The Stability-Controlled Trial and Quasi-Experiment? Learning effects of new treatments without randomization (or ignorability)

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Can we do better than to just warn “this is only suggestive”?
Randomization is great, but...

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- **RCTs may not measure what you want**: Stylized treatment; restrictive eligibility; different population than ultimate treatment-choosers.

- **RCTs may be unethical**: Assigns/denies treatment based on research aims, not what is best for individual. May no longer be ethical if credible alternative exists.
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- **Does require:** One assumption, on how non-treatment outcome would have changed over time.
How it works: start with four observables
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How it works: 2. The LIE doesn’t lie
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How it works: 3. Compare
In other words,

Define the change in non-treatment average outcomes,

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Which identifies \( \mathbb{E}[Y(0)|D = 1, T = 1], \)

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\mathbb{E}[Y(0)|D = 1, T = 1] = \frac{\mathbb{E}[Y(0)|T = 0] - \mathbb{E}[Y(0)|D = 0, T = 1](1 - \pi_1) + \delta}{\pi_1} \\
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Yielding the ATT,

\[ ATT = \mathbb{E}[Y(1)|D = 1, T = 1] - \mathbb{E}[Y(0)|D = 1, T = 1] \]

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Comparison to IV

This is IV with “time as the instrument”, and some twists:

- $\delta$ allows a prescribed deviation from the exclusion restriction
- encouraged to give answer conditionally on $\delta$, rather than producing estimate that is correct only if exclusion true
- we don’t want covariates to buoy assumptions, just $\delta$
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The IV equivalence usefully reminds us:

▶ only need a shift in probability of treatment, not totally new treatment (for LATE instead of ATT).

▶ existing standard error estimators
Comparison to Difference-in-Difference (DID)

Biggest difference compared to DID is where you can use it:

- Both cross-sectional and panel versions of DID require labeling each individual as “would be treated” or not.

- However SCQE works where you have a pre-treatment cohort for whom you cannot say who would have later been treated. E.g. a new medication or policy or media treatment.
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When you can do DID, it is a special case of SCQE:

▶ Parallel trends: the two groups have the same trend in $\mathbb{E}[Y(0)]$
▶ SCQE: There exists an average trend over the two groups, $\delta$
▶ The connection: SCQE is DID if you (i) learn the trend from the controls, and (ii) assume parallel trends
▶ SCQE thus gives alternative route to identification or sensitivity of DID.
Coming up with $\delta$?

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1. **Domain knowledge.** Prior to data analysis, Dr. Maokola registered:
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   - except that reporting may be increasing: guesses rise of 0.5 to 1 percentage point per year due to improved reporting.
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   - no known other reasons for change in TB incidence
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2. **Informed by data.** $\delta$ not identifiable, but if no other major changes, the existing trends may be informative
   - linear model on non-treated periods/clinics. -0.3 [-.1, -0.5].
   - exponential model; annual decay rate of 0.93 [0.89, 0.97]).
Results

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Or if wide range of believable $\delta$, just look:
ATTs as function of $\delta$

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A side benefit: Who takes IPT?

This also sheds light on who takes treatment, not in terms of their $X$ but their $Y(0)$.

- pre-IPT TB average $Y(0)$ was 13%, compared to 16% for controls after IPT
- this signals that, as long $\delta \leq 3\%$ per year, those taking IPT were already “better off”
- may be useful in understanding selection and improving policy
Conclusions 1: SCQE in General

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The SCQE and SCT may be useful in many cases to go beyond observational claims while being rigorous.
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- Even if you like $\delta = 0$, ambiguous impact.
- Ruling out that it is harmful, too, requires an argument (baseline trend did not drop by more than 1%).
- In short: You must defend an assumption to advocate for a result.
Extra slides
Results: Clinic level

Suppose we use the range of $\delta$ offered by the linear estimate above: