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"?

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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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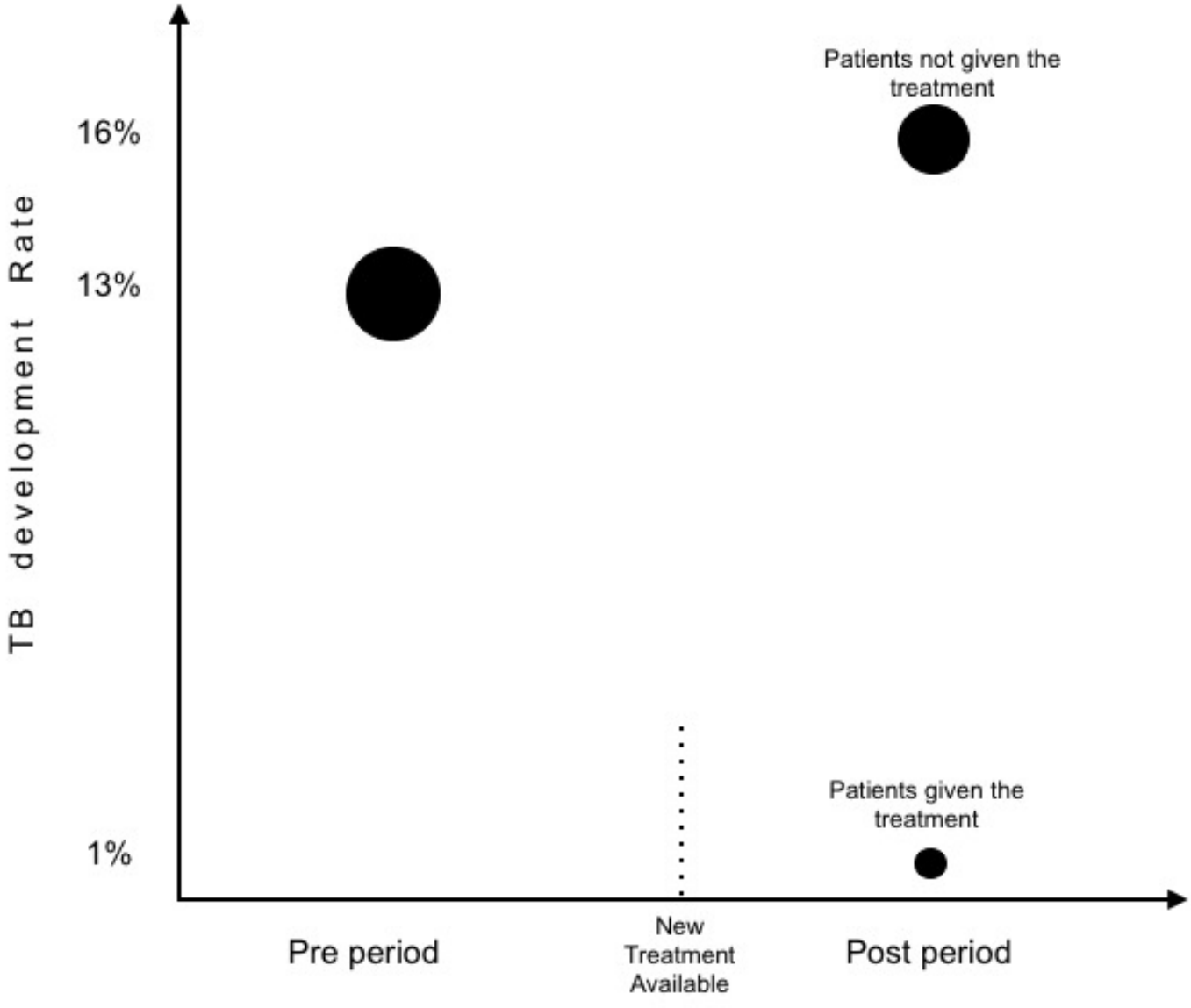
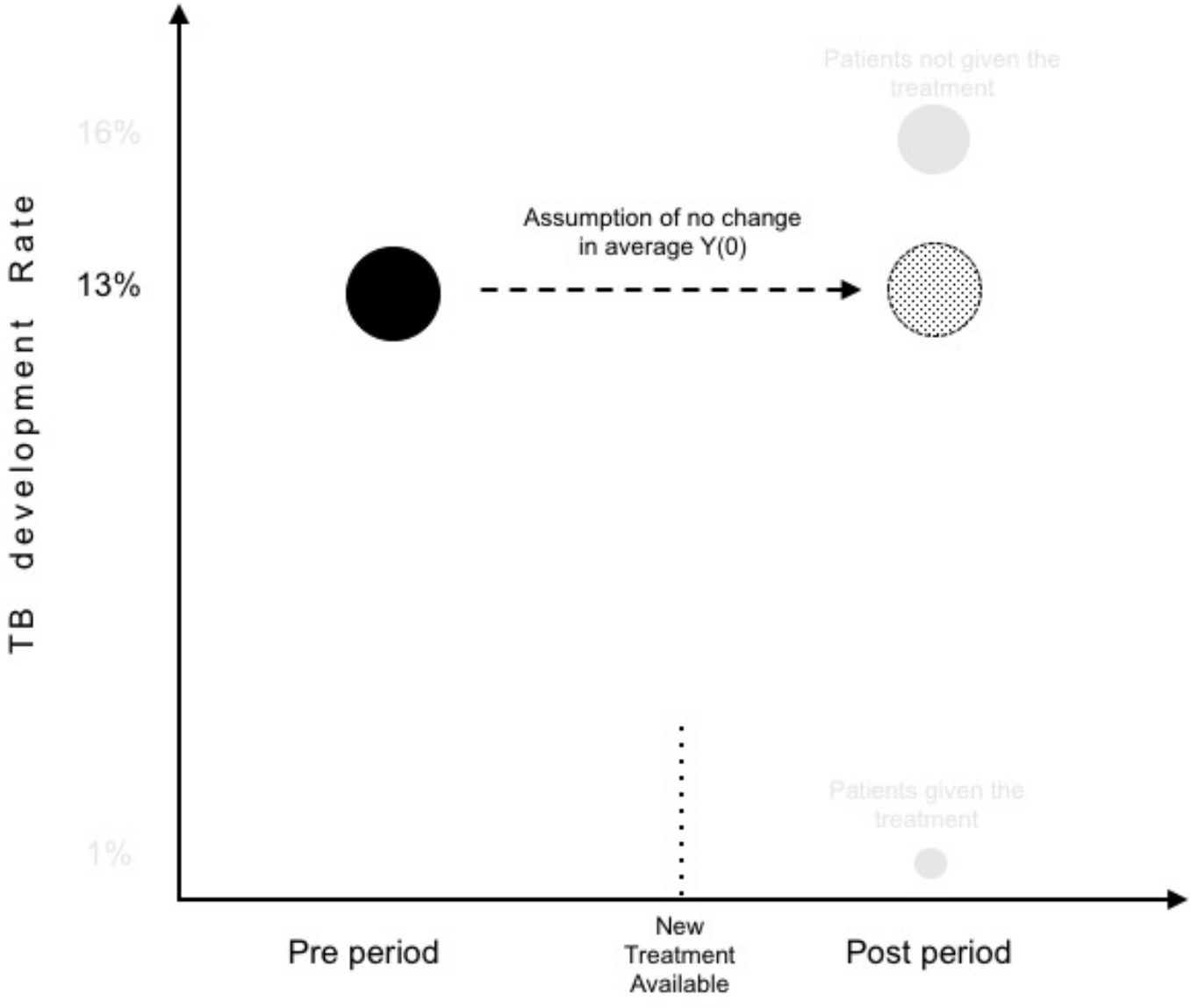
The Stability-Controlled Trial (SCT) and Quasi-Experiment (SCQE) can estimate the ATT for newly available treatments

- Does not require: randomization, any knowledge of treatment assignment, conditional ignorability
- Does require: One assumption, on how non-treatment outcome would have changed over time.

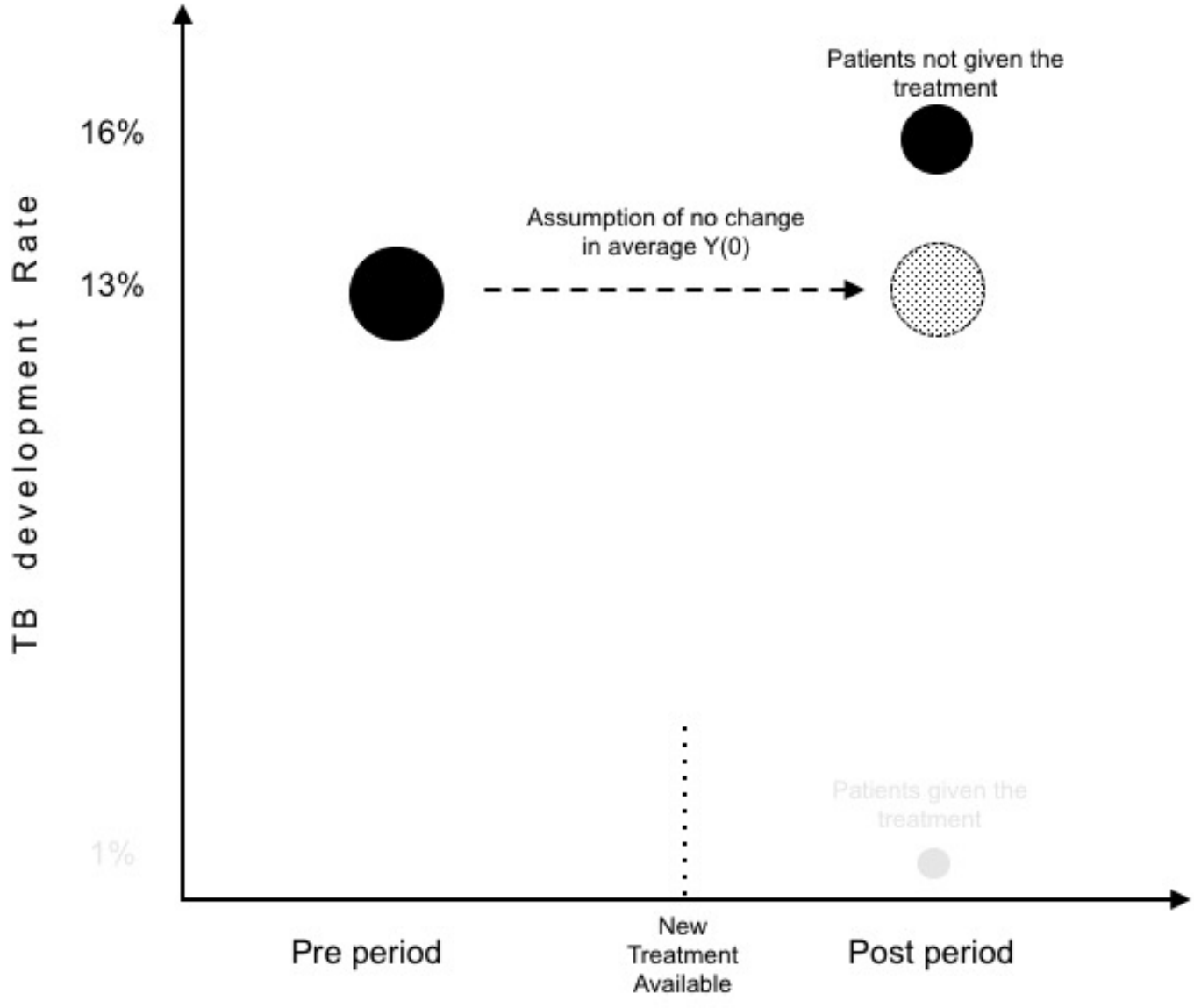
How it works: start with four observables



How it works: 1. Add assumption on change in $\mathbb{E}[Y(0)]$ over time



How it works: 2. The LIE doesn't lie



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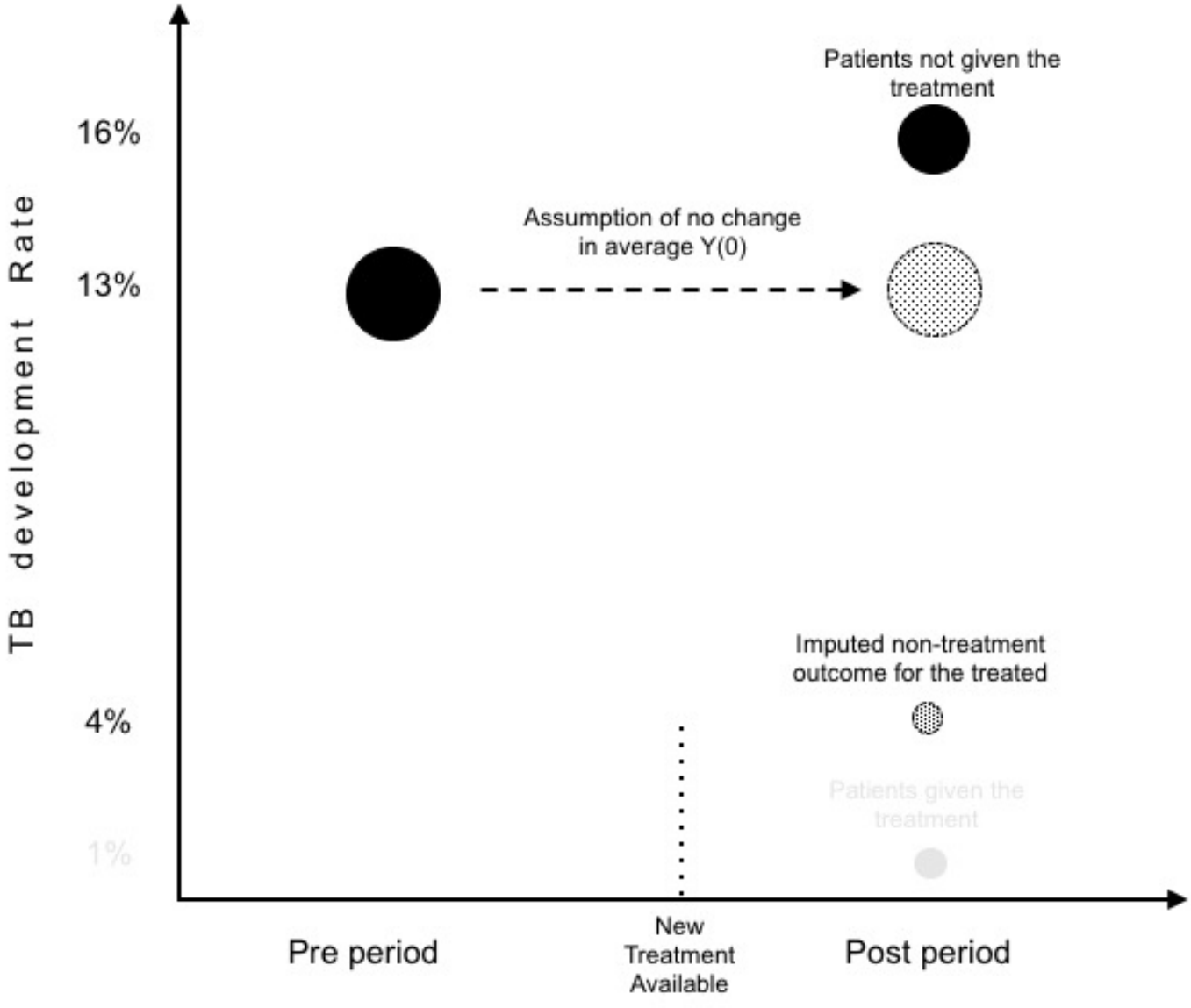
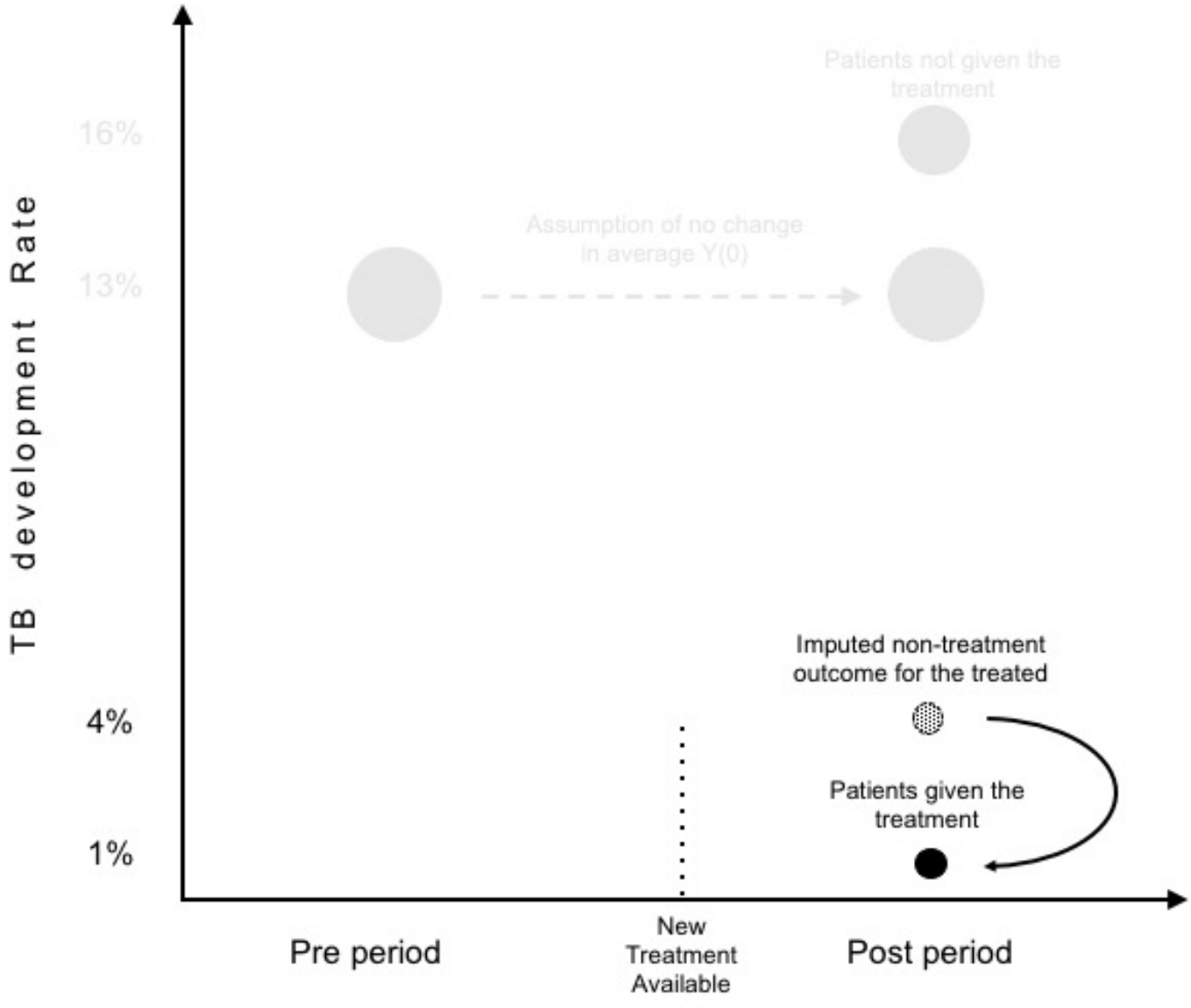


How it works: 3. Compare



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Define the change in non-treatment average outcomes,

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Yielding the ATT,

$$\begin{aligned}ATT &= \mathbb{E}[Y(1)|D=1,T=1] - \mathbb{E}[Y(0)|D=1,T=1] \\ &= \mathbb{E}[Y|D=1,T=1] - \left(\frac{\mathbb{E}[Y|T=0] - \mathbb{E}[Y|D=0,T=1](1-\pi_1)+\delta}{\pi_1}\right).\end{aligned} \tag{3}$$

Comparison to IV

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

- δ allows a prescribed deviation from the exclusion restriction
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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.
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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, δ
- 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.

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1. Domain knowledge. Prior to data analysis, Dr. Maokola registered:
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   - no known other reasons for change in TB incidence
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2. Informed by data. δ 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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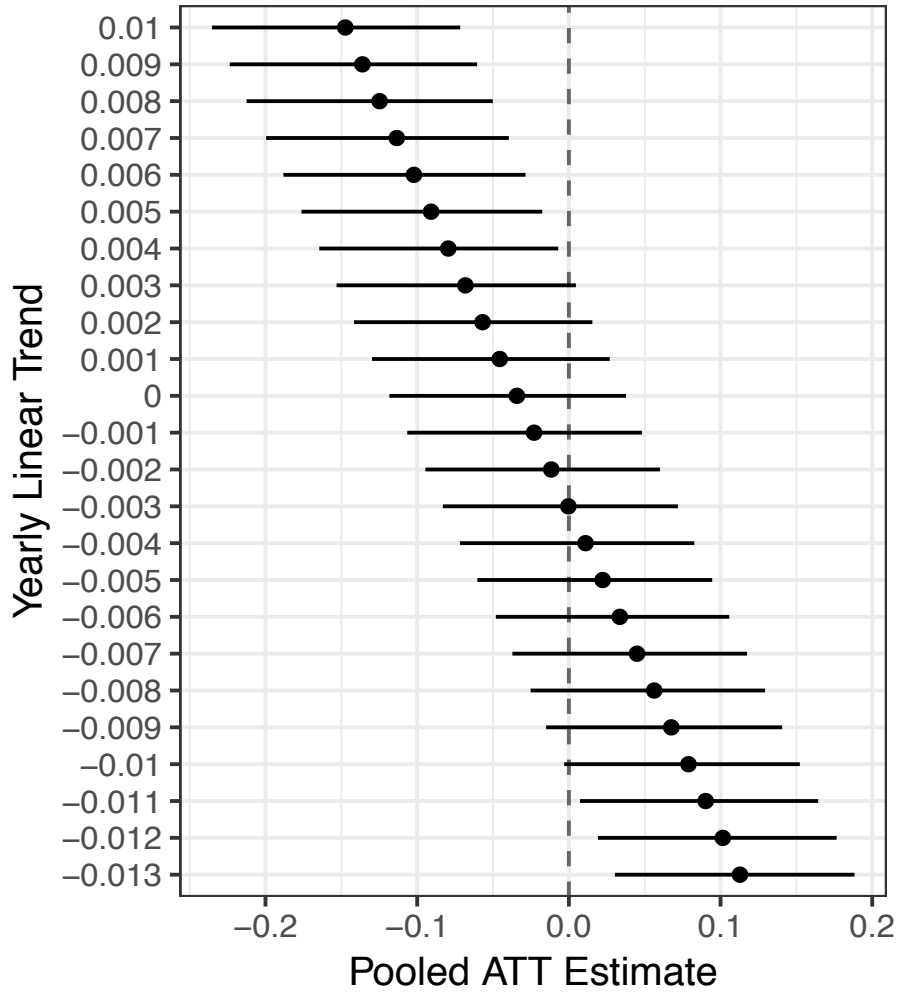
Or if wide range of believable δ, just look:

ATTs as function of δ



95% CI by block boostrap over clinics

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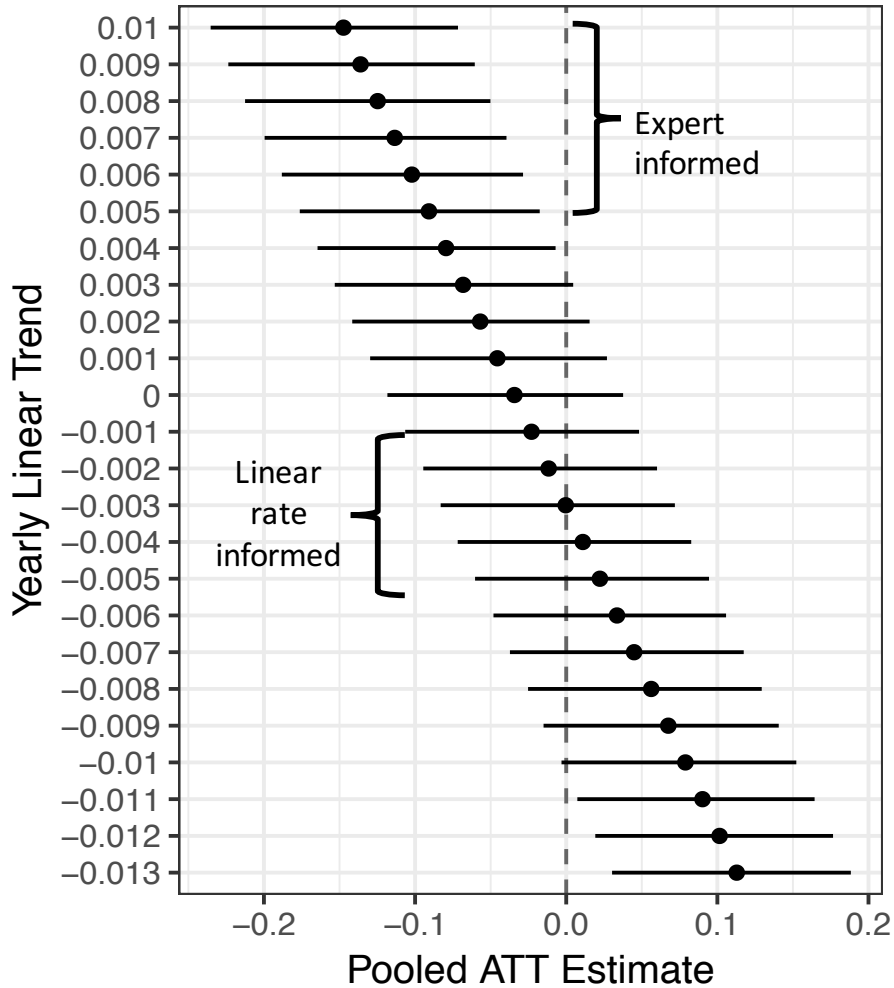

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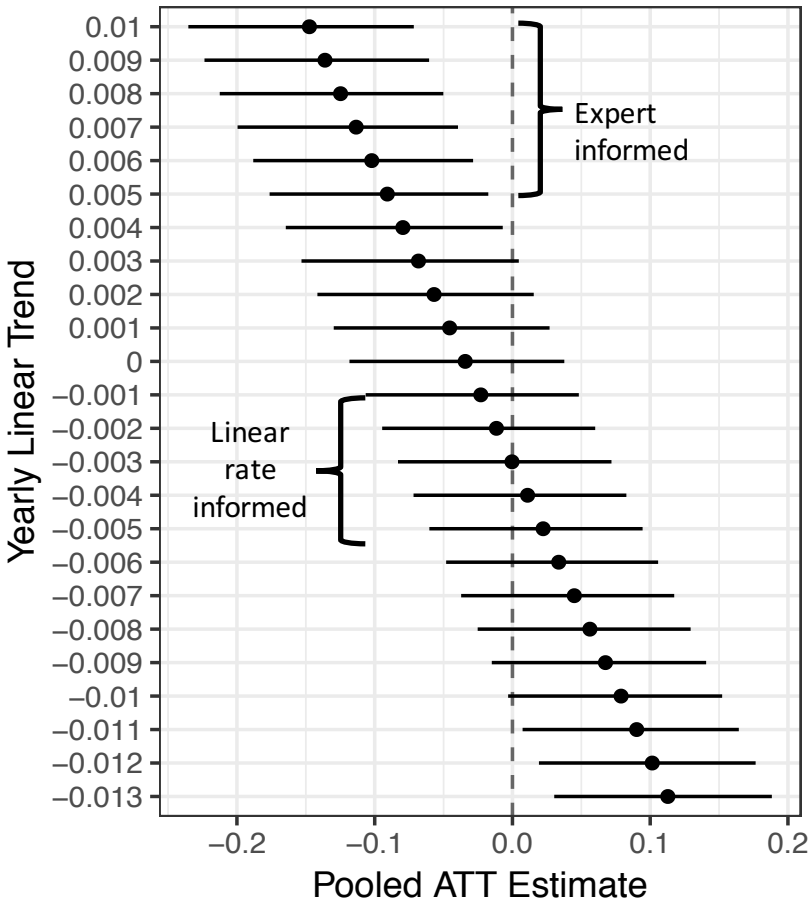

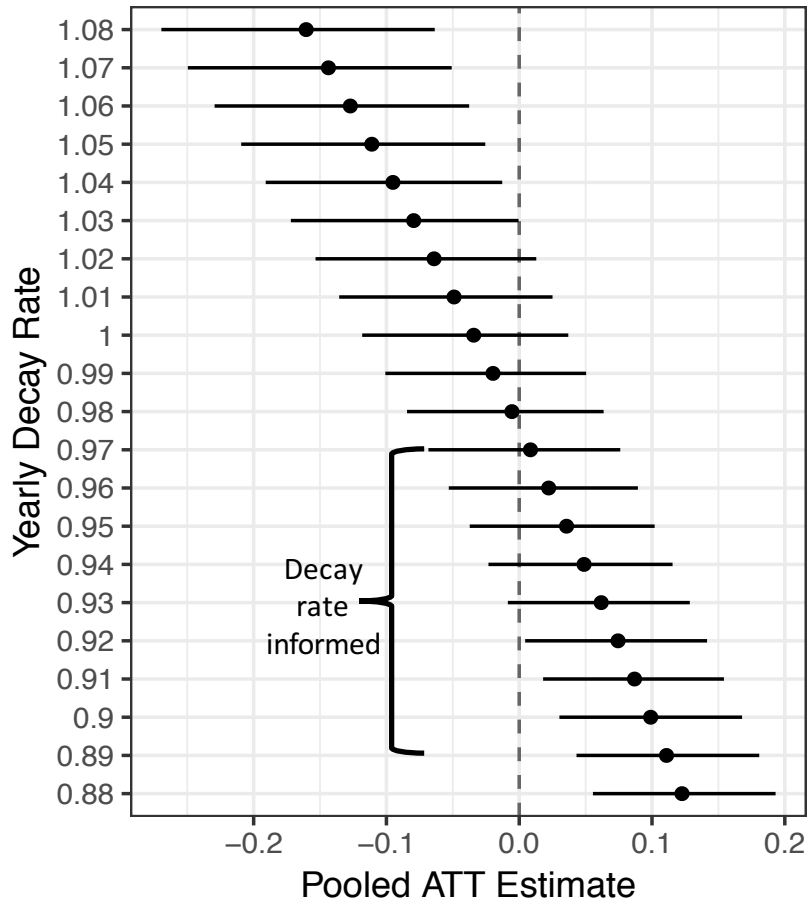

A side benefit: Who takes IPT?

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

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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 δ offered by the linear estimate above: