Interrupted time series (ITS) regression for public health interventions

Tutorial-based deck (Lopez Bernal, Cummins, Gasparrini, IJE 2017)

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1) What ITS is good for

- Evaluating **population-level** interventions at a clearly defined time (laws, bans, guidelines, unplanned shocks).
- Works when **RCTs are infeasible** or interventions are already implemented.
- Provides **counterfactual**: expected trajectory had the intervention not occurred (projected pre-trend).

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2) Impact model first (a priori)

Decide before analysis: **level change? slope change? both?** Immediate or **lagged**? Temporary vs sustained? - Examples (see Fig-style patterns): - (a) Immediate level drop/jump - (b) Gradual slope change - (c) Level + slope change - (d) Lagged slope change - (e) Temporary level change (decays) - (f) Temporary slope change leading to new level

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3) Data & design suitability

- **Outcome types:** counts, continuous, binary/proportions (choose appropriate link/model).
- **Short-term/lag-knowable** outcomes work best.
- **Series length:** power depends on pre/post balance, variability, expected effect, seasonality.
- Visual inspection of **pre-intervention trend** is essential.
- More points → more power, but very long histories can misrepresent current secular trend.
- **Routinely collected** data (admin, registries) are practical; assess validity & recording changes.

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4) Core segmented regression model (single change point)

Let **T** = time since start; **X** = 0 pre, 1 post; **Y** = outcome at time *t*.

$$Y_t = \beta_0 + \beta_1 T + \beta_2 X_t + \beta_3 (T \times X_t) + \varepsilon_t$$

- $\boldsymbol{\beta_0}$ baseline level at *T=0*; $\boldsymbol{\beta_1}$ pre-trend; $\boldsymbol{\beta_2}$ immediate **level** change; $\boldsymbol{\beta_3}$ **slope** change. - For **counts**, use Poisson (or NB) with optional **offset** (e.g., person-time) to model rates. - Exclude terms to match hypothesized impact (e.g., no β_3 if only level change expected).

5) Worked example (from tutorial)

- **Intervention:** National indoor smoking ban (Italy, Jan 2005).
- **Outcome:** Monthly acute coronary event (ACE) admissions (Sicily, 2002–2006), ages 0–69.
- **Impact model:** Immediate **level** reduction (no lag), modeled with Poisson regression and population offset.
- **Finding (illustrative):** ≈11% decrease in ACEs after the ban; robust after seasonality adjustment.

6) Seasonality & long-term trends

- Many health outcomes have **seasonal cycles** → confounding if months are uneven across pre/post.
- Control choices:
- **Month indicators** (stratified by calendar month)
- **Fourier terms** (pairs of sine/cosine)
- **Splines** for flexible long-term trend
- After seasonal adjustment, re-check effect size and residual structure.

7) Time-varying confounders

- ITS resists slow-changing confounders (age structure, SES), but can be biased by **rapidly changing** factors near the intervention (e.g., diagnostic changes, outbreaks, weather).
- If measured, **include as covariates**. If unmeasured, consider **design adaptations** (below).

8) Over-dispersion & autocorrelation (AC)

- **Over-dispersion** (variance > mean) inflates Type I error in Poisson → use scale correction or NB.
- **Autocorrelation**: neighbors in time are correlated.
- Often reduced by modeling seasonality/long trend.
- **Assess:** residual plots, PACF; (Gaussian) tests like Breusch–Godfrey.
- **Adjust if needed:** Prais–Winsten (for continuous outcomes), ARIMA errors, or explicit AR terms.

9) Design adaptations to strengthen causal claims

- **Controlled ITS (CITS):** add a **control group** or a **control outcome** unaffected by the intervention.
- **Multiple baselines (staggered starts):** different places start at different times.
- **Withdrawal/reversal designs:** introduce then remove intervention to test reversibility.

10) Lags, staging, and temporary effects

- Model **lags** explicitly (e.g., shift in effect after k periods) or define a **transition segment**.
- For rollouts, allow **multi-period** effects (ramp-up) matching implementation.

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11) Model checking & sensitivity

- Inspect **residuals** and **partial autocorrelation**.
- Vary plausible **lags**, **impact models**, and **seasonality adjustments** (e.g., different Fourier orders) to test robustness.

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12) Reporting effects (counterfactuals)

- Plot observed series, fitted trend, and **counterfactual** (projected pre-trend).
- Express effects as **absolute** and **relative** differences vs. counterfactual at policy-relevant times.

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13) Power & planning (practical notes)

- Power rises with **number of time points** and **effect size**, and with balanced pre/post.
- Simulate scenarios **a priori** when few points or small effects are expected.
- Avoid excessively long pre-periods if the underlying secular trend has fundamentally shifted.

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14) Strengths & limitations

Strengths - Strong quasi-experimental option when randomization is impossible; often high **external validity**. - Captures **immediate vs gradual**, **temporary vs sustained** changes.

Limitations - Vulnerable to **concurrent events** near the intervention if unmeasured. - Requires careful **seasonality/AC** handling and pre-specification of the **impact model** to avoid data-driven inference.

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15) Practical ITS checklist (tutorial-aligned)

1) Confirm ITS appropriateness (clear timing; suitable outcome). 2) Pre-specify **impact model** (level/slope; lag; permanence). 3) Assemble pre/post data; inspect for trend, seasonality, outliers, coding/definition changes. 4) Choose model family/link; include **offset** if modeling rates. 5) Fit segmented regression; adjust for **seasonality** and **over-dispersion**; assess **AC**. 6) Consider **CITS/multiple baselines/withdrawal** if confounding likely. 7) Report **counterfactual** effects with CIs; include diagnostics. 8) Run **sensitivity analyses** (lags, seasonal terms, alternative impact specs).

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16) Take-home

- Specify the **impact model a priori**, handle **seasonality/AC/over-dispersion**, and use **design extensions** when needed. Done well, ITS provides clear, policy-relevant estimates of intervention impact.