SciencesPo
DEPARTMENT OF ECONOMICS

Applied Data Analysis for Public Policy Studies

Regression Discontinuity Design

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Recap from last week

- ***Differences-in-differences*** policy evaluation method
- Main estimation equation:

$$Y_{it} = \alpha + \beta TREAT_i + \gamma POST_t + \delta(TREAT_i \times POST_t) + \varepsilon_{it}$$

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Today: *Regression Discontinuity Design*

- Life is full of random rules which assign some treatment
- Exploits knowledge of assignment rule
- Key assumption: variable which assigns treatment cannot be manipulated by individuals
- *Empirical application:* effect of alchol consumption on mortality

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- RDD can be applied when we have specific information about the rules determining treatment.
- **RDD** exploits this precise information about allocation to treatment!

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We will focus our analysis on the following discontinuity:

- In the US, the legal drinking age is 21 years old (Carpenter and Dobkin, 2009).

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    - Because there may be unobserved selection into alcohol consumption that may also be a determinant of mortality.
- In the US, alcohol consumption is prohibited before the age of 21.
- Debate on whether the minimum legal drinking age (MLDA) should be lowered to 18, as was the case in the Vietnam-era.

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- 👉 ***Regression discontinuity design*** exploits this allocation to treatment!

Carpenter and Dobkin's data

- Let's take a closer at the data used in the paper

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# install package containing data
devtools::install_github("jrnold/masteringmetrics",
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# load package
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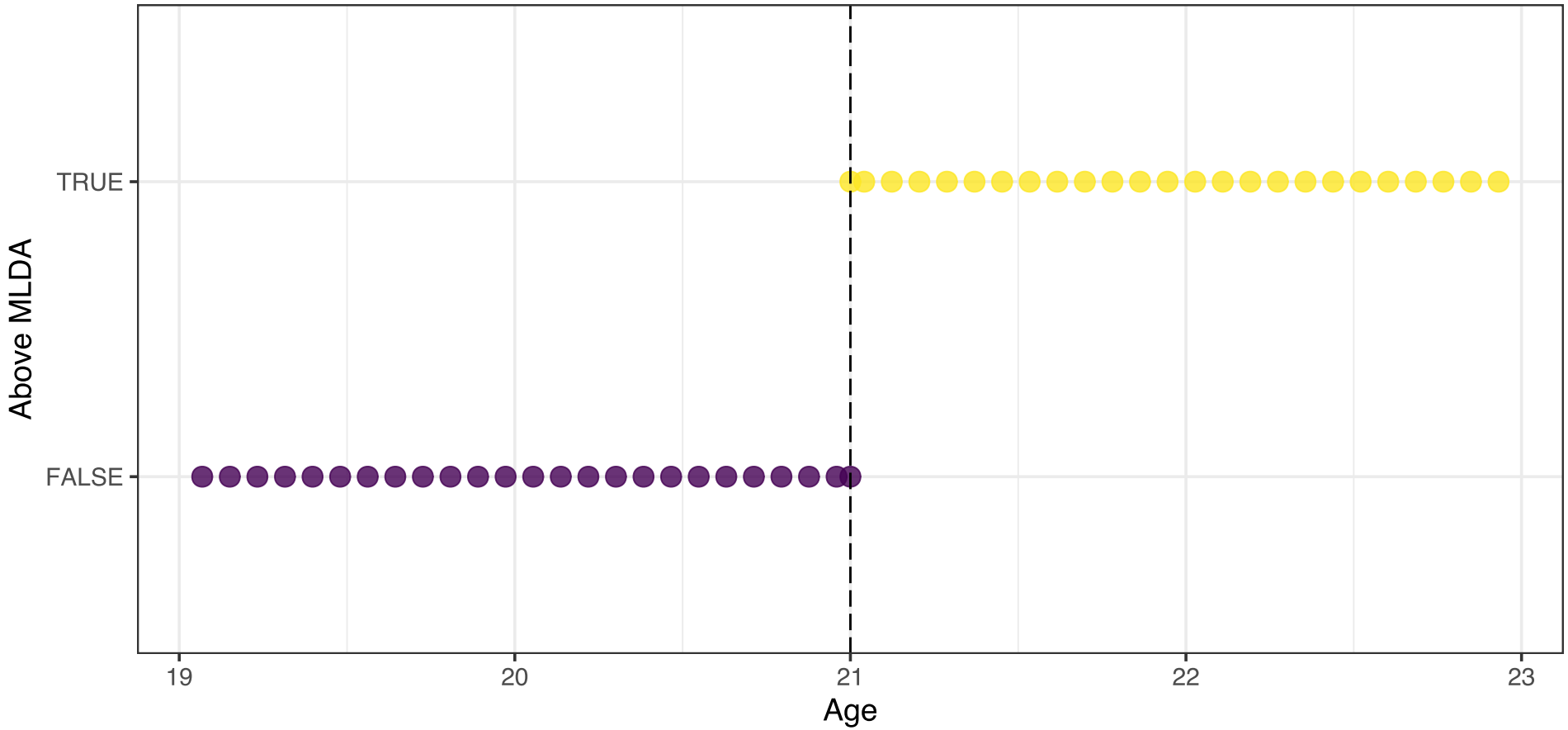
- This dataset contains aggregate death rates (and their causes) for different age groups (`agecell`) between 19 and 23 years old.

Sharp Discontinuity at Cutoff



At the threshold, the probability of being treated jumps from 0 to 1.

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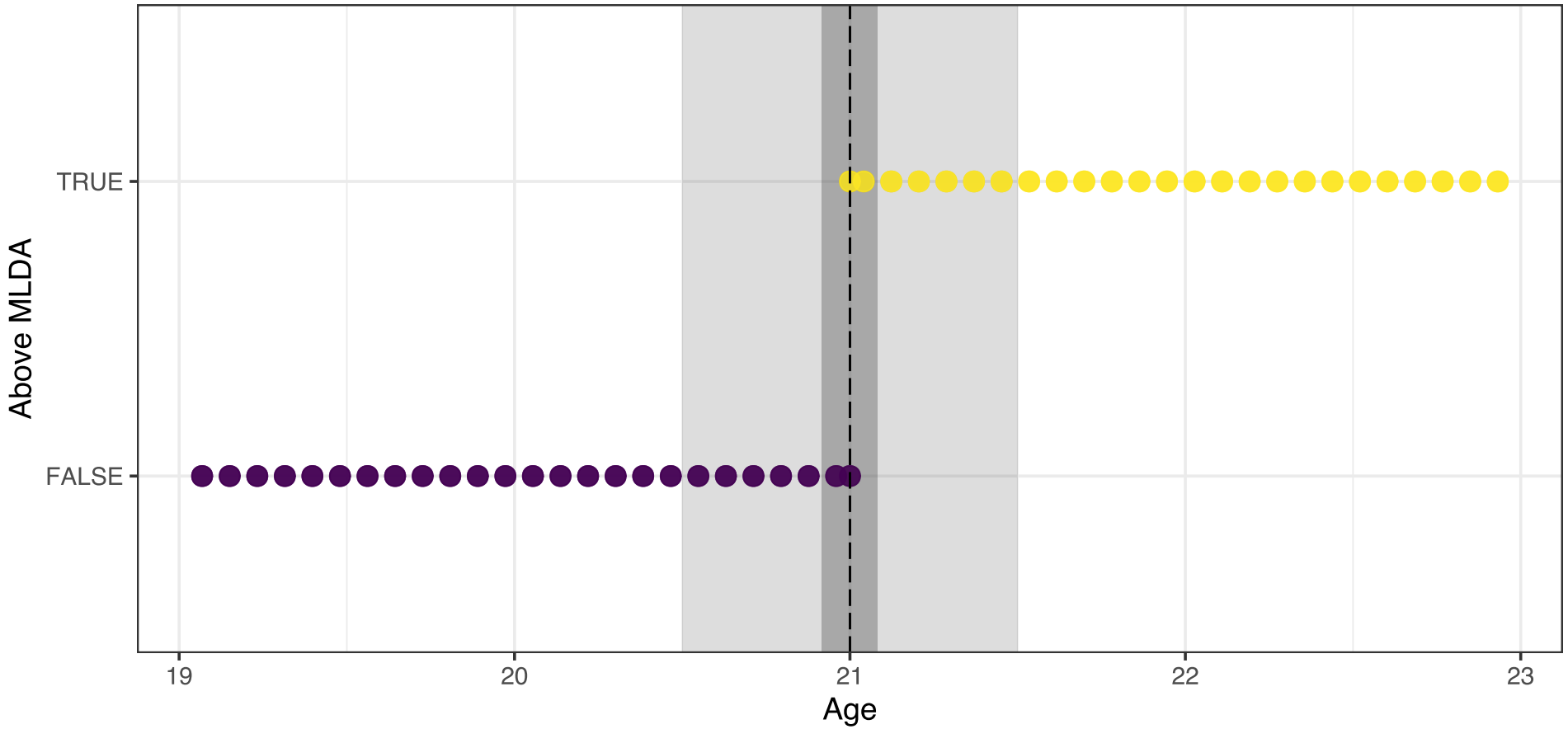

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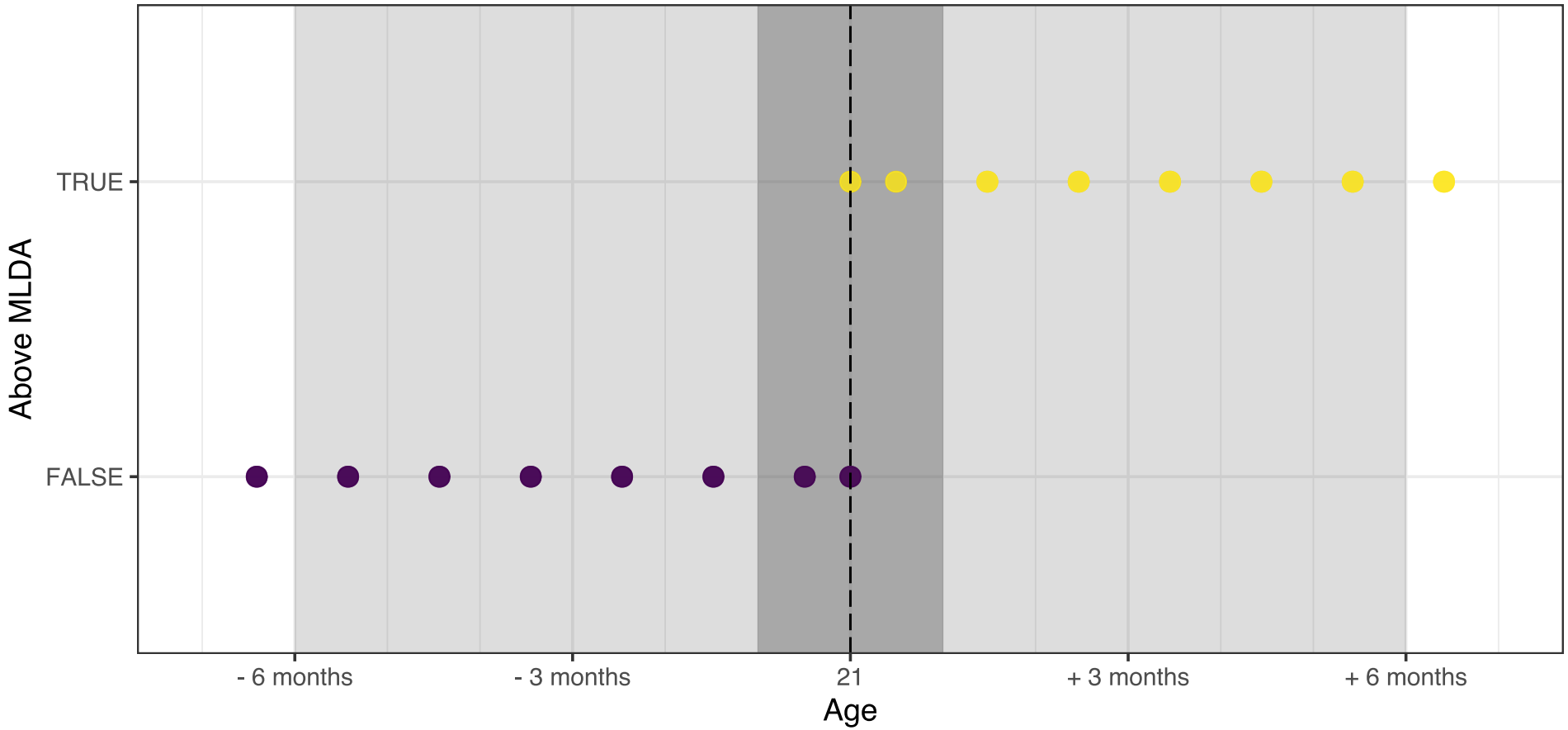

RDD Framework

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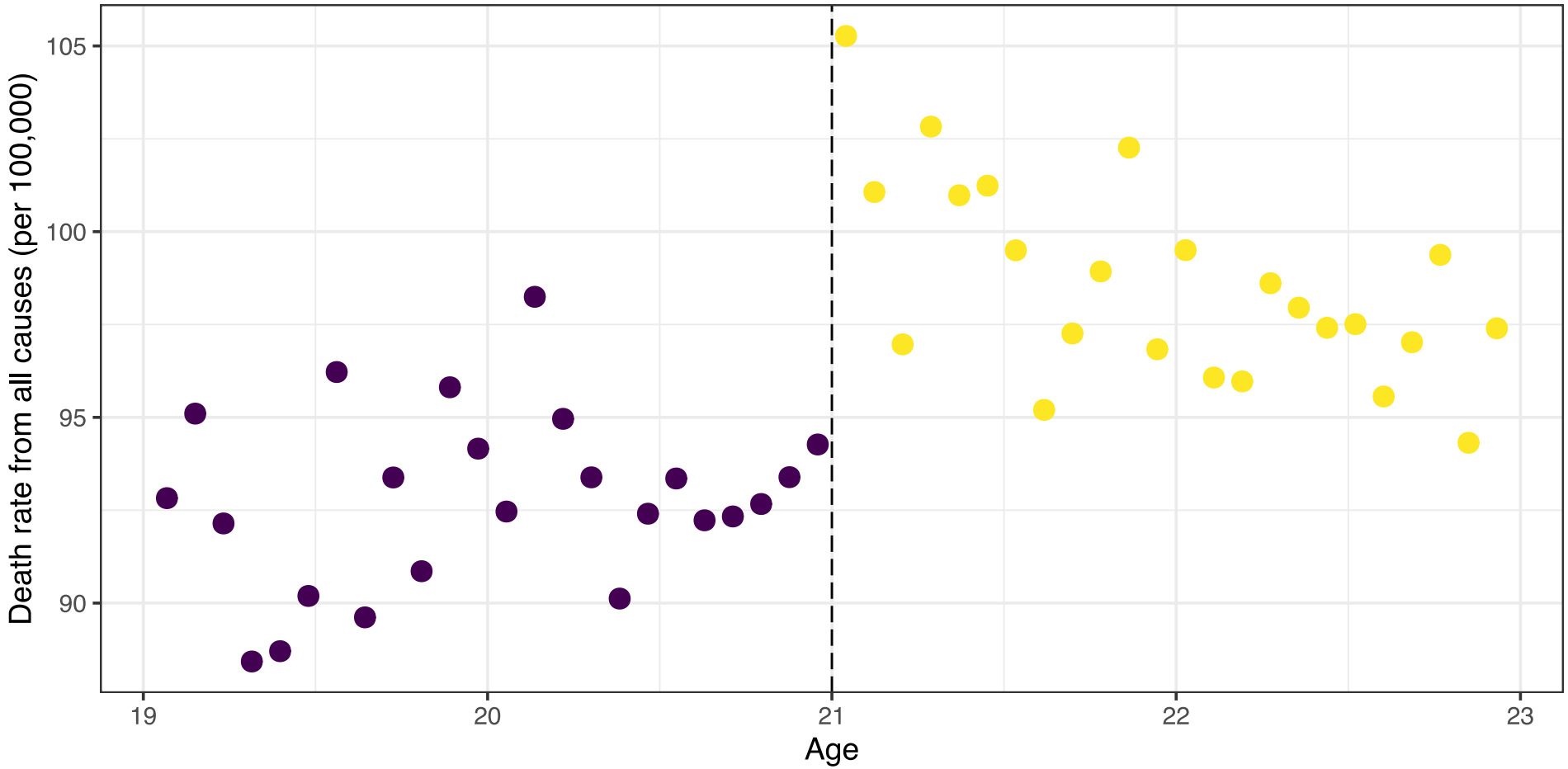
1. Treatment status is a **deterministic** function of $a \rightarrow$ we know the assignment rule
2. Treatment status is a **discontinuous** function of $a \rightarrow$ there is some cutoff level

Task 1 (10 minutes)

1. Import the dataset following the code from slide 7. How many age cells are there?
2. Create a dummy variable for individuals over 21 years old.
3. Plot the death rate for all causes (`all`) as a function of age (`agecell`) colouring observations above and below 21 years old. Does anything seem striking?
4. Add a regression line to the plot. What do you observe?
5. Do the same for motor vehicle-related causes (`mva`) and alcohol-related causes (`alcohol`) as a function of age.

]

Graphical Results: All Death Rates



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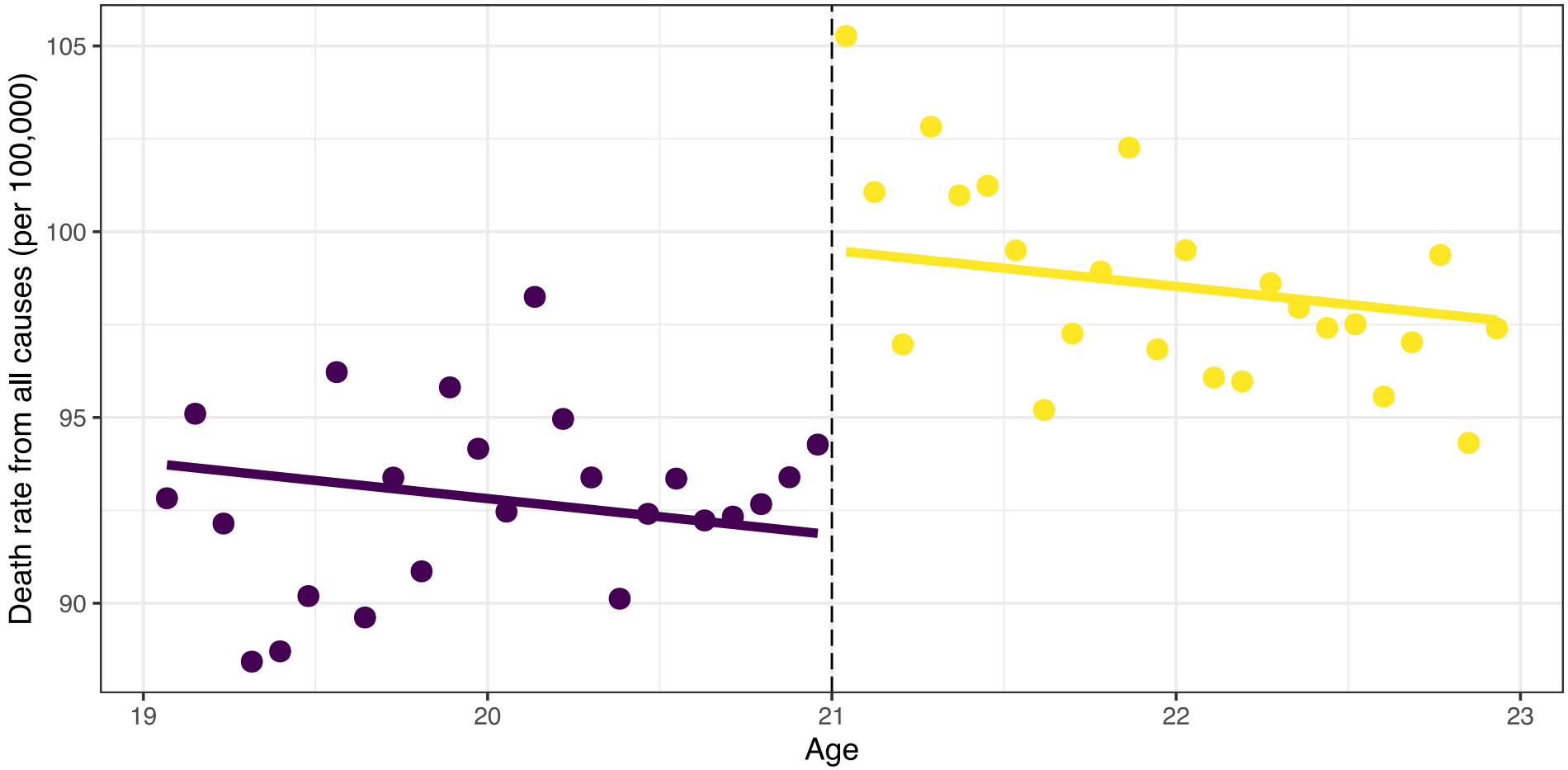

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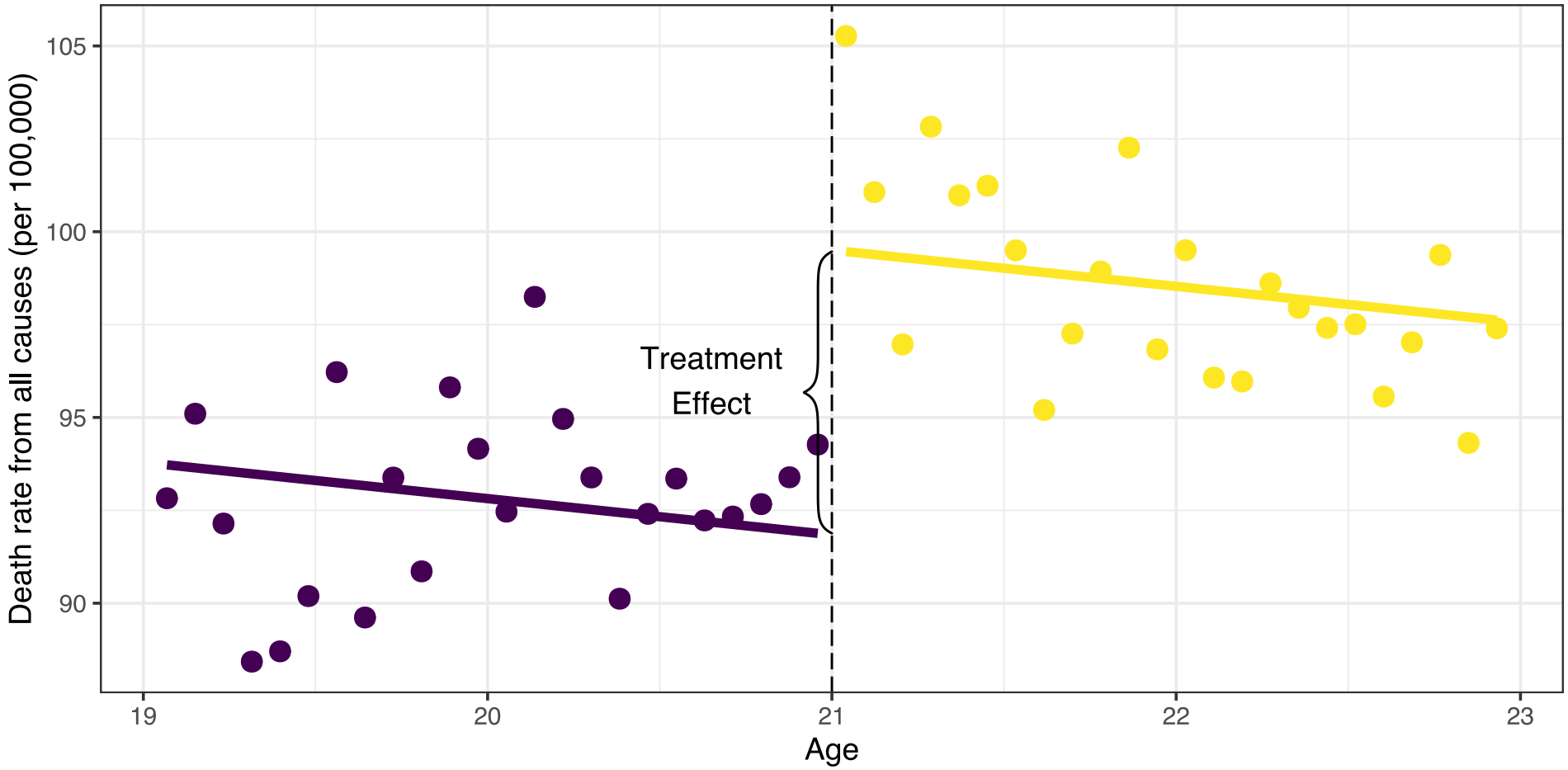

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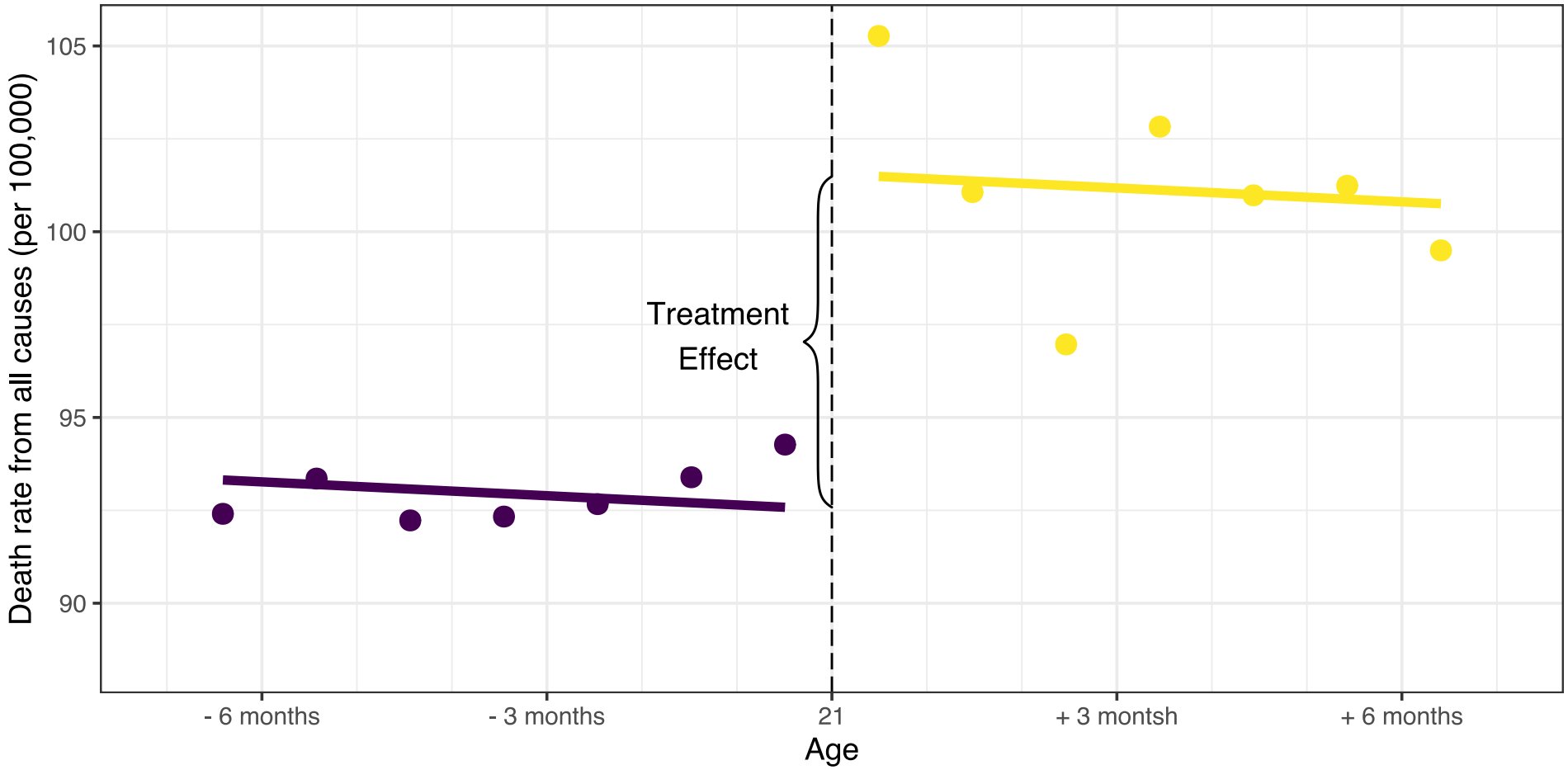

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- Limited ***external validity*** $\rightarrow$ you cannot extrapolate to the entire population.
- Using the 21 year old alcohol restriction age in the RD context will only tell you the effect of this restriction on death rates but *not the general effect of alcohol consumption*.
- One may easily argue that all results from quantitative empirical analyses have a local nature.

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- The RDD estimator exploits a discontinuity at $a = 21$ in the conditional expectation function:

$$\underbrace{\lim_{c \to 21^+} \mathbb{E}[DEATHRATE_a | a = c]}_{\alpha + \delta} - \underbrace{\lim_{c \to 21^-} \mathbb{E}[DEATHRATE_a | a = c]}_{\alpha} = \delta$$

Task 2 (5 minutes)

1. Estimate the following model on all death causes.

$$DEATHRATE_a = \alpha + \delta D_a + \beta a + \varepsilon_i,$$

   Does the RDD coefficient correspond to the graphical illustration?

2. How do you interpret each coefficient?

3. What is the causal effect of legal access to alcohol on death rates?

Estimation #1: Simple Linear Model

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  mutate(over21 = (agecell >= 21),
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rdd <- lm(all ~ agecell_21 + over21, mlda)

library(broom)
tidy(rdd)
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## # A tibble: 3 x 5
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Interpretation:

On average, the MLDA increases death rates from all causes by 7.66 percentage points.

This is a big effect considering the average death rate for individuals between 19 and 22 is:

```
mean(mlda$all, na.rm = TRUE)
```

```
## [1] 95.67272
```

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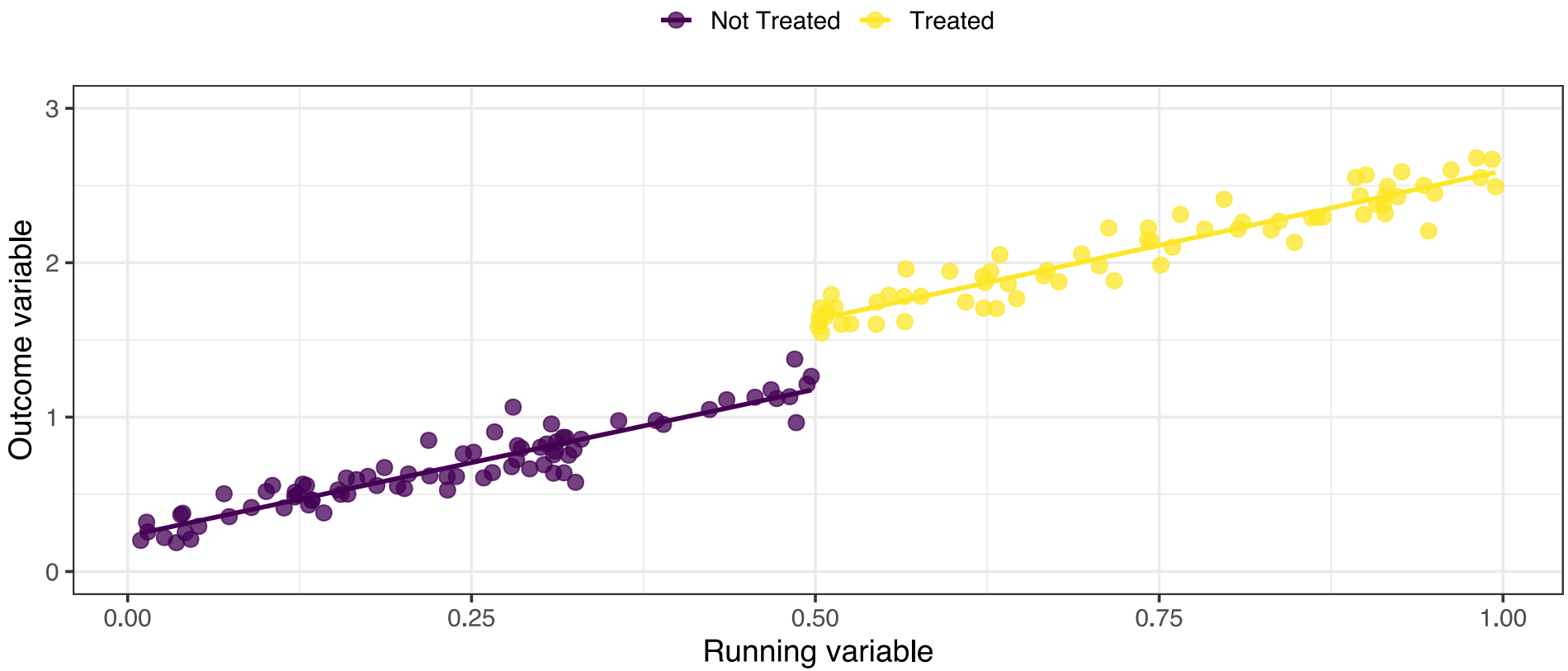
  $\rightarrow$ an overly flexible specification reduces precision and runs the risk of overfitting.

Simulations - Linear Relationship and Clear Discontinuity



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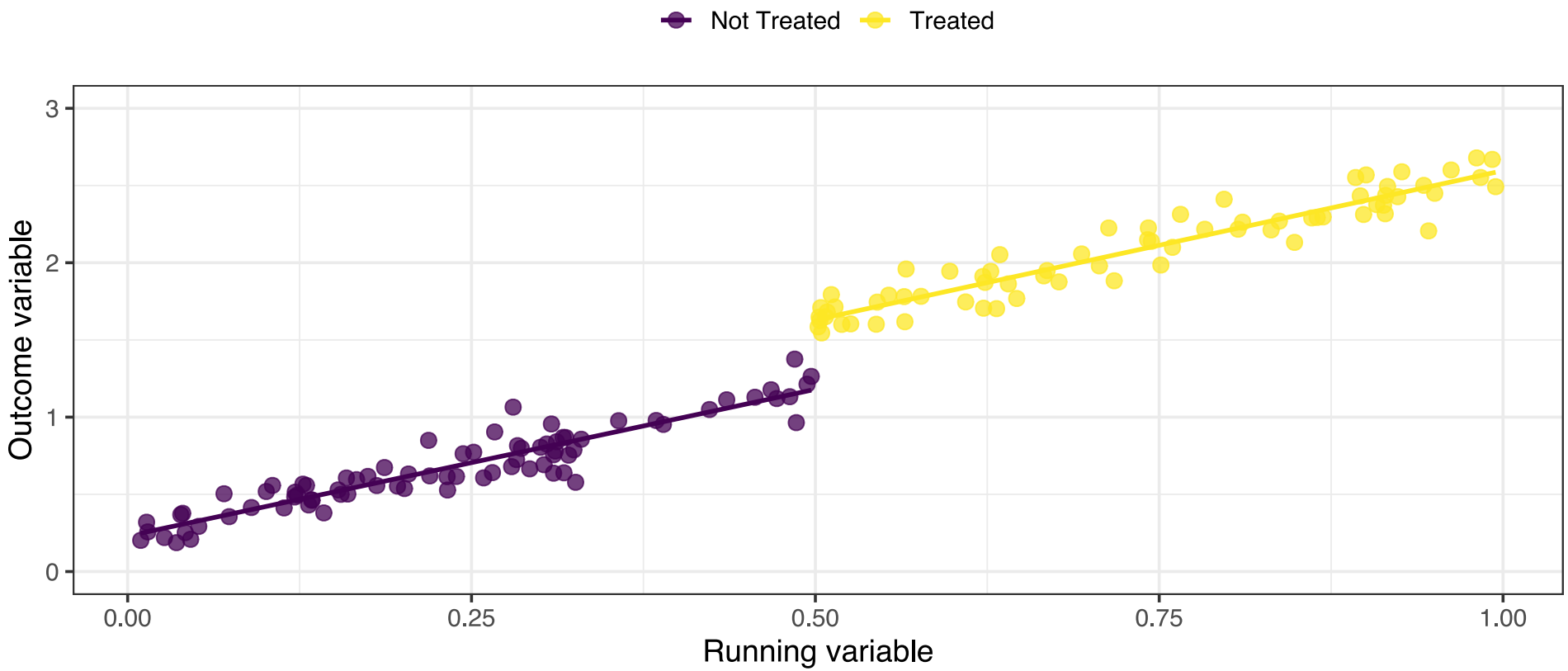

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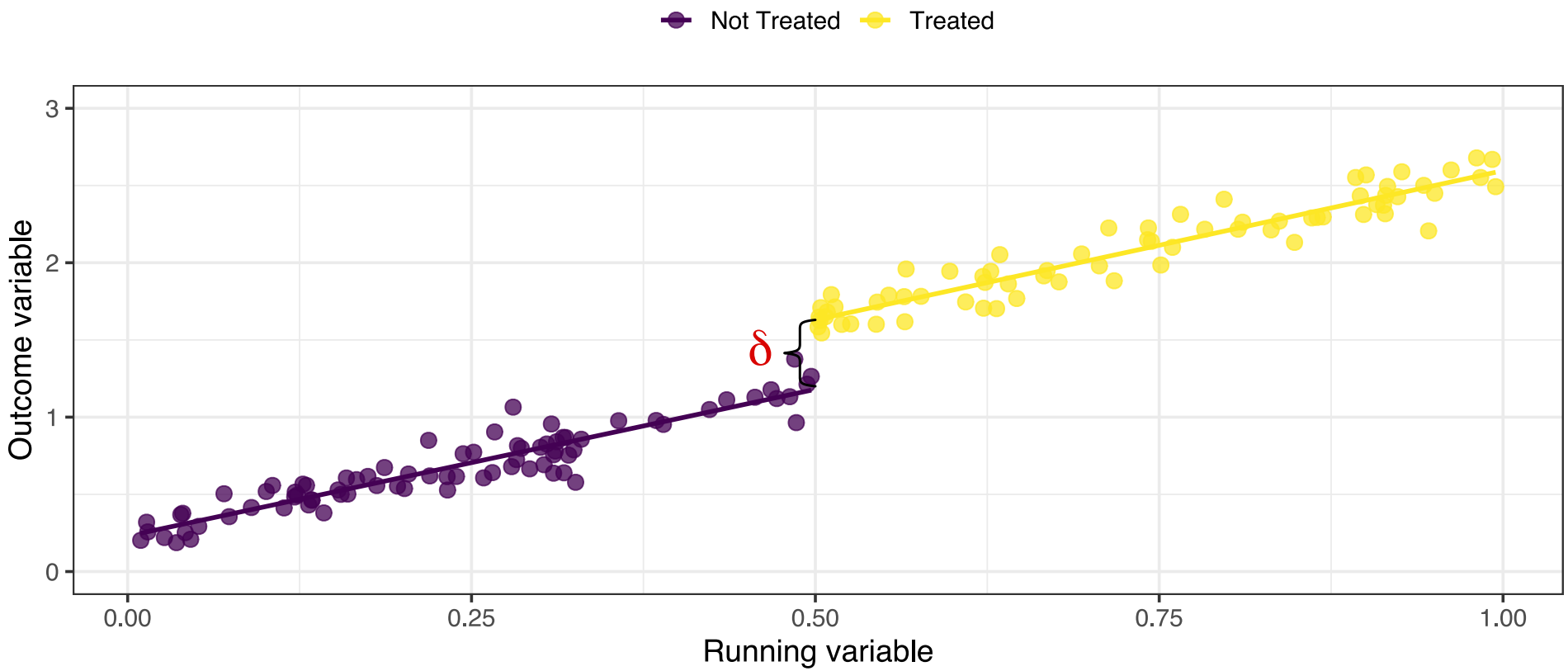

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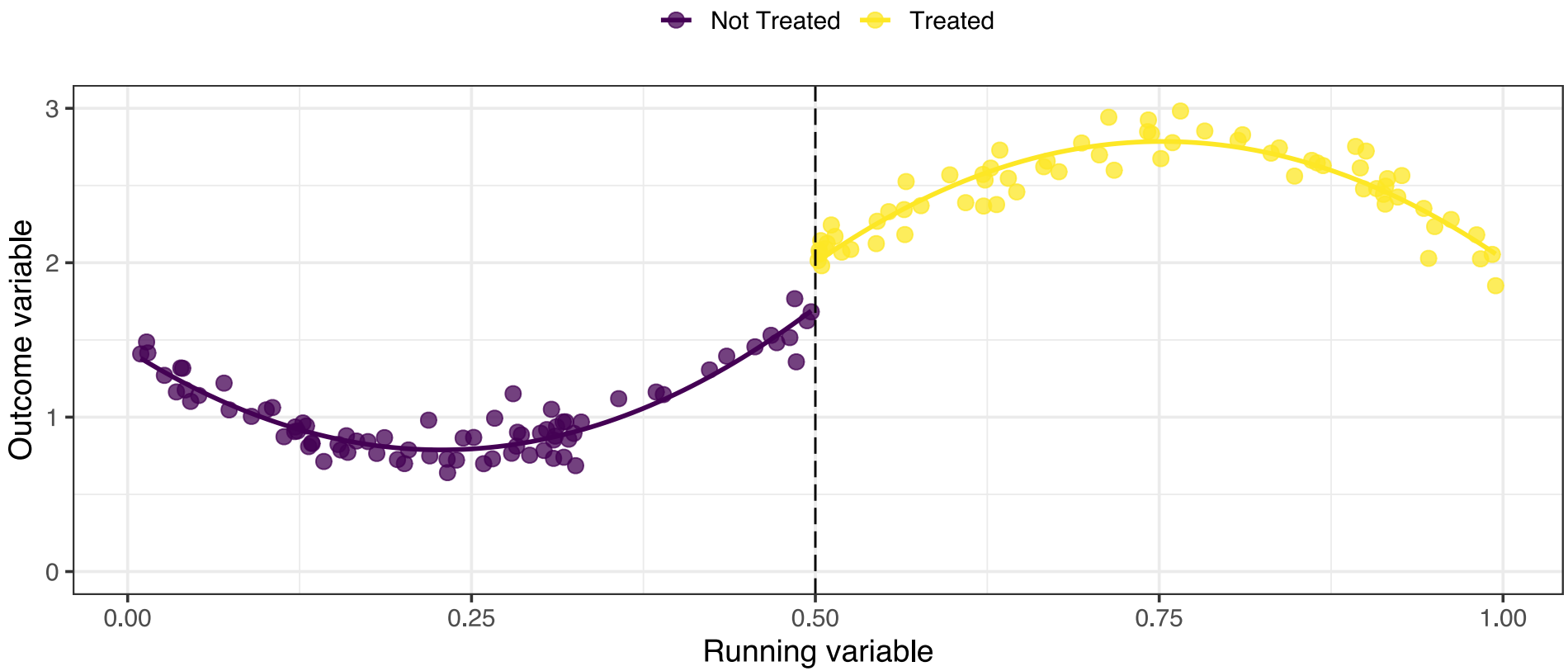

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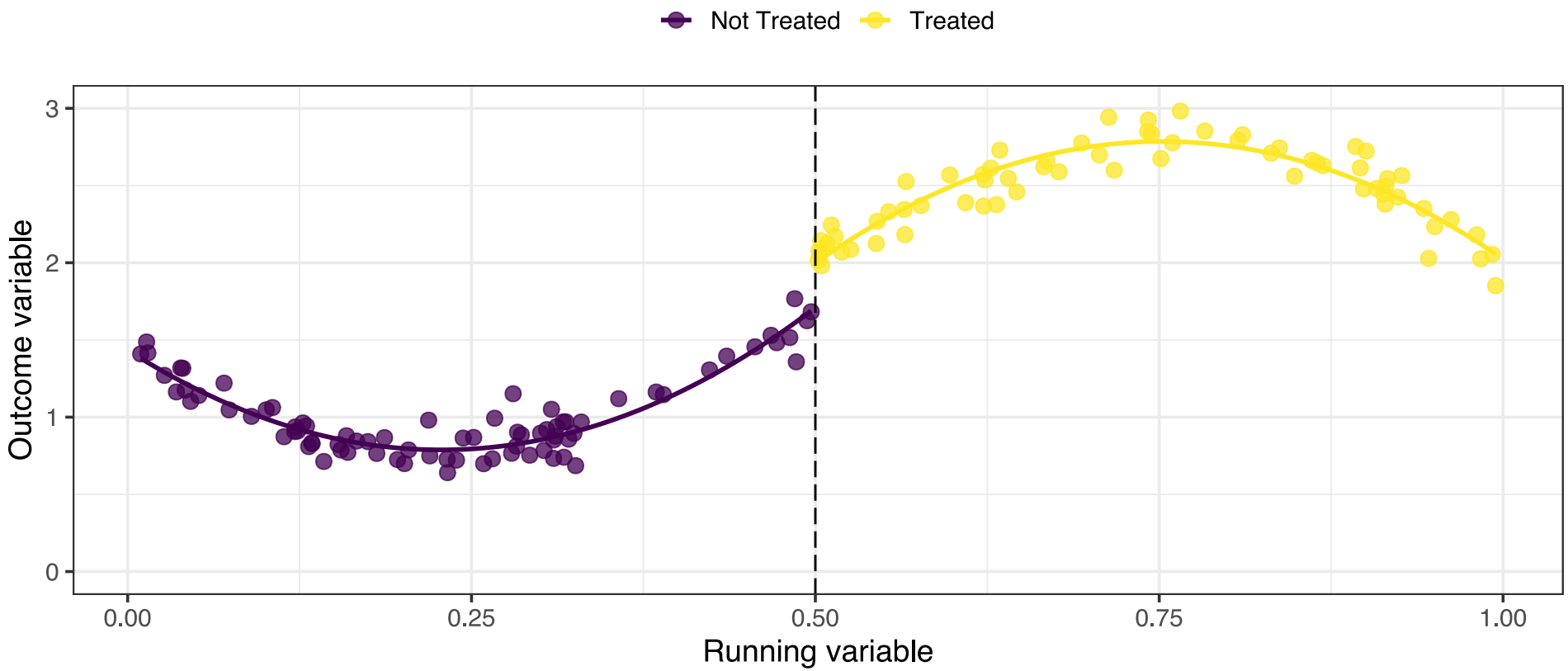
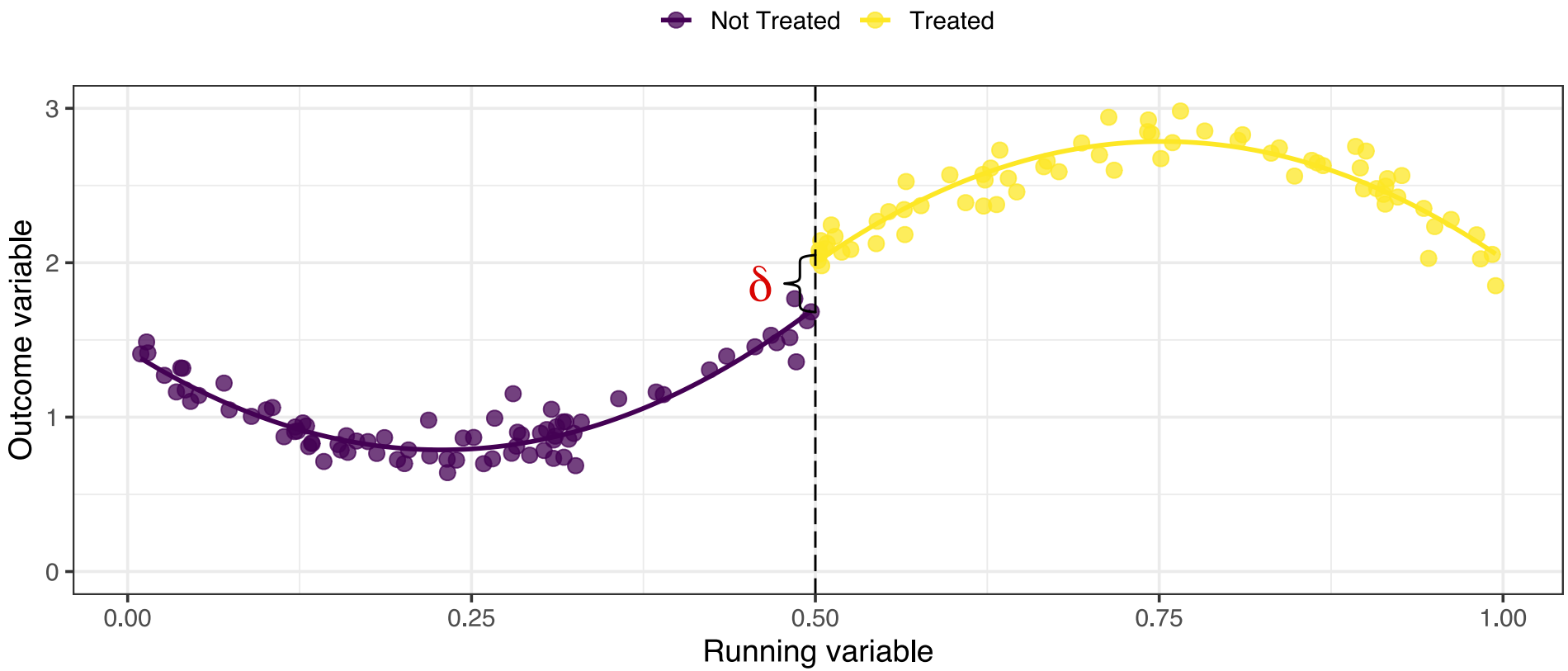


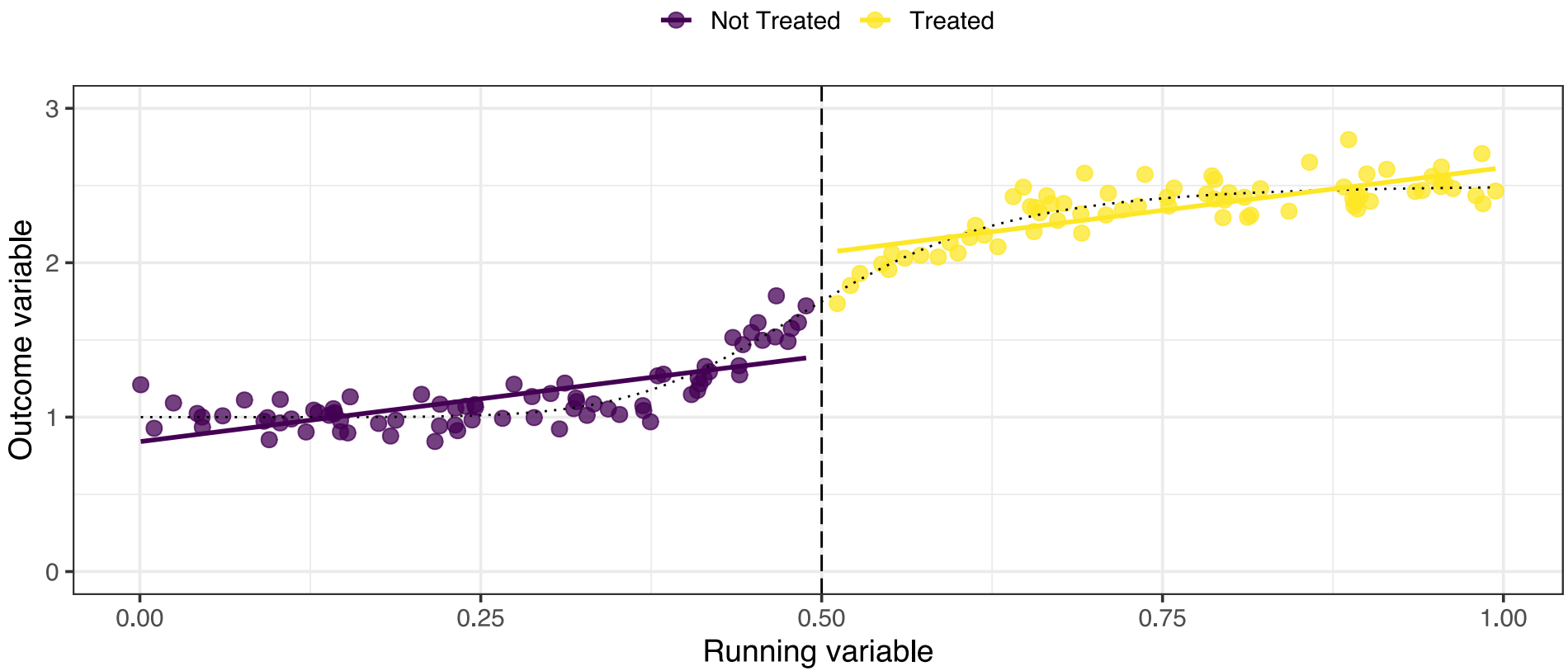
$$outcome_i = \alpha + \delta treatment_i + \beta_1 running_i + \beta_2 running_i^2 + e_i,$$

Simulations - Quadratic Relationship and Clear Discontinuity

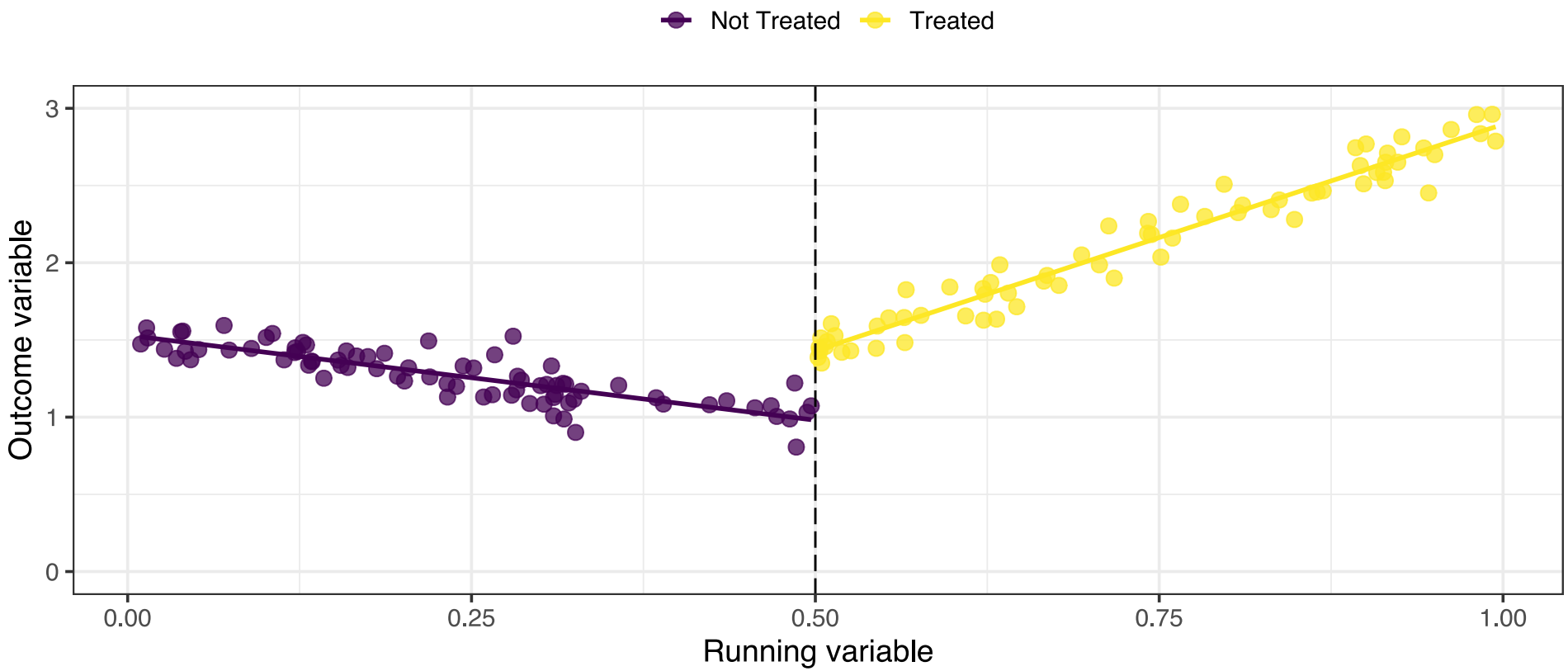


$$outcome_i = \alpha + \delta treatment_i + \beta_1 running_i + \beta_2 running_i^2 + e_i,$$

Simulations - Linear Relationship but NO Discontinuity



Simulations - Different Slopes



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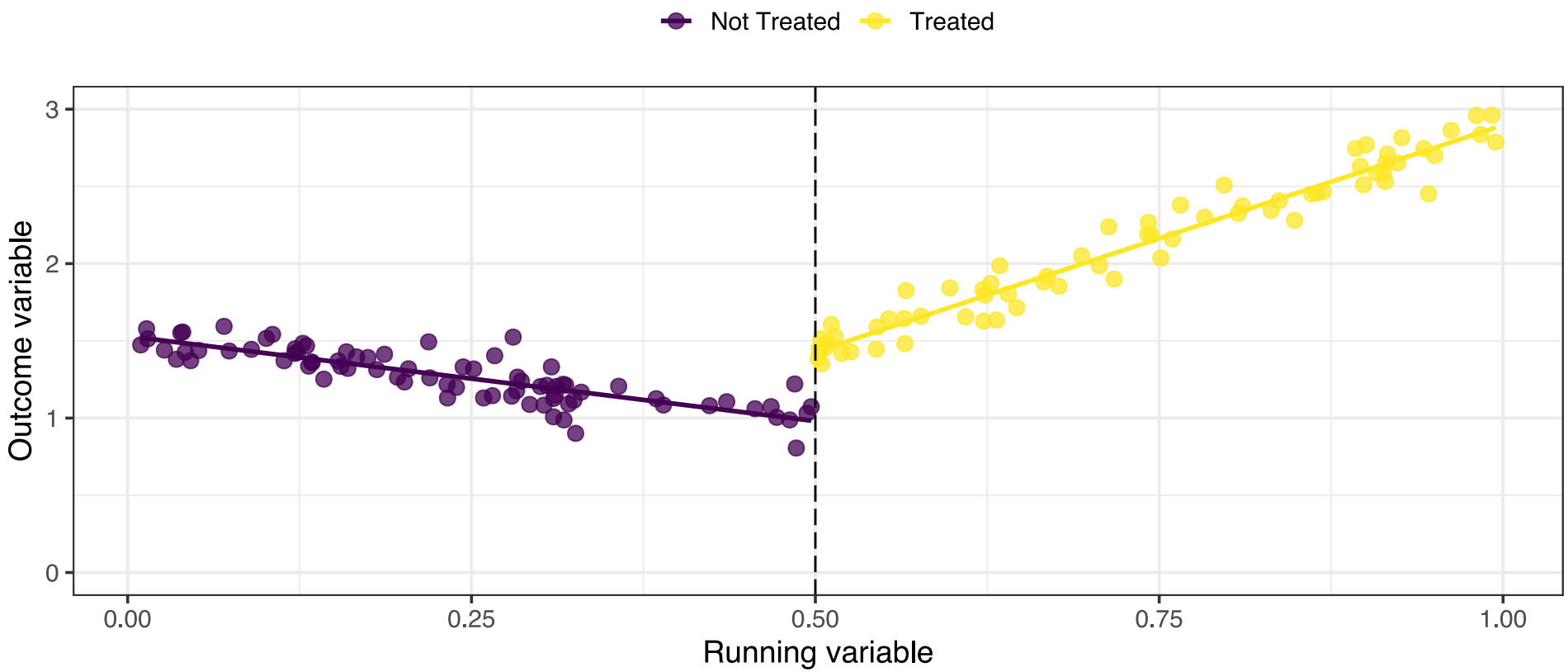

$$outcome_i = \alpha + \delta treatment_i + \beta(running_i - cutoff) +$$
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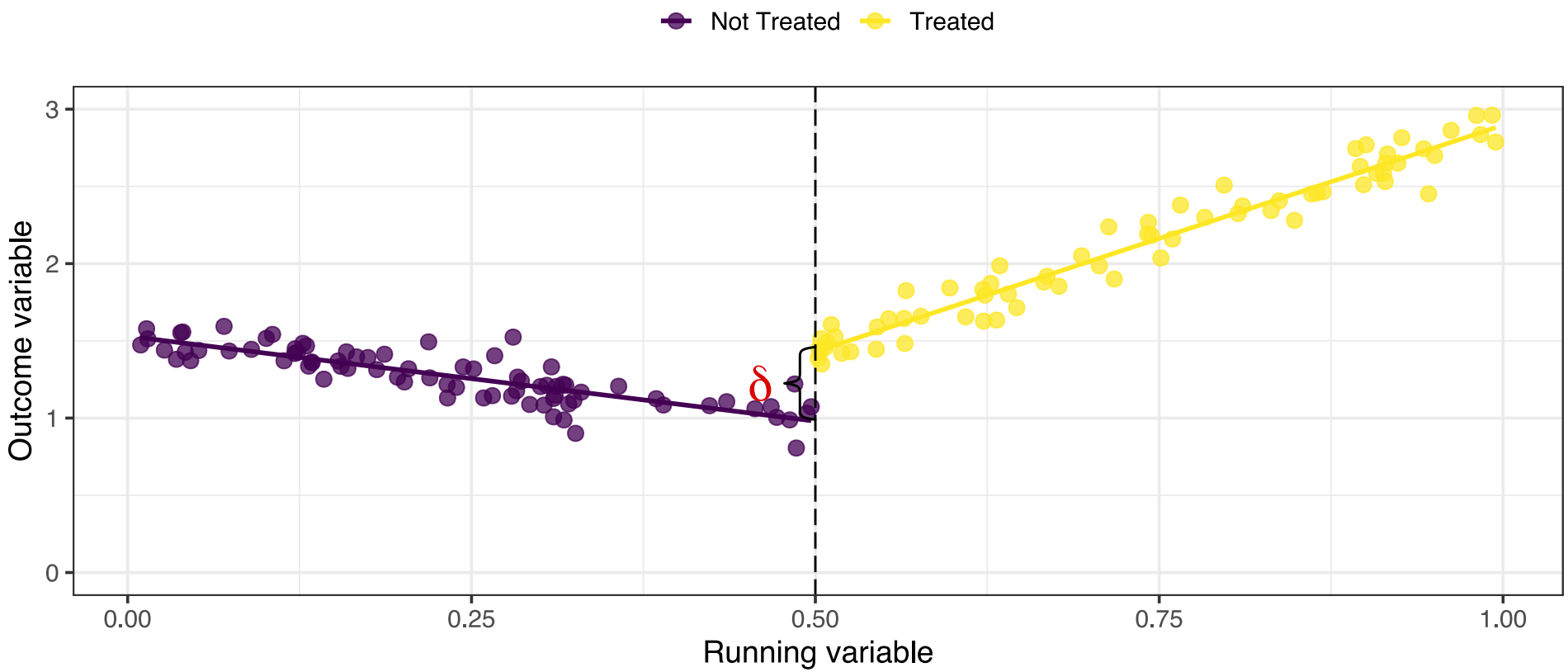
Simulations - Different (Linear) Slopes



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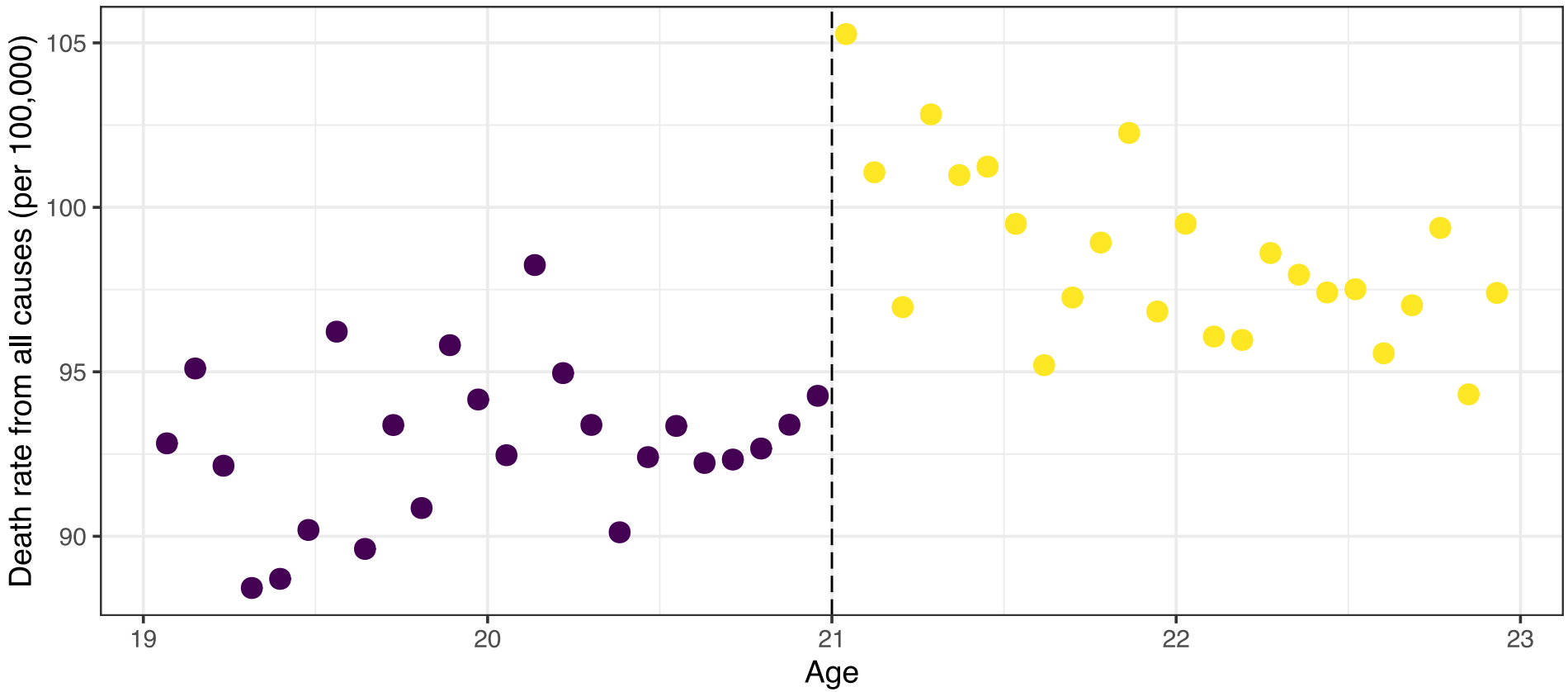
- Coefficients across models shouldn't vary too much.
- Should we expect the relationship between the outcome variable and the running variable to be nonlinear? Should we expect it to differ around the cutoff?
- Gelman and Imbens (2019), "Why High-Order Polynomials Should Not Be Used in Regression Discontinuity Designs":
  "We recommend researchers [...] use estimators based on local linear or quadratic polynomials or other smooth functions."

Going Back to our Example: Nonlinearities / $\neq$ Slopes?



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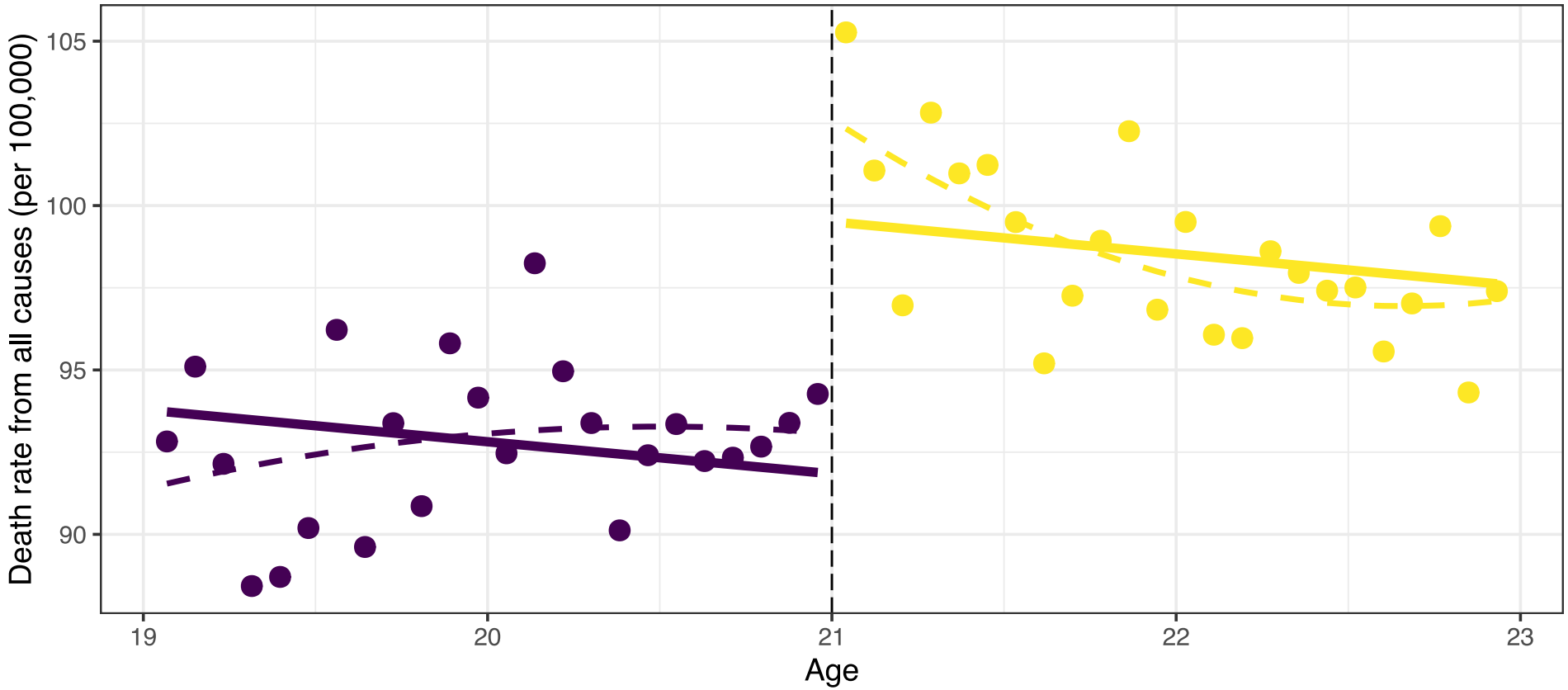

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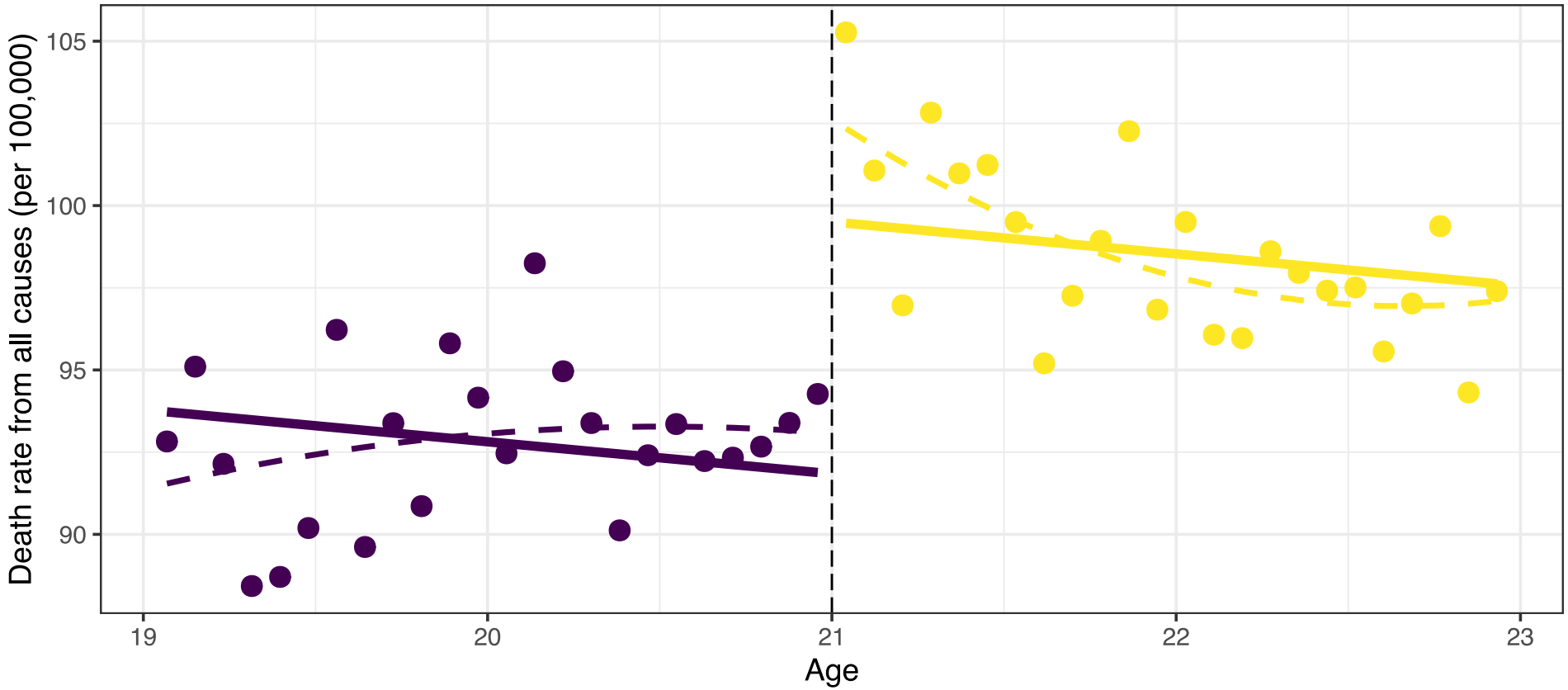


Gap between the lines is roughly the same for both specifications.

Task 3 (15 minutes)

1. Estimate the following *quadratic* model on all death causes. Does the RDD coefficient differ from the linear model?

$$DEATHRATE_a = \alpha + \delta D_a + \beta a + \beta a^2 + \varepsilon_a,$$

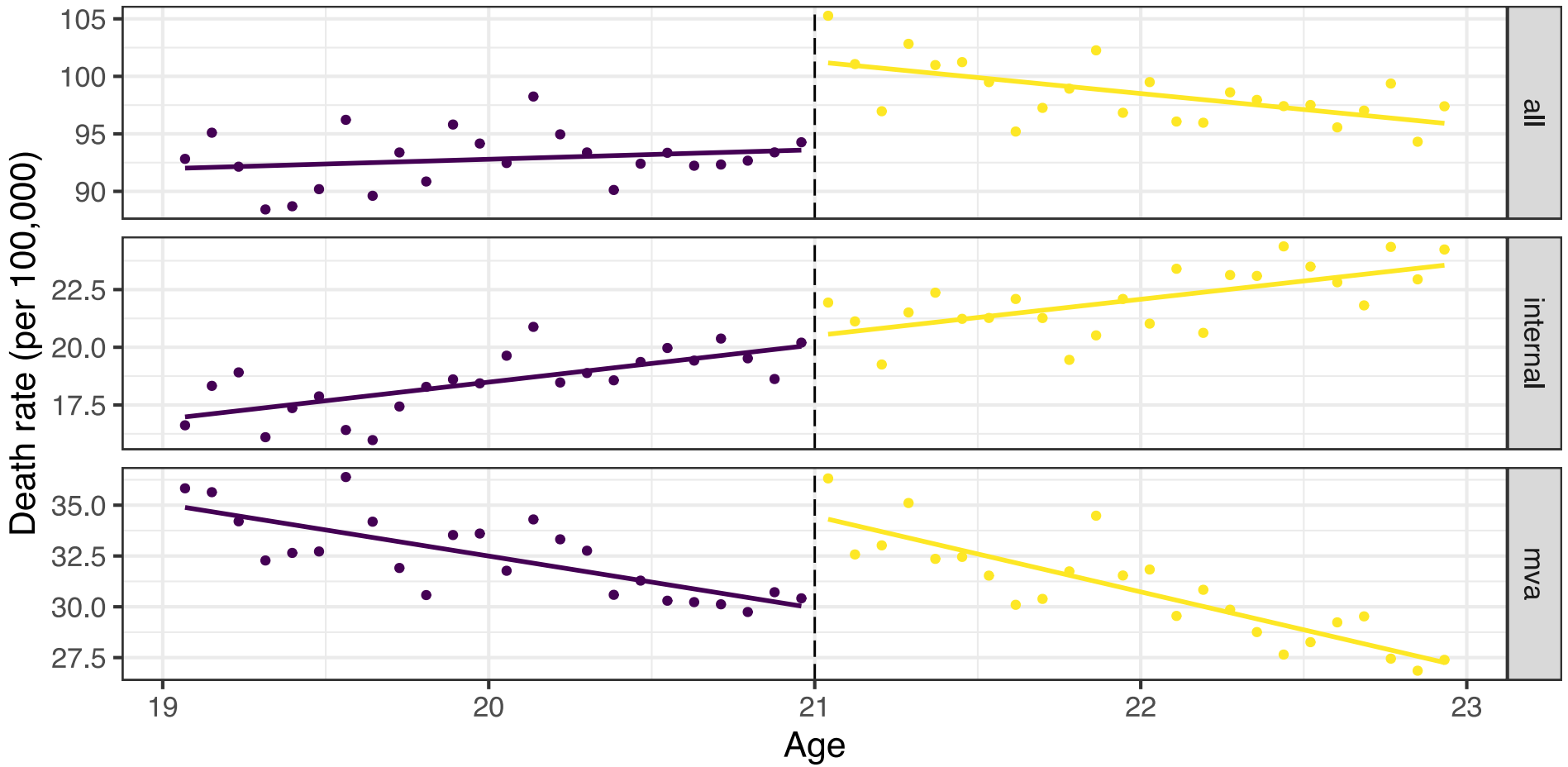
2. Recall that the regression model allowing for different slopes on each side of the cutoff is:

$$DEATHRATE_a = \alpha + \delta D_a + \beta(a - 21) + \gamma D_a * (a - 21) + \varepsilon_a,$$

   - Why do we need to substract the `cutoff` from `running_i`? (Hint: compute $\mathbb{E}(DEATHRATE_a | a = 21)$)
   - Should we expect the relationship between death rates and age to change at 21?
   - Estimate this model. How different is the RDD coefficient from the other models you have estimated?

- Re-run these models (linear, quadratic, different slopes) for the following death causes: motor vehicle accidents (`mva`), alcohol-related (`alcohol`), and internal (`internal`).

Graphical Representation of the Regression Results



Nonparametric Estimation

- Give more weight to observations close to the cutoff level

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Luckily there's an `R` package that chooses these settings optimally based on fancy algorythms: `rdrobust`.

Identifying Assumptions

RDD Assumptions

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  - Knowing the cutoff value in itself does not violate the assumption, only ability to manipulate running variable does.

RDD Assumptions

> *Key assumption*: ***Potential outcomes are smooth at the threshold.***

If the assumption holds, we have:

$$
\begin{aligned}
&\lim_{r \to c^+} \mathbb{E}[Y_i | R_i = r] - \lim_{r \to c^-} \mathbb{E}[Y_i | R_i = r] \\
=&\lim_{r \to c^+} \mathbb{E}[Y_i^1 | R_i = r] - \lim_{r \to c^-} \mathbb{E}[Y_i^0 | R_i = r] \\
=&\mathbb{E}[Y_i^1 | R_i = c] - \mathbb{E}[Y_i^0 | R_i = c] \\
=&\mathbb{E}[Y_i^1 - Y_i^0 | R_i = c]
\end{aligned}
$$

RDD Assumptions

> *Key assumption*: ***Potential outcomes are smooth at the threshold.***

If the assumption holds, we have:

$$
\begin{aligned}
&\lim_{c \to 21^+} \mathbb{E}[Y_i | a_i = c] - \lim_{a \to 21^-} \mathbb{E}[Y_i | a_i = c] \\
=&\lim_{c \to 21^+} \mathbb{E}[Y_i^1 | a_i = c] - \lim_{c \to 21^-} \mathbb{E}[Y_i^0 | a_i = c] \\
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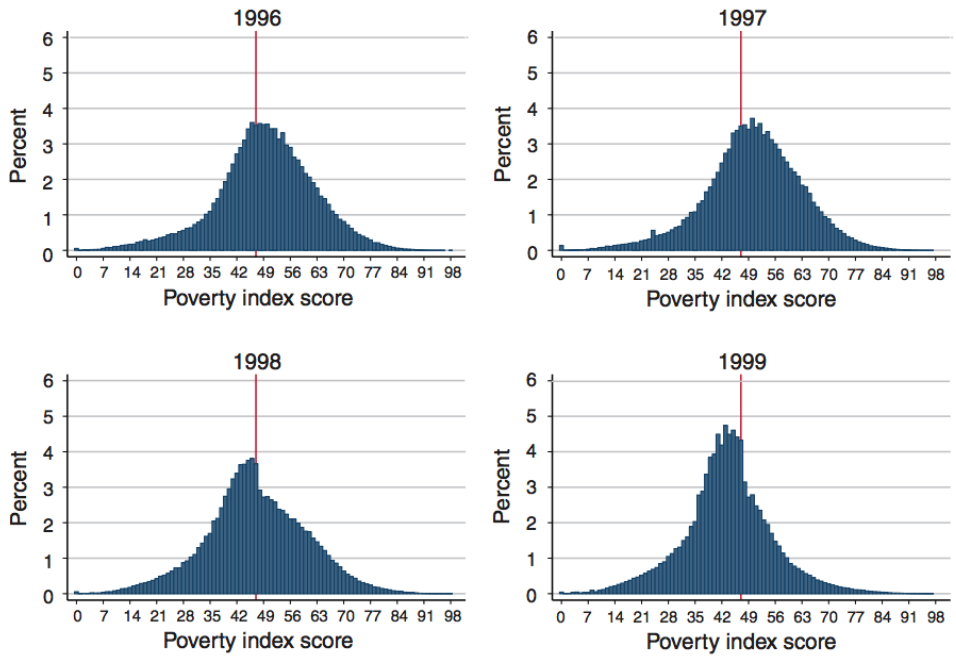
\end{aligned}
$$

Example of Manipulation: Camacho and Conover (2011)

What happens when threshold for eligibility to social assistance programs becomes known?



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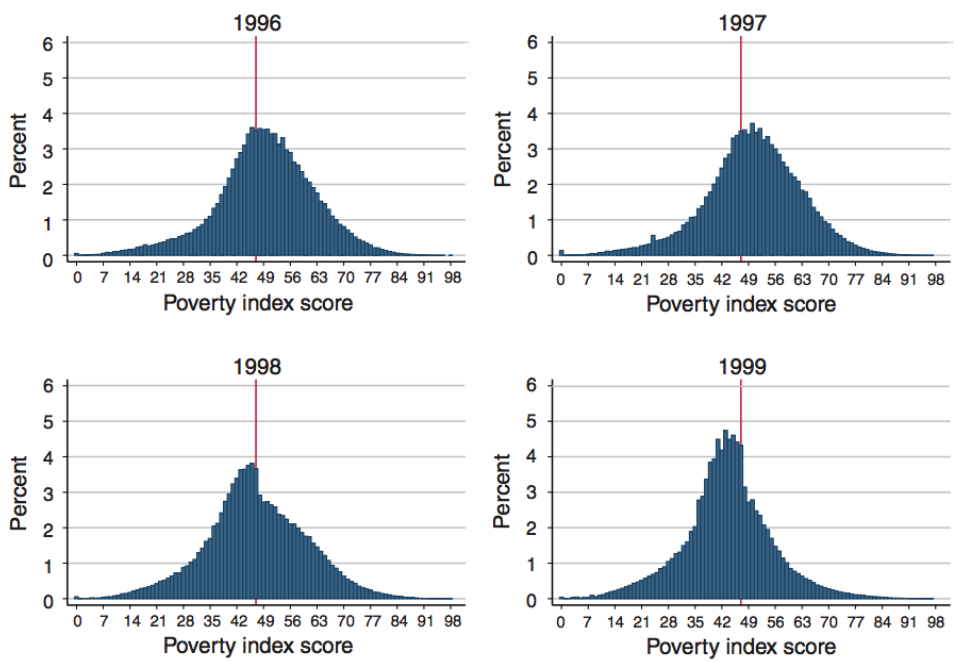

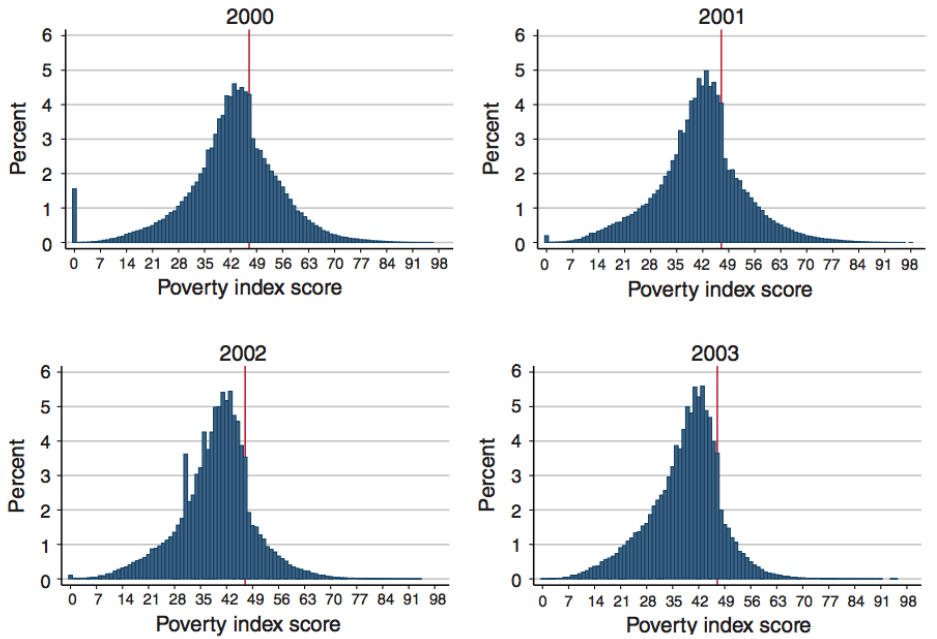

Noncompliance

What if the running variable does not *fully* determine assignment to treatment?

$\rightarrow$ ***Fuzzy RDD***

- Even if all observations that satisfy the treatment condition are not treated, there is still a jump in the probability of being treated.
- For you, just know that problem of imperfect determination of allocation to treatment can still be solved

5 Steps for Conducting RDD in Practice[1]

Step #1: *Is assignment to treatment rule-based?*

[1] Taken from Andrew Heiss' wonderful course on RDD.

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Step #5: *How big is the gap?*

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END

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