Segmented regression of interrupted time series (ITS)

Medication use research, per Wagner et al., 2002

---

1) Why ITS for policy & program evaluation

- RCTs are often infeasible for system-wide policies.
- ITS is a strong quasi-experimental design for longitudinal effects.
- Graphs + segmented regression quantify immediate (level) and gradual (trend) changes.

---

2) Core concepts

- **Time series**: outcome measured at **regular, equally spaced** intervals.
- **Change point** (interruption): policy/event start, stop, or component change.
- **Level**: value at segment start; **Trend**: within-segment slope.
- Effects: **abrupt** (level shift) and/or **gradual** (slope change).

---

3) Data requirements

- Equally spaced intervals (e.g., monthly).
- Sufficient span to see patterns:
- Practical rule: ~12 pre and ~12 post points (to assess seasonality).
- Adequate per-point sample size ($\approx \geq 100$ obs per time point desirable).
- Routinely collected data sources (dispensing, claims, registries) work well.

---

4) Model specification (single change point)

Let the intervention occur at month T_0.

$$Y_t = \beta_0 + \beta_1\, time_t + \beta_2\, I(t \geq T_0) + \beta_3\, time\_after_t + \varepsilon_t$$

- `time_t`: months from series start.
- `I(t ≥ T0)`: 0 pre, 1 post (immediate level change).
- `time_after_t`: 0 pre, *(time − T0+1)* post (slope change).
- Post-intervention slope = **$\beta_1 + \beta_3$**.

---

5) Interpreting coefficients

- β_0: baseline level at start of series.
- β_1: baseline trend (pre-intervention slope).
- β_2: immediate jump/drop at intervention.
- β_3: change in slope after intervention.

---

6) Quantifying effects via counterfactual

- Predict outcome at time *t* **with** intervention model.
- Predict counterfactual using **baseline level + trend only**.
- Effect size: difference or % change = (pred_with − pred_without)/pred_without.

---

7) Worked example: NH Medicaid 3-drug cap

- Baseline ≈ **5 prescriptions/patient/month**.
- After cap: **immediate level drop ≈ −2.6 Rx/patient/month**.
- No significant change in slope after the cap.
- Practical message: large abrupt utilization reduction attributable to policy.

---

8) Multiple change points (three segments)

- 11 months later: cap **replaced by $1 copay** → level and slope increased again.
- End of observation ≈ **4.7 Rx/patient/month**.
- Model with two change points:

$$Y_t = \beta_0 + \beta_1 time_t + \beta_2 I_1 + \beta_3 time\_after_1 + \beta_4 I_2 + \beta_5 time\_after_2 + \varepsilon_t$$

- Use to evaluate sequential components, withdrawals, or unrelated shifts.

---

9) Lags & multi-period rollouts

- Effects can lag (e.g., **2–3 months** transition to substitute meds).
- For staged rollouts (education programs), effects accrue over periods.
- Options: exclude transition window **or** model it as its own segment.

---

10) Autocorrelation (AC) & seasonality

- OLS assumes independent errors; time series often violate this.
- Detect via residual plots & statistics (e.g., Durbin–Watson ≈ 2 → little AC).

- Model AC terms when needed; assess seasonality (same month across years).
- To model seasonal AC reliably, aim for ≥**24 monthly points**.

---

11) Handling outliers (“wild points”)

- Causes: real phenomena (e.g., anticipatory stockpiling) or measurement error.
- If explained/erroneous: include an indicator for that period.
- If random: treat as regular; run sensitivity analyses with/without.

---

12) Control strategies to bolster validity

- **Separate population control** (unexposed jurisdiction/group).
- **Control outcome** unlikely to respond to intervention (internal control).
- **Unaffected subgroup** (e.g., prescribers never exposed to product).
- Even single-group ITS improves over pre–post by using pre-trend as control.

---

13) Model building & diagnostics

- Start with full model (baseline + all level/slope changes).
- Stepwise removal of non-significant terms → **parsimonious** model.
- Retain theoretically important covariates (e.g., baseline trend, confounders), regardless of p-value.
- Check residuals: normality & no time-pattern → assumptions reasonable.

---

14) Strengths

- Strong quasi-experimental evidence where RCTs aren’t feasible.
- Quantifies immediate vs. gradual, transient vs. sustained effects.
- Controls for baseline trends; visually intuitive.

---

15) Limitations

- Assumes **within-segment linearity**; diffusion/curvilinear effects may need other forms.
- Aggregation by time point → typically no individual-level covariates.
- Box-Jenkins/ARIMA useful for forecasting but less suited to discrete change-point inference and often require many points.

---

16) Practical workflow (checklist)

1) Define policy dates & hypothesized lags. 2) Assemble evenly spaced series; verify ≥ pre/post points; per-point N. 3) Plot data; mark change points; inspect anomalies. 4) Fit segmented model; test AC/seasonality; refit with corrections. 5) Express effects with counterfactuals at policy-relevant times. 6) Test robustness: outliers, lags, alternative segment codings. 7) If possible, add a control (group/outcome/subgroup). 8) Report estimates, CIs, and assumptions transparently.

---

17) Key takeaways

- Segmented regression of ITS provides **credible, quantified** policy impact estimates.
- Mind the mechanics: **equally spaced measurements, AC/seasonality, lags, controls**.
- Use **counterfactuals** to communicate magnitude at decision-relevant times.

Prepared as a teaching deck based on Wagner et al., 2002; includes example details from New Hampshire Medicaid policies.