Interrupted Time Series Without a Comparison Group
## Deity’s Dataset

<table>
<thead>
<tr>
<th>Unit</th>
<th>Time period</th>
<th>Y(0)</th>
<th>Y(1)</th>
<th>Treatment Effect</th>
</tr>
</thead>
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<td>10</td>
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<td>10</td>
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</tbody>
</table>
Deity Treatment Effect

![Graph showing Deity Treatment Effect with time period on the x-axis and Y(1) - Y(0) on the y-axis. The graph includes two lines, one for Y(0) and one for Y(1).]
Analyzing ITS Using *Our* Observed Data
Steps

• Run a regression and obtain predicted coefficients

\[ Y_t = \beta_0 + \beta_1 \text{Treatment}_t + \beta_2 f(\text{Time})_t + \beta_3 \text{Treatment}_t \times f(\text{Time})_t + \epsilon_t \]

• Use the predicted coefficients to calculate estimated Y0s and Y1s for time periods post intervention

• Estimate the treatment effect at each time period by taking the difference in our estimated \( Y(1) \) and \( Y(0) \) at the time period of interest
Assumptions for ITS

1. Pre and post-intervention time series is correctly modeled.
2. Control potential outcomes function is stable across time
A1: Pre and Post-Intervention Time Series Correctly Modeled

Y0 is quadratic
But we assumed it was linear!

Y₀ is quadratic
Approaches to Addressing A1

• Use parametric regression to estimate predicted regression between outcome and time
• Compare predicted regression function to non-parametric estimates (local means)
• Relax functional form assumptions by using a saturated model

• Many of the skills you learned in the analysis of RD is going to come in handy for addressing A1.
A2: Control potential outcomes function is stable across time

Function of $Y(0)$s across time

Function of $Y(1)$s across time
But we have assumed that it is linear

Function of $Y(0)$s across time

Function of $Y(1)$s across time
Approaches to Addressing A2

• Think about whether there is a substantive reason for why the control time series should change over time
• Observe comparison time series
ITS and RDD

• Theoretically, ITS can be considered as an RDD with *time* as the assignment variable. However, a typical ITS differs from RDD in several aspects:
  – *Discrete* (instead of continuous) measures at *fixed points* in time
  – Only *one* (*aggregated*) *measure per time point* (ITS designs with multiple measures per time point are also common)
  – *Delayed* (*lagged*) effects
  – Effects of interest:
    • change in *level* (intercept) → discontinuity
    • change in *slope* and *cycles* (e.g., seasonality)
    • change in *variation*