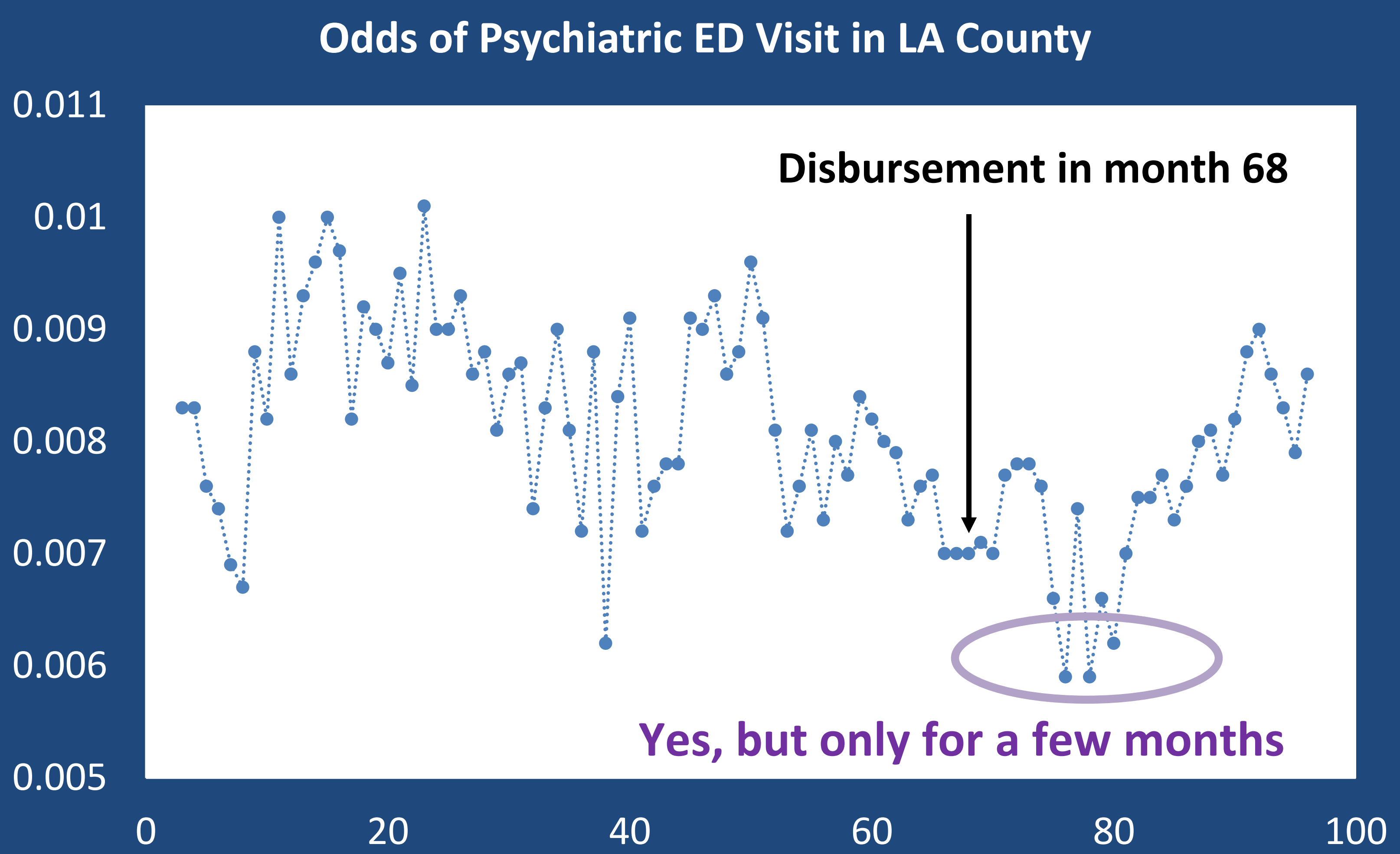
- Must examine ACF, PACF

- If there is residual autocorrelation, re-specify the error term

- If there is none, interpret coefficient (SE)



Did receipt of funds reduce ED visits?



Extensions

Extensions: Control Series

- Insert a control series unaffected by intervention
  - Comparison place, or comparison pop’n w/in place
    - analagous to a falsification test
  - Benefit: minimizes « history » rival of broader changes
  - Confounder would have to
    - be specific to your study population
    - be unpatterned
    - occur only after the intervention but not be caused by it
- Important that control is theorized to be unaffected!

Extensions: Combined Approach

- If you want individual-level inference
  - augment individual-level data with a time propensity
- Time propensity is derived from a best-fitted value of the outcome, conditional ONLY on time
  - Often much more efficient than year & month indicators
  - Better captures the nuance of patterned Y
- Use time propensity as a covariate in an individual-based approach

Pitfalls to avoid

- "My outcome has no temporal patterns"
  - Did you check?
- "Year, month indicators remove all patterns in outcome"
  - Inspection of ACF and PACF is only way to diagnose

Pitfalls to avoid

- “I can pre-specify patterns without empirical examination (e.g., cubic spline)”
  - Could work, but double-check ACF and PACF
- “I have an exogenous shock; I can compare means pre- and post- shock”
  - Is it truly exogenous? Most policies not randomly assigned in place & time
  - Patterns, especially preceding shock, are most insidious & require control

Summary

- **If interested in**
  - acute ecological exposure

AND

  - data availability permit

ITS represents an appealing option, consistent with experimental logic, that minimizes bias due to confounding

Resources

- **ARIMA**
  - Flexible in terms of applications, and model choice
  - Strong outlier detection routines
  - Is available in R, SAS, **SCA*** (No ACF/PACF output in STATA)
  - No *a priori* assumptions about autocorrelation

- **Others (e.g., spline, sine wave, linear regression)**
  - Makes assumptions about functional form
    - Must be verified by analyst
  - Can capture autocorrelation for some Y's

*** my preference**

Resources

- References:
  - Box, G. E. P., G. M. Jenkins, and G. C. Reinsel. *Time Series Analysis: Forecasting and Control* 3rd ed. Englewood Cliffs, NJ: Prentice Hall, 1994.
  - Chatfield C. The Analysis of Time Series: An Introduction, 6th Edn. 2016
  - For time propensity: Catalano R, Ahern J, **Bruckner T.** Estimating the health effects of macrosocial shocks: a collaborative approach. In: Galea, S. (ed.). *Macrosocial Determinants of Health.* Springer; New York, 2008.
  - https://doi.org/10.1093/oxfordjournals.aje.a114712

- Software Packages
  - SCA: http://www.scausa.com/scatsa.php
  - SAS: Proc ARIMA https://support.sas.com/rnd/app/ets/procedures/ets_arima.html
  - R: http://a-little-book-of-r-for-time-series.readthedocs.io/en/latest/src/timeseries.html

- Practical examples/papers:
  - http://faculty.sites.uci.edu/bruckner/
  - search "UCLA Stats ARIMA"
  - Tutorial in Intl J Epid: https://doi.org/10.1093/ije/dyw098

Thank you

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