SciencesPo
DEPARTMENT OF ECONOMICS

ScPoEconometrics

Regression Discontinuity Design

Florian Oswald, Gustave Kenedi and Pierre Villedieu
SciencesPo Paris
2020-04-20

Recap from last week

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

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

- Key assumption: ***parallel trends***

Recap from last week

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

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

- Key assumption: ***parallel trends***

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

Regression Discontinuity Design (RDD)

- Very common research design in applied research because it provides credible causal estimates.

Regression Discontinuity Design (RDD)

- Very common research design in applied research because it provides credible causal estimates.

- Starting point: subjects are ***not*** randomly allocated to treatment ⚠️

Regression Discontinuity Design (RDD)

- Very common research design in applied research because it provides credible causal estimates.
- Starting point: subjects are ***not*** randomly allocated to treatment ⚠️
- RDD can be applied when we have specific information about the rules determining treatment.

Regression Discontinuity Design (RDD)

- Very common research design in applied research because it provides credible causal estimates.
- Starting point: subjects are ***not*** randomly allocated to treatment ⚠️
- RDD can be applied when we have specific information about the rules determining treatment.
- **RDD** exploits this precise information about allocation to treatment!

Discontinuities are Everywhere

There are many arbitrary rules in life that determine assignment to some treatment:

Discontinuities are Everywhere

There are many arbitrary rules in life that determine assignment to some treatment:

- In North Carolina, you used to have to have reached the age of five by October 16 in the relevant year to be eligible to enter kindergarten (Cook and Kang, 2016);

Discontinuities are Everywhere

There are many arbitrary rules in life that determine assignment to some treatment:

- In North Carolina, you used to have to have reached the age of five by October 16 in the relevant year to be eligible to enter kindergarten (Cook and Kang, 2016);
- In the US, a new born baby weighing less than 1,500 grams is considered to be of "very low birth weight" and receive additional treatment (Almond et al., 2010);

Discontinuities are Everywhere

There are many arbitrary rules in life that determine assignment to some treatment:

- In North Carolina, you used to have to have reached the age of five by October 16 in the relevant year to be eligible to enter kindergarten (Cook and Kang, 2016);
- In the US, a new born baby weighing less than 1,500 grams is considered to be of "very low birth weight" and receive additional treatment (Almond et al., 2010);
- Flagship state universities use a certain SAT cutoff level to select their students (Hoekstra, 2009);

Discontinuities are Everywhere

There are many arbitrary rules in life that determine assignment to some treatment:

- In North Carolina, you used to have to have reached the age of five by October 16 in the relevant year to be eligible to enter kindergarten (Cook and Kang, 2016);
- In the US, a new born baby weighing less than 1,500 grams is considered to be of "very low birth weight" and receive additional treatment (Almond et al., 2010);
- Flagship state universities use a certain SAT cutoff level to select their students (Hoekstra, 2009);
- In Italy, there are quotas of residence permits for illegal immigrants that are allocated on a first-come first-served basis until quota is exhausted (Pinotti, 2017);

Discontinuities are Everywhere

There are many arbitrary rules in life that determine assignment to some treatment:

- In North Carolina, you used to have to have reached the age of five by October 16 in the relevant year to be eligible to enter kindergarten (Cook and Kang, 2016);
- In the US, a new born baby weighing less than 1,500 grams is considered to be of "very low birth weight" and receive additional treatment (Almond et al., 2010);
- Flagship state universities use a certain SAT cutoff level to select their students (Hoekstra, 2009);
- In Italy, there are quotas of residence permits for illegal immigrants that are allocated on a first-come first-served basis until quota is exhausted (Pinotti, 2017);

We will focus our analysis on the following discontinuity:

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

An Example: Alcohol Consumption and Mortality

An Example: Alcohol Consumption and Mortality

- Imagine you are interested in assessing the **causal** impact of alcohol consumption by young adults on mortality.

An Example: Alcohol Consumption and Mortality

- Imagine you are interested in assessing the **causal** impact of alcohol consumption by young adults on mortality.
- Why is this not that straightforward? Why can't you just regress alcohol consumption on dying age and cause of death?

An Example: Alcohol Consumption and Mortality

- Imagine you are interested in assessing the **causal** impact of alcohol consumption by young adults on mortality.
- Why is this not that straightforward? Why can't you just regress alcohol consumption on dying age and cause of death?
  - Because there may be unobserved selection into alcohol consumption that may also be a determinant of mortality.

An Example: Alcohol Consumption and Mortality

- Imagine you are interested in assessing the **causal** impact of alcohol consumption by young adults on mortality.
- Why is this not that straightforward? Why can't you just regress alcohol consumption on dying age and cause of death?
  - 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.

An Example: Alcohol Consumption and Mortality

- Imagine you are interested in assessing the **causal** impact of alcohol consumption by young adults on mortality.
- Why is this not that straightforward? Why can't you just regress alcohol consumption on dying age and cause of death?
    - 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.

Key Terms and Intuition

> ***Running variable:*** variable that determines assignment to treatment.

Key Terms and Intuition

> ***Running variable:*** variable that determines assignment to treatment.

$\longrightarrow a$ = age

Key Terms and Intuition

> *Running variable:* variable that determines assignment to treatment.

$\rightarrow a$ = age

> *Cutoff level:* level of the *running variable* above (or below) which individuals are treated (or not).

Key Terms and Intuition

> ***Running variable:*** variable that determines assignment to treatment.

$\rightarrow a$ = age

> ***Cutoff level:*** level of the ***running variable*** above (or below) which individuals are treated (or not).

$\rightarrow c = 21$ year old birthday

Key Terms and Intuition

> ***Running variable:*** variable that determines assignment to treatment.

$\rightarrow a$ = age

> ***Cutoff level:*** level of the ***running variable*** above (or below) which individuals are treated (or not).

$\rightarrow c = 21$ year old birthday

Causal intuition:

- How different are individuals *just before* and *just after* their 21st birthday, other than legal access to alcohol?

Key Terms and Intuition

> *Running variable:* variable that determines assignment to treatment.

$\rightarrow a$ = age

> *Cutoff level:* level of the *running variable* above (or below) which individuals are treated (or not).

$\rightarrow c = 21$ year old birthday

Causal intuition:

- How different are individuals *just before* and *just after* their 21st birthday, other than legal access to alcohol?
- Around the threshold, allocation to treatment is *as good as random*.

Key Terms and Intuition

> *Running variable:* variable that determines assignment to treatment.

$\rightarrow a$ = age

> *Cutoff level:* level of the *running variable* above (or below) which individuals are treated (or not).

$\rightarrow c = 21$ year old birthday

Causal intuition:

- How different are individuals *just before* and *just after* their 21st birthday, other than legal access to alcohol?
- Around the threshold, allocation to treatment is *as good as random*.
- 👉 *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

```r
# install package containing data
devtools::install_github("jrnold/masteringmetrics",
                         subdir = "masteringmetrics")

# load package
library(masteringmetrics)
# load data
data("mlda", package = "masteringmetrics")
```

Carpenter and Dobkin's data

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

```r
# install package containing data
devtools::install_github("jrnold/masteringmetrics",
                         subdir = "masteringmetrics")

# load package
library(masteringmetrics)
# load data
data("mlda", package = "masteringmetrics")
```

```
## # A tibble: 6 x 7
##   agecell   all internal external alcohol homicide suicide
##     <dbl> <dbl>    <dbl>    <dbl>   <dbl>    <dbl>   <dbl>
## 1    19.1  92.8     16.6     76.2   0.639     16.3    11.2
## 2    19.2  95.1     18.3     76.8   0.677     16.9    12.2
## 3    19.2  92.1     18.9     73.2   0.866     15.2    11.7
## 4    19.3  88.4     16.1     72.3   0.867     16.7    11.3
## 5    19.4  88.7     17.4     71.3   1.02      14.9    11.0
## 6    19.5  90.2     17.9     72.3   1.17      15.6    12.2
```

Carpenter and Dobkin's data

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

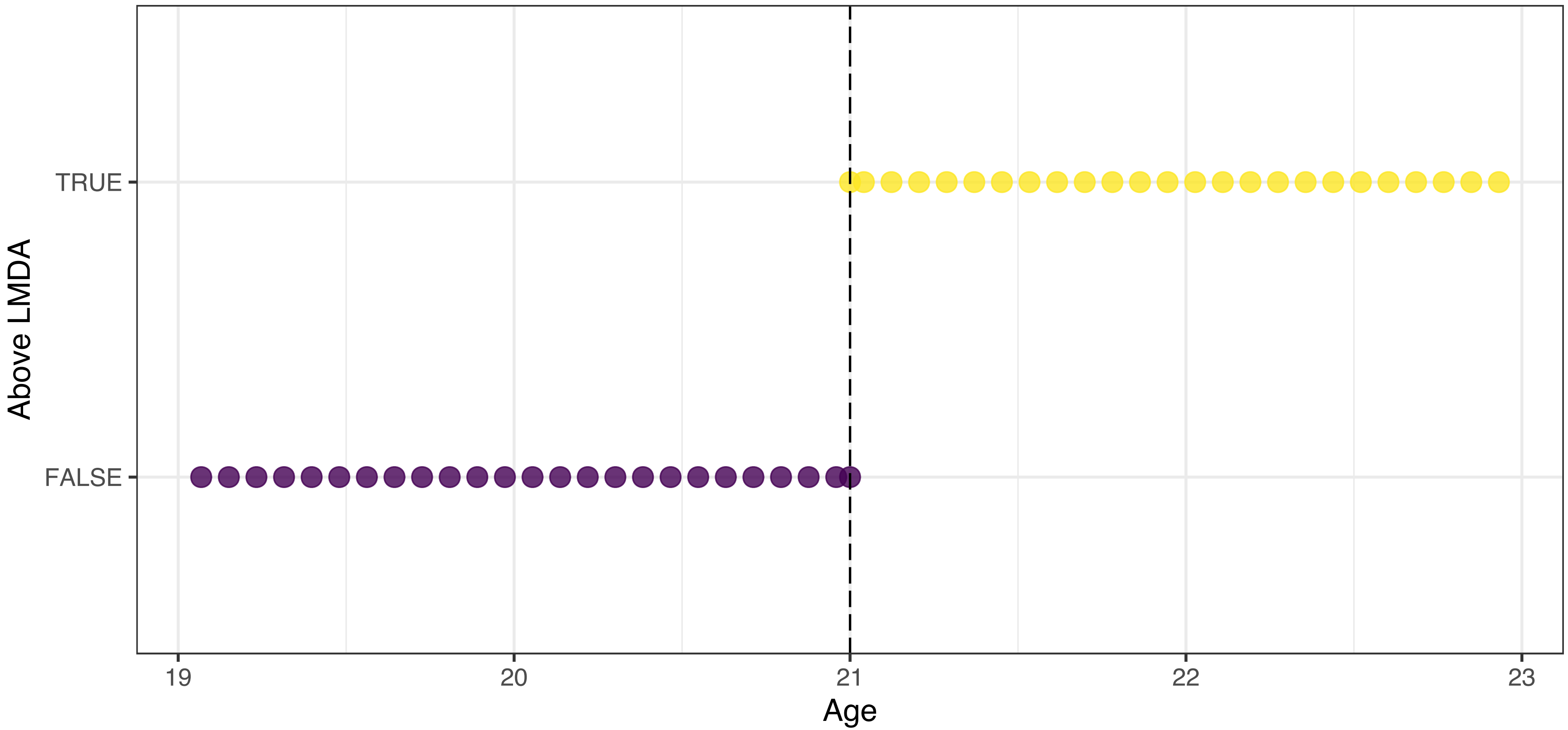
```r
# install package containing data
devtools::install_github("jrnold/masteringmetrics",
                         subdir = "masteringmetrics")

# load package
library(masteringmetrics)
# load data
data("mlda", package = "masteringmetrics")
```

```
## # A tibble: 6 x 7
##   agecell   all internal external alcohol homicide suicide
##     <dbl> <dbl>    <dbl>    <dbl>   <dbl>    <dbl>   <dbl>
## 1    19.1  92.8     16.6     76.2   0.639     16.3    11.2
## 2    19.2  95.1     18.3     76.8   0.677     16.9    12.2
## 3    19.2  92.1     18.9     73.2   0.866     15.2    11.7
## 4    19.3  88.4     16.1     72.3   0.867     16.7    11.3
## 5    19.4  88.7     17.4     71.3   1.02      14.9    11.0
## 6    19.5  90.2     17.9     72.3   1.17      15.6    12.2
```

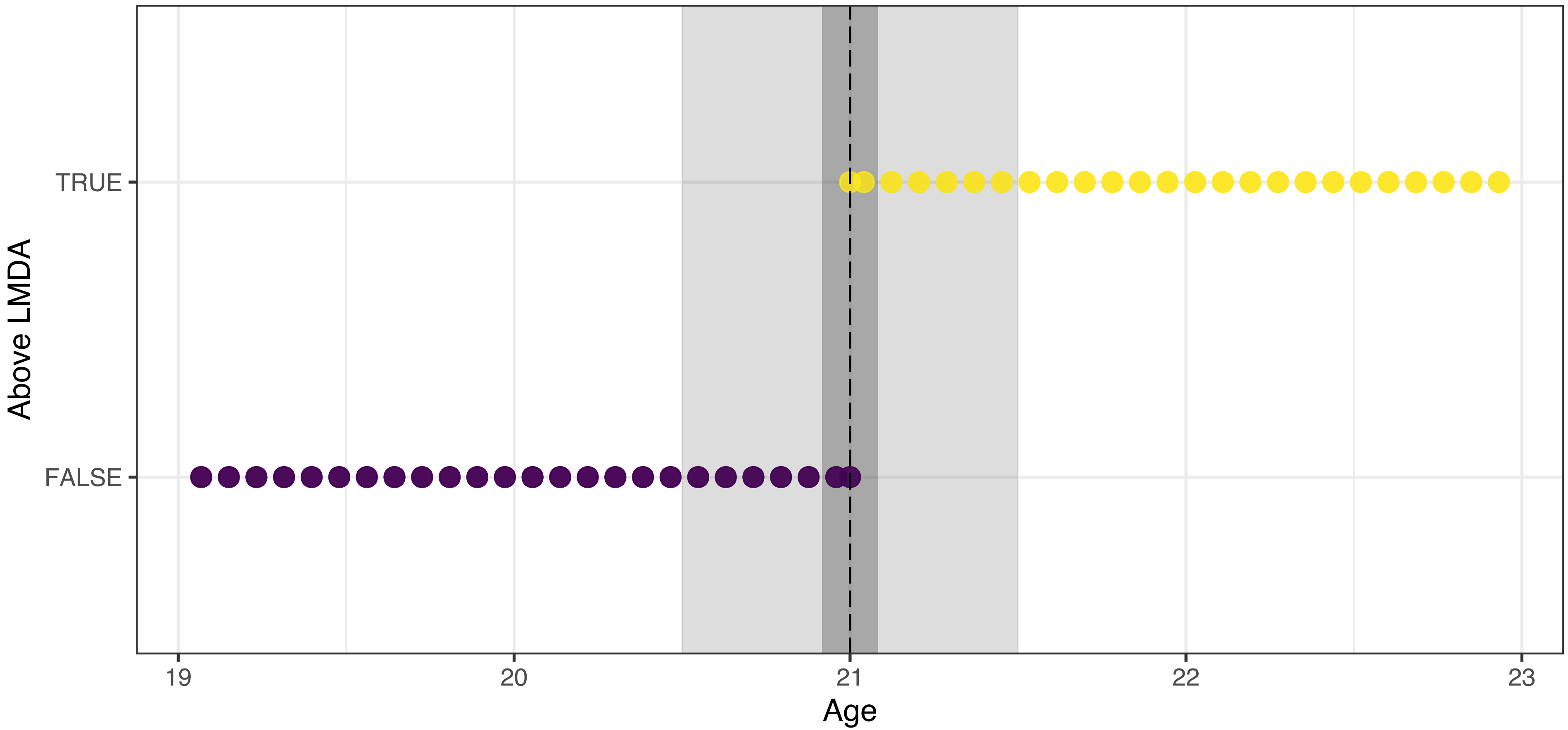
- This dataset contains aggregate death rates (and their causes) for different age groups (`agecell`) between 19 and 23 years old.

Sharp Discontinuity at Cutoff

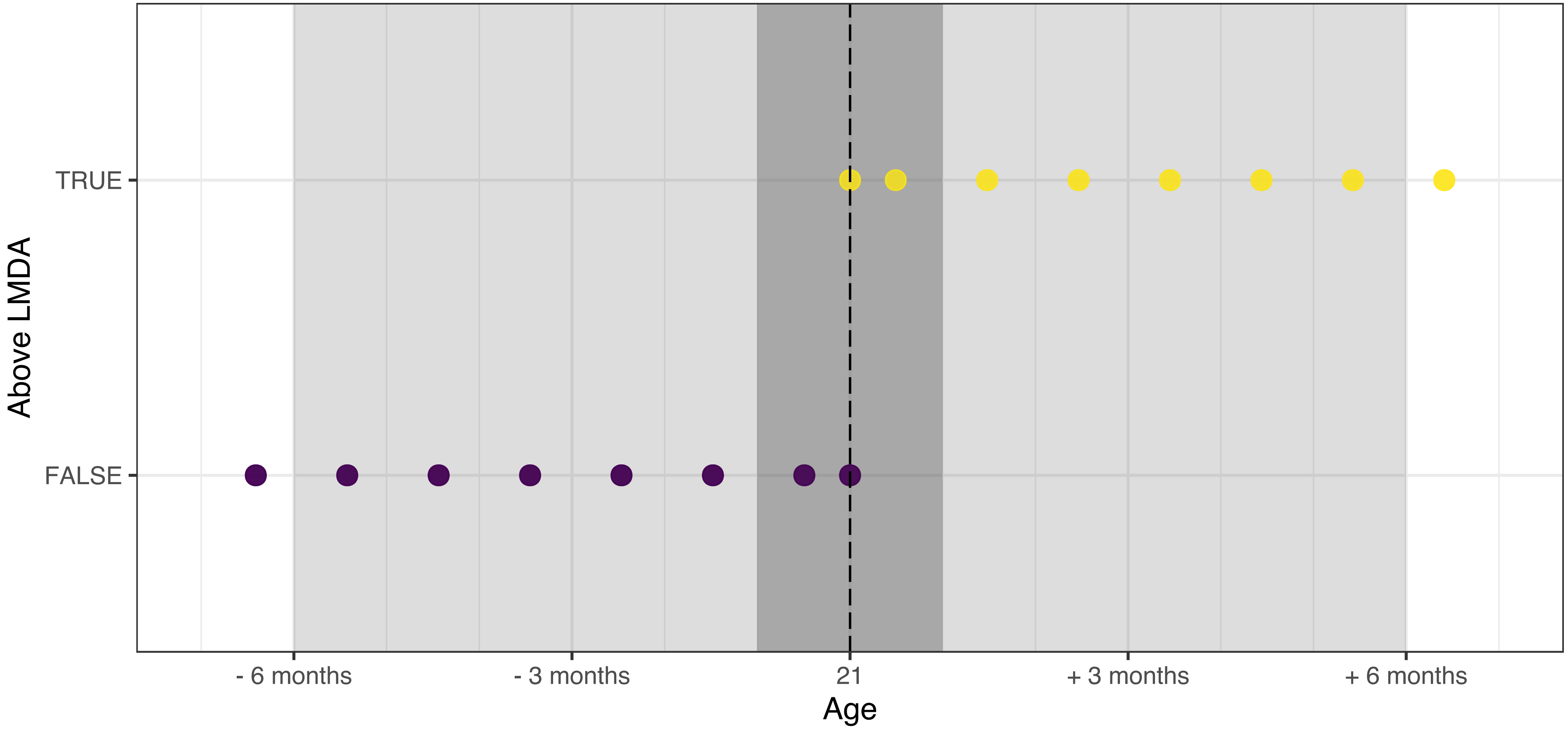


At the threshold, the probability of being treated jumps from 0 to 1.

Sharp Discontinuity at Cutoff



Sharp Discontinuity at Cutoff



RDD Framework

- ***Treatment variable***: D_a

RDD Framework

- ***Treatment variable***: D_a
  - $D_a = 1$ if individual is over 21 years old, $D_a = 0$ if not.

RDD Framework

- ***Treatment variable***: D_a
  - D_a = 1 if individual is over 21 years old, D_a = 0 if not.
  - D_a is a function of the individual's age, a, which is the ***running variable***.

RDD Framework

- ***Treatment variable***: D_a
  - D_a = 1 if individual is over 21 years old, D_a = 0 if not.
  - D_a is a function of the individual's age, a, which is the ***running variable***.
- The ***cutoff*** age, 21, separates those who can drink legally and those who can't:

$$D_a = \begin{cases} 1 & \text{if } a \geq 21 \\ 0 & \text{if } a < 21 \end{cases}$$

Key features of RD designs

1. Treatment status is a **deterministic** function of $a \rightarrow$ we know the assignment rule

RDD Framework

- ***Treatment variable***: D_a
  - D_a = 1 if individual is over 21 years old, D_a = 0 if not.
  - D_a is a function of the individual's age, a, which is the ***running variable***.
- The ***cutoff*** age, 21, separates those who can drink legally and those who can't:

$$D_a = \begin{cases} 1 & \text{if } a \geq 21 \\ 0 & \text{if } a < 21 \end{cases}$$

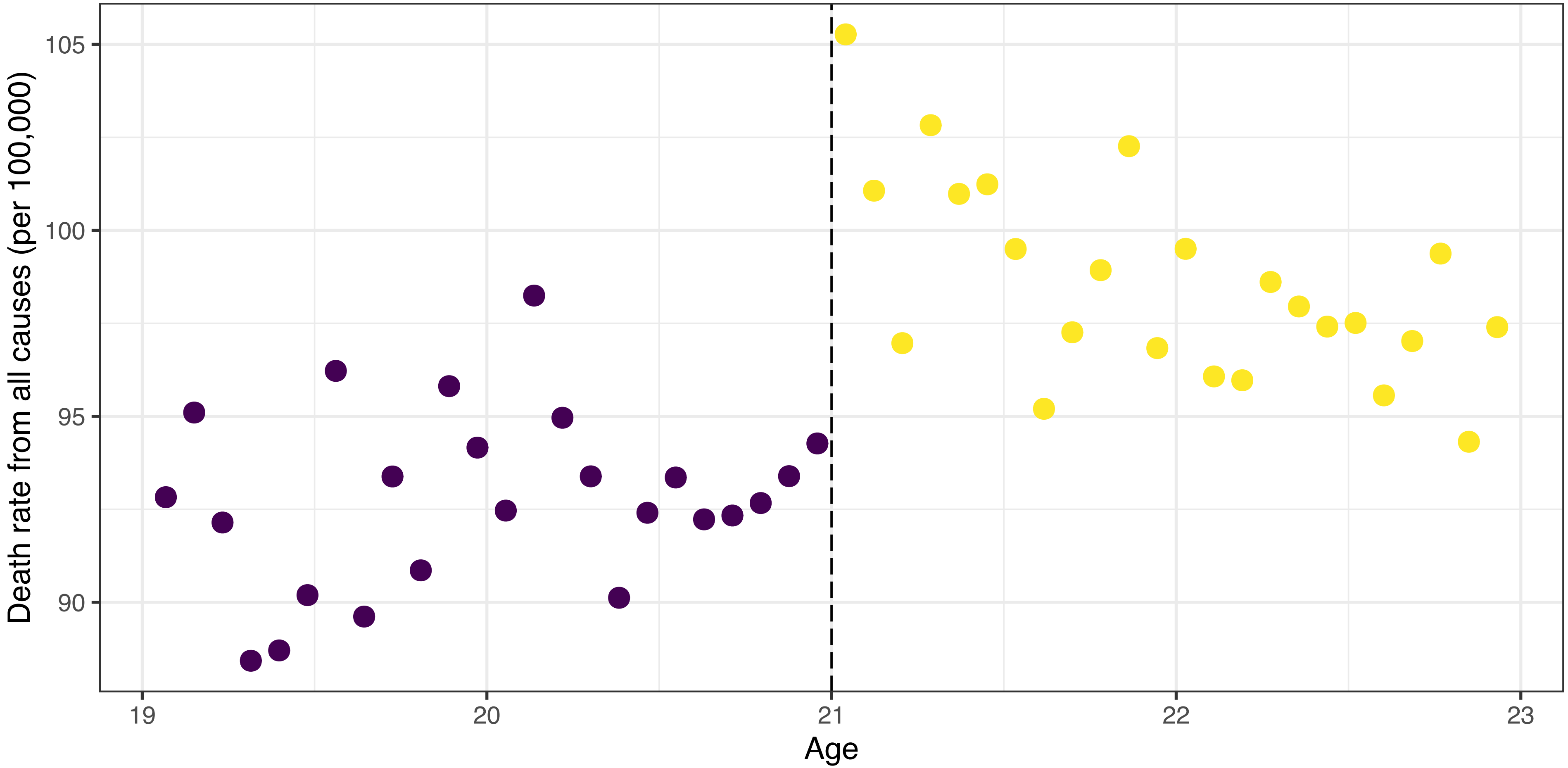
Key features of RD designs

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

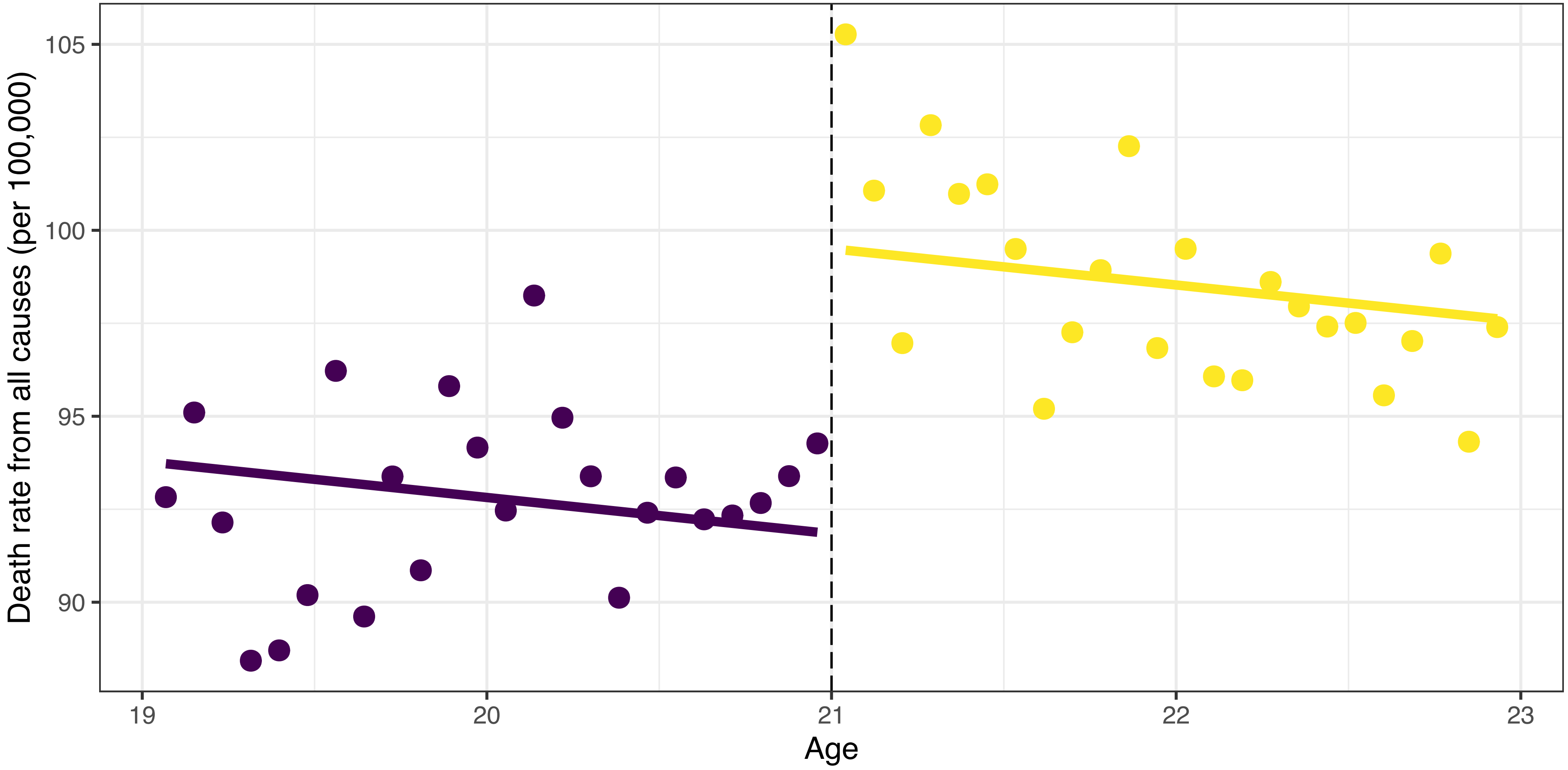
Task 1 (10 minutes)

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.

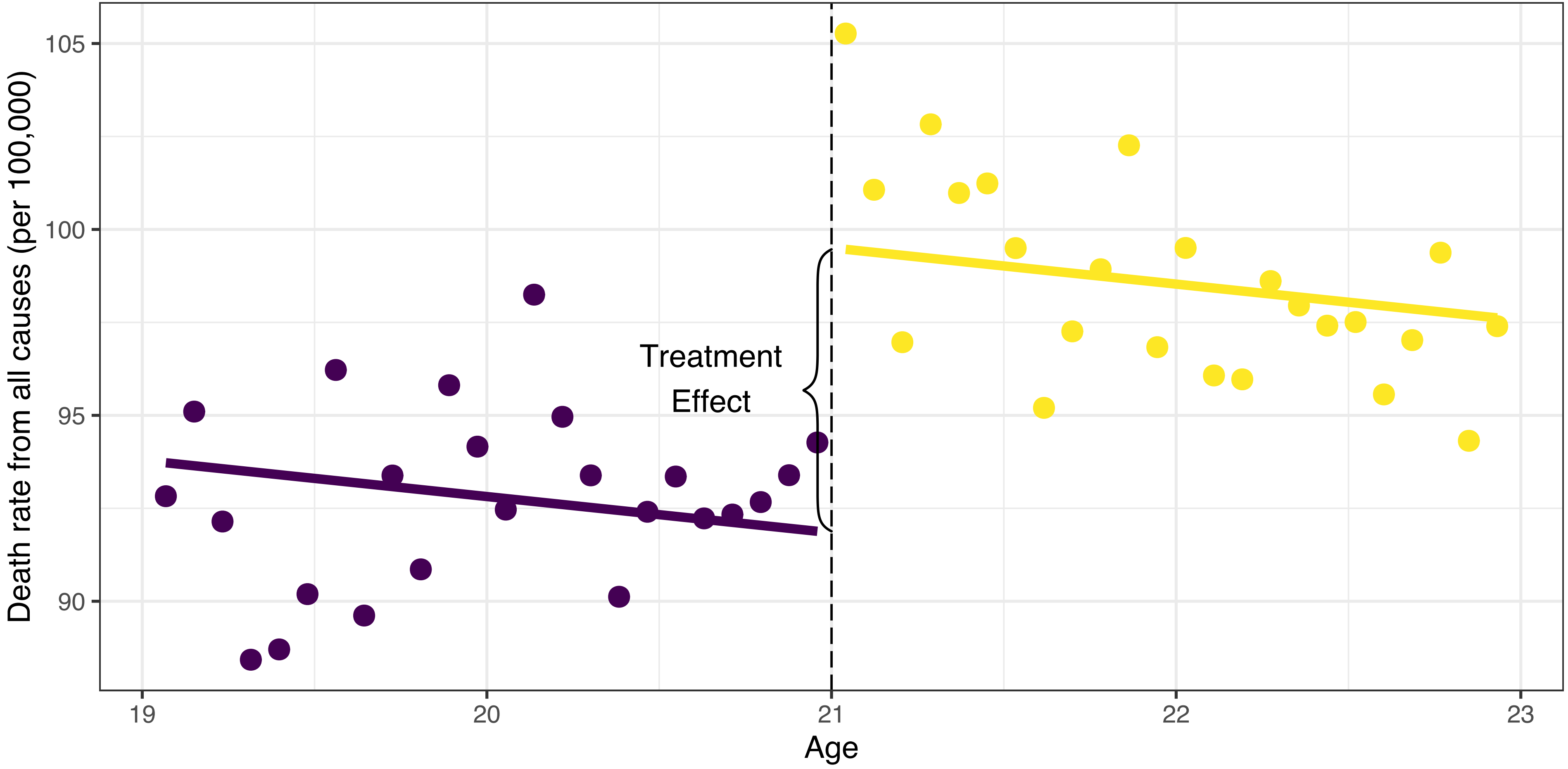
Graphical Results: All Death Rates



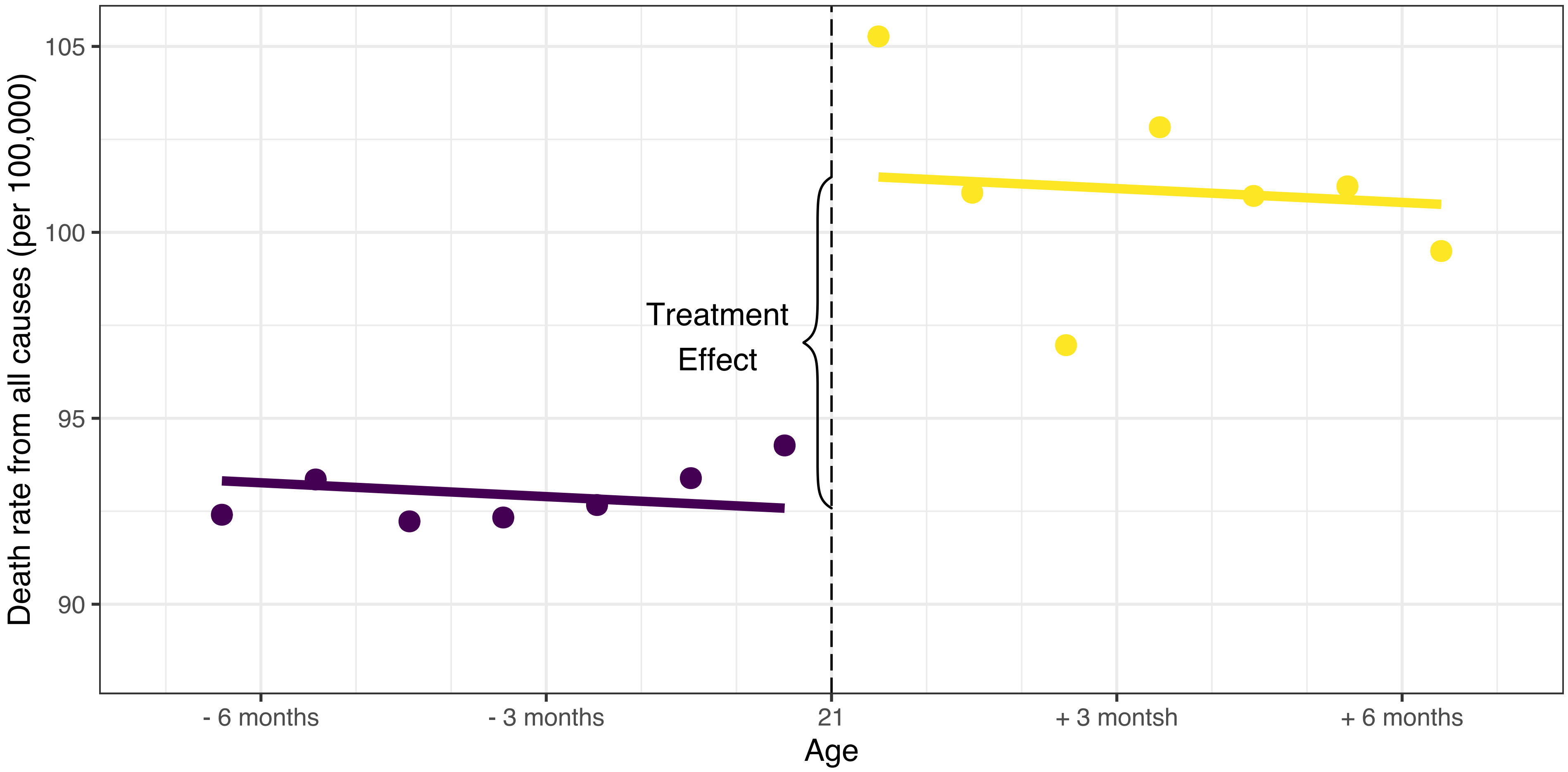
Graphical Results: All Death Rates



Graphical Results: All Death Rates



Graphical Results: All Death Rates



RDD as Local Average Treatment Effect (LATE)

- The RD estimator is a **local average treatment effect (LATE)**.

RDD as Local Average Treatment Effect (LATE)

- The RD estimator is a **local average treatment effect (LATE)**.
- It only tells you the impact of treatment D on outcome Y ***around*** the cutoff value of the running variable.

RDD as Local Average Treatment Effect (LATE)

- The RD estimator is a **local average treatment effect (LATE)**.
- It only tells you the impact of treatment D on outcome Y ***around*** the cutoff value of the running variable.
- Limited ***external validity*** $\rightarrow$ you cannot extrapolate to the entire population.

RDD as Local Average Treatment Effect (LATE)

- The RD estimator is a **local average treatment effect (LATE)**.
- It only tells you the impact of treatment D on outcome Y ***around*** the cutoff value of the running variable.
- 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.

RDD as Local Average Treatment Effect (LATE)

- The RD estimator is a **local average treatment effect (LATE)**.
- It only tells you the impact of treatment D on outcome Y ***around*** the cutoff value of the running variable.
- 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.

Estimation

Estimation

- *Objective:* measure ***gap*** between the two lines at the cutoff.

Estimation

- *Objective:* measure ***gap*** between the two lines at the cutoff.
- In its simplest form, we can write the following regression model:

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

where $DEATHRATE_a$ is the death rate at age a, D_a is the treatment dummy, and a is age (defined in months relative to 21st birthday).

Estimation

- *Objective:* measure ***gap*** between the two lines at the cutoff.
- In its simplest form, we can write the following regression model:

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

where $DEATHRATE_a$ is the death rate at age a, D_a is the treatment dummy, and a is age (defined in months relative to 21st birthday).

$\rightarrow \delta$ captures the **jump in death rate** between individuals above and below 21 years old.

Estimation

- *Objective:* measure ***gap*** between the two lines at the cutoff.
- In its simplest form, we can write the following regression model:

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

where $DEATHRATE_a$ is the death rate at age a, D_a is the treatment dummy, and a is age (defined in months relative to 21st birthday).

$\rightarrow \delta$ captures the **jump in death rate** between individuals above and below 21 years old.

- 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

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

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

library(broom)
tidy(rdd)
```

```
## # A tibble: 3 x 5
##   term        estimate std.error statistic  p.value
##   <chr>          <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)   91.8       0.805    114.   4.59e-57
## 2 agecell_21    -0.975     0.632     -1.54 1.30e- 1
## 3 over21TRUE     7.66      1.44       5.32 3.15e- 6
```

Estimation #1: Simple Linear Model

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

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

library(broom)
tidy(rdd)
```

```
## # A tibble: 3 x 5
##   term        estimate std.error statistic  p.value
##   <chr>          <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)   91.8       0.805    114.   4.59e-57
## 2 agecell_21    -0.975     0.632     -1.54 1.30e- 1
## 3 over21TRUE     7.66      1.44       5.32 3.15e- 6
```

Interpretation:

Estimation #1: Simple Linear Model

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

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

library(broom)
tidy(rdd)
```

```
## # A tibble: 3 x 5
##   term        estimate std.error statistic  p.value
##   <chr>          <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)   91.8       0.805    114.   4.59e-57
## 2 agecell_21    -0.975     0.632     -1.54 1.30e- 1
## 3 over21TRUE     7.66      1.44       5.32 3.15e- 6
```

Interpretation:

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

Estimation #1: Simple Linear Model

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

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

library(broom)
tidy(rdd)
```

```
## # A tibble: 3 x 5
##   term        estimate std.error statistic  p.value
##   <chr>          <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)   91.8       0.805    114.   4.59e-57
## 2 agecell_21    -0.975     0.632     -1.54 1.30e- 1
## 3 over21TRUE     7.66      1.44       5.32 3.15e- 6
```

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
```

Estimation Issues

- The ***functional form*** used to approximate the lines really matters!

Estimation Issues

- The *functional form* used to approximate the lines really matters!

  $\rightarrow$ an insufficiently flexible specification runs the risk of mistaking nonlinearity for treatment effect;

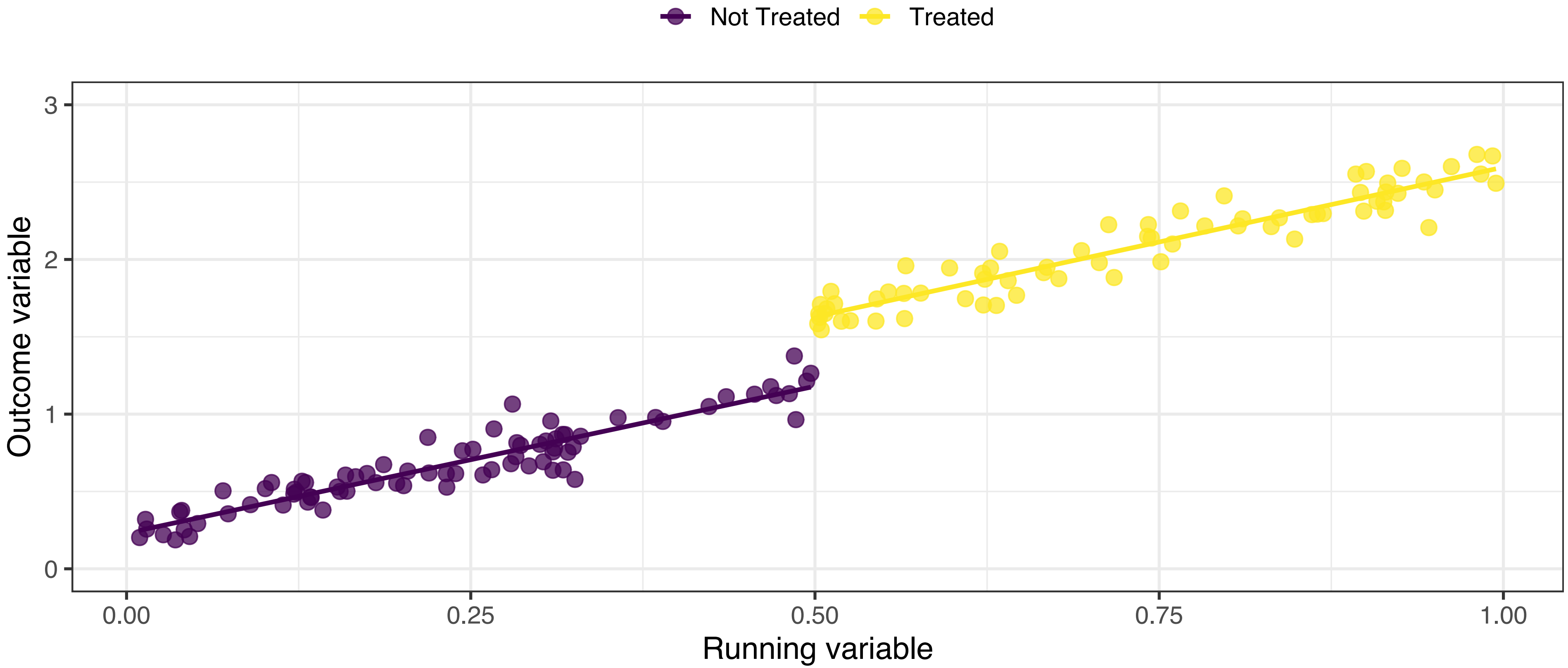
Estimation Issues

- The *functional form* used to approximate the lines really matters!

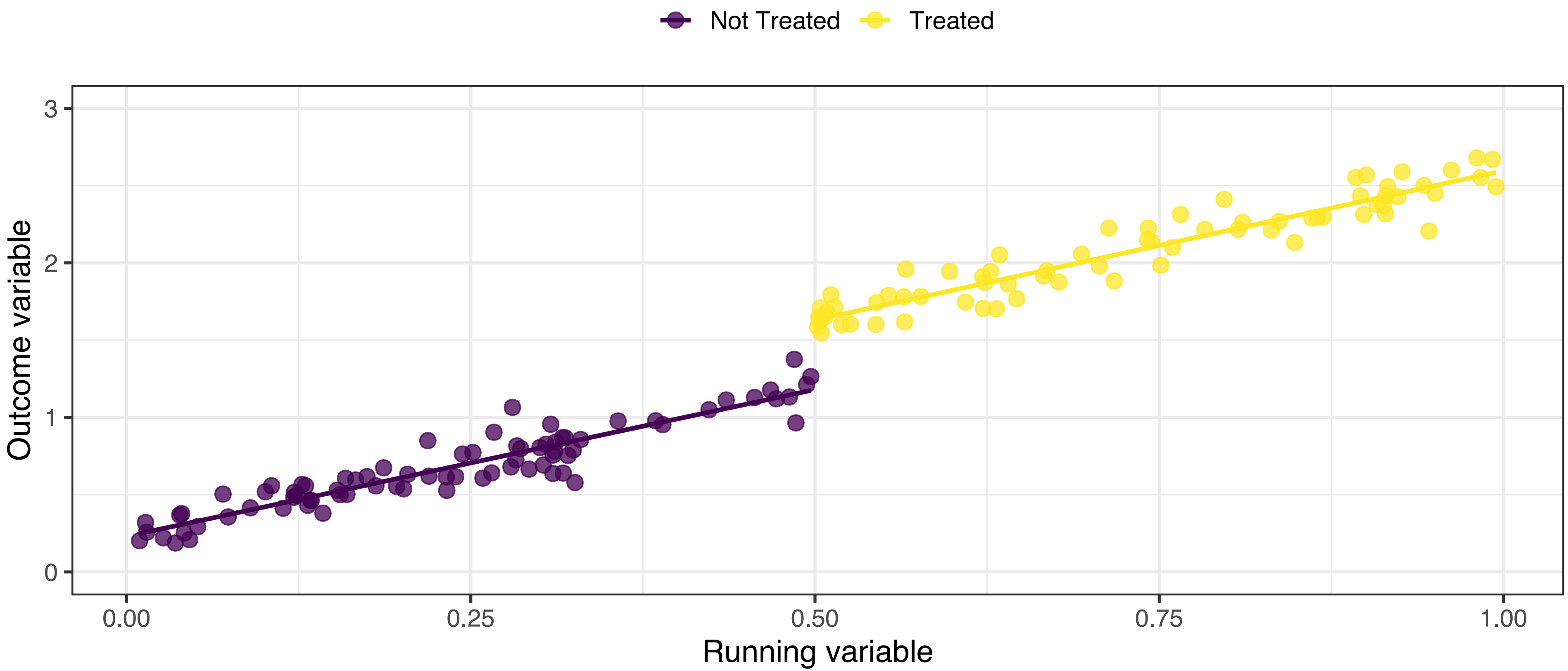
  $\rightarrow$ an insufficiently flexible specification runs the risk of mistaking nonlinearity for treatment effect;

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

Simulations - Linear Relationship and Clear Discontinuity

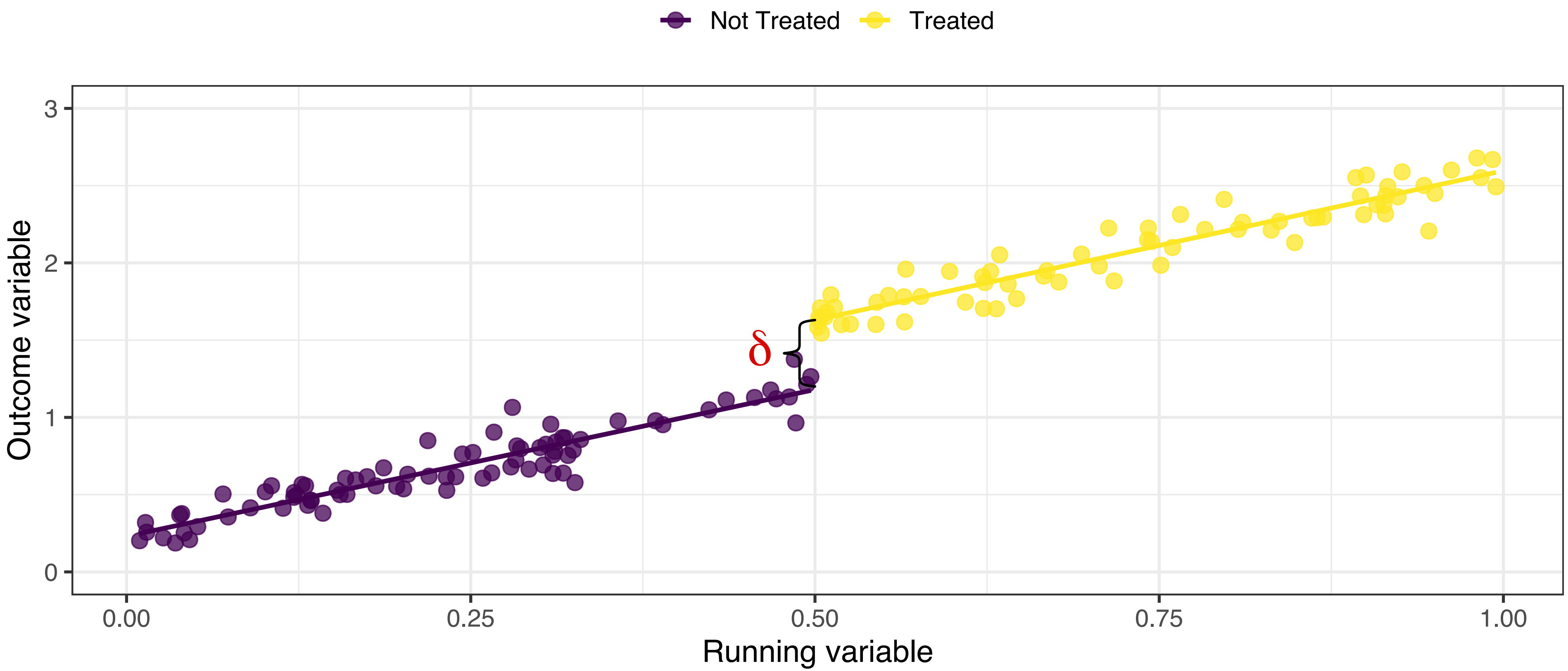


Simulations - Linear Relationship and Clear Discontinuity



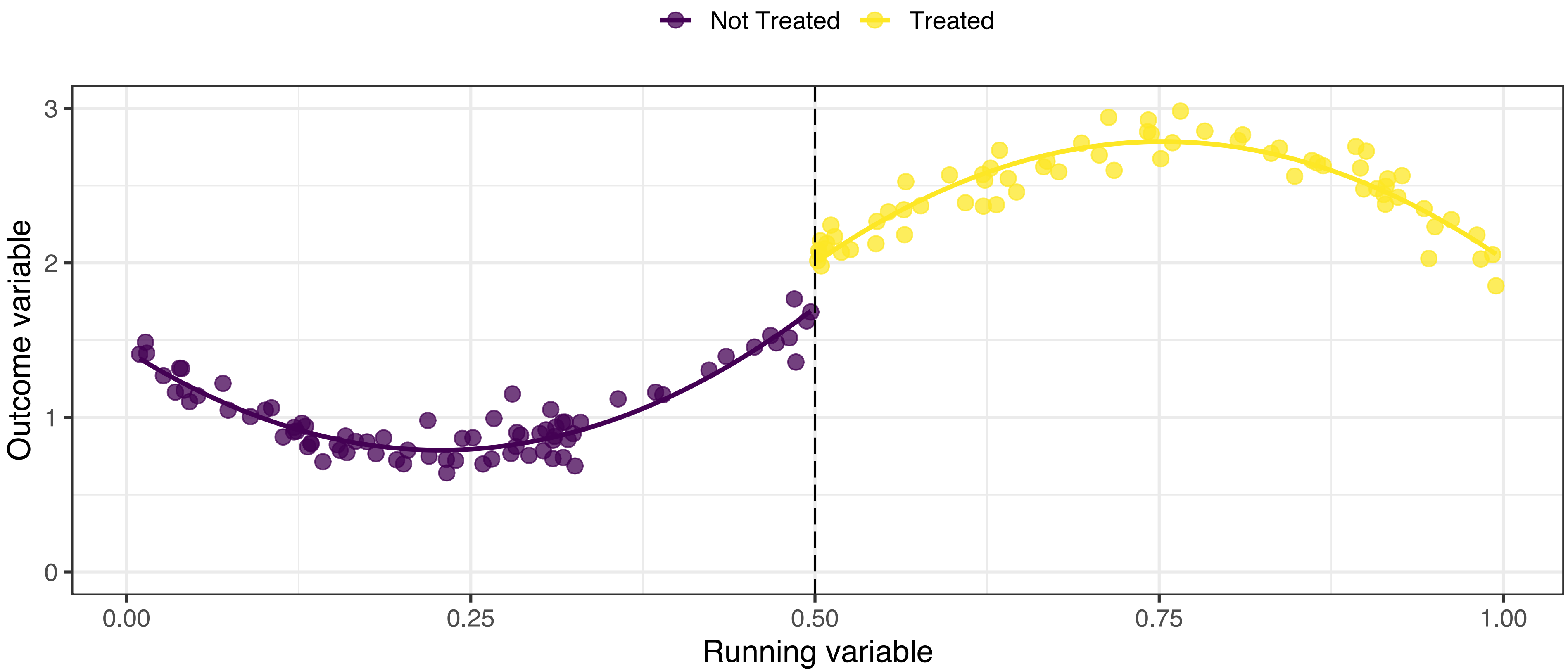
$$outcome_i = \alpha + \delta treatment_i + \beta running_i + e_i,$$

Simulations - Linear Relationship and Clear Discontinuity

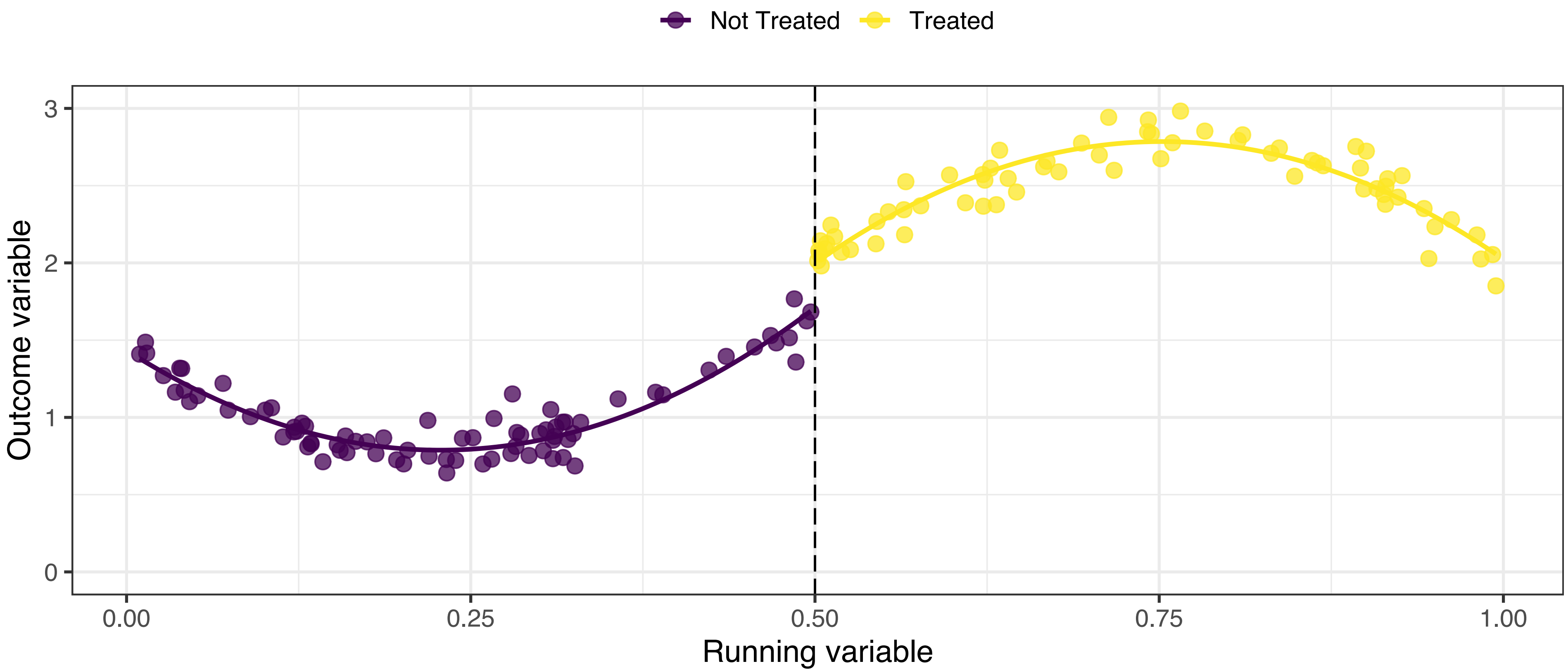


$$outcome_i = \alpha + \delta treatment_i + \beta running_i + e_i,$$

Simulations - Quadratic Relationship and Clear Discontinuity

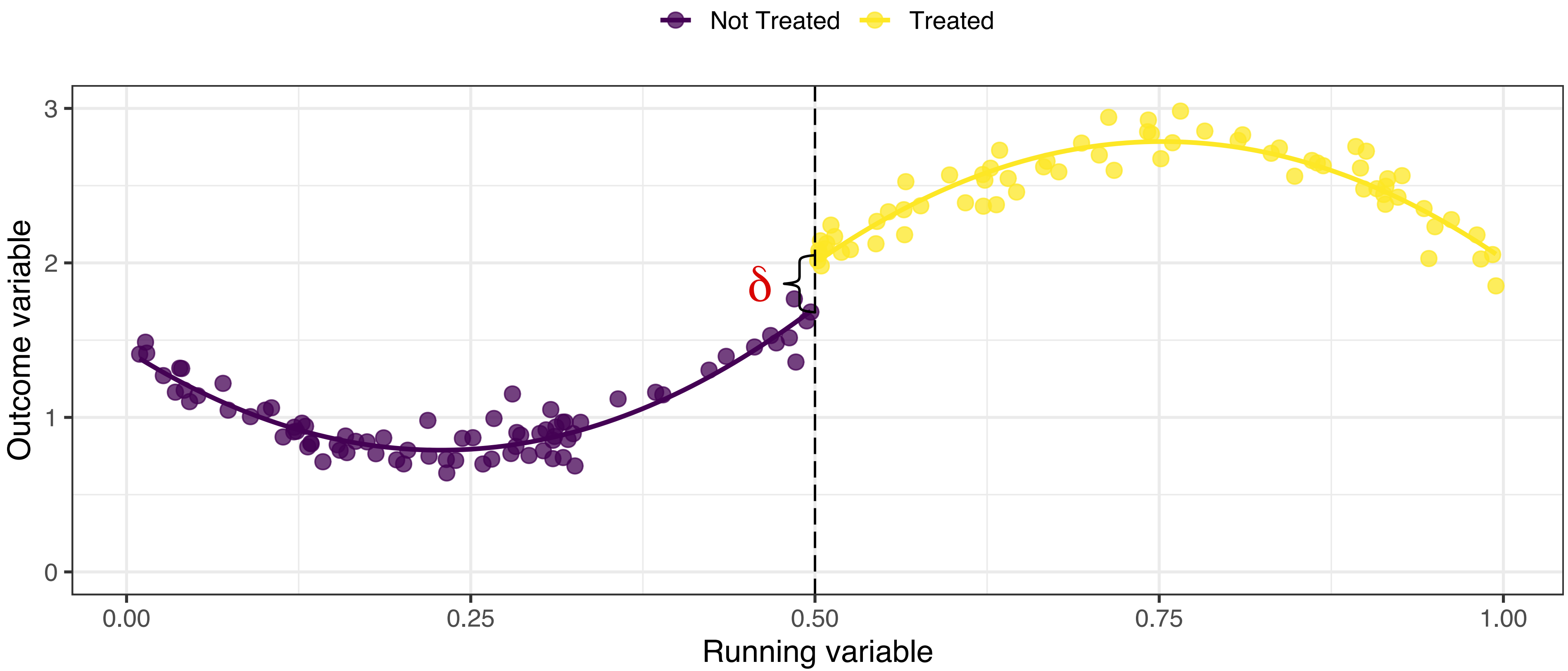


Simulations - Quadratic Relationship and Clear Discontinuity



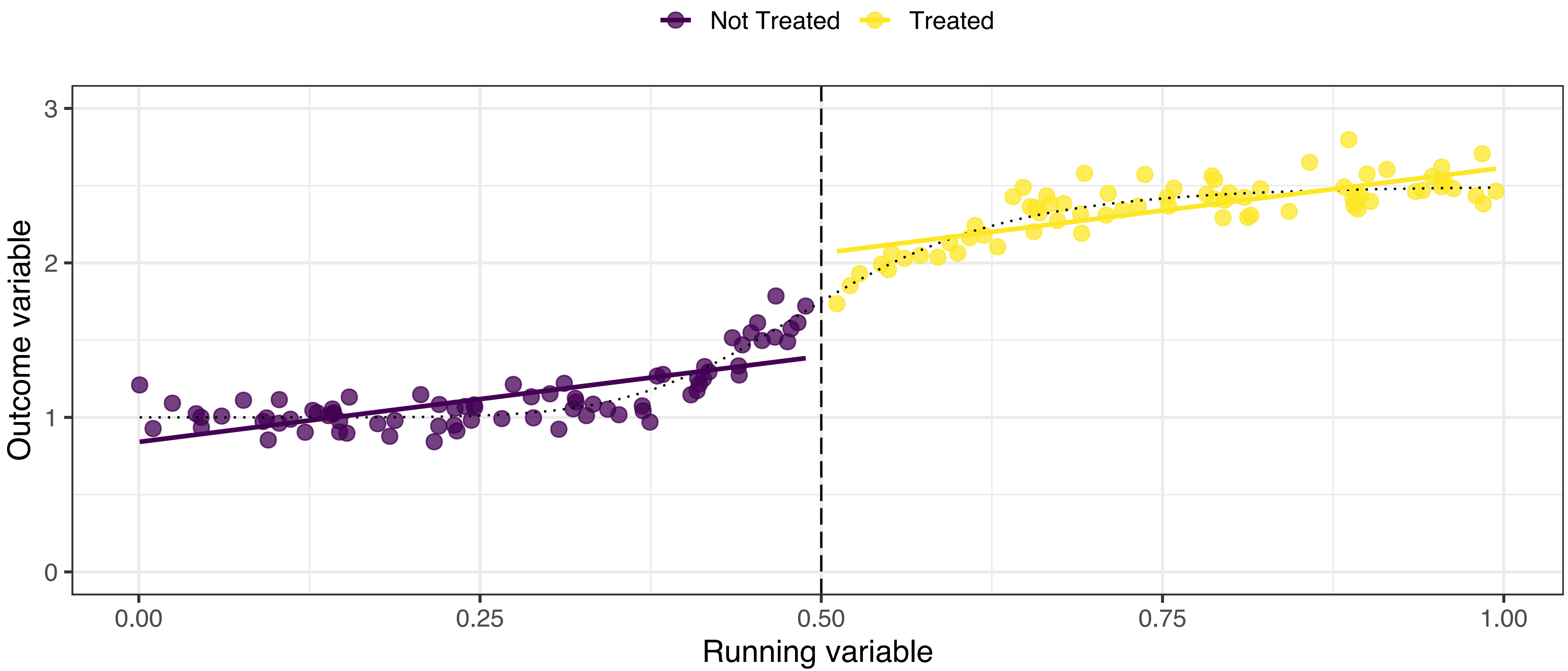
$$outcome_i = \alpha + \delta treatment_i + \beta_1 running_i + \beta_2 running_i^2 + e_i,$$

Simulations - Quadratic Relationship and Clear Discontinuity

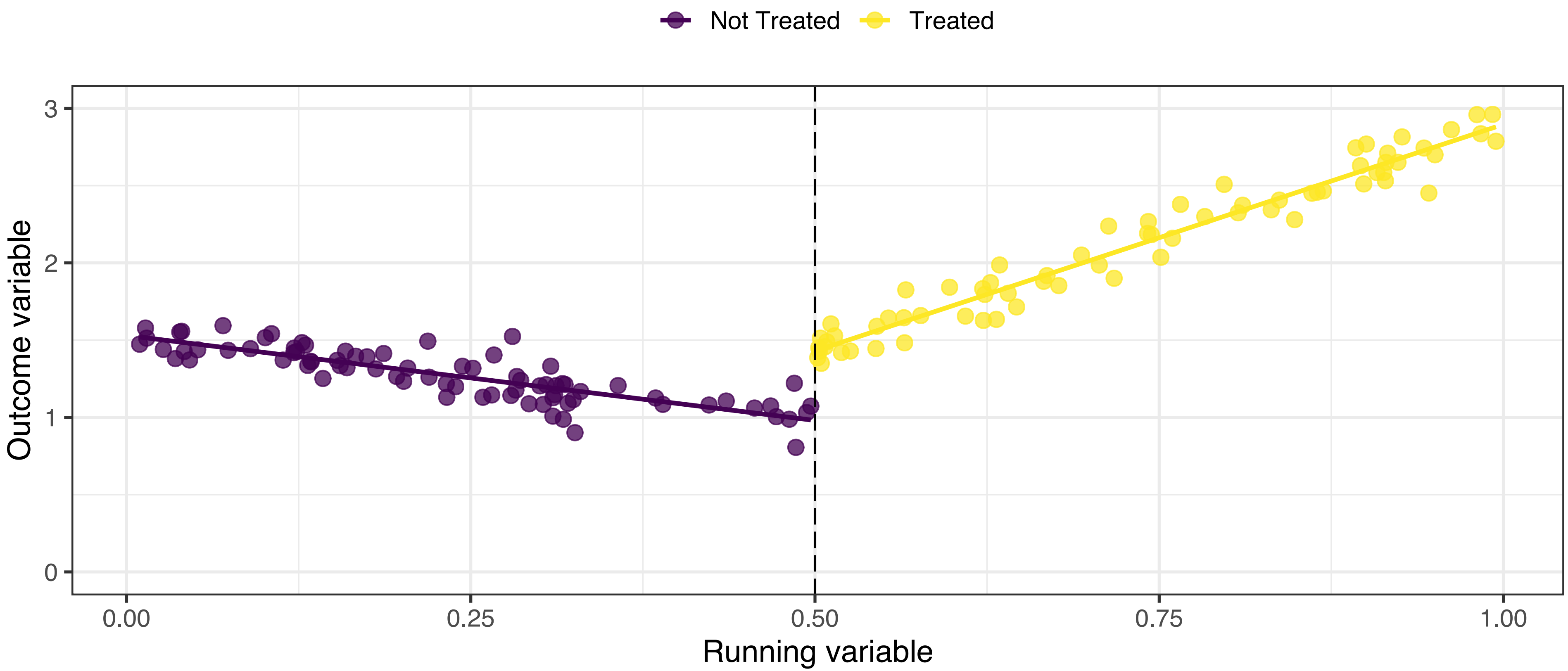


$$outcome_i = \alpha + \delta treatment_i + \beta_1 running_i + \beta_2 running_i^2 + e_i,$$

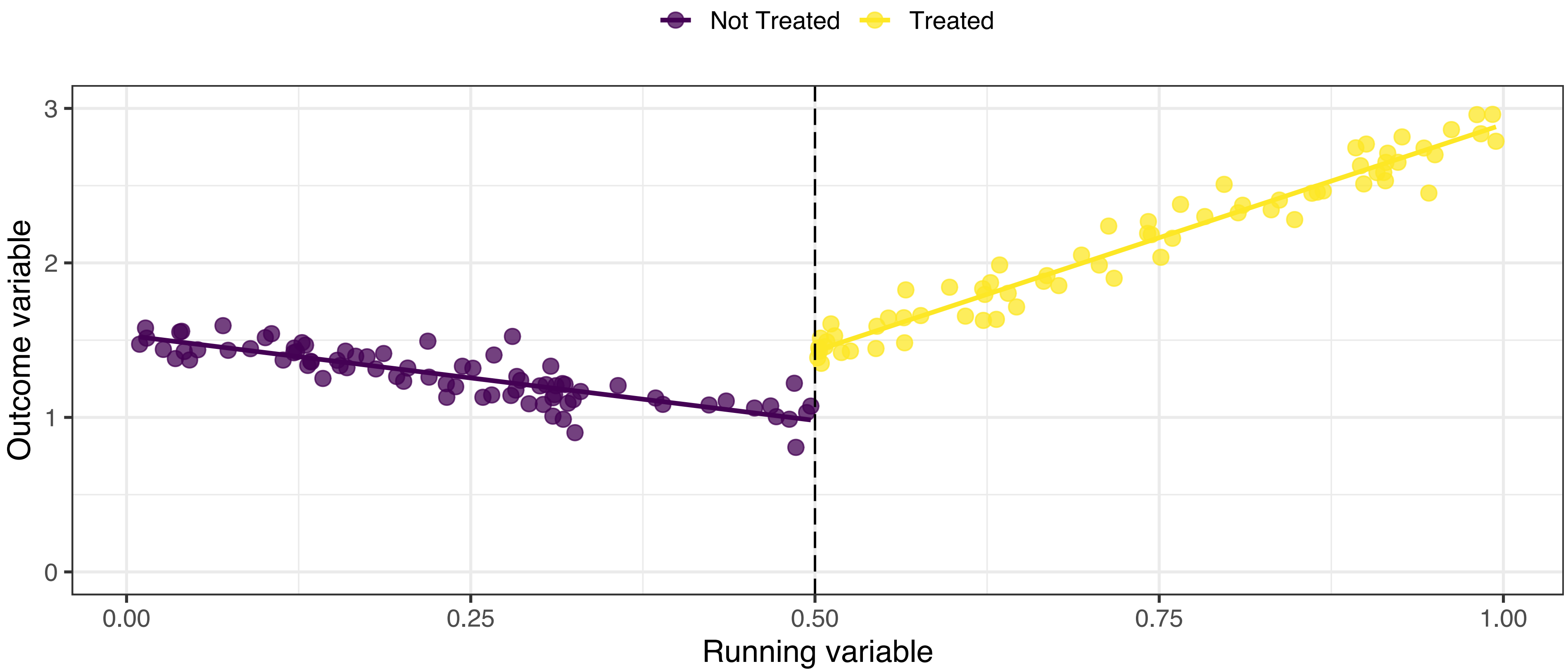
Simulations - Linear Relationship but NO Discontinuity



Simulations - Different Slopes

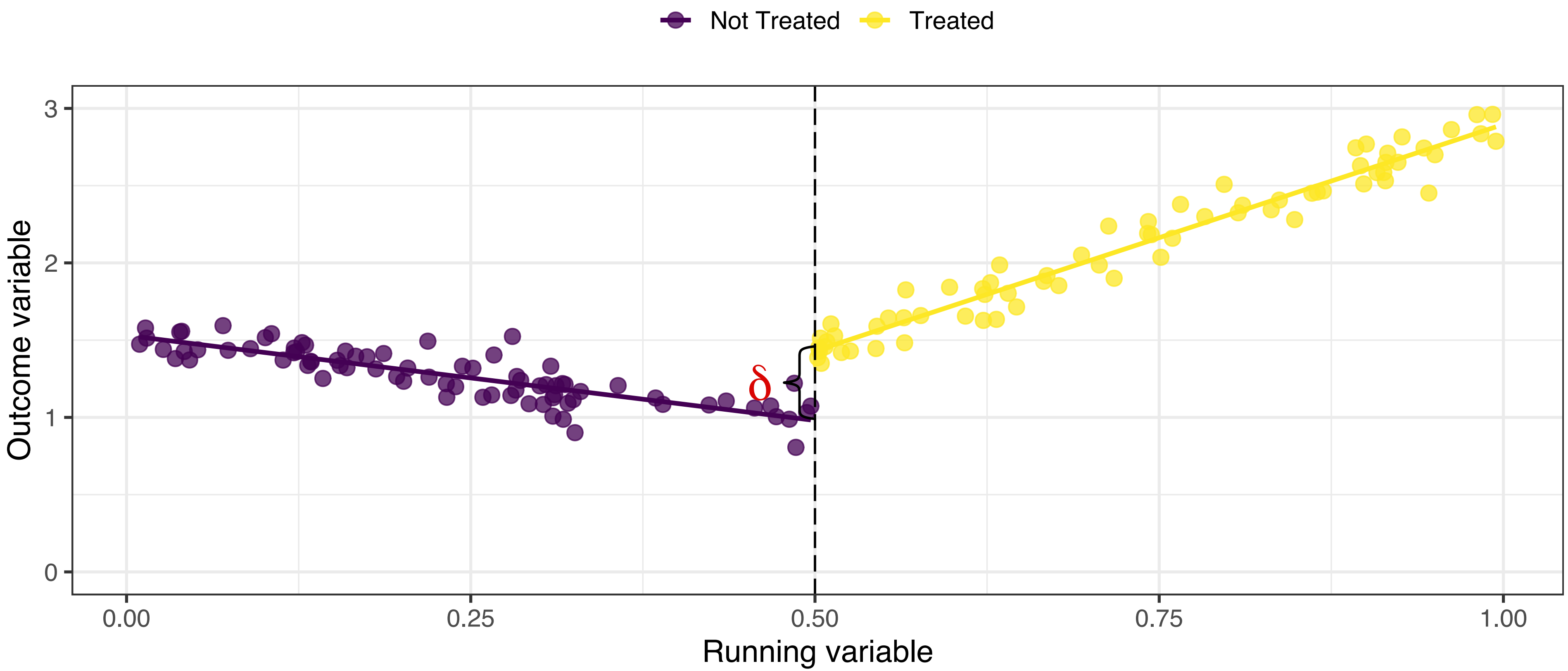


Simulations - Different Slopes



$$outcome_i = \alpha + \delta treatment_i + \beta(running_i - cutoff) +$$
$$\gamma treatment_i * (running_i - cutoff) + e_i,$$

Simulations - Different (Linear) Slopes



$$outcome_i = \alpha + \delta treatment_i + \beta(running_i - cutoff) +$$
$$\gamma treatment_i * (running_i - cutoff) + e_i,$$

How to Choose Appropriate Functional Form?

- Essential to **visualise** the data!

How to Choose Appropriate Functional Form?

- Essential to **visualise** the data!
- Coefficients across models shouldn't vary too much.

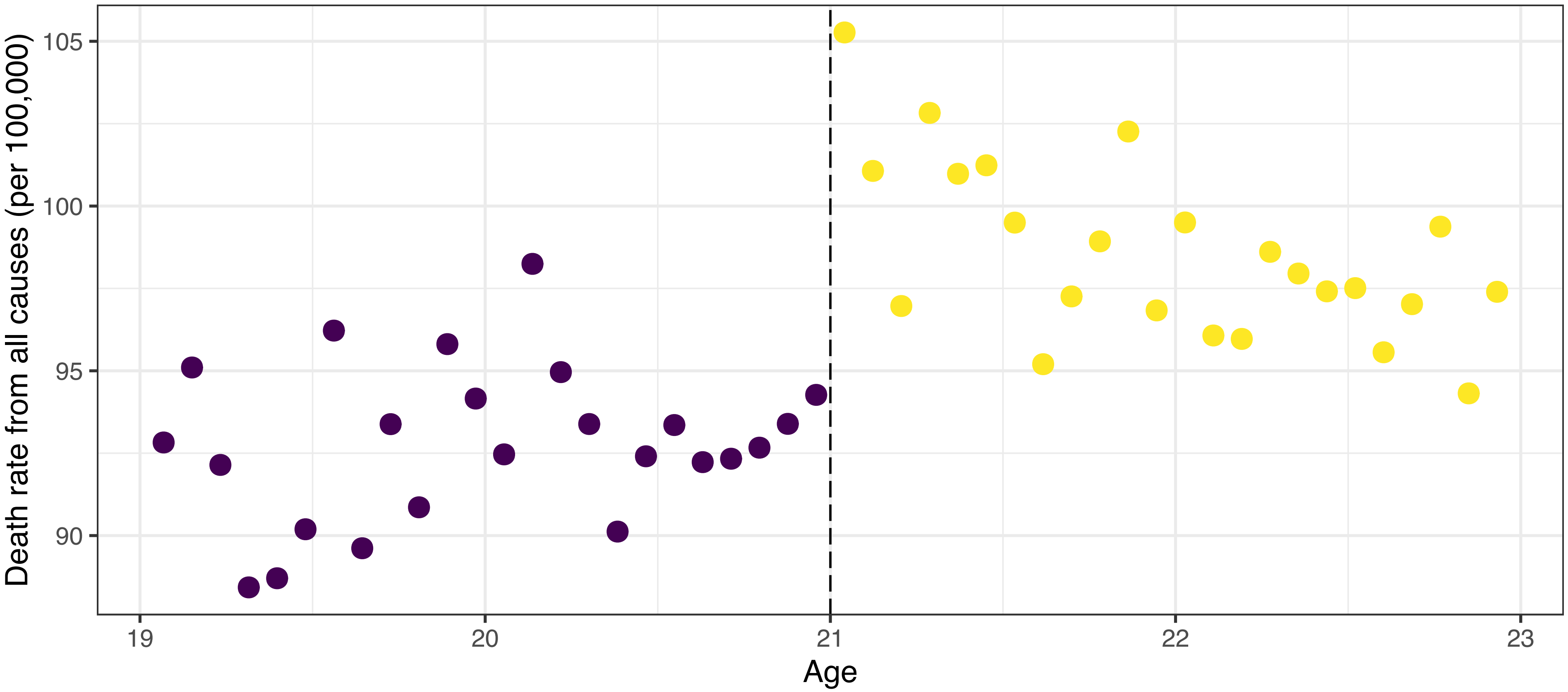
How to Choose Appropriate Functional Form?

- Essential to **visualise** the data!
- 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?

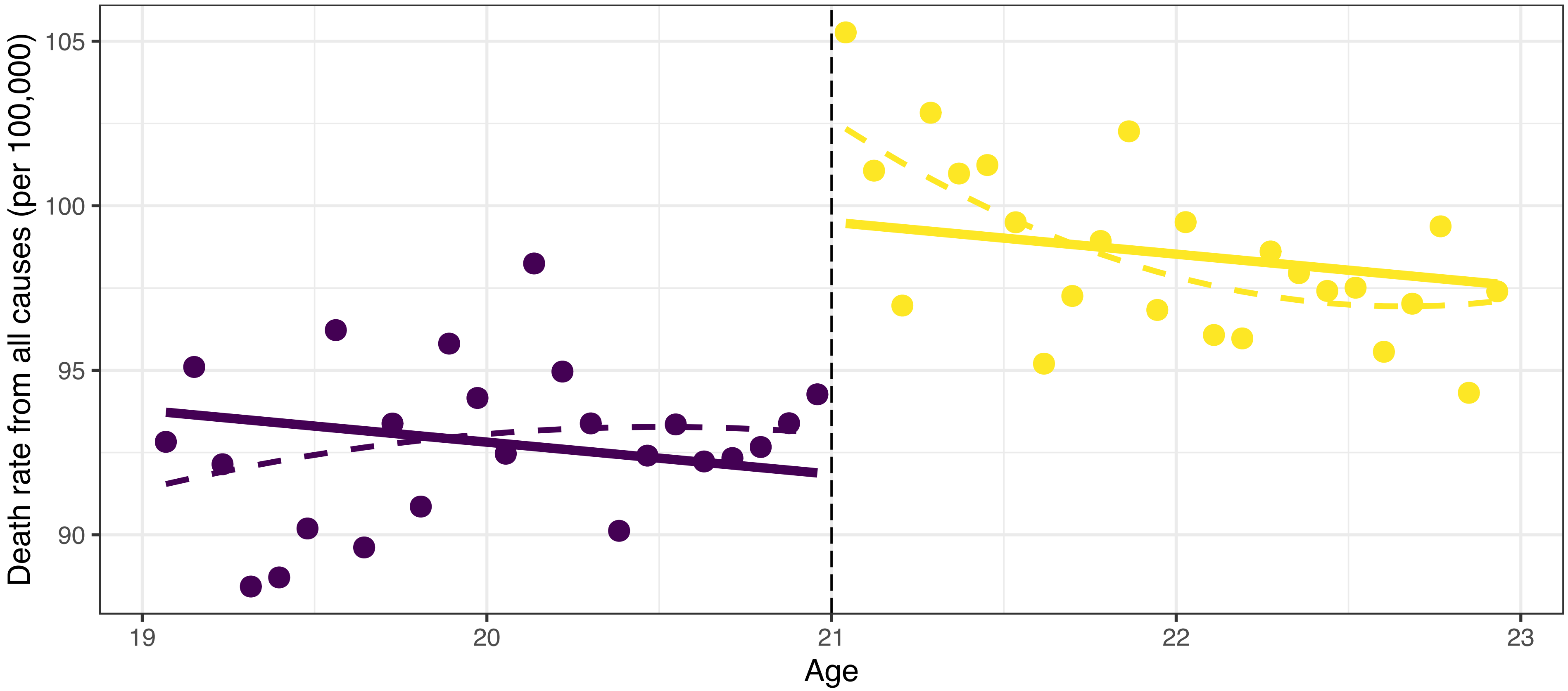
How to Choose Appropriate Functional Form?

- Essential to **visualise** the data!
- 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."

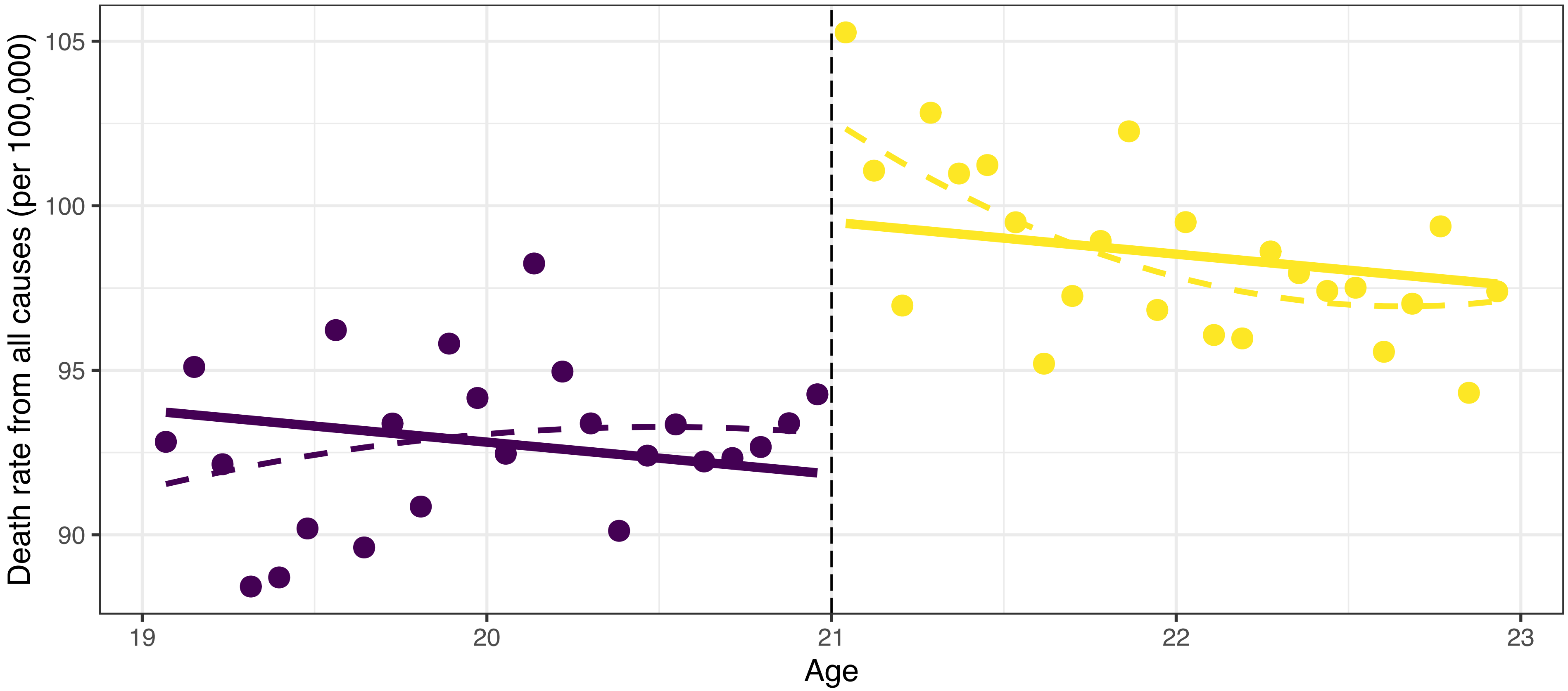
Going Back to our Example: Nonlinearities / $\neq$ Slopes?



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



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



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?

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

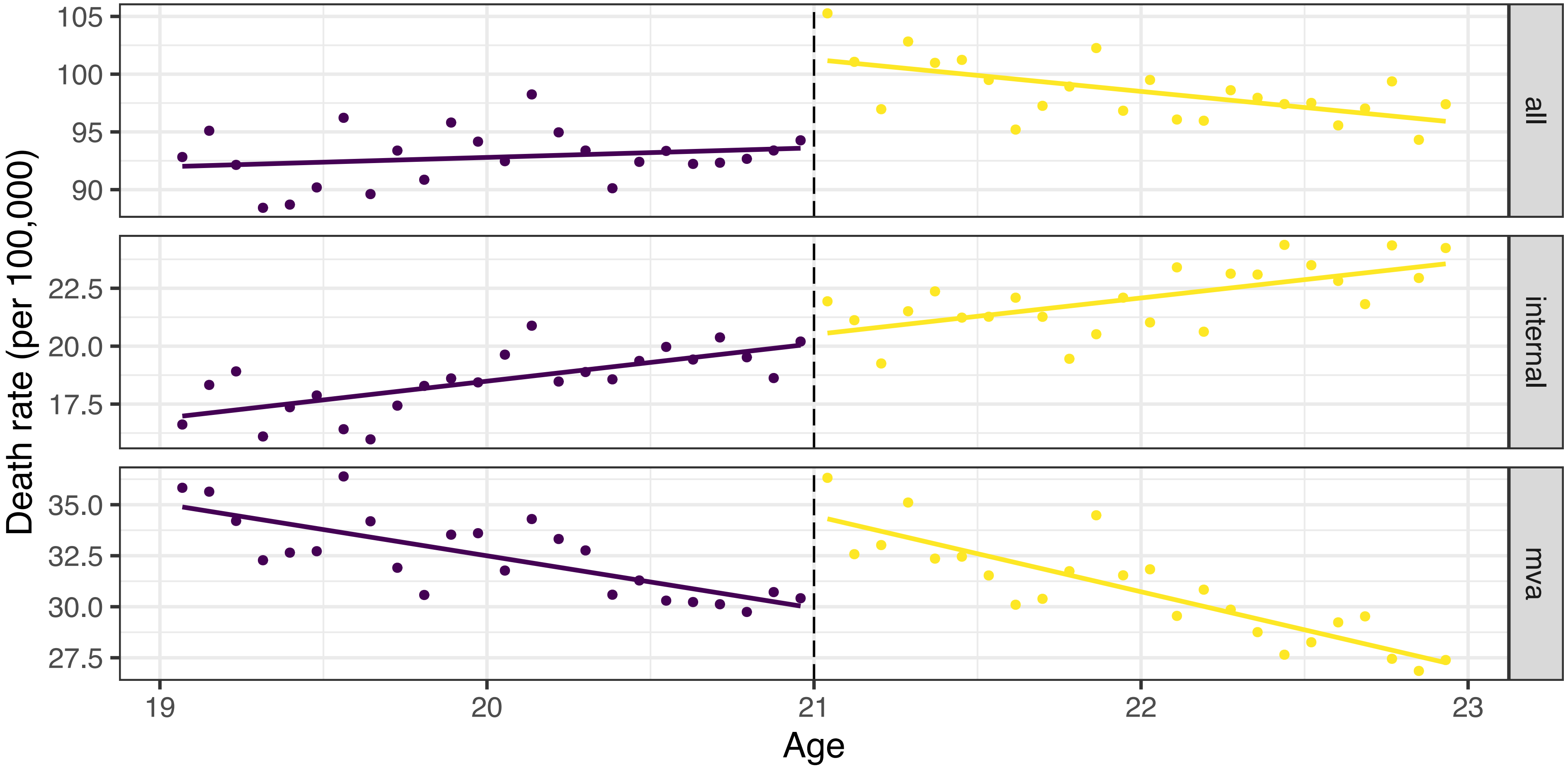
2. Recall that the regression model allowing for different slopes on each side of the cutoff is:

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

   - 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

Nonparametric Estimation

- Give more weight to observations close to the cutoff level

2 settings:

- How much more weight?

Nonparametric Estimation

- Give more weight to observations close to the cutoff level

2 settings:

- How much more weight?

  $\rightarrow$ depends on the chosen ***kernel***.

Nonparametric Estimation

- Give more weight to observations close to the cutoff level

2 settings:

- How much more weight?

  $\rightarrow$ depends on the chosen ***kernel***.

- How far away from the cutoff do observations need to be to be discarded?

Nonparametric Estimation

- Give more weight to observations close to the cutoff level

2 settings:

- How much more weight?

  $\rightarrow$ depends on the chosen ***kernel***.

- How far away from the cutoff do observations need to be to be discarded?

  $\rightarrow$ depends on the chosen ***bandwidth***.

Nonparametric Estimation

- Give more weight to observations close to the cutoff level

2 settings:

- How much more weight?

  $\rightarrow$ depends on the chosen ***kernel***.

- How far away from the cutoff do observations need to be to be discarded?

  $\rightarrow$ depends on the chosen ***bandwidth***.

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

Identifying Assumptions

RDD Assumptions

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

RDD Assumptions

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

$\rightarrow$ assignment variable cannot be manipulated!

RDD Assumptions

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

$\rightarrow$ assignment variable cannot be manipulated!

$$\lim_{r \to c+} E[Y_i^d | r] = \lim_{r \to c-} E[Y_i^d | r], d \in \{0, 1\}$$

RDD Assumptions

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

$\rightarrow$ assignment variable cannot be manipulated!

$$\lim_{r \rightarrow c+} E[Y_i^d | r] = \lim_{r \rightarrow c-} E[Y_i^d | r], d \in \{0, 1\}$$

- The population just below must not be discretely different from the population just above the cutoff.

RDD Assumptions

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

$\rightarrow$ assignment variable cannot be manipulated!

$$\lim_{r \rightarrow c+} E[Y_i^d | r] = \lim_{r \rightarrow c-} E[Y_i^d | r], d \in \{0, 1\}$$

- The population just below must not be discretely different from the population just above the cutoff.
- Assumption is violated if people can manipulate the running variable because they know the cutoff value.

RDD Assumptions

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

$\rightarrow$ assignment variable cannot be manipulated!

$$\lim_{r \to c+} E[Y_i^d | r] = \lim_{r \to c-} E[Y_i^d | r], d \in \{0, 1\}$$

- The population just below must not be discretely different from the population just above the cutoff.
- Assumption is violated if people can manipulate the running variable because they know the cutoff value.
    - 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:

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

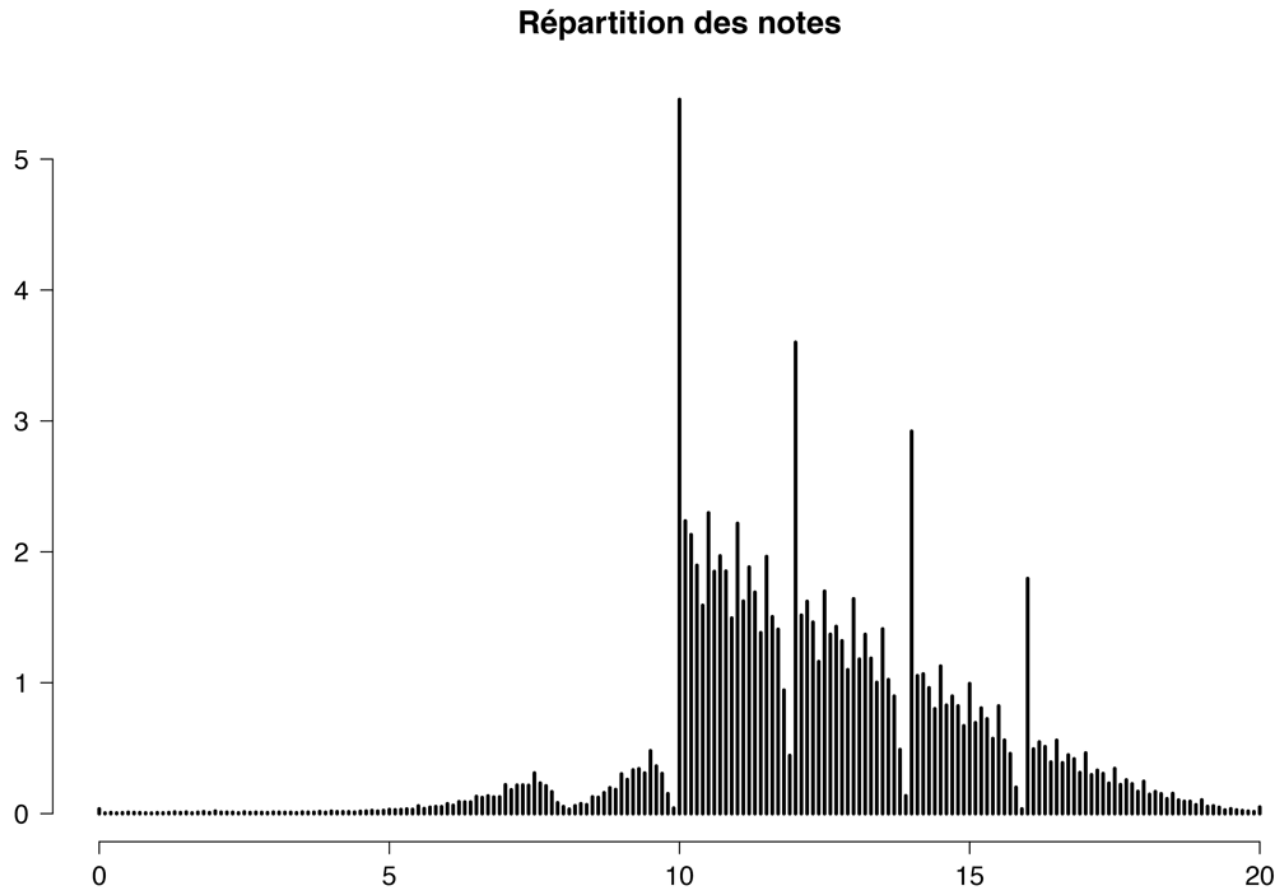
RDD Assumptions

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

If the assumption holds, we have:

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

Example of Manipulation: French Baccalaureate Grades



source : MENESR–DEPP, Distribution des candidats présents au baccalauréat général
selon la moyenne finale obtenue, 2006–2013
Réalisation : http://coulmont.com

Noncompliance

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

$\longrightarrow$ ***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.

5 Steps for Conducting RDD in Practice[1]

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

Step #2: *Is design sharp or fuzzy?*

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

5 Steps for Conducting RDD in Practice[1]

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

Step #2: *Is design sharp or fuzzy?*

Step #3: *Is there a discontinuity in running variable at cutoff?*

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

5 Steps for Conducting RDD in Practice[1]

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

Step #2: *Is design sharp or fuzzy?*

Step #3: *Is there a discontinuity in running variable at cutoff?*

Step #4: *Is there a discontinuity in outcome variable at cutoff in running variable?*

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

5 Steps for Conducting RDD in Practice[1]

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

Step #2: *Is design sharp or fuzzy?*

Step #3: *Is there a discontinuity in running variable at cutoff?*

Step #4: *Is there a discontinuity in outcome variable at cutoff in running variable?*

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

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

SciencesPo
DEPARTMENT OF ECONOMICS

END

	florian.oswald@sciencespo.fr
	Slides
	Book
	@ScPoEcon
	@ScPoEcon