

QTM 101 Midterm 2 Cheat Sheet

Section 1, 10am-11:15am, Wed, Nov 8th, 2023

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From Midterm 1

- $\underbrace{\text{Estimate}}_{\text{what we see in data}} = \underbrace{\text{Estimand}}_{\text{what we want to know}} + \text{Bias} + \text{Noise}$
 - ATE = $E[Y_1] - E[Y_0]$

The only observable effect (Estimate) is $E[Y_1 | T = 1] - E[Y_0 | T = 0]$

- Bias: Systematic error; Not apples-to-apples; Inaccuracy
 - Bias = $E[Y_0 | T = 1] - E[Y_0 | T = 0]$
 - Eliminating bias: **randomization**.
- Noise: Random error; $E[\text{Noise} = 0]$; Imprecision
 - Everything is noisy.
 - Measured by standard error
 - If we repeat our experiment for enough times, our Noise should be 0.

Regression

- General formula:

$$Y_i = \alpha + \beta T_i + \gamma V_i + r_i$$

- Y : dependent variable; T : independent variable/treatment; V : control variable/confounder
- $\alpha = E[Y_0]$: intercept
- $\beta = \text{ATE}$: slope (estimand)
- r : error term/residual
- Omitted Variable Bias (Confounders):
 - Confounders must affect treatment AND outcome
 - Short (uncontrolled):

$$Y_i = \alpha + \beta^S T_i + r_i$$

- Long (controlled):

$$Y_i = \alpha + \beta^L T_i + \gamma V_i + r_i$$

- Omitted Variable Bias (OVB):
$$\text{OVB} = \beta^S - \beta^L.$$
- If β^S and β^L are negative, we compare $|\beta^S|$ and $|\beta^L|$. If $|\beta^S| > |\beta^L|$, then we overestimate the negative treatment effect. β^L is a **less biased** estimate of the ATE than β^S .

Difference-in-Difference

- Key: Parallel Trends. Outcomes must change at the similar rates; lines should have similar slopes.
- Two approaches: Difference over time and different between subjects: Treated minus untreated; post-treatment minus pre-treatment.
- Violation of parallel trends: overestimate and underestimate.

Regression Discontinuity Design (RDD)

- Running variable, threshold, treatment status
- Local Average Treatment Effect (LATE):
$$\text{LATE} = E[Y_1 | X = \text{threshold}] - E[Y_0 | X = \text{threshold}]$$
 - If we change the bin, we will get different LATEs.
 - Different ways to get LATEs:
 - naïve way: choose a bin and compute the bin at both sides of the bin
 - local linear/polynomial: choose a window and run linear/polynomial regressions then compute the limit
- Continuity Assumption: Points must have the same **potential outcomes** at the threshold. **Capacity to manipulate** treatment assignment cannot be related to outcome.

Noncompliance and Instrument

- Types of Populations:
 - Always Takers
 - Compliers: What we are interested in.
 - Never Takers
 - Defiers: we assume there are no defiers.
- Z : our assignment. T : whether the subjects receive the treatment.
- $Z \neq T$; Z is randomized $\implies Z = 0$ and $Z = 1$ are apples-to-apples
 - Given $Z = 1$:
 - $T = 1$: always takers + compliers
 - $T = 0$: never takers
 - Given $Z = 0$:
 - $T = 1$: always takers
 - $T = 0$: never takers + compliers
- We can compute the proportion of compliers by
$$1 - P(\text{always takers}) - P(\text{never takers}).$$

- First Stage Treatment:

$$\begin{aligned} & \text{Avg}[T \mid Z = 1] - \text{Avg}[T \mid Z = 0] \\ &= \text{P}(\text{always takers}) + \text{P}(\text{compliers}) - \text{P}(\text{always takers}) \\ &= \text{P}(\text{compliers}) \end{aligned}$$

- Intent-to-Treat (ITT):

$$\text{Avg}[Y \mid Z = 1] - \text{Avg}[Y \mid Z = 0]$$

- ITT underestimates CATE because it averages in always takers and never takers with treatment effect of 0.
- We can scale ITT back to the CATE up by the proportion of compliers.

- Complier Average Treatment Effect (CATE):

$$\text{CATE} = \frac{\text{ITT}}{\text{P}(\text{compliers})}$$

- Assumptions:

- No defiers
- Some compliers
- Exclusion (Z is only associated with T)
- Exogeneity (random or as-if random)

- Exclusion + evidence (in context): It's hard to argue that the ITT alone causes any sort of other outcome that affects the outcomes than whether or not the individual receives treatment.
- Exchangeability – because Z is randomized, it cannot correlate with any pre-existing confounder

- *Should we expect that the CATE to be a good estimate of the true average treatment effect for **all** individuals?*

- CATE is local/only for compliers + context
- Compliers being different from non-compliers + evidence in context

- *The continuity assumption that is critical to RDD. The relationship between the continuity assumption, “as-if” randomization, and apples-to-apples comparisons.*

- The continuity assumption: the potential outcomes functions continue smoothly across the threshold – as we transition from what we can see to what we cannot, there are no jumps at the threshold.
- This assumption bakes in the apples-to-apples comparison at the threshold + explanation with context Y of subjects below the threshold is identical to Y of subjects above the threshold.
- This is equivalent to random assignment about the threshold, so the LATE is free from bias.

- *Is LATE a good estimator of all populations?*

- Not really.
- The LATE only applies to individuals at the threshold. Using this design, we learn nothing about the treatment effect for those away from the threshold – it is wholly possible that the potential outcomes for the treated in a world where they are not treated do not follow the “trend” discovered on the left of the threshold.

Useful Phrasings

- *The intention to treat (Z) is an admissible instrument for the actual treatment status (T) in this randomized experiment with noncompliance.*

The intention to treat should meet 3 conditions to be a proper instrumental variable:

- Relevance + ITT is strongly correlated with actual treatment uptake + evidence: % of compliers

	Regression	DiD	RDD	IV
When to use	Anytime	Treated and untreated, before and after treatment	Sharp threshold (Treated one side, untreated the other)	Experiments with non-compliance
Assumptions	controlling for all confounders (Omitted Variable Bias)	Parallel trends	Continuity (Manipulation of score)	Exogeneity, Exclusion, Compliers, no defiers
Name for Estimate	ATE	ATT or DiD	LATE	CATE