Advanced Statistical Methods for Observational Studies

LECTURE 07

class management

class management

- Problem set 1 due today.

class management

- Problem set 1 due today.
- If you're taking this class for three credits then you'll be giving a presentation on some related work:
  - Tuesday - June 05, 2:15-3:15PM
  - Tuesday- June 12, 2-5 PM

class management

- Problem set 1 due today.
- If you're taking this class for three credits then you'll be giving a presentation on some related work:
  - Tuesday - June 05, 2:15-3:15PM
  - Tuesday- June 12, 2-5 PM
- Questions?

regression discontinuity

RD designs

RD designs

- Intuition:

RD designs

- Intuition: What if there's a known assignment mechanism and someone is just a smidge on one side and someone is a smidge on the other side?

RD designs

- Intuition: What if there's a known assignment mechanism and someone is just a smidge on one side and someone is a smidge on the other side? How'd they end up there?

RD designs

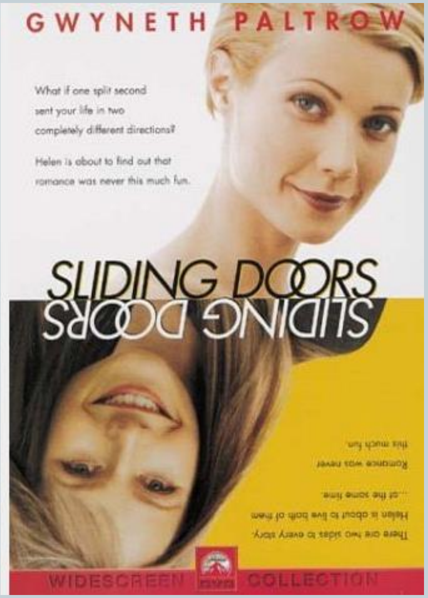
- Intuition: What if there's a known assignment mechanism and someone is just a smidge on one side and someone is a smidge on the other side? How'd they end up there? Could they be the same?

RD designs

- Intuition: What if there's a known assignment mechanism and someone is just a smidge on one side and someone is a smidge on the other side? How'd they end up there? Could they be the same? Couldn't I have ended up on the other side?

RD designs

- Intuition: What if there's a known assignment mechanism and someone is just a smidge on one side and someone is a smidge on the other side? How'd they end up there? Could they be the same? Couldn't I have ended up on the other side?



RD designs

RD designs

- Example: The National Merit Scholarship.

RD designs

- Example: The National Merit Scholarship.
- Research question:

RD designs

- Example: The National Merit Scholarship.
- Research question: How much benefit does the student receive from being given support for college?

RD designs

- Example: The National Merit Scholarship.
- Research question: How much benefit does the student receive from being given support for college?
- The naïve comparison is horrid:

RD designs

- Example: The National Merit Scholarship.
- Research question: How much benefit does the student receive from being given support for college?
- The naïve comparison is horrid: Those who work to get the NMS are outstanding…

RD designs

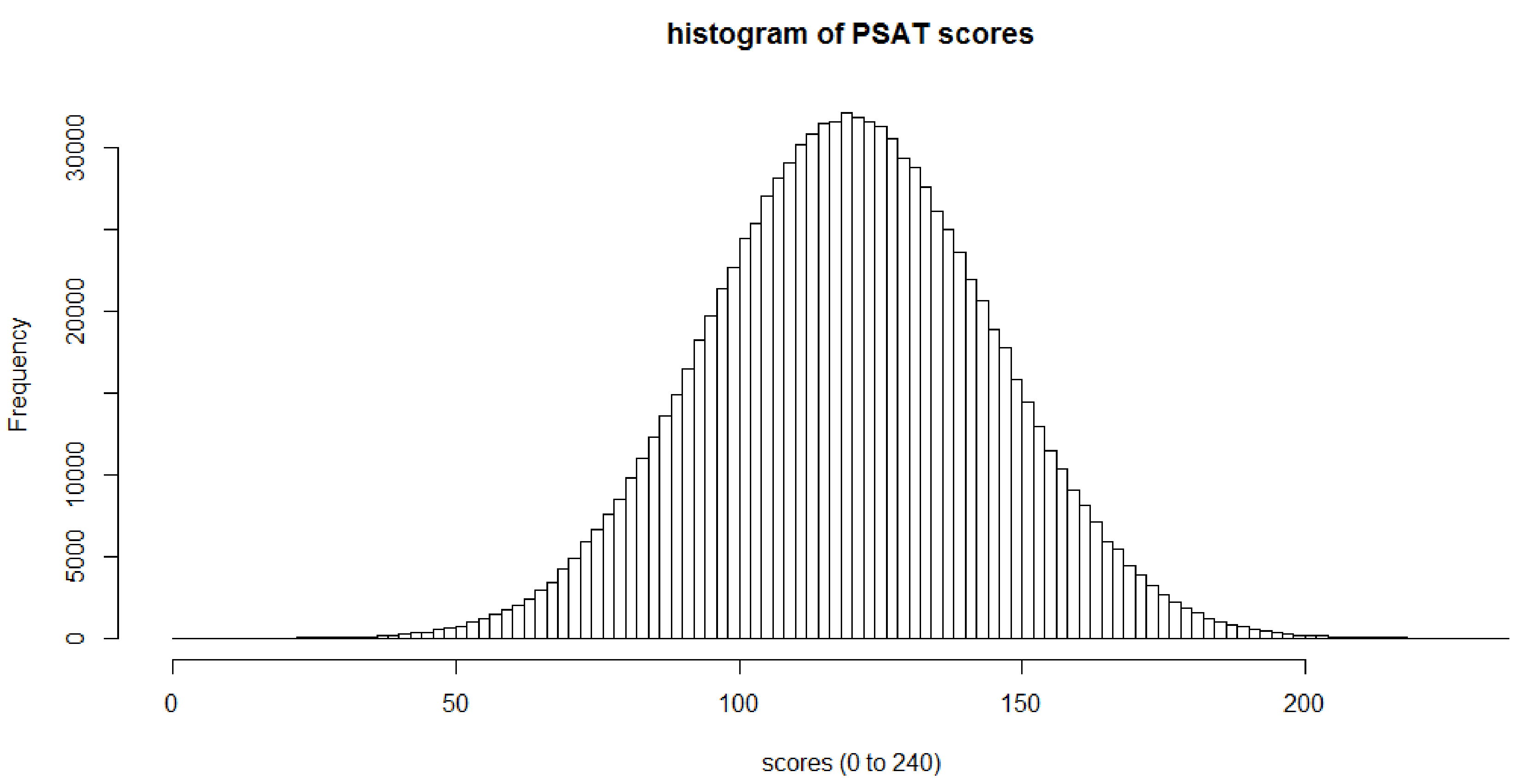
- Example: The National Merit Scholarship.
- Research question: How much benefit does the student receive from being given support for college?
- The naïve comparison is horrid: Those who work to get the NMS are outstanding and those who don’t get it are a mixed bag.

RD designs

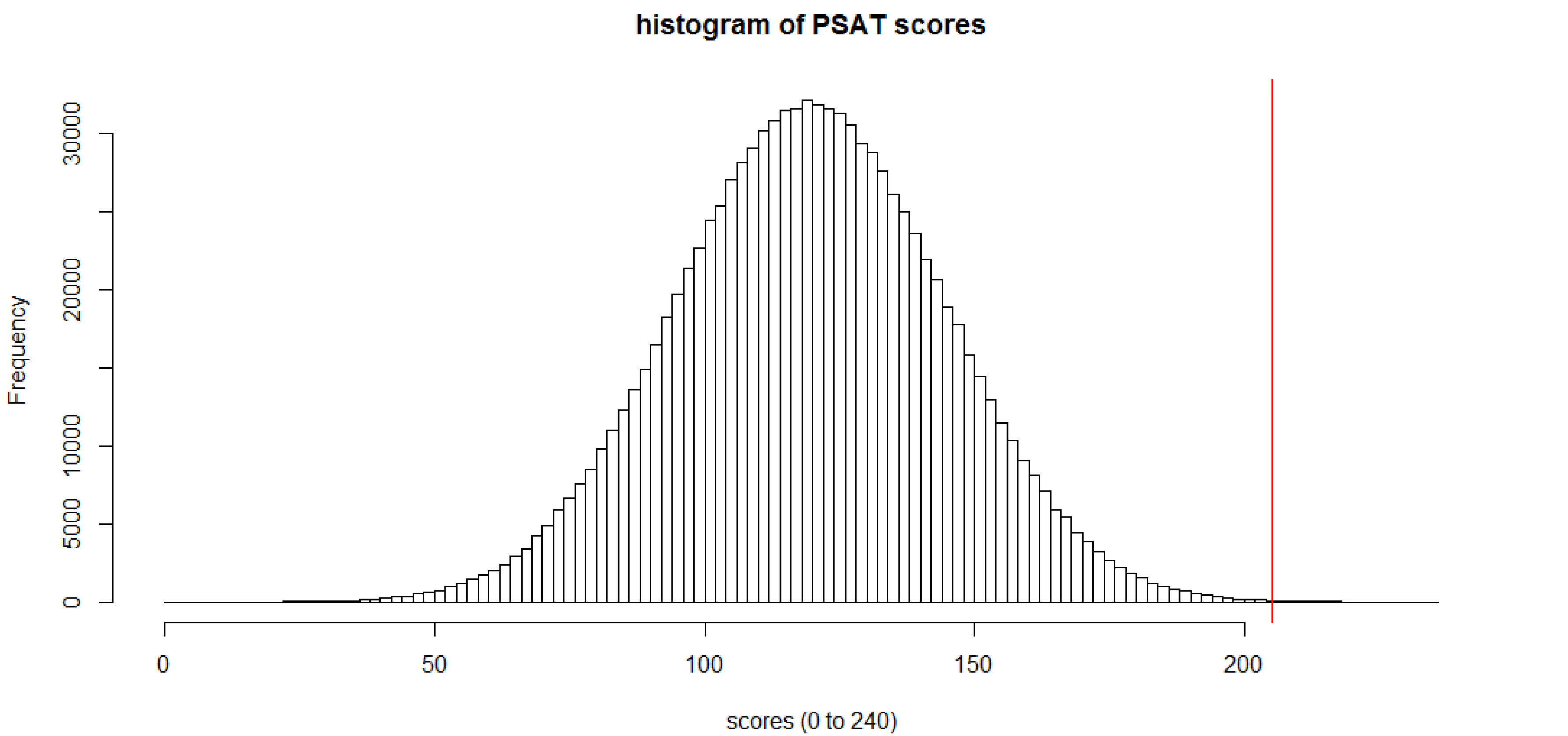
- Example: The National Merit Scholarship.
- Research question: How much benefit does the student receive from being given support for college?
- The naïve comparison is horrid: Those who work to get the NMS are outstanding and those who don’t get it are a mixed bag.
- But there are millions of students who take the PSAT every year, maybe we can find a subgroup.

RD design: National Merit Scholarship

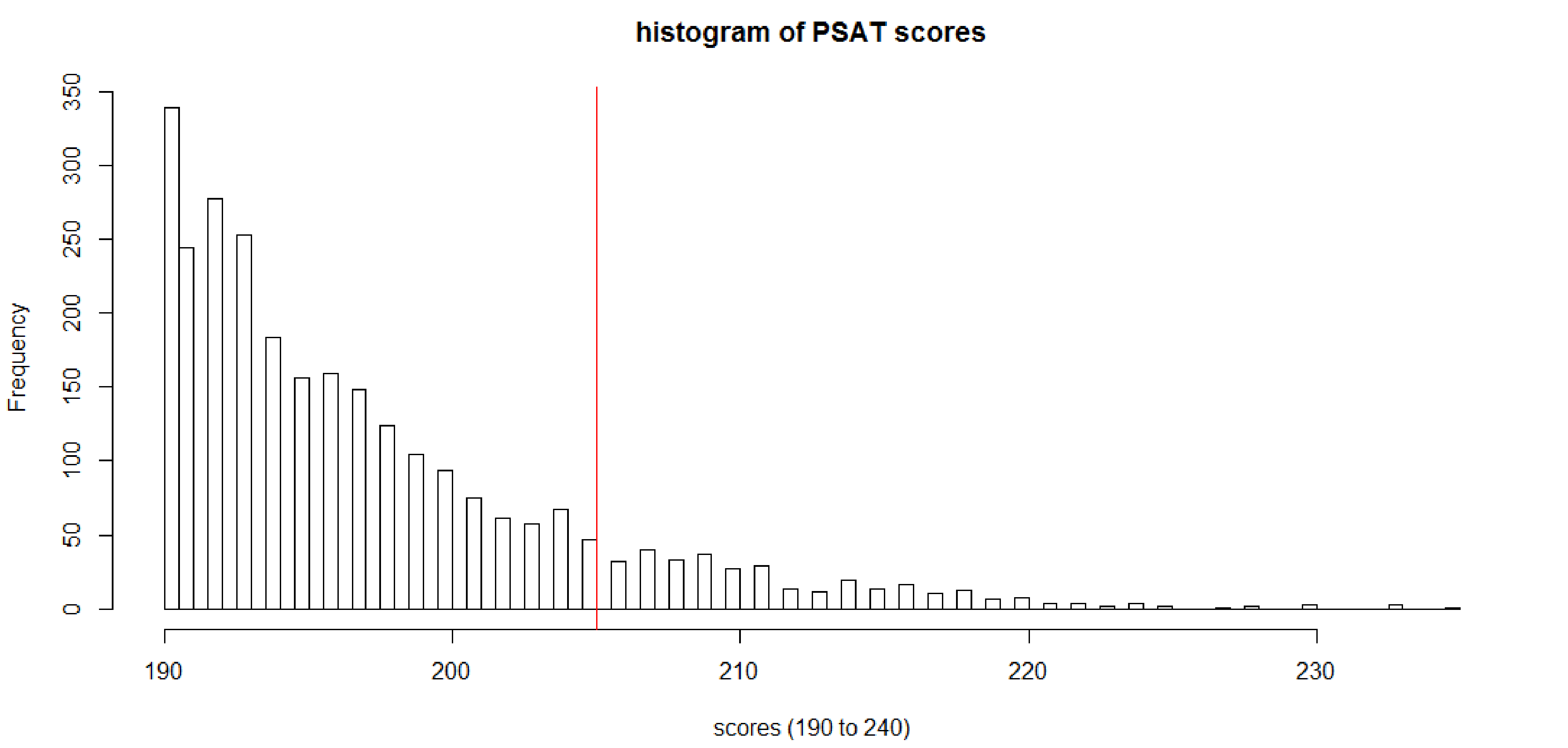
RD design: National Merit Scholarship



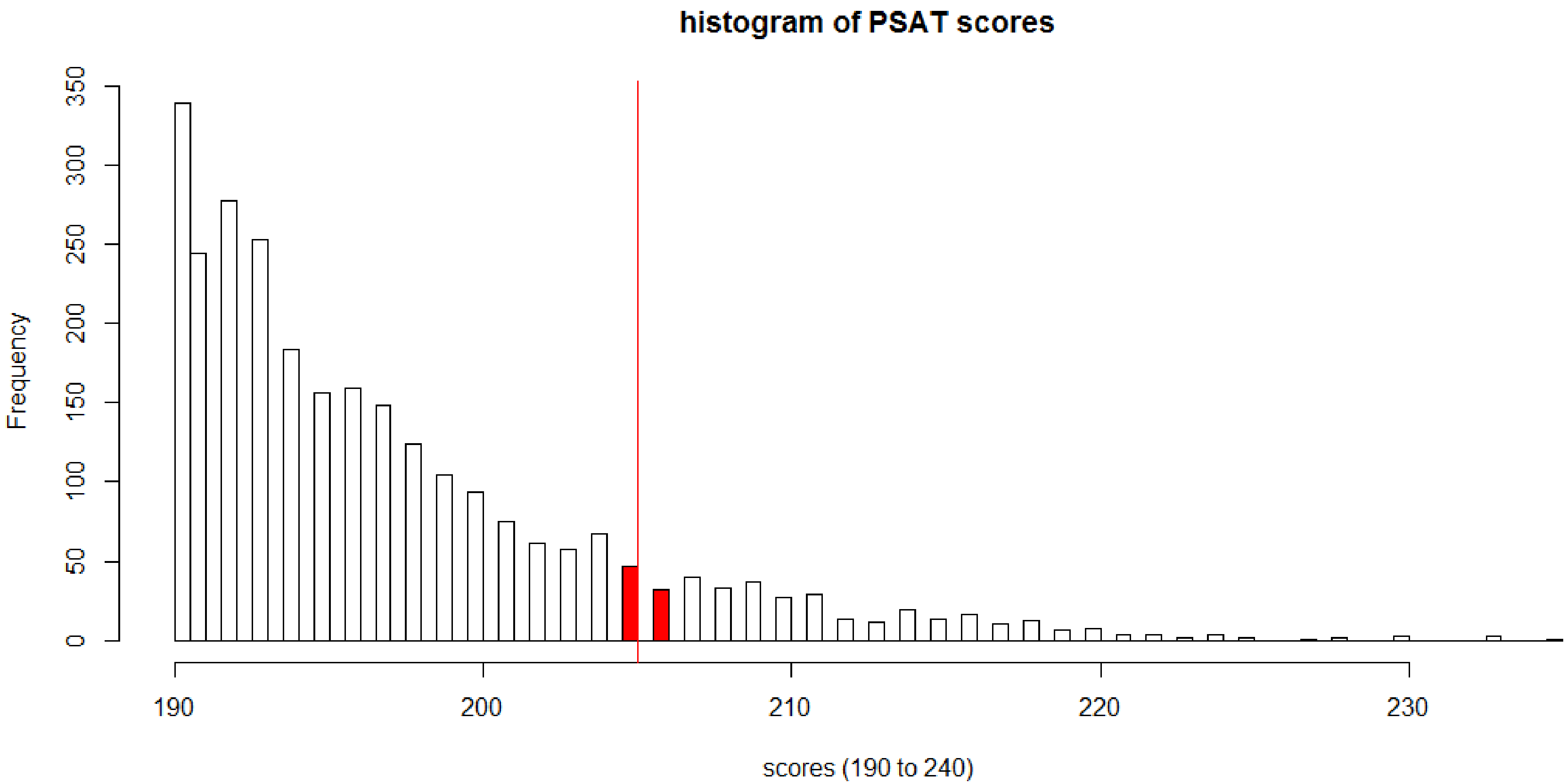
RD design: National Merit Scholarship



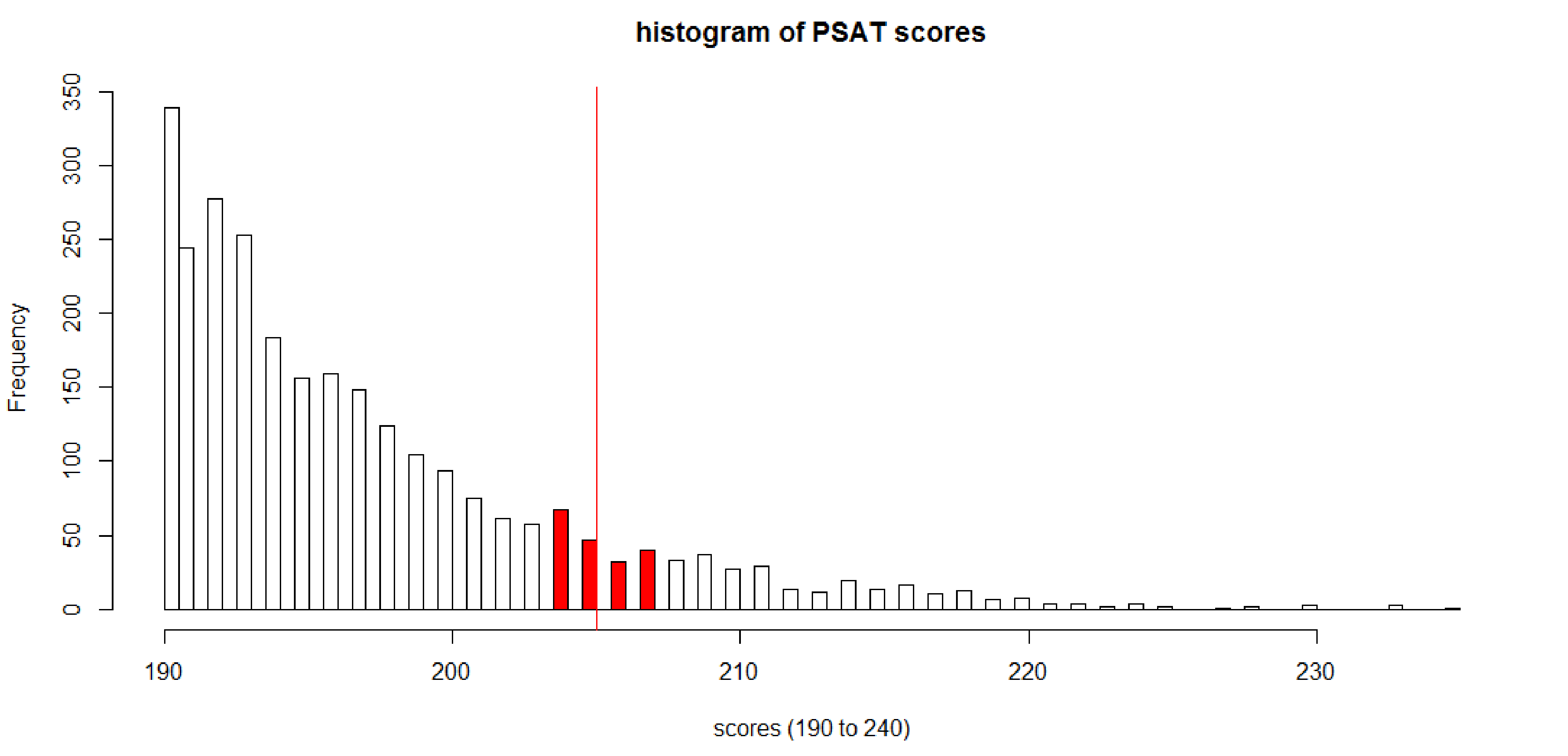
RD design: National Merit Scholarship



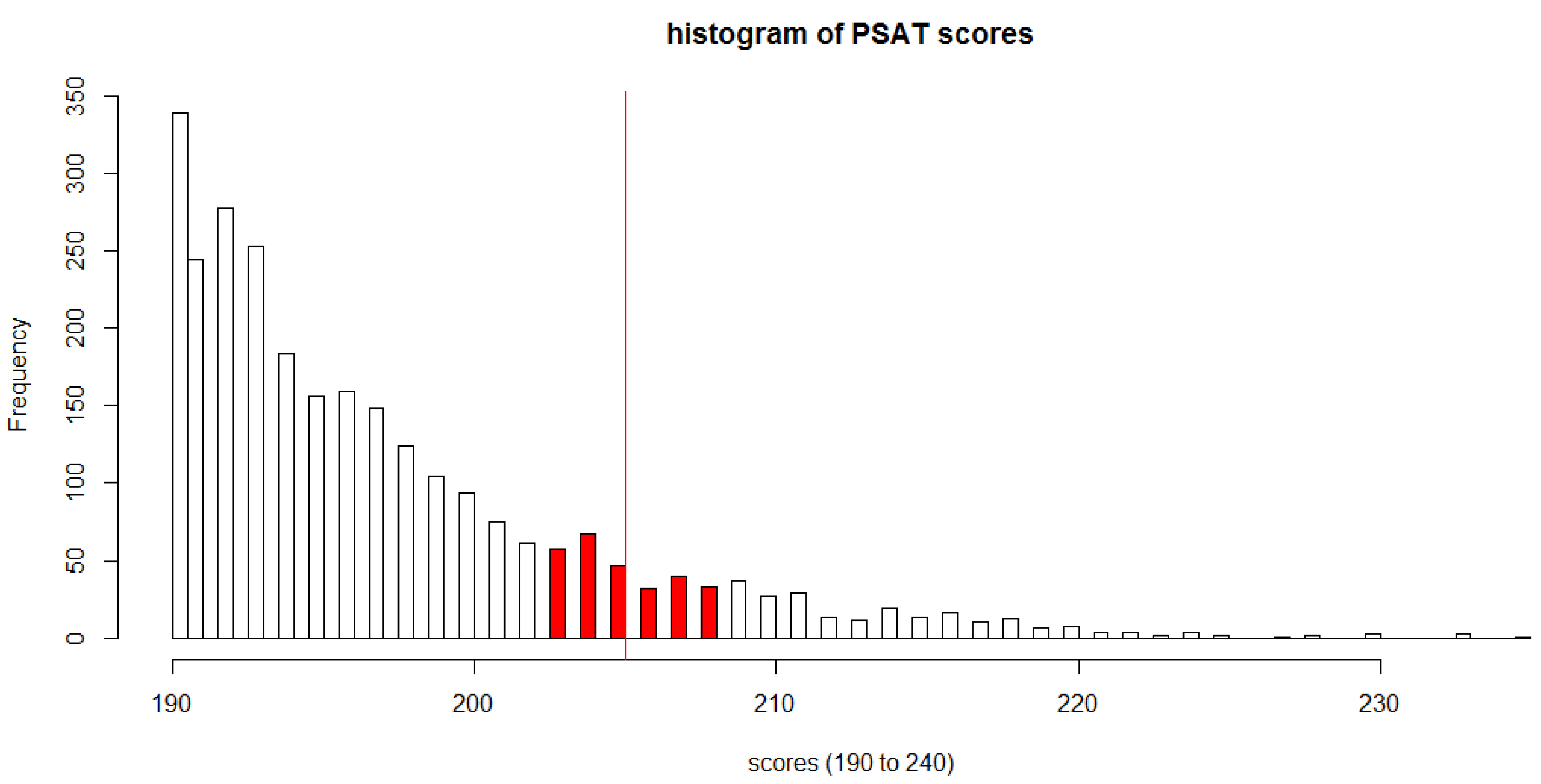
RD design: National Merit Scholarship



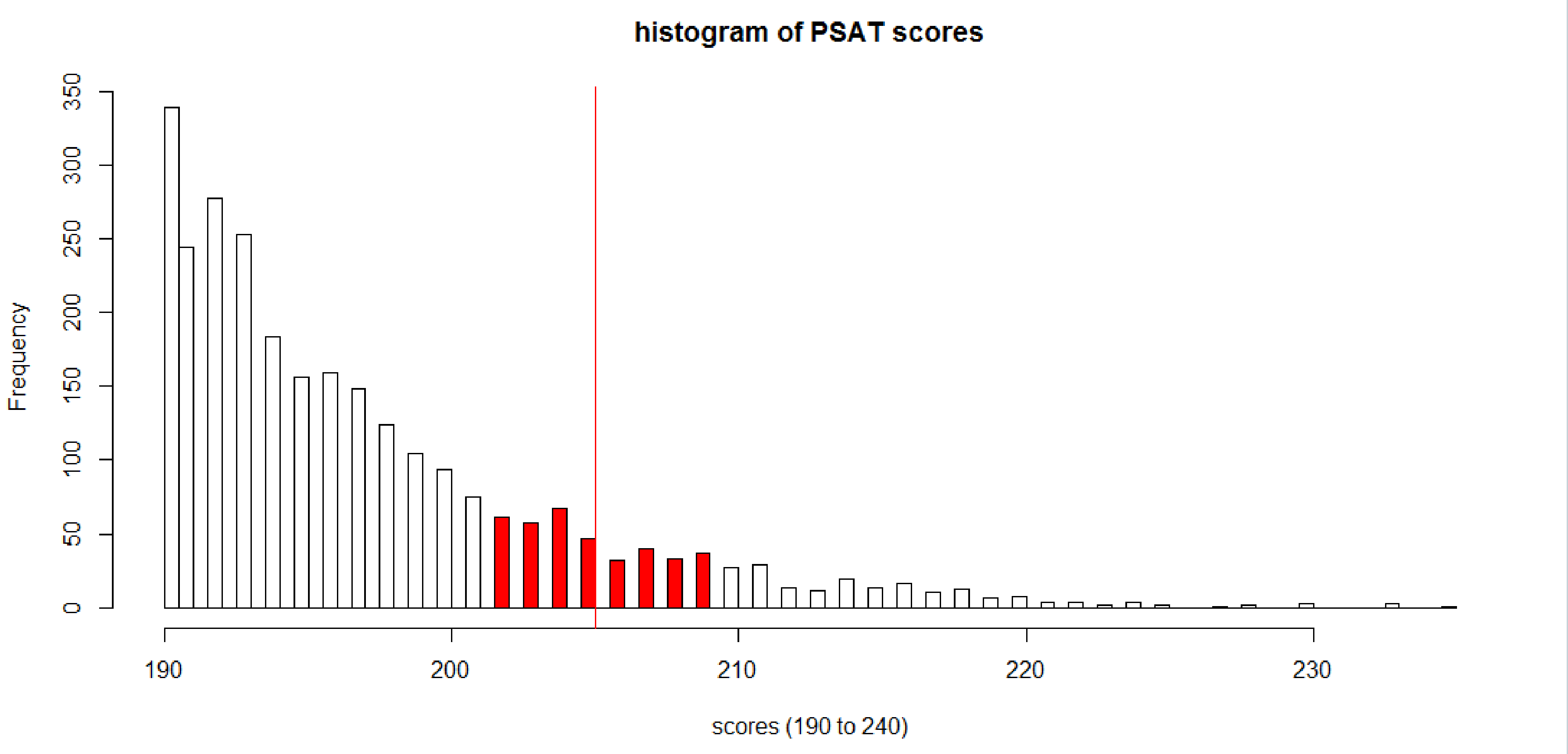
RD design: National Merit Scholarship



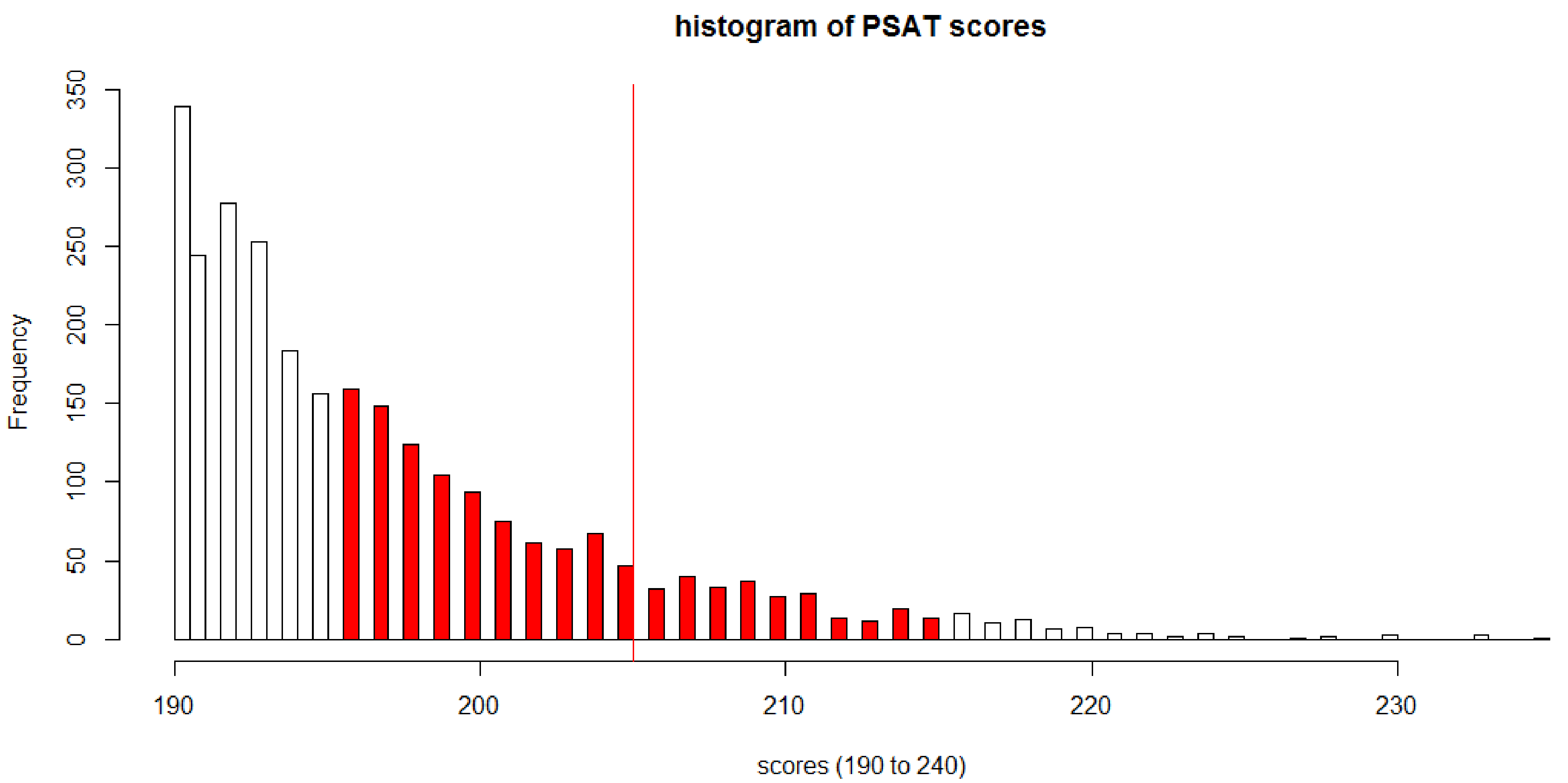
RD design: National Merit Scholarship



RD design: National Merit Scholarship



RD design: National Merit Scholarship

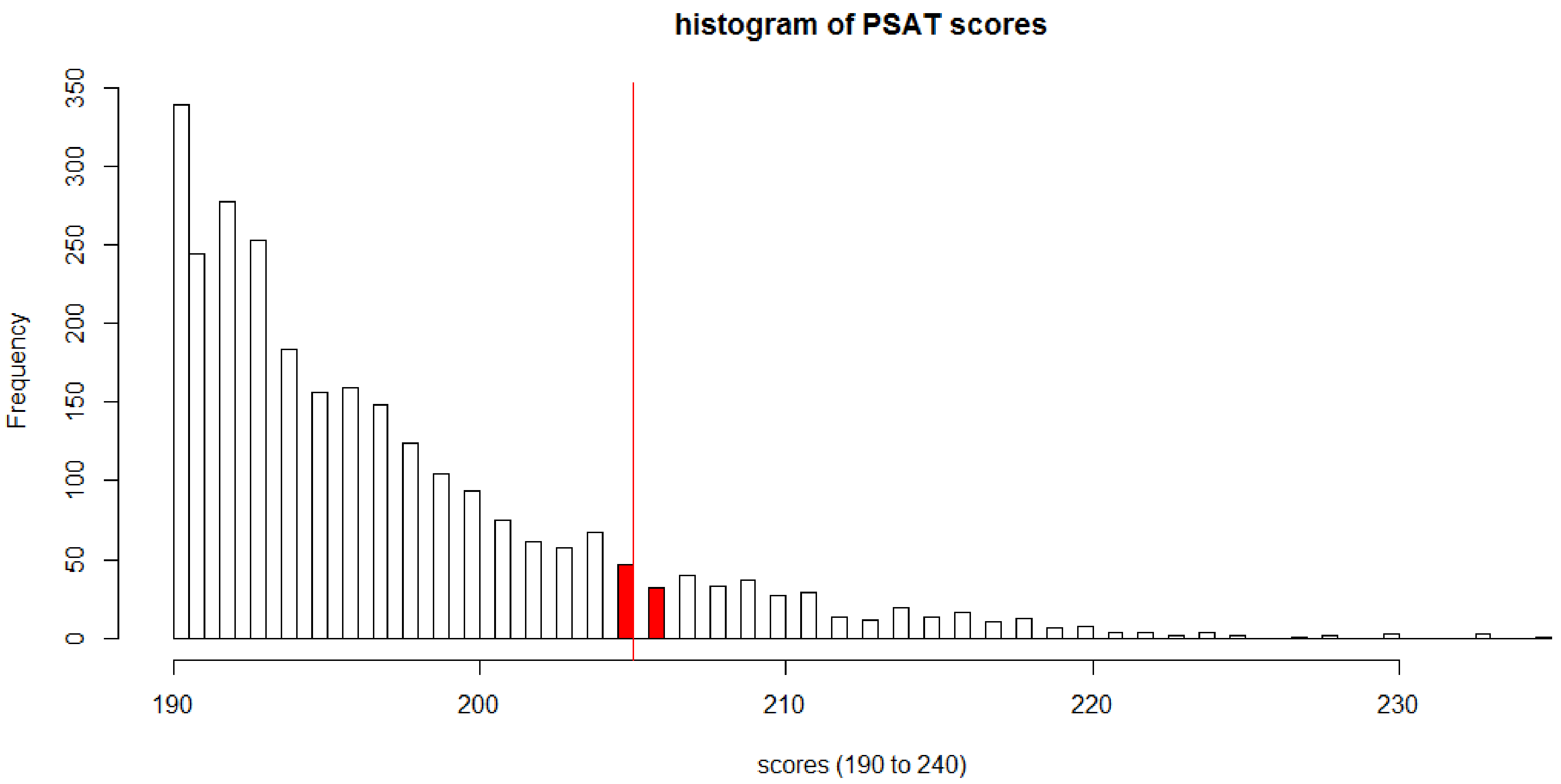


RD design: National Merit Scholarship

- How did they end up on one side versus the other?

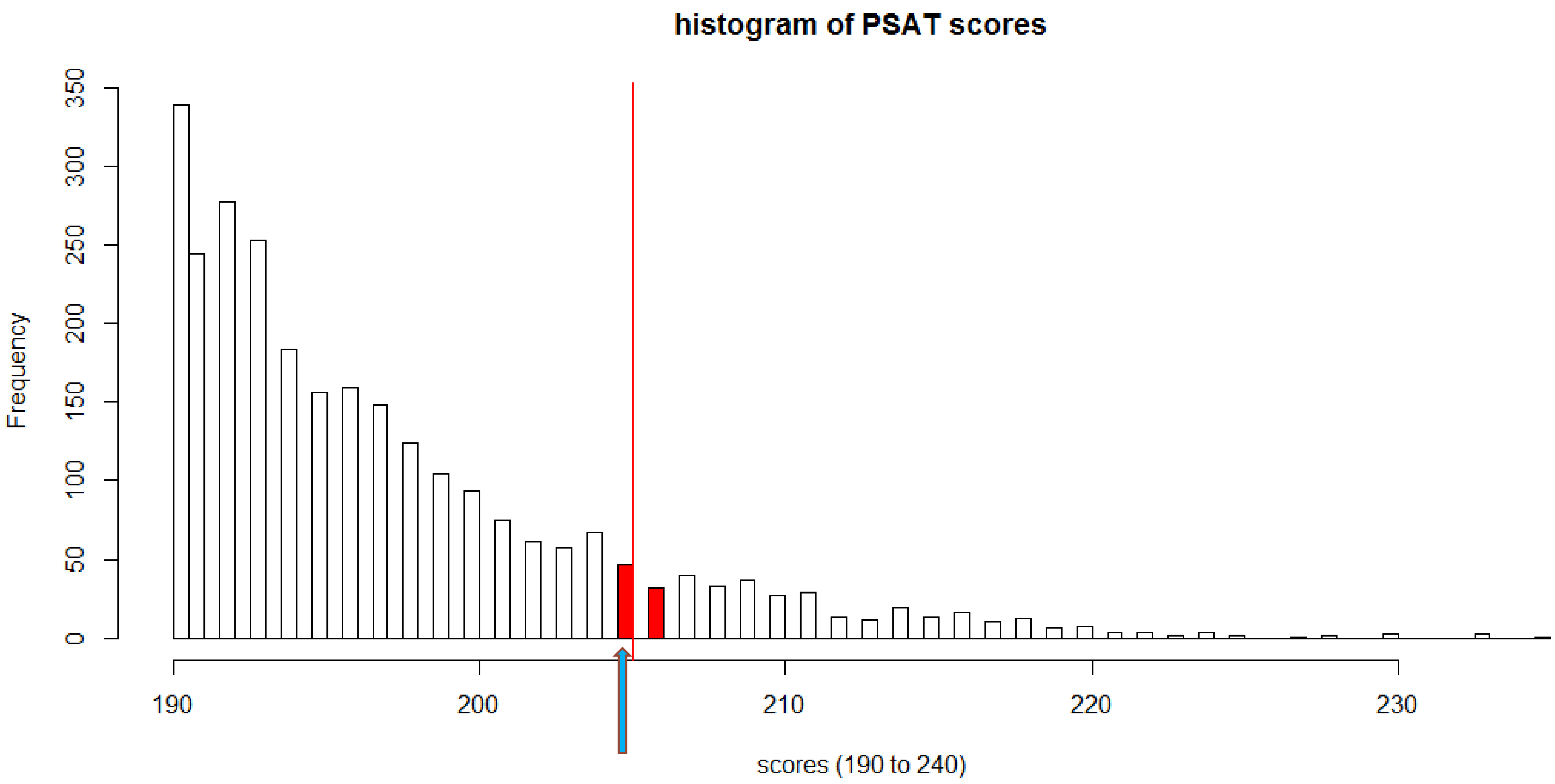
RD design: National Merit Scholarship

- How did they end up on one side versus the other?



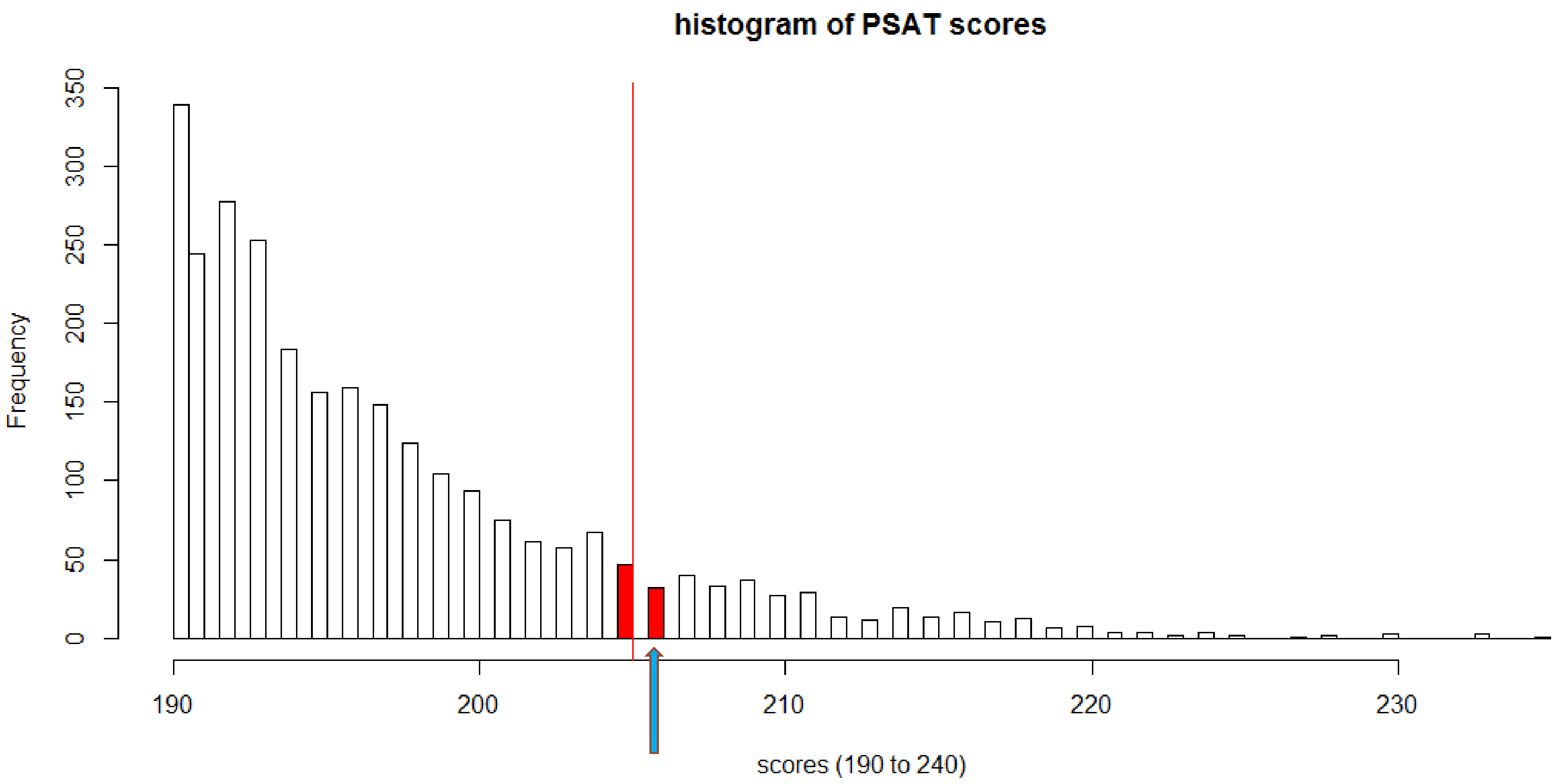
RD design: National Merit Scholarship

- How did they end up on one side versus the other?



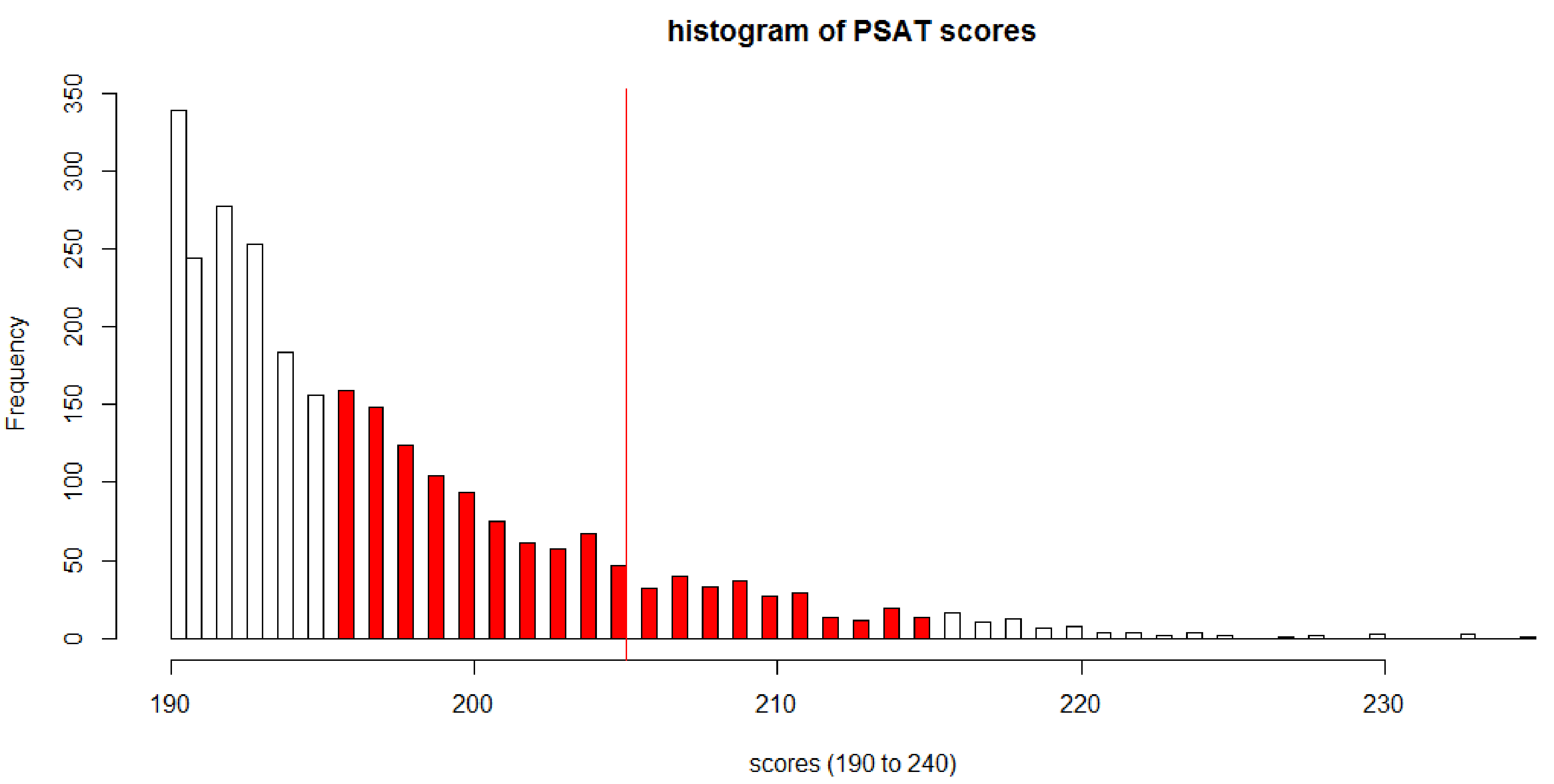
RD design: National Merit Scholarship

- How did they end up on one side versus the other?



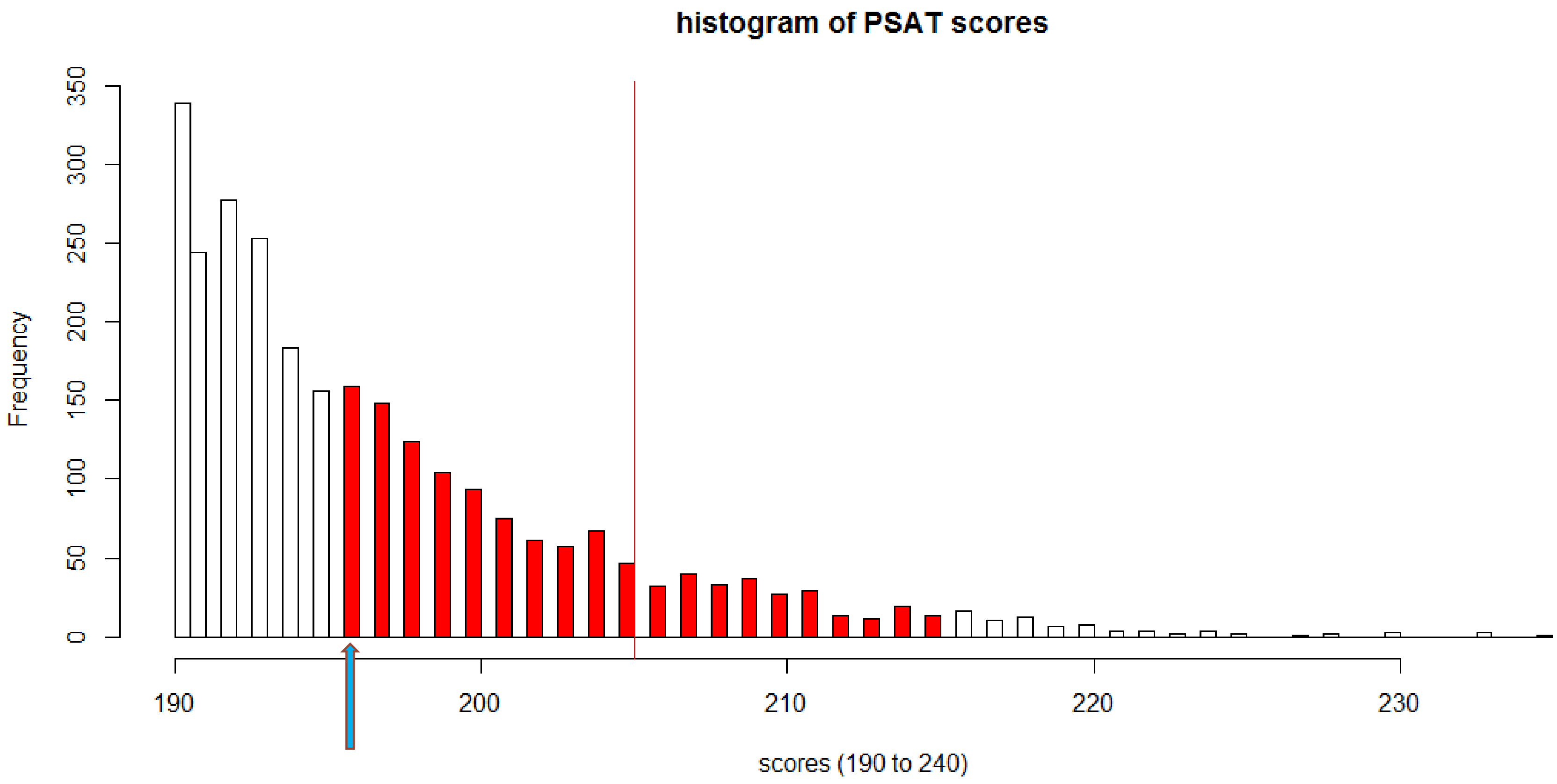
RD design: National Merit Scholarship

- How did they end up on one side versus the other?



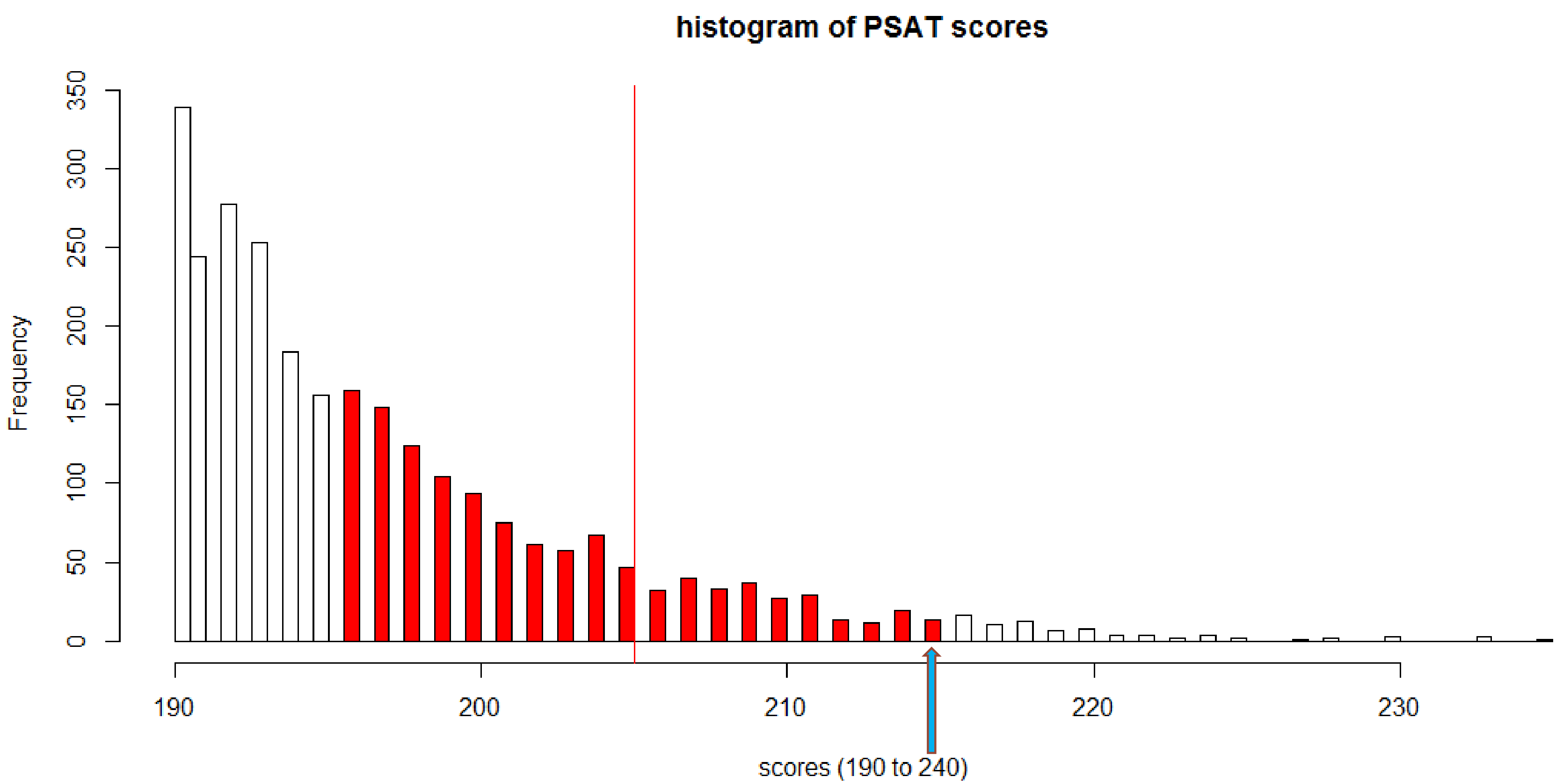
RD design: National Merit Scholarship

- How did they end up on one side versus the other?



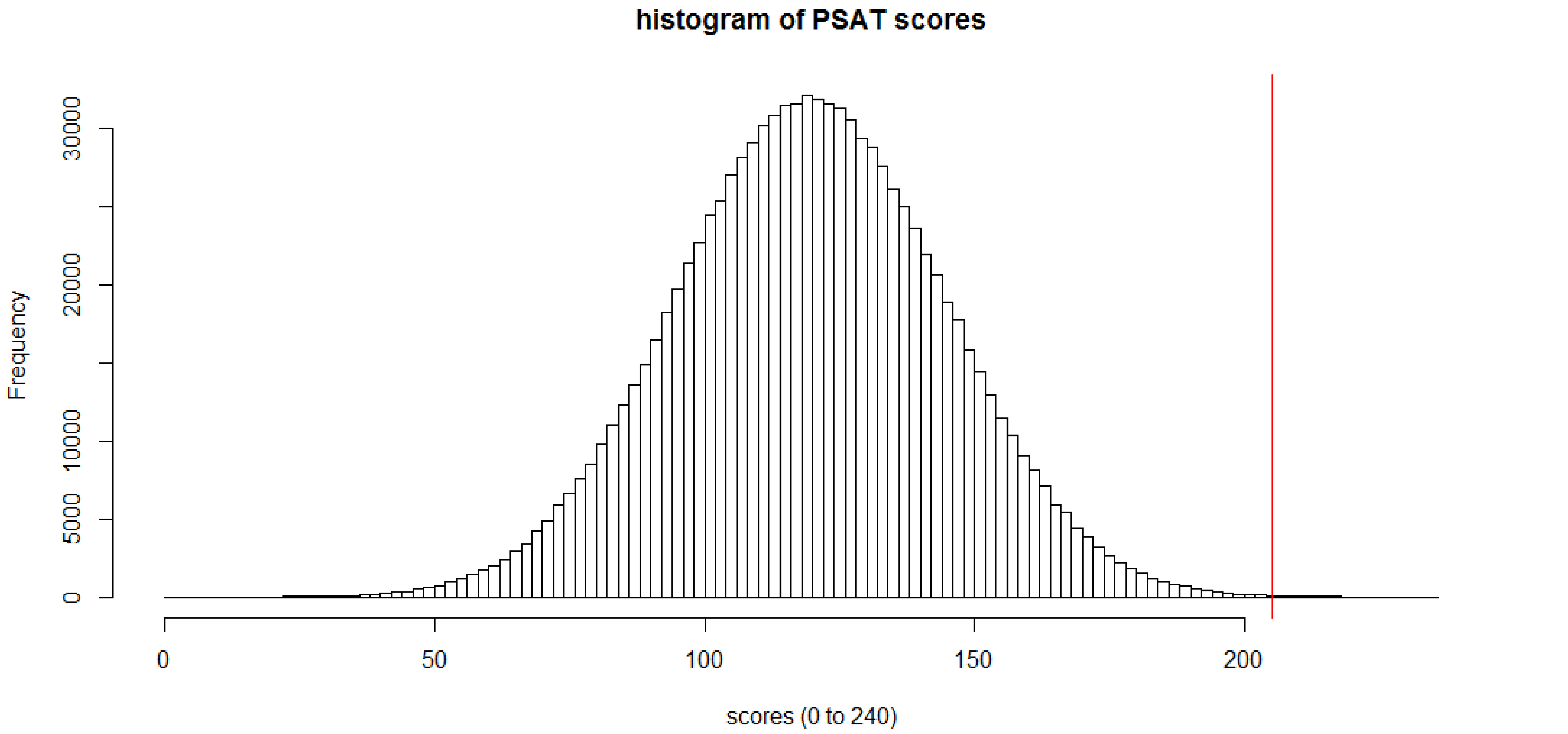
RD design: National Merit Scholarship

- How did they end up on one side versus the other?



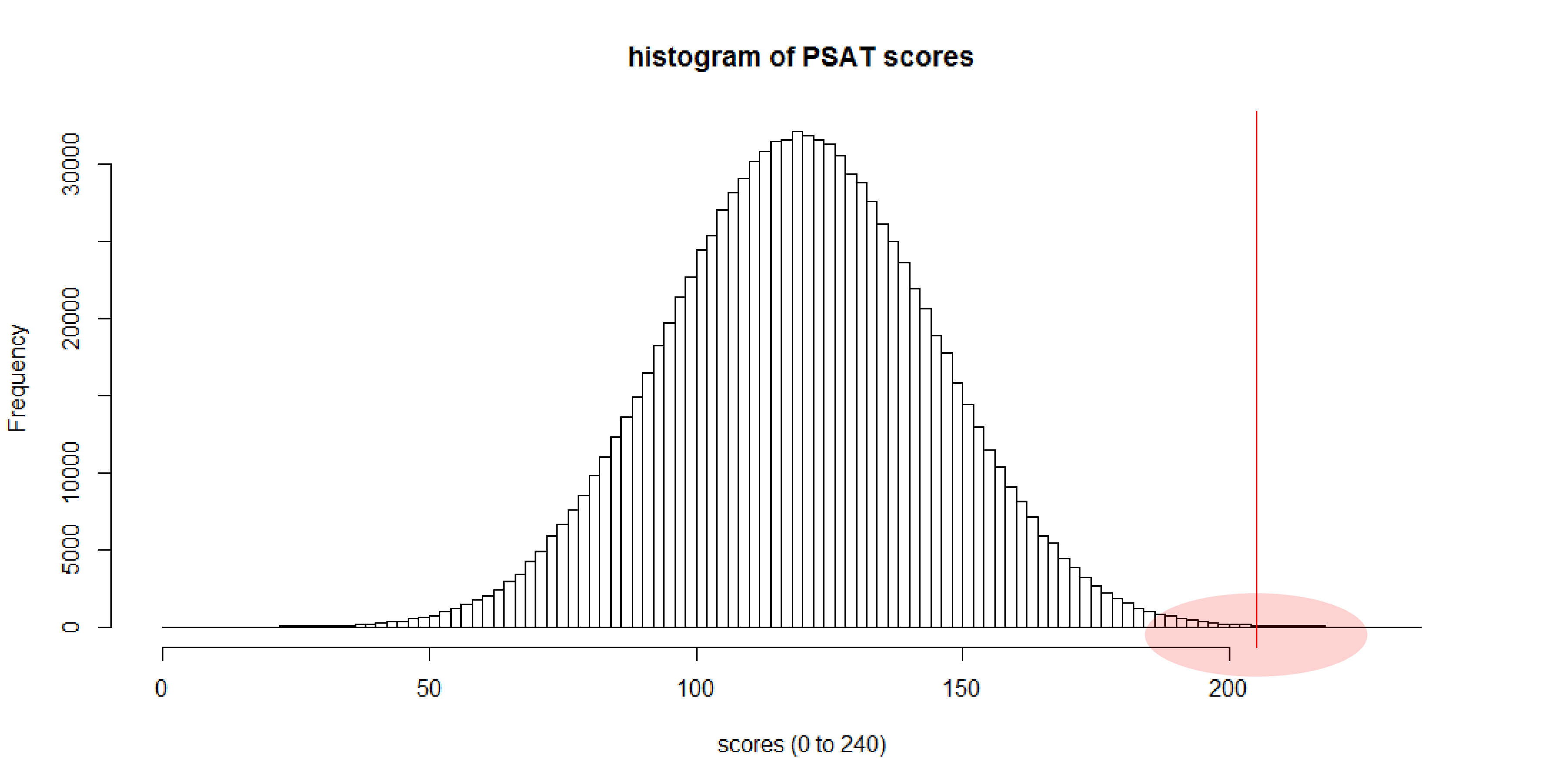
RD design: National Merit Scholarship

- How did they end up on one side versus the other?



RD design: National Merit Scholarship

- How did they end up on one side versus the other?



RD designs

- Features of an RD

RD designs

- Features of an RD
  - RD designs can be invalid if individuals can precisely manipulate the "assignment variable".

RD designs

- Features of an RD
  - RD designs can be invalid if individuals can precisely manipulate the "assignment variable".
  - RD design is analogous to a "local" randomized experiment.

RD designs

- Features of an RD
  - RD designs can be invalid if individuals can precisely manipulate the "assignment variable".
  - RD design is analogous to a "local" randomized experiment.
- The "randomness" comes from the lack of precise control above and below the cut off line

RD designs

- Features of an RD
  - RD designs can be invalid if individuals can precisely manipulate the "assignment variable".
  - RD design is analogous to a "local" randomized experiment.
- The "randomness" comes from the lack of precise control above and below the cut off line (e.g., didn't eat breakfast that morning)

RD designs

- Features of an RD
  - RD designs can be invalid if individuals can precisely manipulate the "assignment variable".
  - RD design is analogous to a "local" randomized experiment.
- The "randomness" comes from the lack of precise control above and below the cut off line (e.g., didn't eat breakfast that morning)
  - Could be thought of as $y_{i,j} = \theta_i + \varepsilon_{i,j}$.

RD designs

- Features of an RD
  - RD designs can be invalid if individuals can precisely manipulate the "assignment variable".
  - RD design is analogous to a "local" randomized experiment.
- The "randomness" comes from the lack of precise control above and below the cut off line (e.g., didn't eat breakfast that morning)
  - Could be thought of as $y_{i,j} = \theta_i + \varepsilon_{i,j}$.
  - (observed score) – (cut off) = (randomness)

RD designs

- Features of an RD
  - RD designs can be invalid if individuals can precisely manipulate the "assignment variable".
  - RD design is analogous to a "local" randomized experiment.
- The "randomness" comes from the lack of precise control above and below the cut off line (e.g., didn't eat breakfast that morning)
  - Could be thought of as $y_{i,j} = \theta_i + \varepsilon_{i,j}$.
  - (observed score) – (cut off) = (randomness)
- The *localness* is really important.

RD designs

- Features of an RD
  - RD designs can be invalid if individuals can precisely manipulate the “assignment variable”.
  - RD design is analogous to a “local” randomized experiment.
- The “randomness” comes from the lack of precise control above and below the cut off line (e.g., didn’t eat breakfast that morning)
  - Could be thought of as $y_{i,j} = \theta_i + \varepsilon_{i,j}$.
  - (observed score) – (cut off) = (randomness)
- The *localness* is really important. Think:

RD designs

- Features of an RD
  - RD designs can be invalid if individuals can precisely manipulate the "assignment variable".
  - RD design is analogous to a "local" randomized experiment.
- The "randomness" comes from the lack of precise control above and below the cut off line (e.g., didn't eat breakfast that morning)
  - Could be thought of as $y_{i,j} = \theta_i + \varepsilon_{i,j}$.
  - (observed score) – (cut off) = (randomness)
- The *localness* is really important. Think: the exact cutoff point is a bit arbitrary…

RD designs

- Features of an RD
  - RD designs can be invalid if individuals can precisely manipulate the "assignment variable".
  - RD design is analogous to a "local" randomized experiment.
- The "randomness" comes from the lack of precise control above and below the cut off line (e.g., didn't eat breakfast that morning)
  - Could be thought of as $y_{i,j} = \theta_i + \varepsilon_{i,j}$.
  - (observed score) – (cut off) = (randomness)
- The *localness* is really important. Think: the exact cutoff point is a bit arbitrary, but it's being made in a covariate that is really important and meaningful for the context.

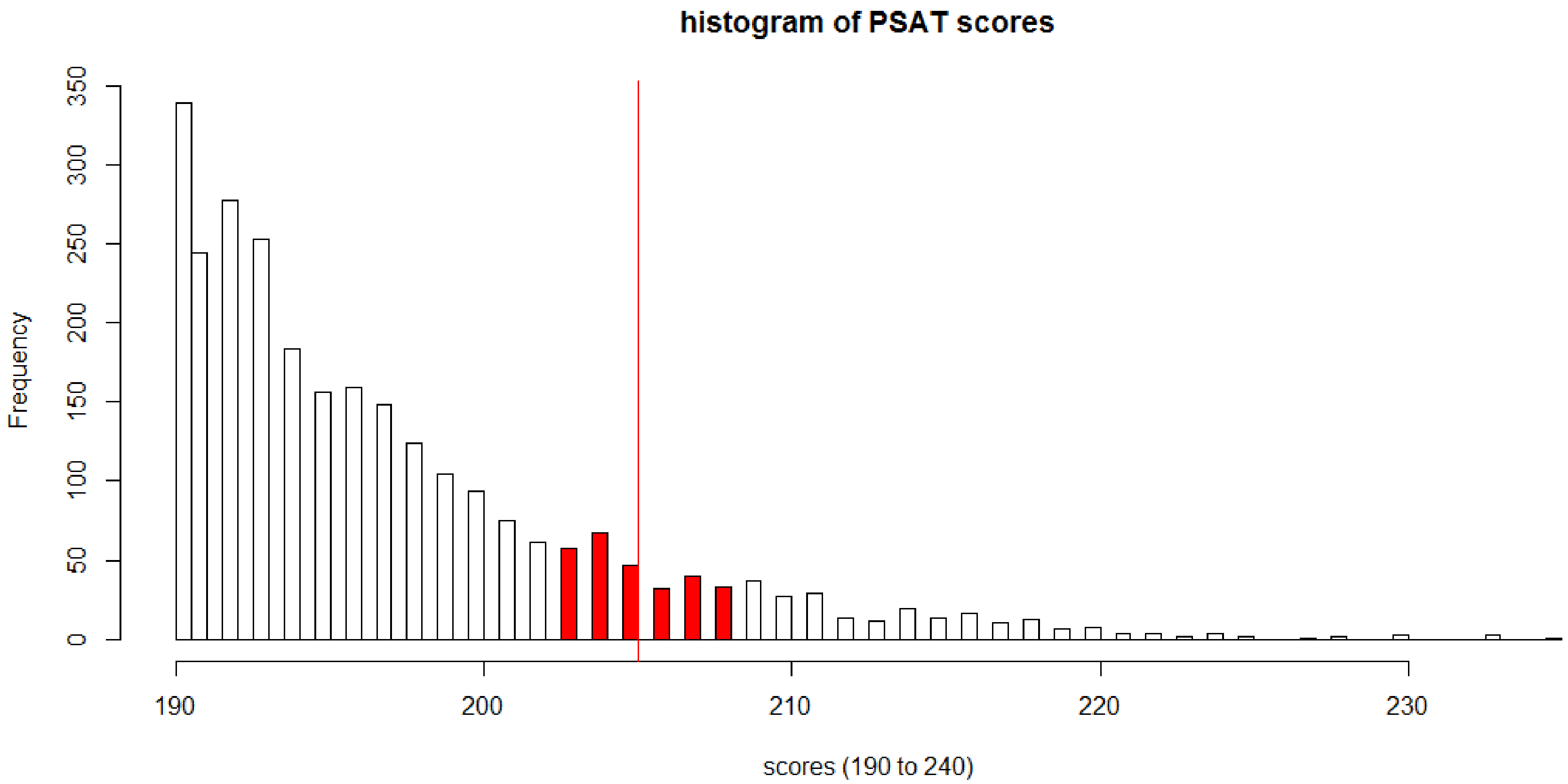
RD design: National Merit Scholarship

- Inference:

RD design: National Merit Scholarship

- Inference: RDs are usually analyzed assuming random assignment above and below the cutoff point.

RD design: National Merit Scholarship



RD design: National Merit Scholarship

- Inference: RDs are usually analyzed assuming random assignment above and below the cutoff point.

RD design: National Merit Scholarship

- Inference: RDs are usually analyzed assuming random assignment above and below the cutoff point.
- While the argument is that being above or below the cutoff is more or less random…

RD design: National Merit Scholarship

- Inference: RDs are usually analyzed assuming random assignment above and below the cutoff point.
- While the argument is that being above or below the cutoff is more or less random, you can enhance your argument by verifying in the covariates.

RD design: National Merit Scholarship

- Inference: RDs are usually analyzed assuming random assignment above and below the cutoff point.
- While the argument is that being above or below the cutoff is more or less random, you can enhance your argument by verifying in the covariates.
- Consider matching individuals on covariates.

RD design: National Merit Scholarship

- Inference: RDs are usually analyzed assuming random assignment above and below the cutoff point.
- While the argument is that being above or below the cutoff is more or less random, you can enhance your argument by verifying in the covariates.
- Consider matching individuals on covariates.
  - Then you can perform a permutation based test (e.g., Wilcoxon signed rank test).

RD design: National Merit Scholarship

- Inference: RDs are usually analyzed assuming random assignment above and below the cutoff point.
- While the argument is that being above or below the cutoff is more or less random, you can enhance your argument by verifying in the covariates.
- Consider matching individuals on covariates.
  - Then you can perform a permutation based test (e.g., Wilcoxon signed rank test).
  - Perform a sensitivity analysis.

RD design: National Merit Scholarship

- Inference: RDs are usually analyzed assuming random assignment above and below the cutoff point.
- While the argument is that being above or below the cutoff is more or less random, you can enhance your argument by verifying in the covariates.
- Consider matching individuals on covariates.
  - Then you can perform a permutation based test (e.g., Wilcoxon signed rank test).
  - Perform a sensitivity analysis.
  - Looks much like what we learned in pscore.

RD design: National Merit Scholarship

- Inference: RDs are usually analyzed assuming random assignment above and below the cutoff point.
- While the argument is that being above or below the cutoff is more or less random, you can enhance your argument by verifying in the covariates.
- Consider matching individuals on covariates.
  - Then you can perform a permutation based test (e.g., Wilcoxon signed rank test).
  - Perform a sensitivity analysis.
  - Looks much like what we learned in pscore.
- Many economists will use some kind of SEM:

$$y_{i,j} = \theta_i + \beta * d_j + \varepsilon_{i,j}$$

RD designs

RD designs

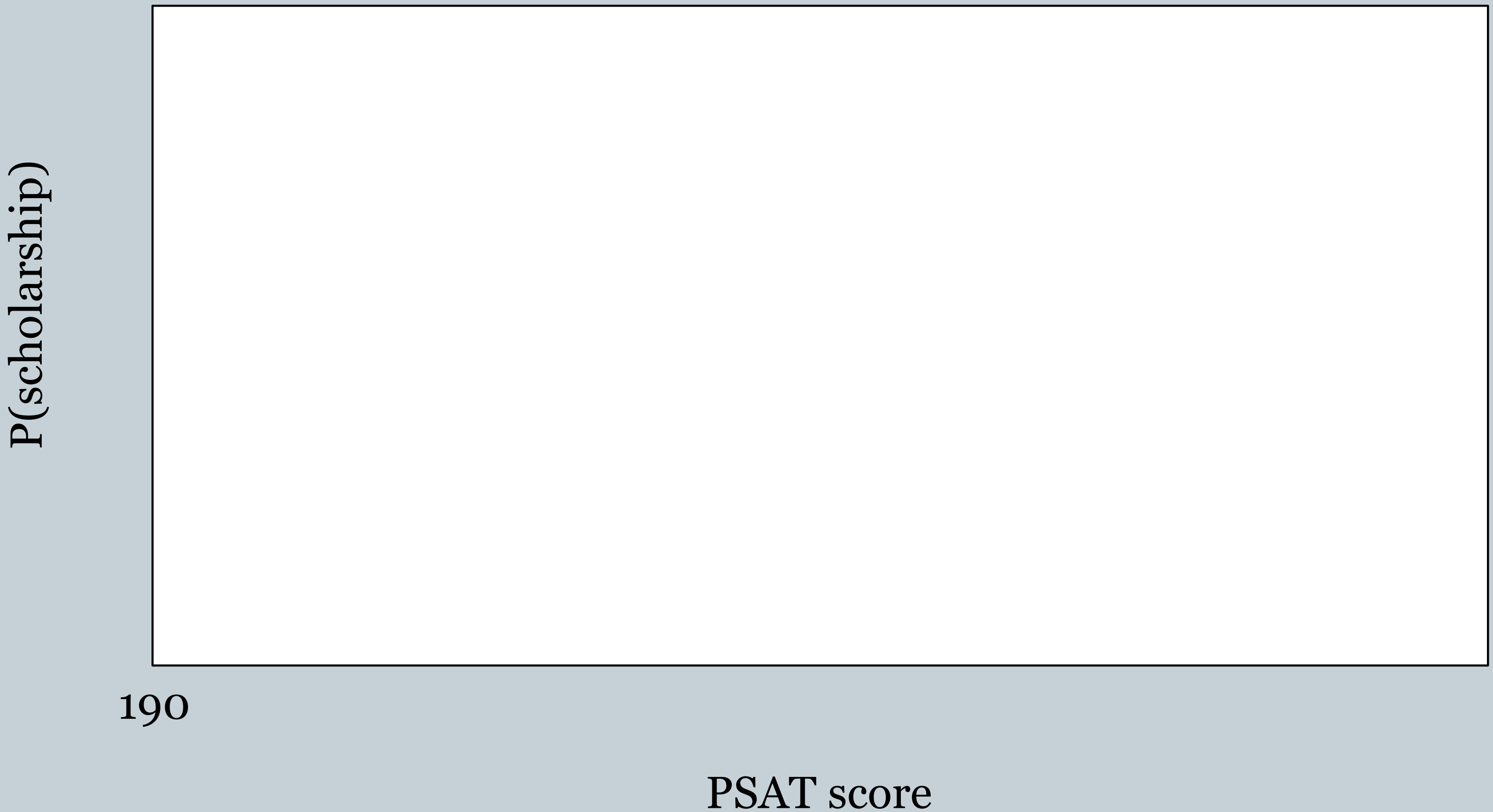
P(scholarship)

RD designs

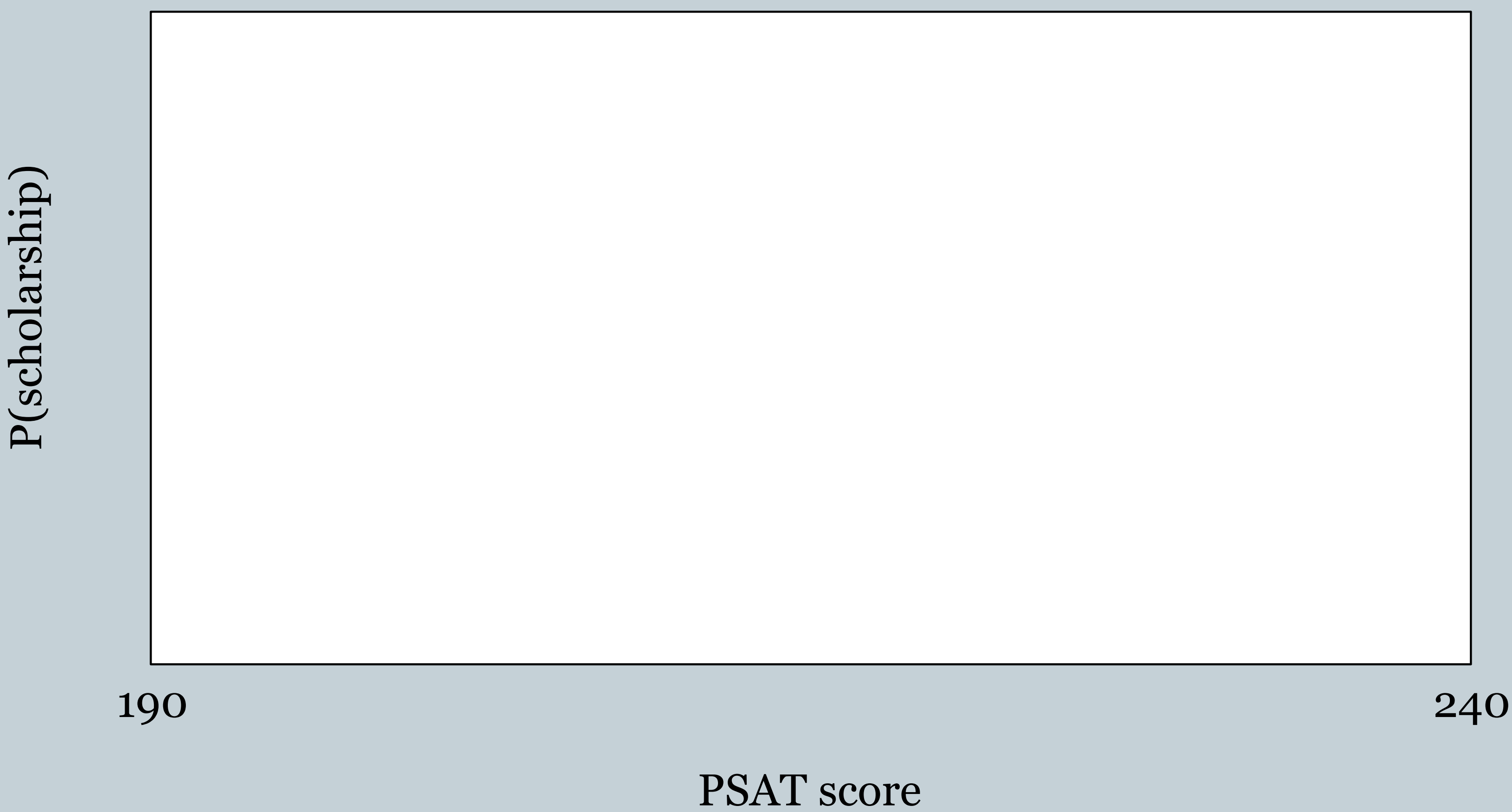
P(scholarship)

PSAT score

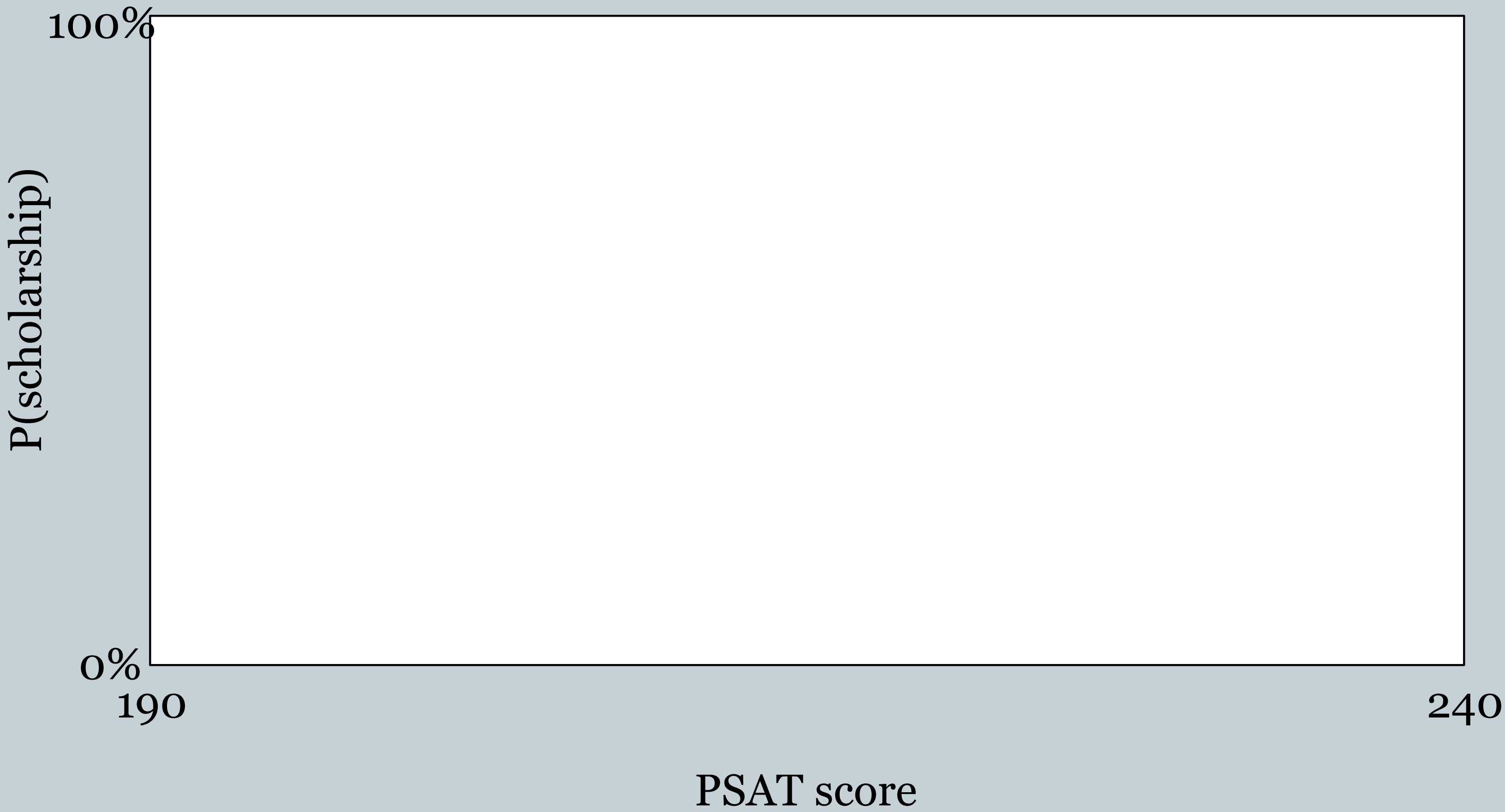
RD designs



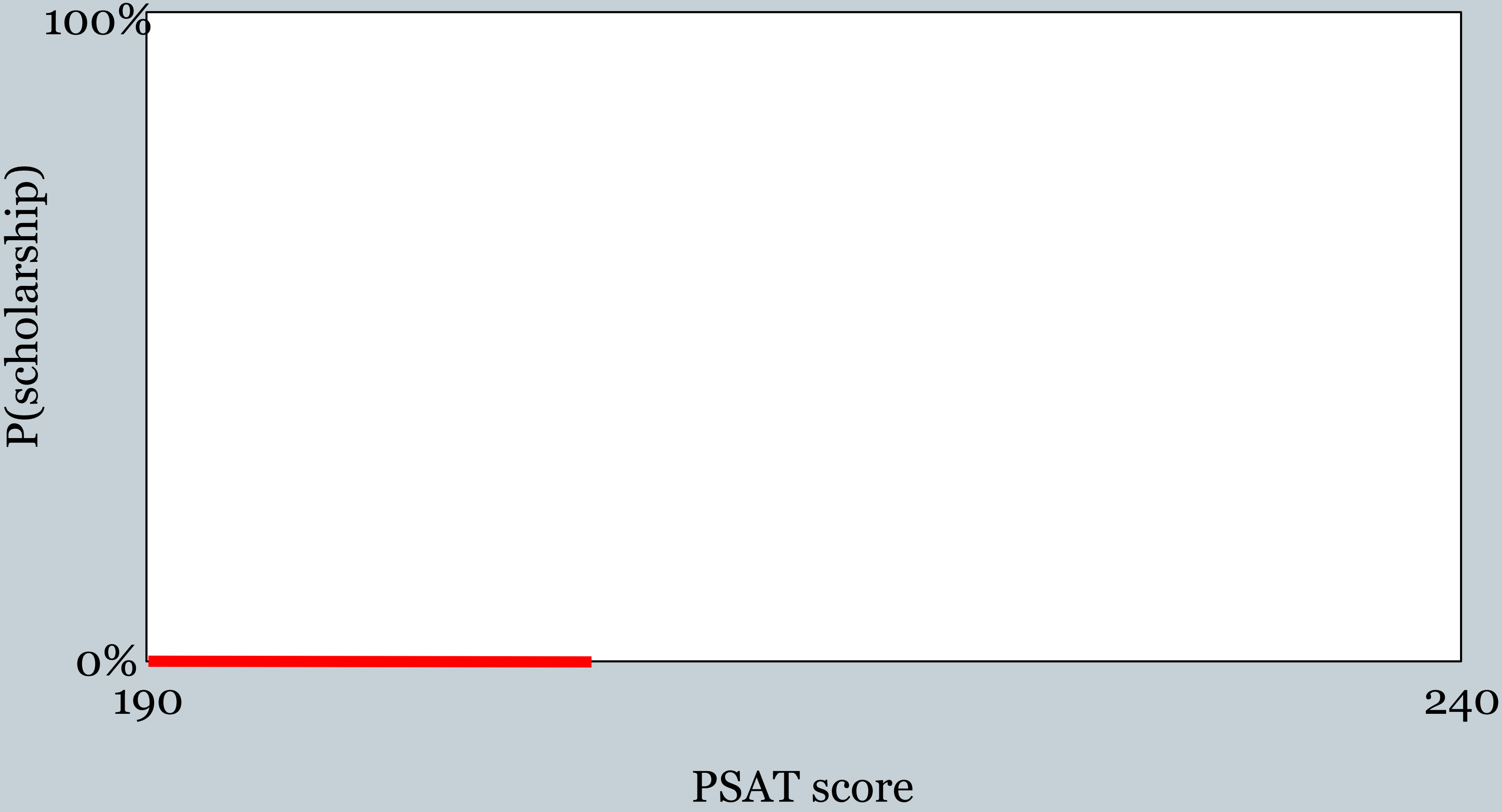
RD designs



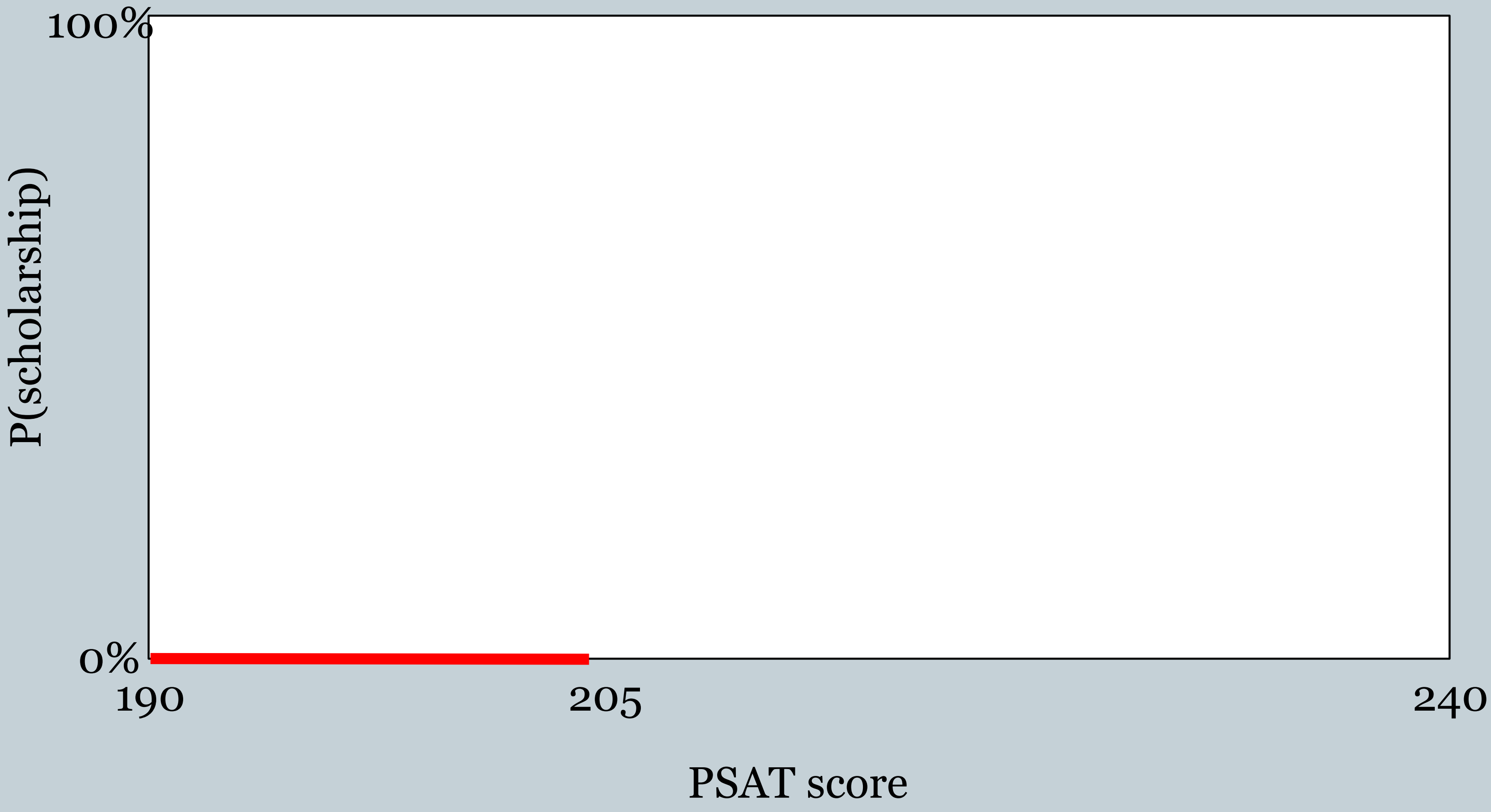
RD designs



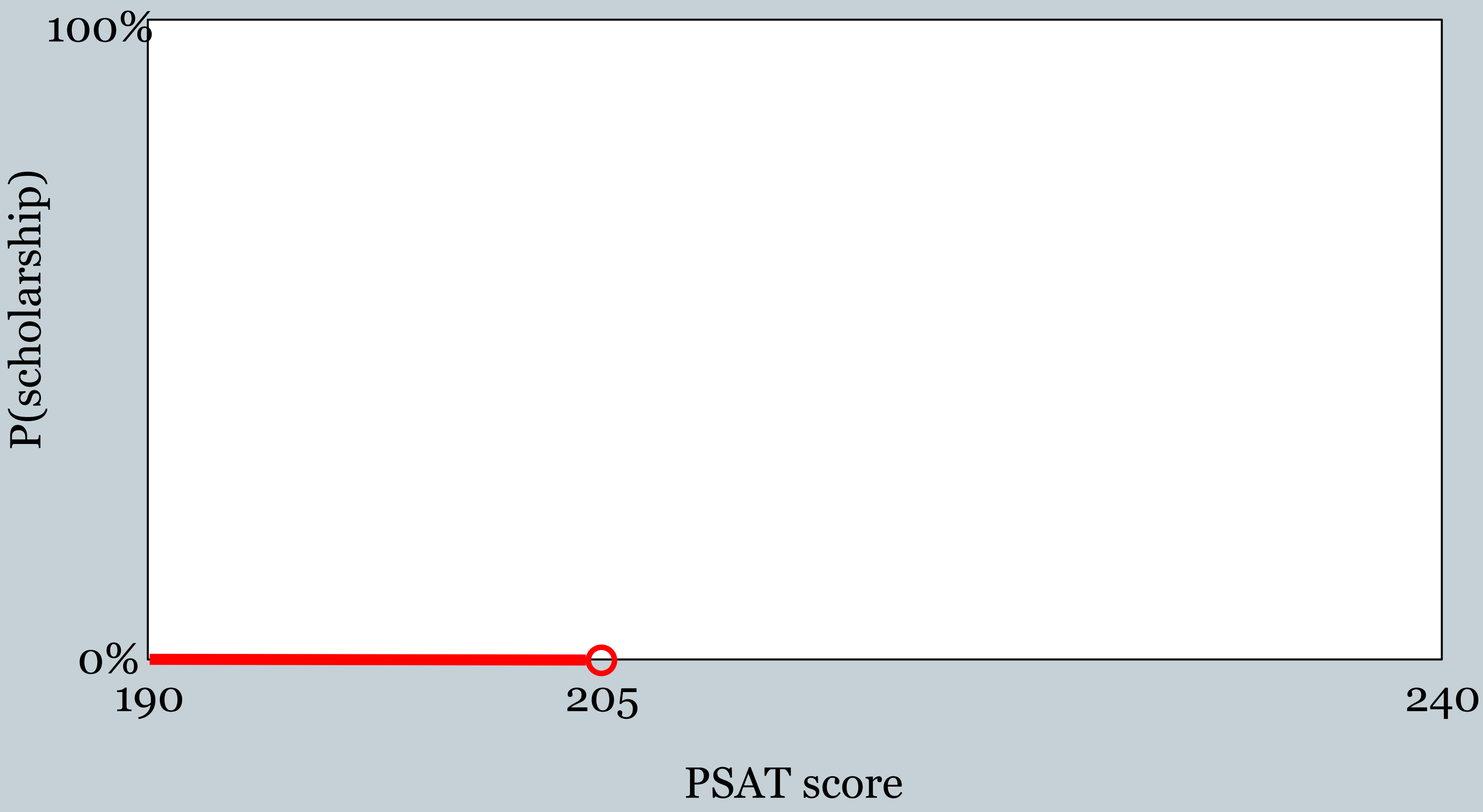
RD designs



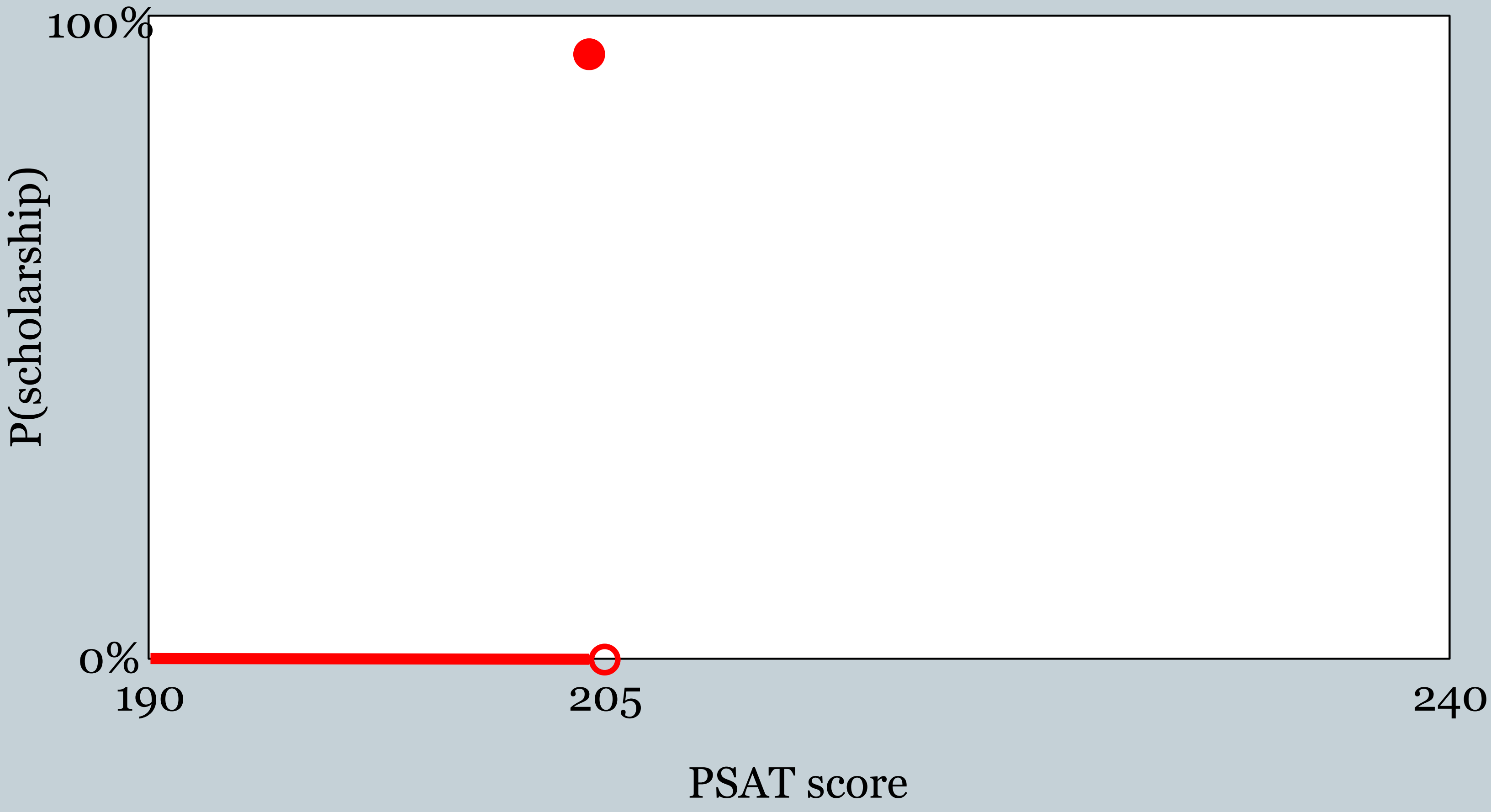
RD designs



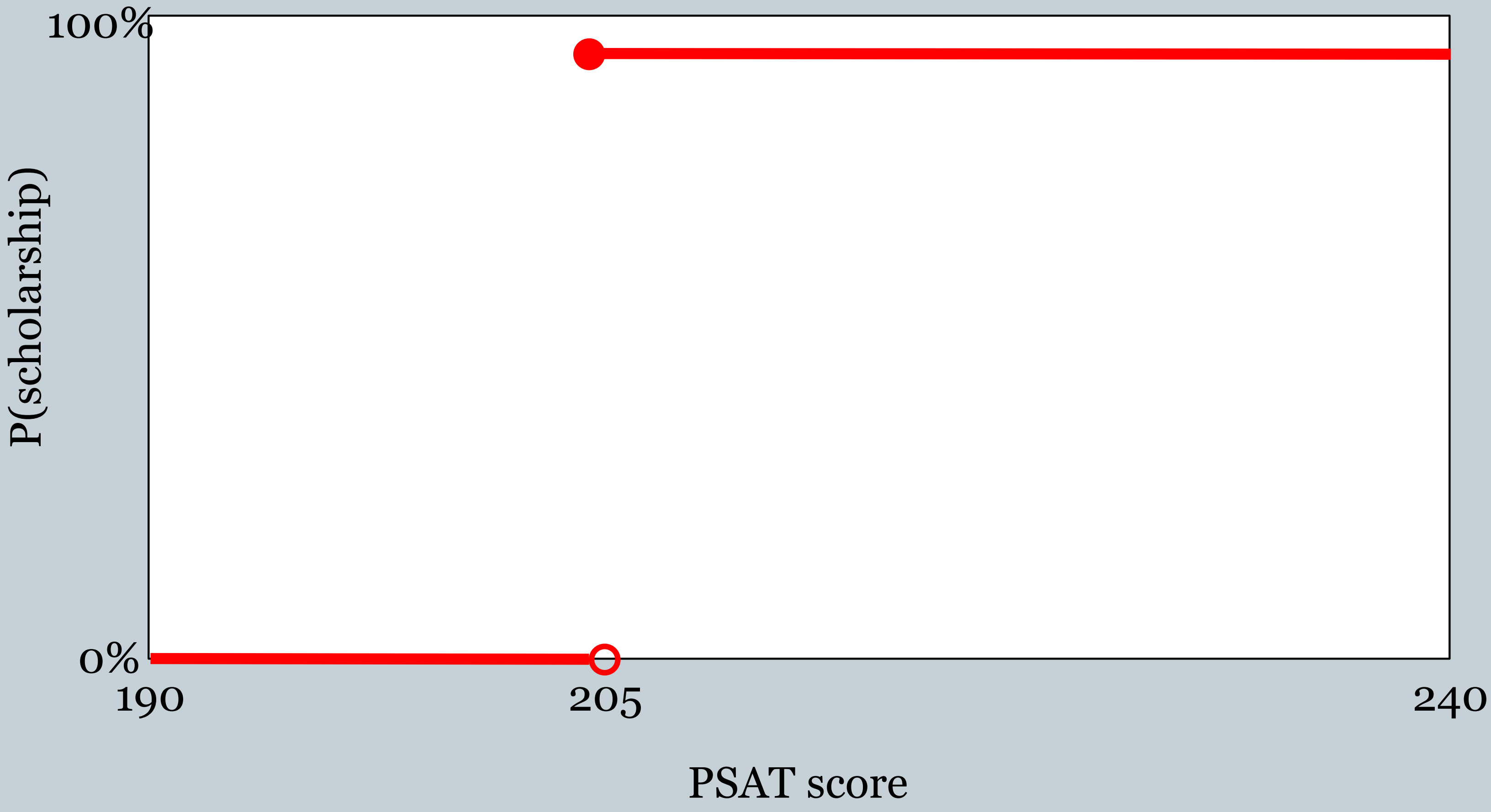
RD designs



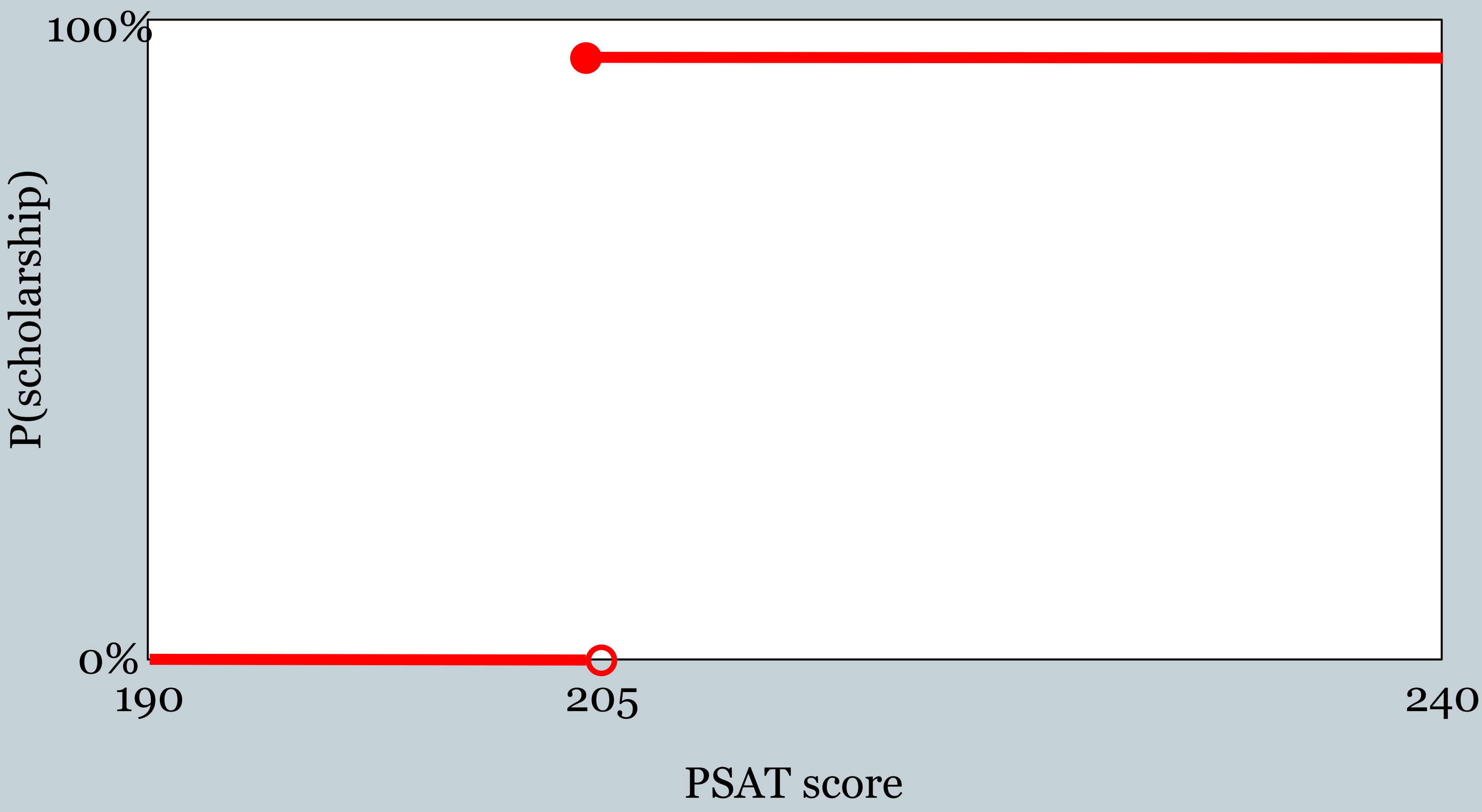
RD designs



RD designs



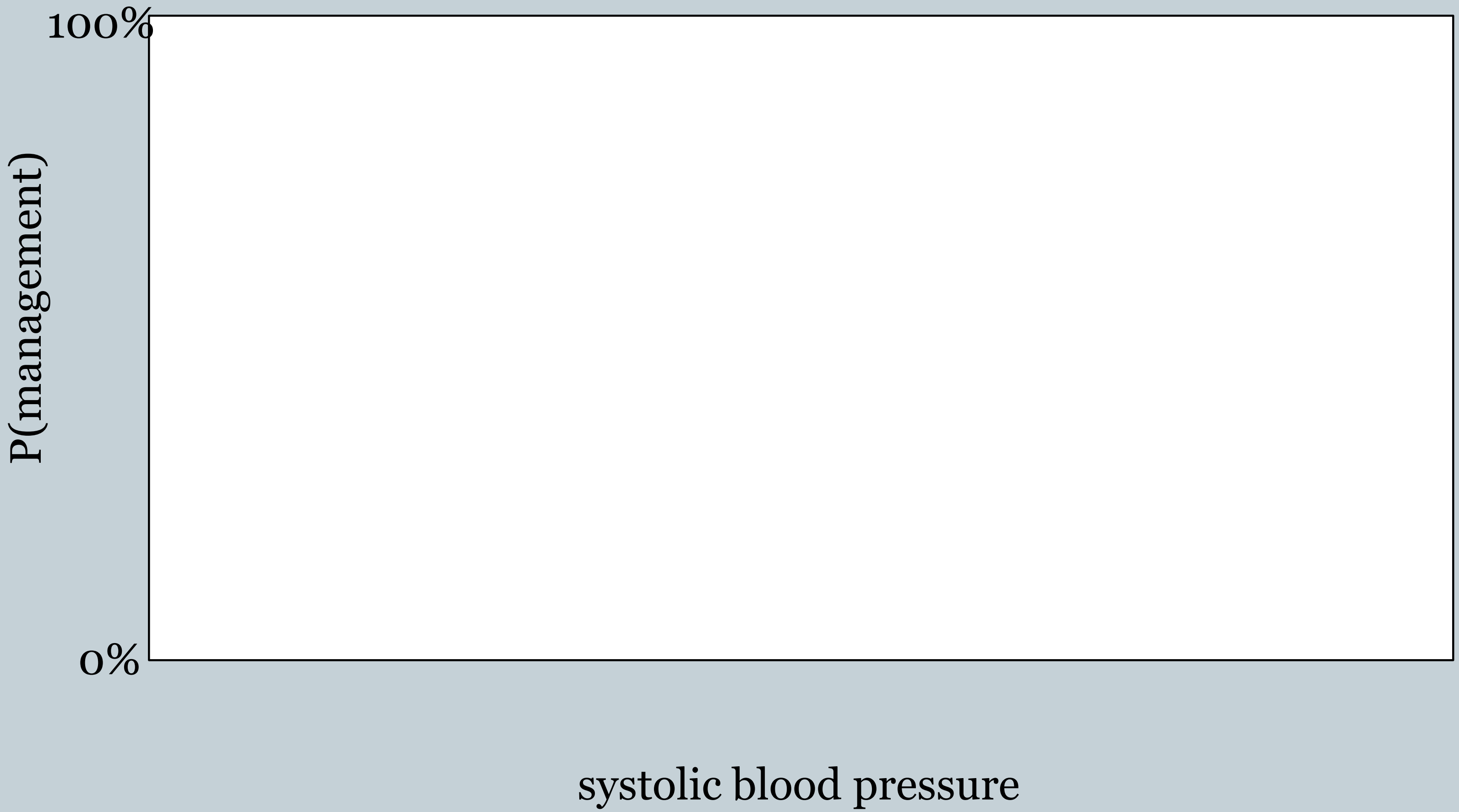
fuzzy RD designs



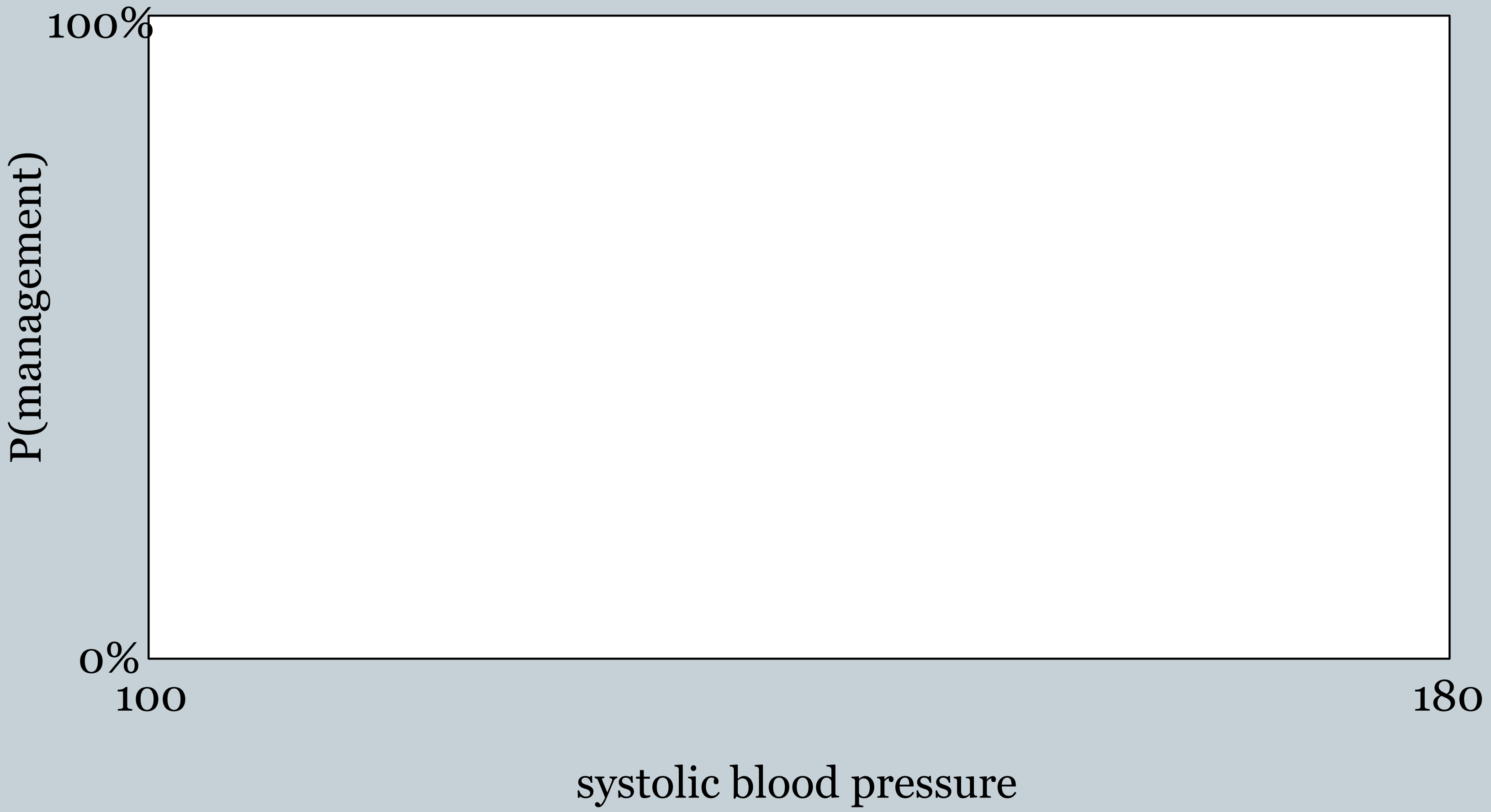
fuzzy RD designs: Blood Pressure

fuzzy RD designs: Blood Pressure

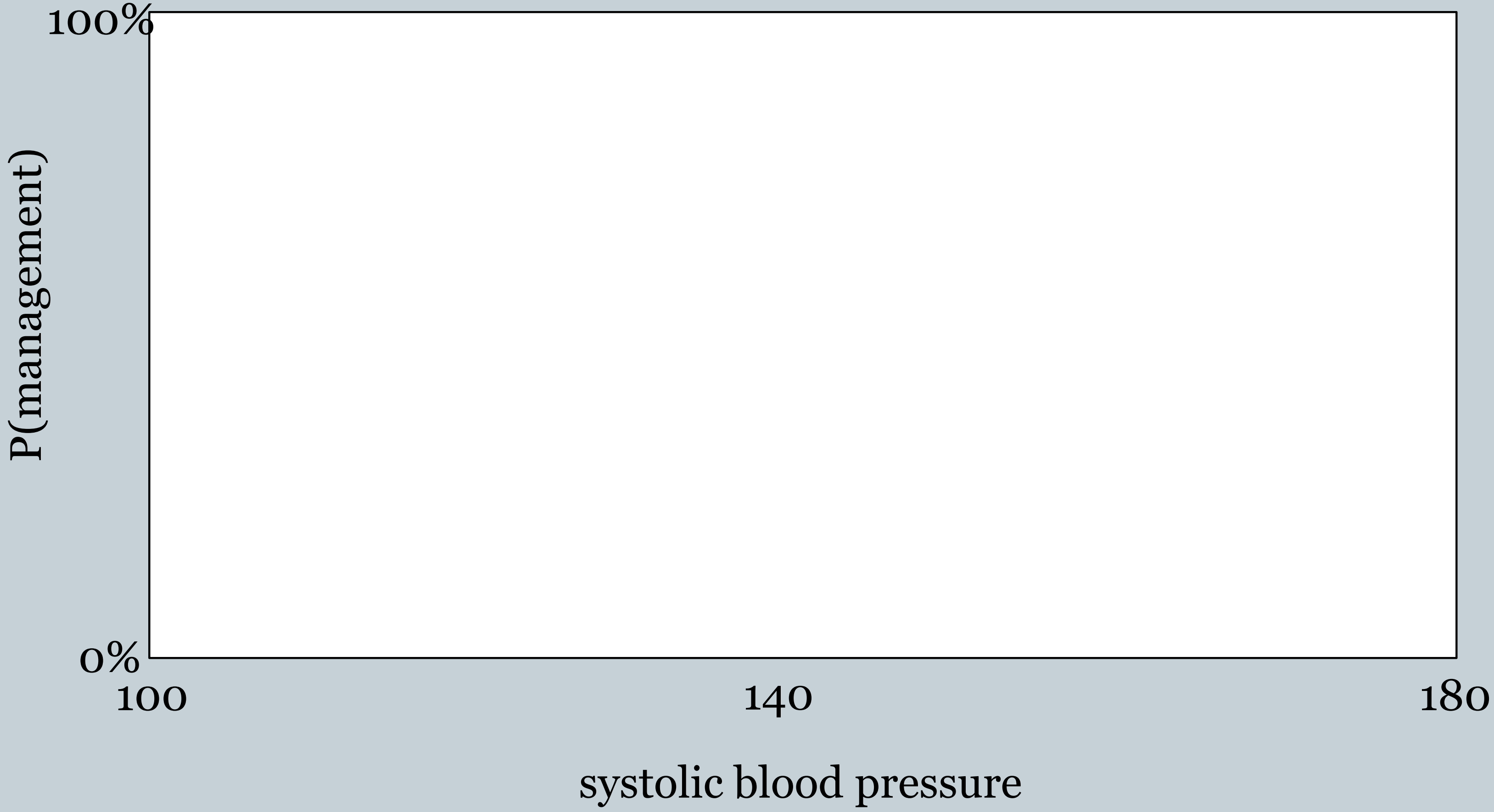
fuzzy RD designs: Blood Pressure



fuzzy RD designs: Blood Pressure

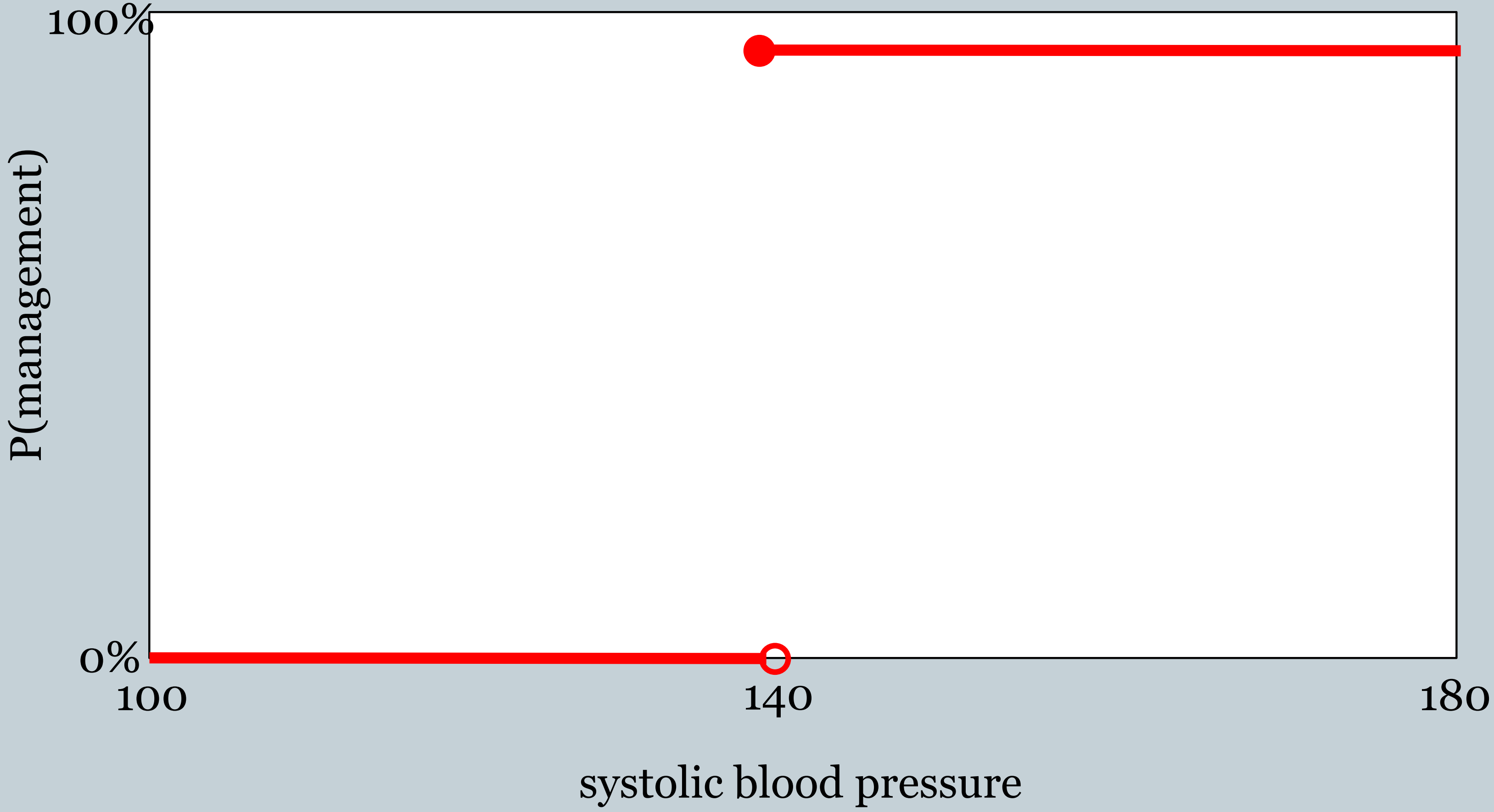


fuzzy RD designs: Blood Pressure

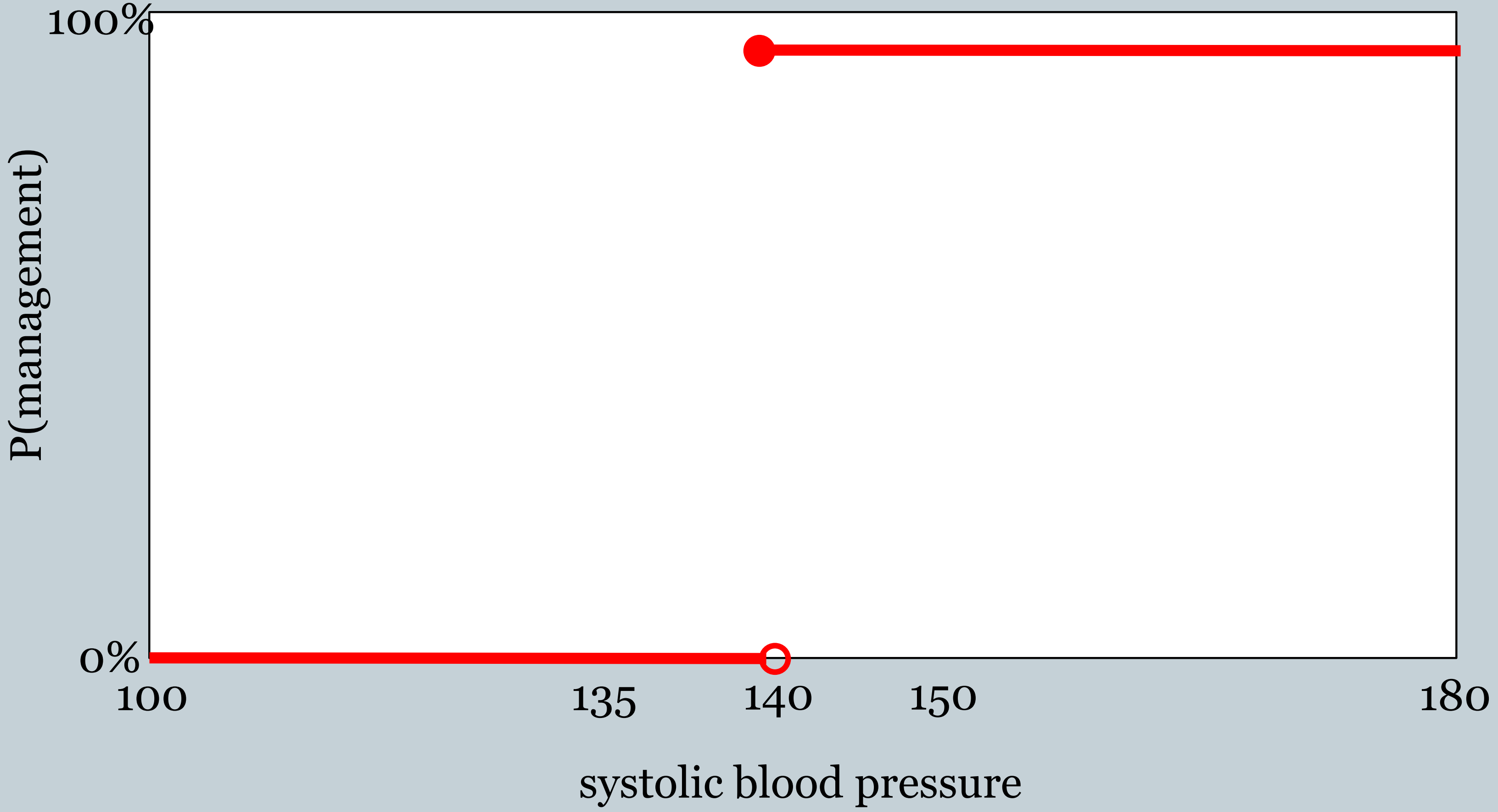


fuzzy

RD designs: Blood Pressure

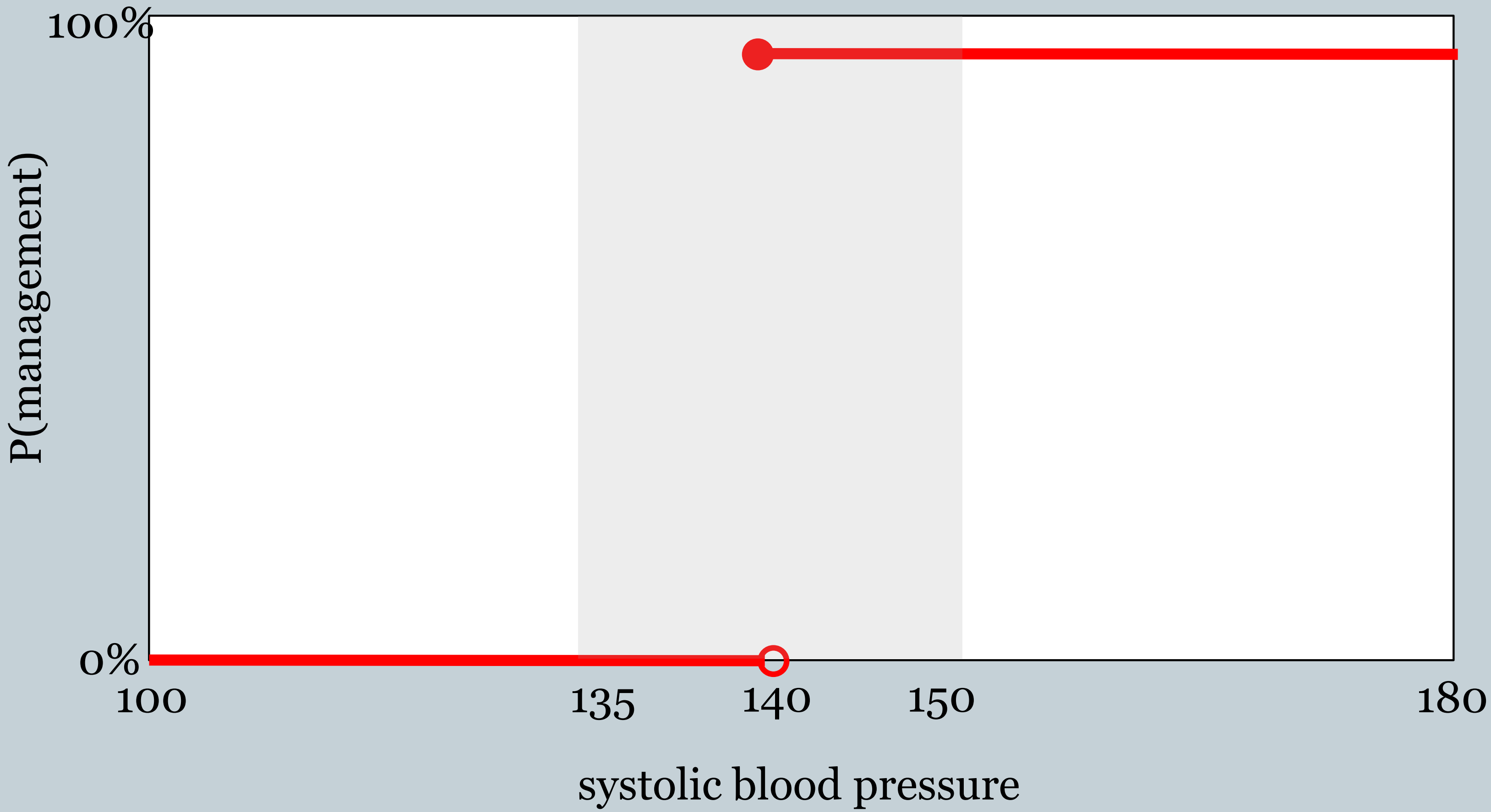


fuzzy
RD designs: Blood Pressure



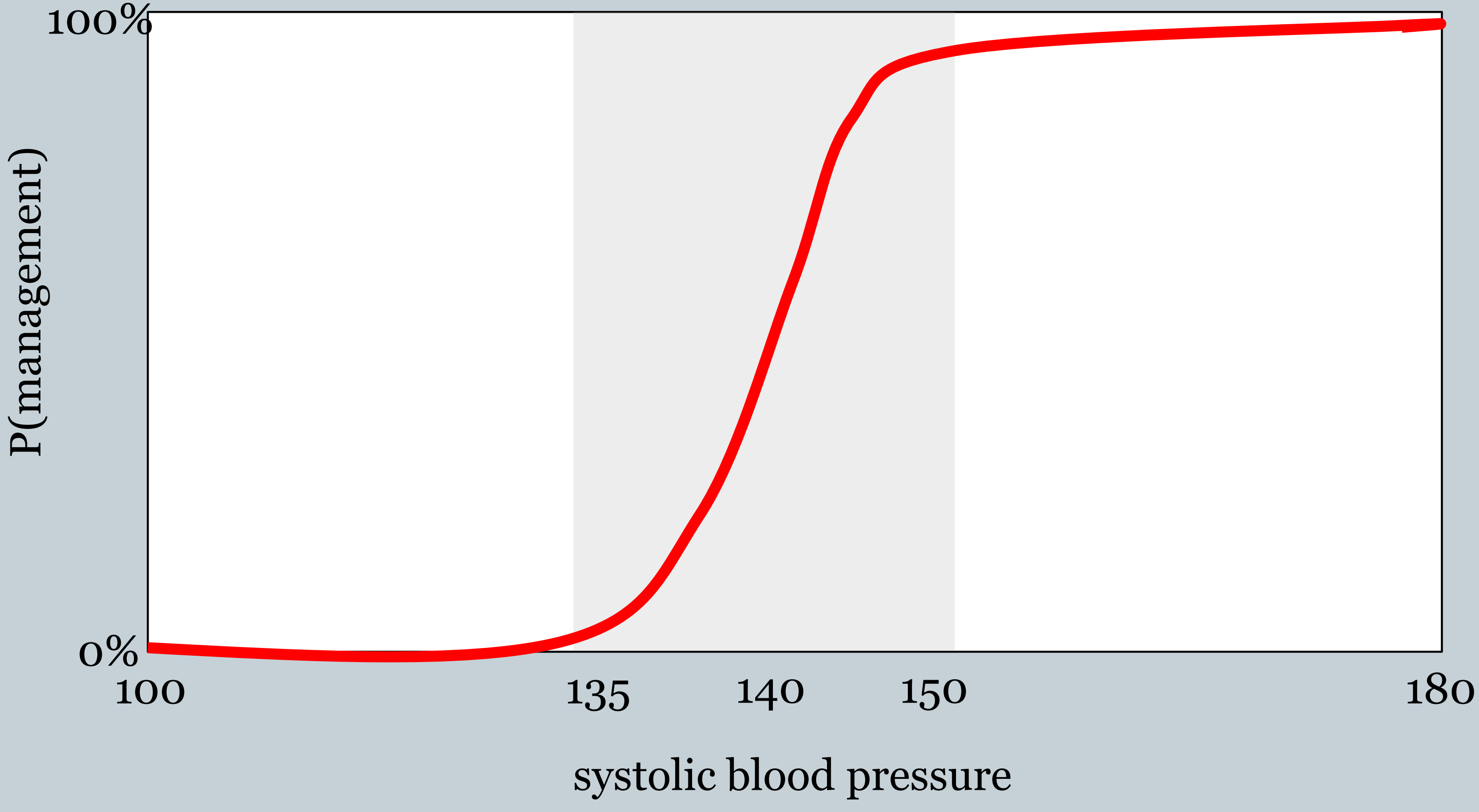
fuzzy

RD designs: Blood Pressure



fuzzy

RD designs: Blood Pressure



RD designs

RD designs

- Discuss the randomness

RD designs

- Discuss the randomness
  - Comes from lack of precise control around the cutoff point.

RD designs

- Discuss the randomness
  - Comes from lack of precise control around the cutoff point.
  - Is the randomness really unconnected with the variables you are concerned may be causing confounding?

RD designs

- Discuss the randomness
  - Comes from lack of precise control around the cutoff point.
  - Is the randomness really unconnected with the variables you are concerned may be causing confounding?
- Consider how far from the cutoff point to use.

RD designs

- Discuss the randomness
  - Comes from lack of precise control around the cutoff point.
  - Is the randomness really unconnected with the variables you are concerned may be causing confounding?
- Consider how far from the cutoff point to use.
- Do a Table 1 of above and below cutoff.

RD designs

- Discuss the randomness
  - Comes from lack of precise control around the cutoff point.
  - Is the randomness really unconnected with the variables you are concerned may be causing confounding?
- Consider how far from the cutoff point to use.
- Do a Table 1 of above and below cutoff.
  - Consider matching on covariates to improve balance.

RD designs

- Discuss the randomness
  - Comes from lack of precise control around the cutoff point.
  - Is the randomness really unconnected with the variables you are concerned may be causing confounding?
- Consider how far from the cutoff point to use.
- Do a Table 1 of above and below cutoff.
  - Consider matching on covariates to improve balance.
- Bottom line: RD tries set up like an RCT.

RD designs

- Discuss the randomness
  - Comes from lack of precise control around the cutoff point.
  - Is the randomness really unconnected with the variables you are concerned may be causing confounding?
- Consider how far from the cutoff point to use.
- Do a Table 1 of above and below cutoff.
  - Consider matching on covariates to improve balance.
- Bottom line: RD tries set up like an RCT. The randomness, though, is still “off-stage.”

RD designs

- Discuss the randomness
  - Comes from lack of precise control around the cutoff point.
  - Is the randomness really unconnected with the variables you are concerned may be causing confounding?
- Consider how far from the cutoff point to use.
- Do a Table 1 of above and below cutoff.
  - Consider matching on covariates to improve balance.
- Bottom line: RD tries set up like an RCT. The randomness, though, is still “off-stage.”
- Inference can be done like the pscore set up (sharp RD).

difference-in-differences

diff-in-diff

- Intuition:

diff-in-diff

- Intuition: difference-in-difference approaches try to reduce the variation in your estimate due to unit-to-unit differences.

diff-in-diff

- Intuition: difference-in-difference approaches try to reduce the variation in your estimate due to unit-to-unit differences. It does this by focusing on differencing a pre-treatment and post-post measurement.

diff-in-diff

- Intuition: difference-in-difference approaches try to reduce the variation in your estimate due to unit-to-unit differences. It does this by focusing on differencing a pre-treatment and post-post measurement.
- Keep in mind:

diff-in-diff

- Intuition: difference-in-difference approaches try to reduce the variation in your estimate due to unit-to-unit differences. It does this by focusing on differencing a pre-treatment and post-post measurement.
- Keep in mind: diff-in-diff is an approach that can often be pared with other aspects of design

diff-in-diff

- Intuition: difference-in-difference approaches try to reduce the variation in your estimate due to unit-to-unit differences. It does this by focusing on differencing a pre-treatment and post-post measurement.
- Keep in mind: diff-in-diff is an approach that can often be pared with other aspects of design (e.g., pscore matching, IVs, RCTs).

diff-in-diff

pre-treatment

treatment

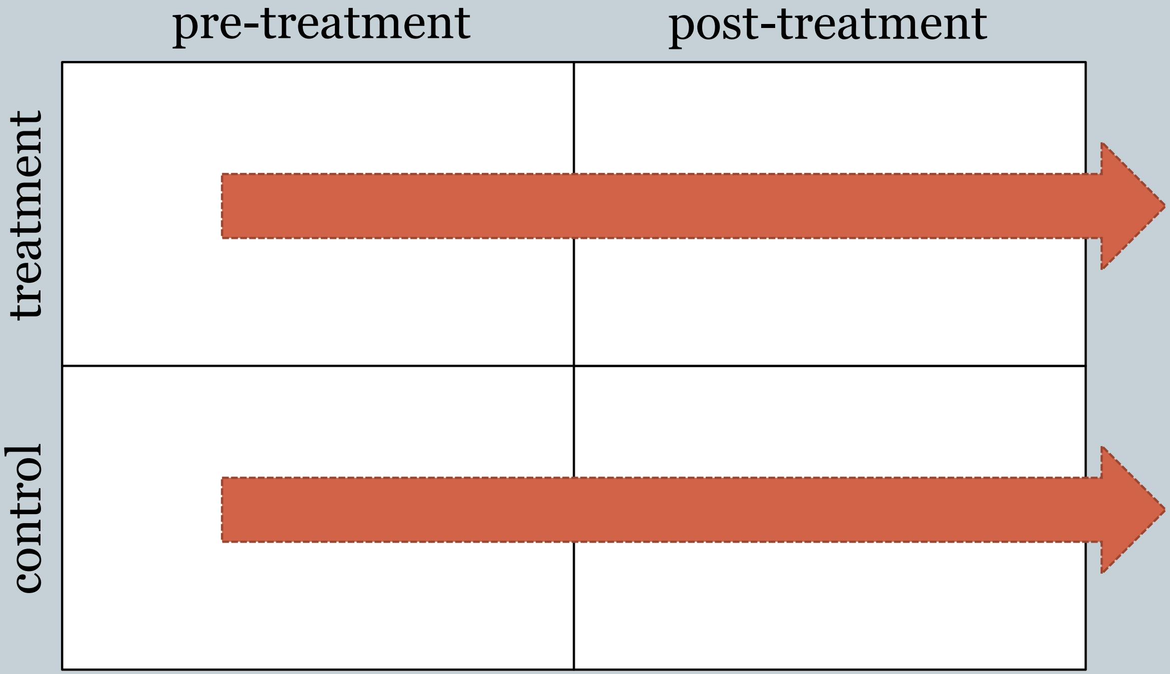
diff-in-diff

	pre-treatment	post-treatment
treatment		

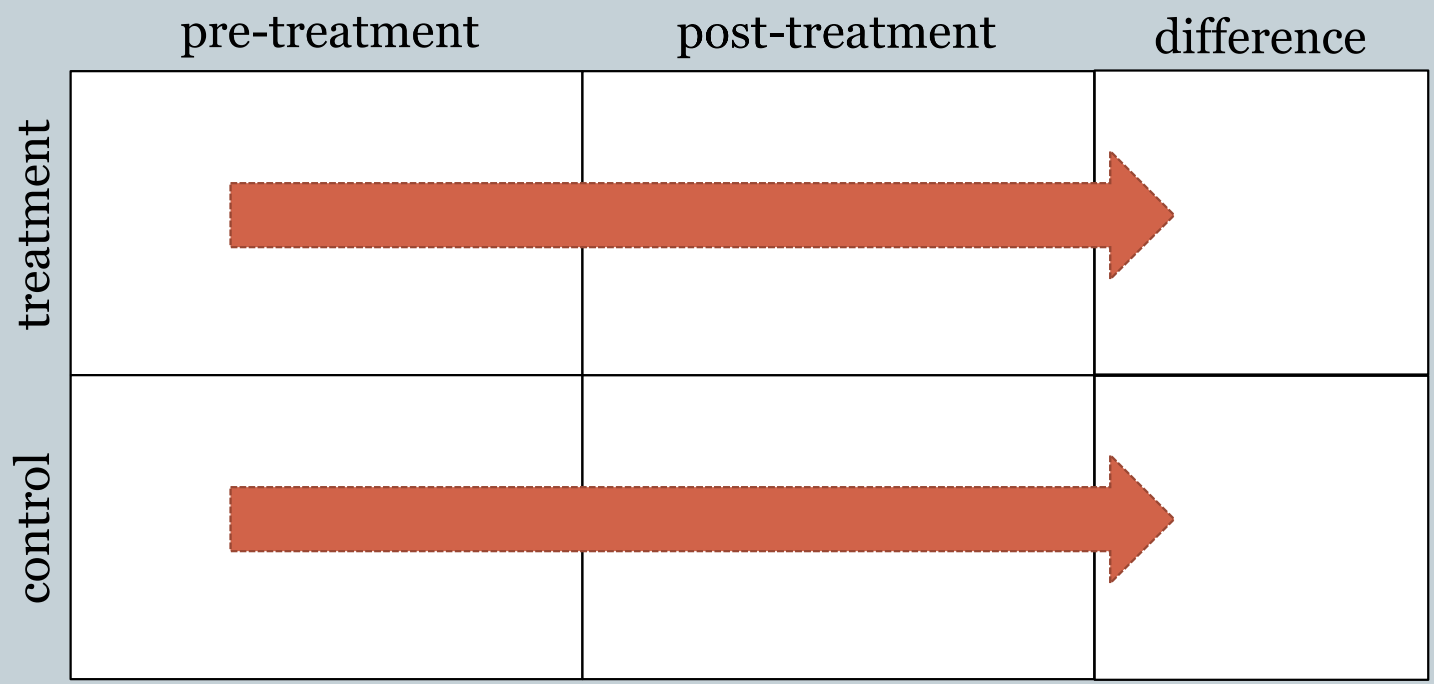
diff-in-diff

	pre-treatment	post-treatment
treatment		
control		

diff-in-diff



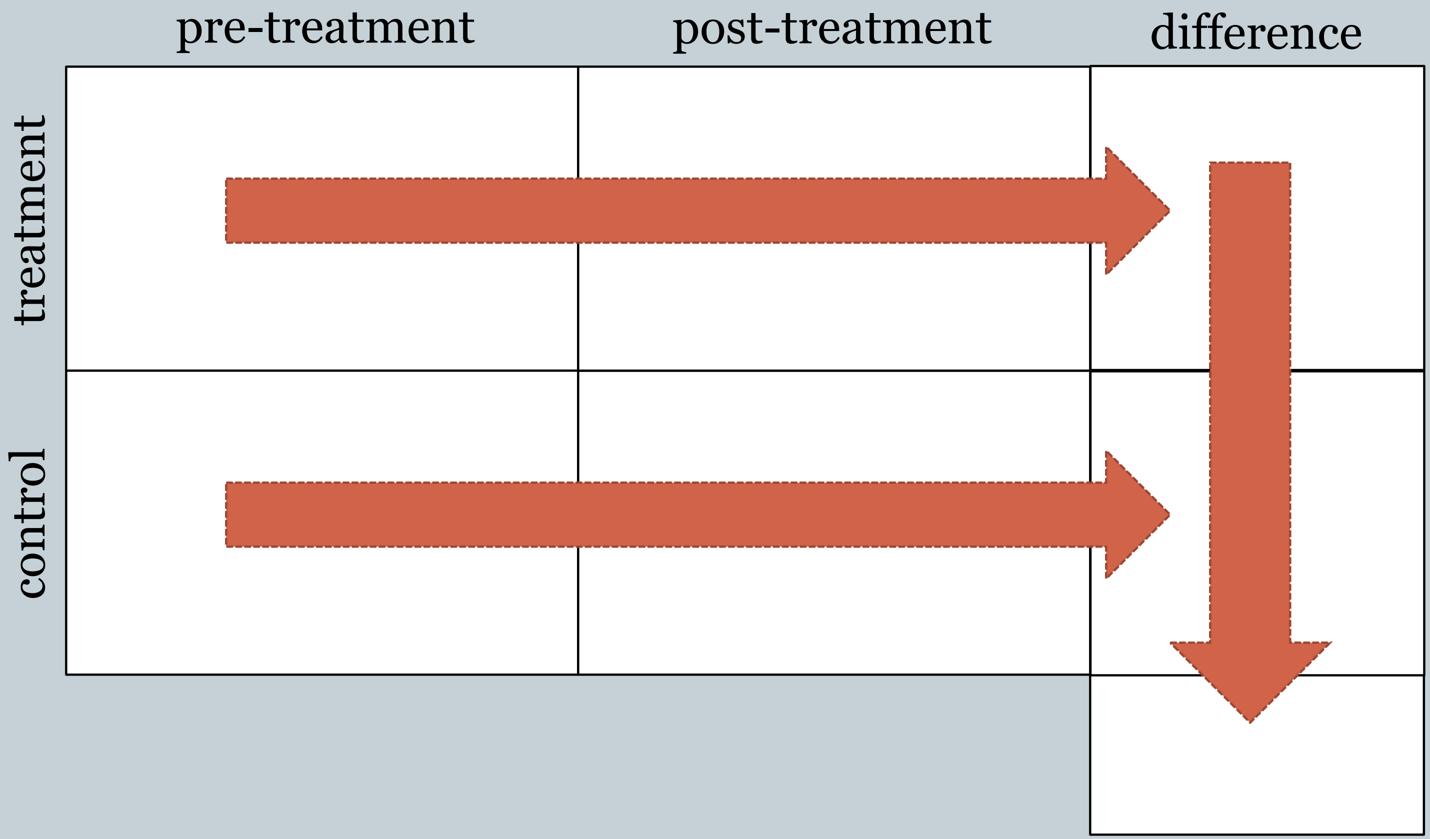
diff-in-diff


pre-treatment
post-treatment
difference
treatment
control

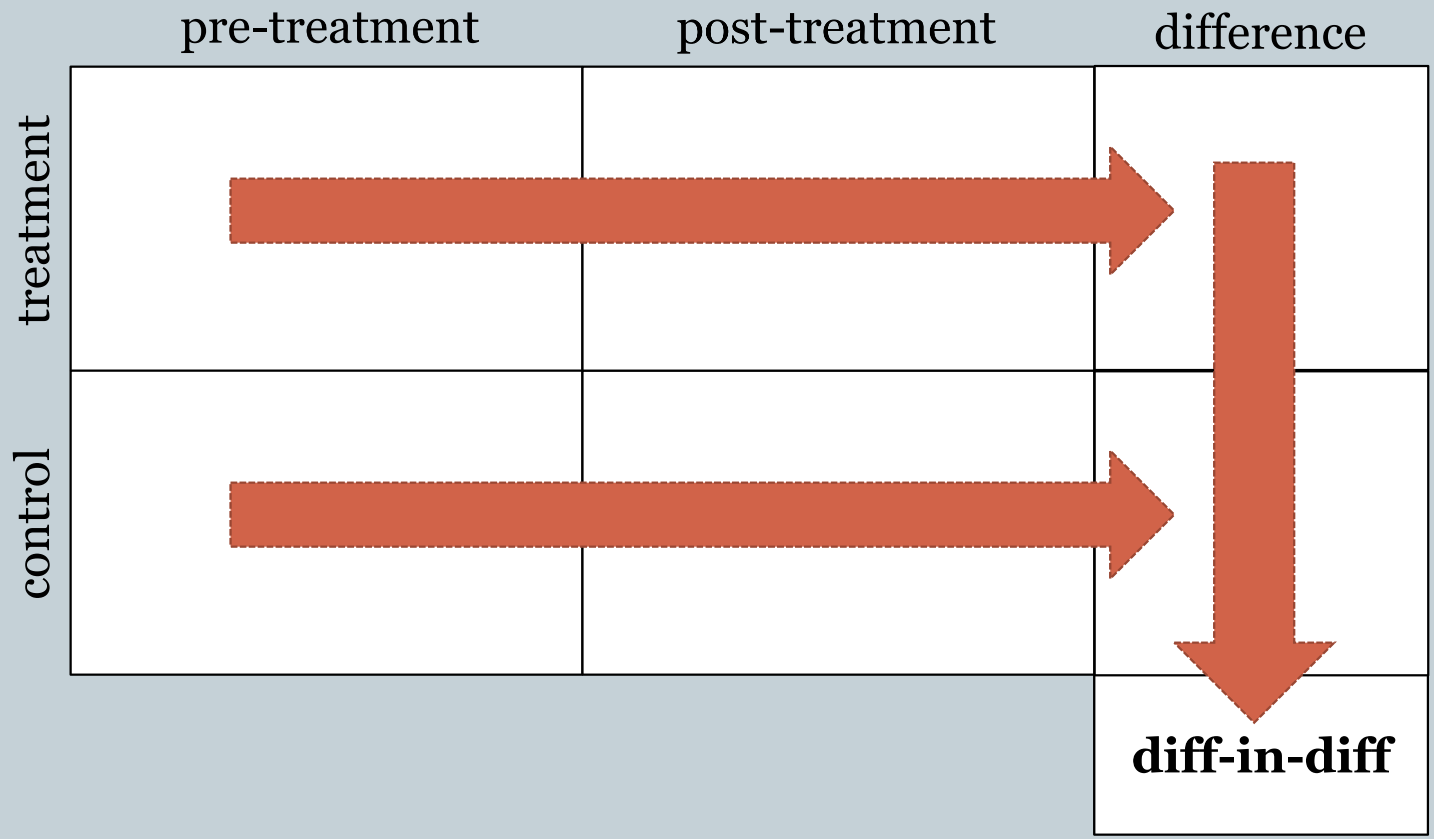
diff-in-diff


pre-treatment
post-treatment
difference
treatment
control

diff-in-diff


pre-treatment
post-treatment
difference
treatment
control

diff-in-diff


pre-treatment
post-treatment
difference
treatment
control
diff-in-diff

diff-in-diff: inference

- Inference:

diff-in-diff: inference

- Inference: When someone invoke a “diff-in-diff design” they haven’t necessarily identified their source of randomization.

diff-in-diff: inference

- Inference: When someone invoke a “diff-in-diff design” they haven’t necessarily identified their source of randomization. You still need to chase this out.

diff-in-diff: inference

- Briefly consider the example of Card and Krueger (1994):

diff-in-diff: inference

- Briefly consider the example of Card and Krueger (1994):

  New Jersey minimum wage increased, but Pennsylvania's did not. Looked at fast food restaurants near the border of the two states. Wanted the impact on employment.

diff-in-diff: inference

- Briefly consider the example of [Card and Krueger](#) (1994):

  New Jersey minimum wage increased, but Pennsylvania's did not. Looked at fast food restaurants near the border of the two states. Wanted the impact on employment.
- Belief is that the restaurants were the same before the change, and would have continued but for the minimum wage change.

diff-in-diff: inference

- Briefly consider the example of [Card and Krueger] (1994):

  New Jersey minimum wage increased, but Pennsylvania's did not. Looked at fast food restaurants near the border of the two states. Wanted the impact on employment.
- Belief is that the restaurants were the same before the change, and would have continued but for the minimum wage change.
- Design consideration:

diff-in-diff: inference

- Briefly consider the example of Card and Krueger (1994):

  New Jersey minimum wage increased, but Pennsylvania's did not. Looked at fast food restaurants near the border of the two states. Wanted the impact on employment.
- Belief is that the restaurants were the same before the change, and would have continued but for the minimum wage change.
- Design consideration: try to look at "burn in" period prior to the intervention.

diff-in-diff: inference

- Briefly consider the example of [Card and Krueger](#) (1994):

  New Jersey minimum wage increased, but Pennsylvania's did not. Looked at fast food restaurants near the border of the two states. Wanted the impact on employment.
- Belief is that the restaurants were the same before the change, and would have continued but for the minimum wage change.
- Design consideration: try to look at "burn in" period prior to the intervention. The more you can get the two groups similar prior, the easier your case will be.

diff-in-diff: inference

- Briefly consider the example of Card and Krueger (1994):

  New Jersey minimum wage increased, but Pennsylvania's did not. Looked at fast food restaurants near the border of the two states. Wanted the impact on employment.
- Belief is that the restaurants were the same before the change, and would have continued but for the minimum wage change.
- Design consideration: try to look at "burn in" period prior to the intervention. The more you can get the two groups similar prior, the easier your case will be.
  - Researchers end up using matching a lot in diff-in-diff designs.

diff-in-diff: inference

- In a structural equation model approach:

diff-in-diff: inference

- In a structural equation model approach:

$$y_{i,t} = \beta_0 + \beta_t * t_i + \beta_d * d_i + \beta_{t*d} t_i * d_i + \varepsilon_{i,t}$$

diff-in-diff: inference

- In a structural equation model approach:

$$y_{i,t} = \beta_0 + \beta_t * t_i + \beta_d * d_i + \beta_{t*d} t_i * d_i + \varepsilon_{i,t}$$

where t is time (pre=0, post=1) and d is the intervention (control=0,intervention=1) and $t_i * d_i$ is an interaction term.

diff-in-diff: inference

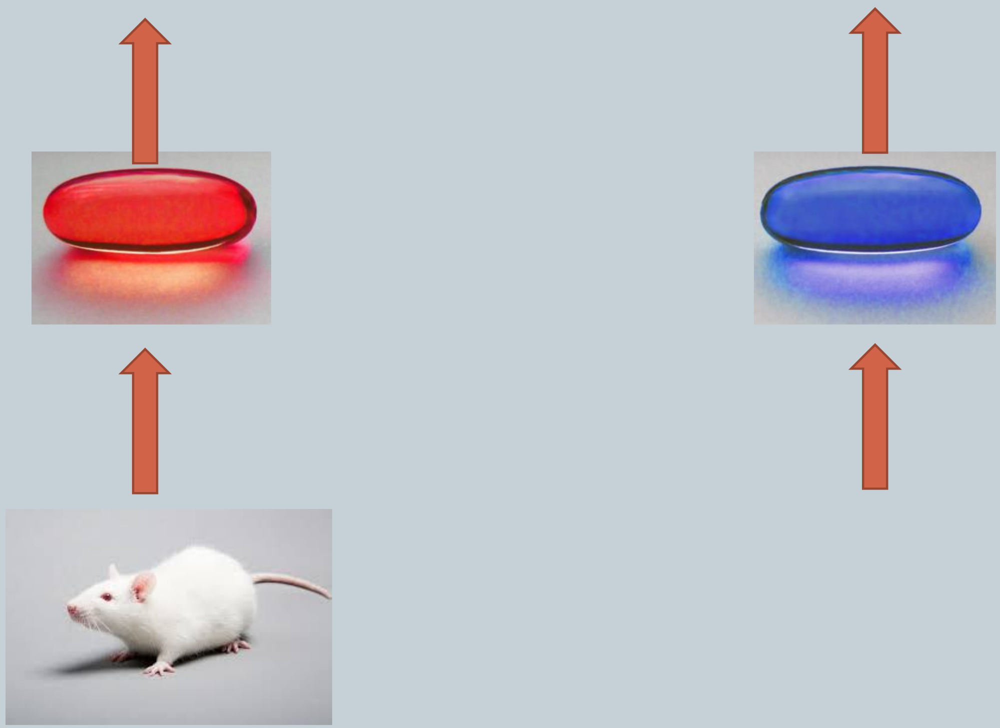
- In a structural equation model approach:

$$y_{i,t} = \beta_0 + \beta_t * t_i + \beta_d * d_i + \beta_{t*d} t_i * d_i + \varepsilon_{i,t}$$

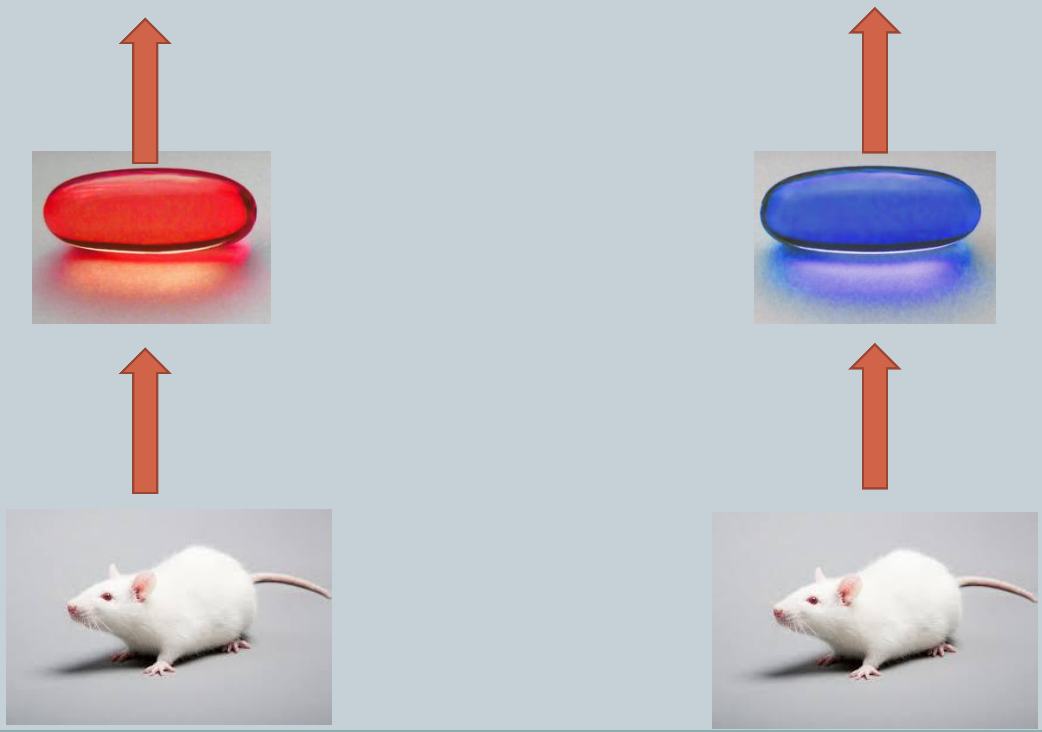
where t is time (pre=0, post=1) and d is the intervention (control=0,intervention=1) and $t_i * d_i$ is an interaction term. The quantity of interest is β_{t*d}.

method of difference

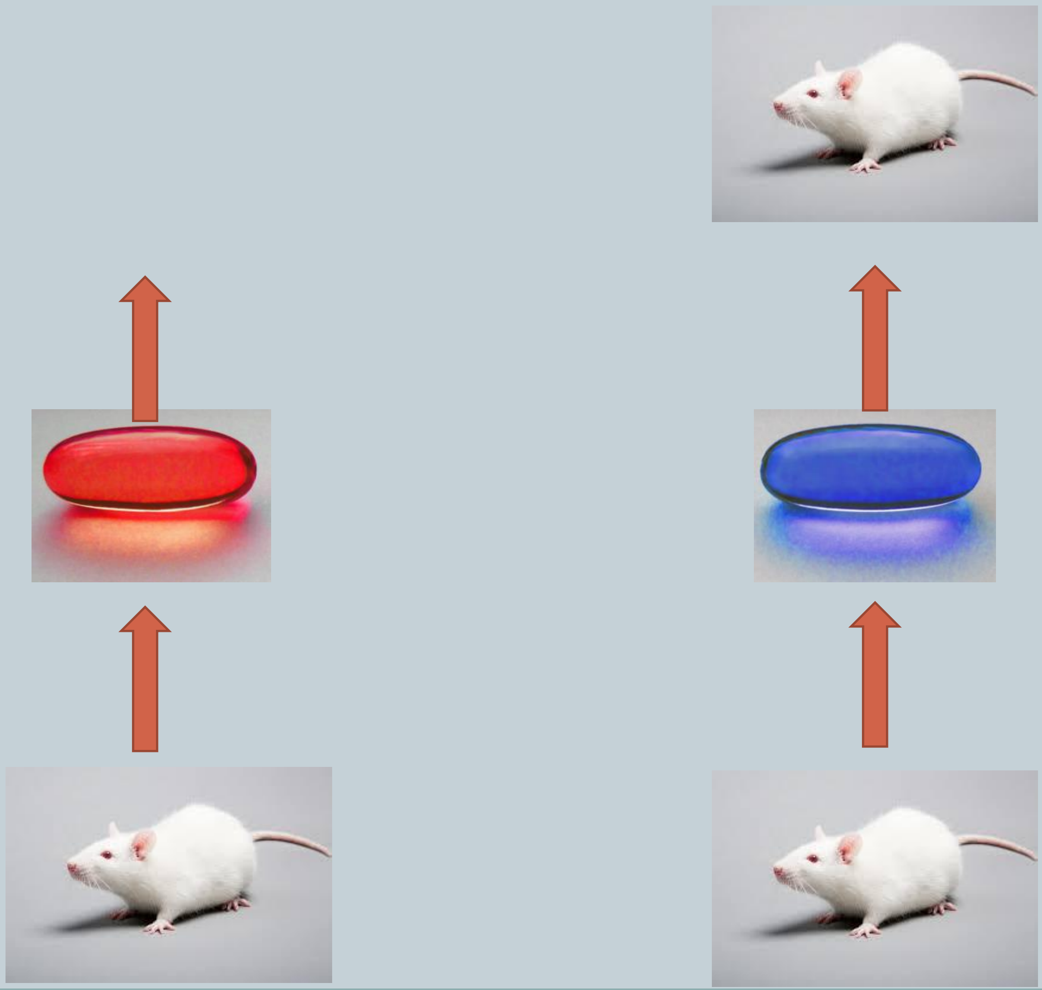
method of difference



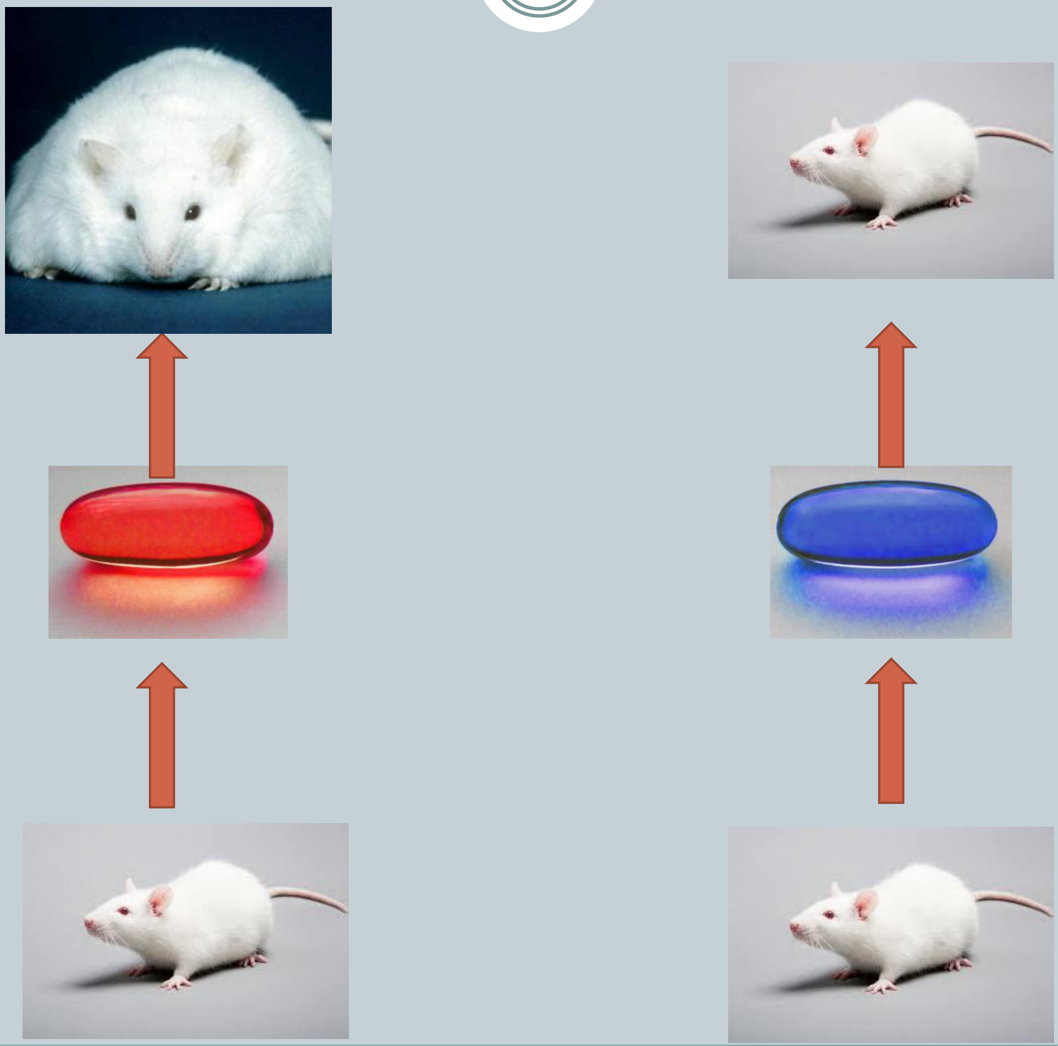
method of difference

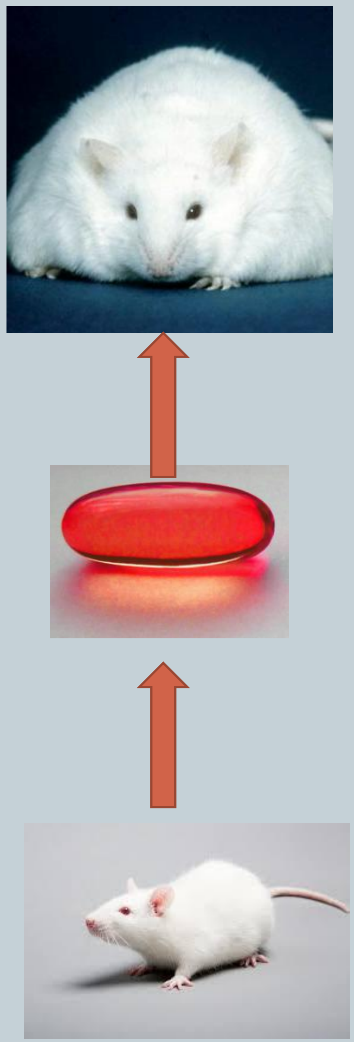


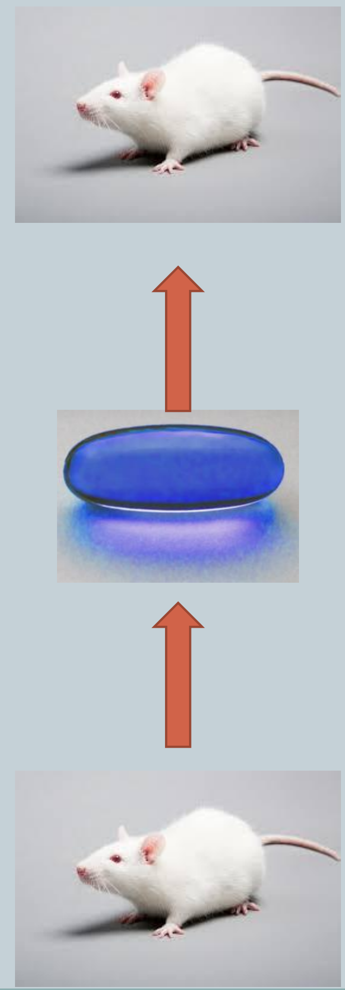
method of difference

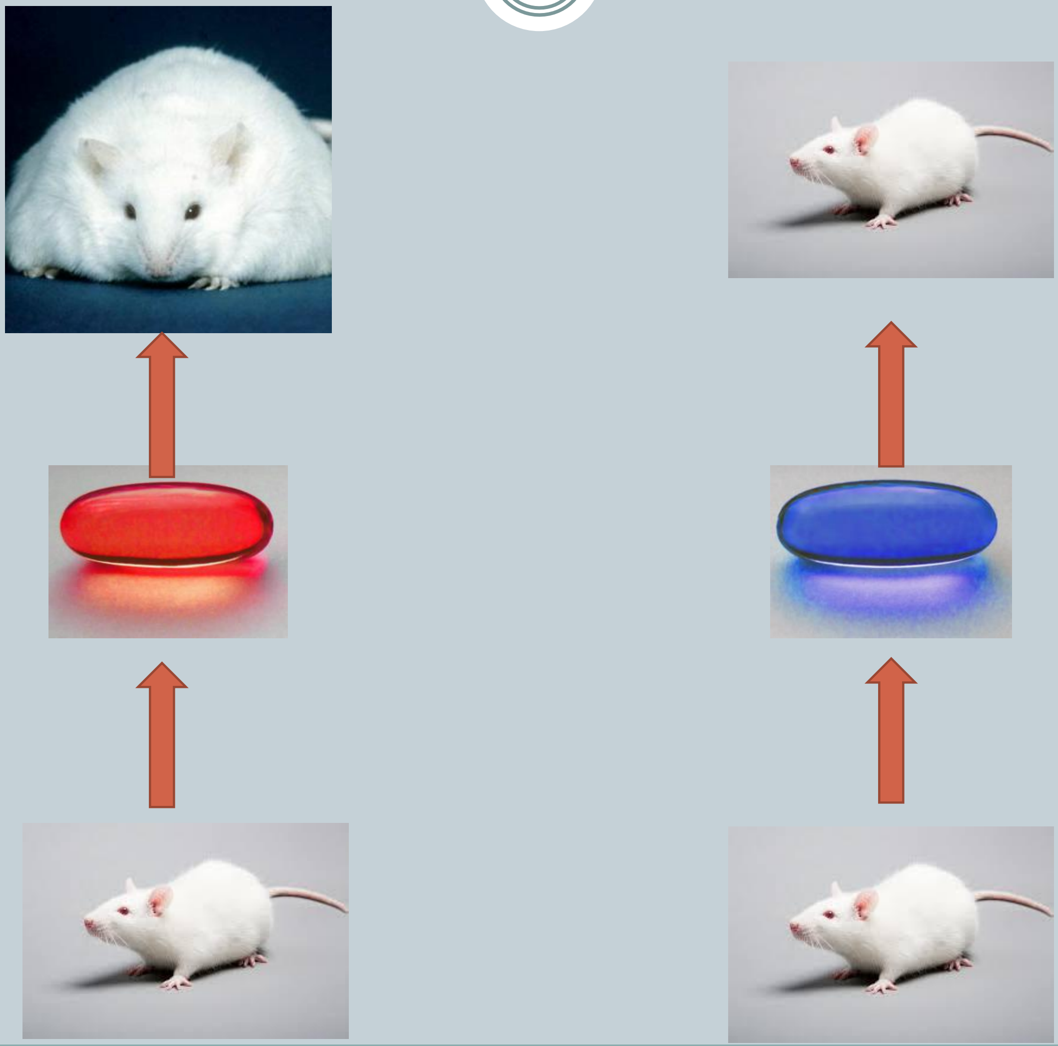


method of difference



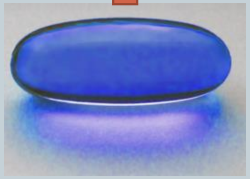






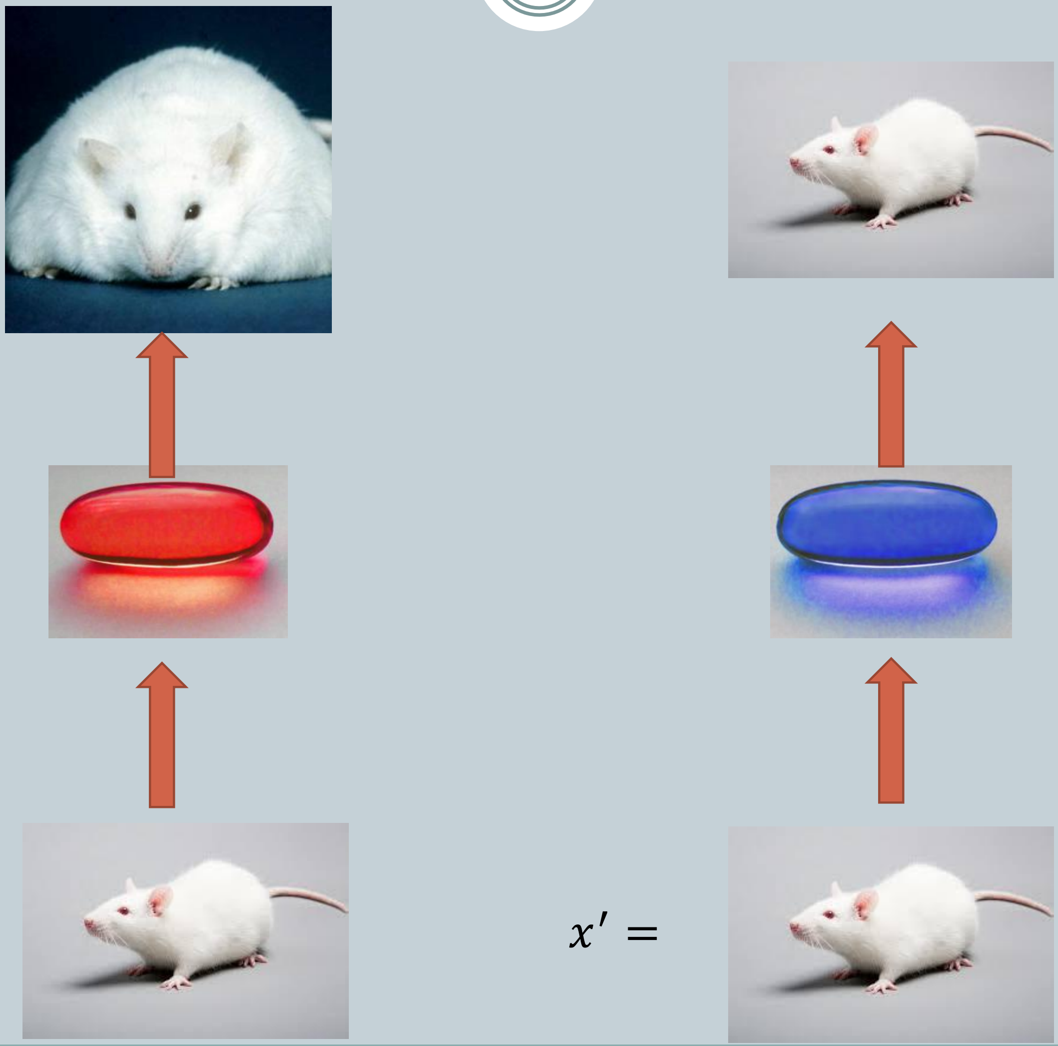
$x =$

$x =$



$x' =$

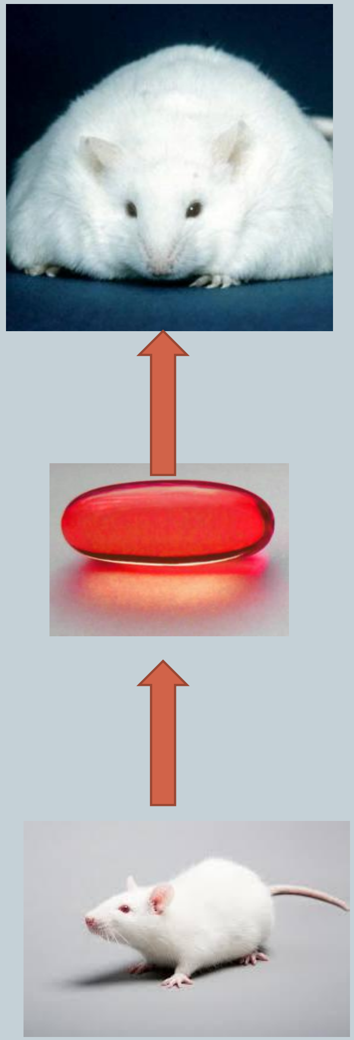
$r_T = f(d = 1, X = x)$ $r_C = f(d = 0, X = x')$



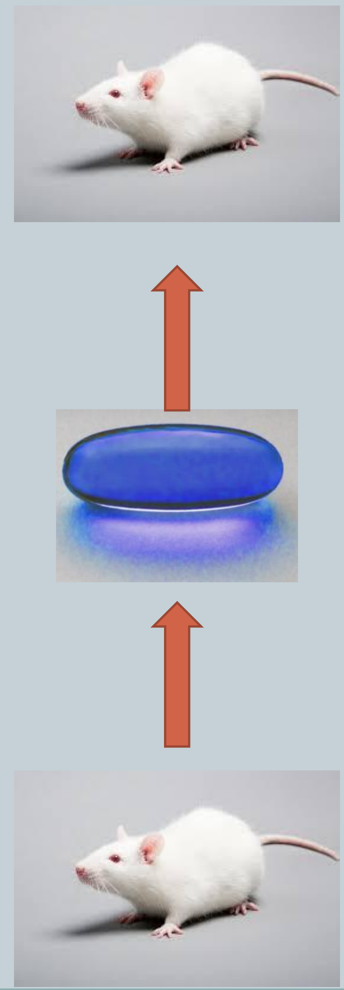
$x =$ $x' =$

$$r_T = f(d = 1, X = x)$$

$$r_C = f(d = 0, X = x')$$



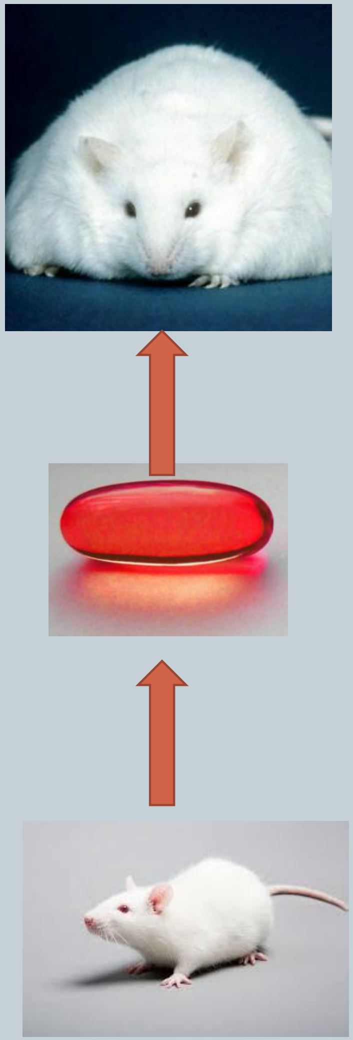
$x =$



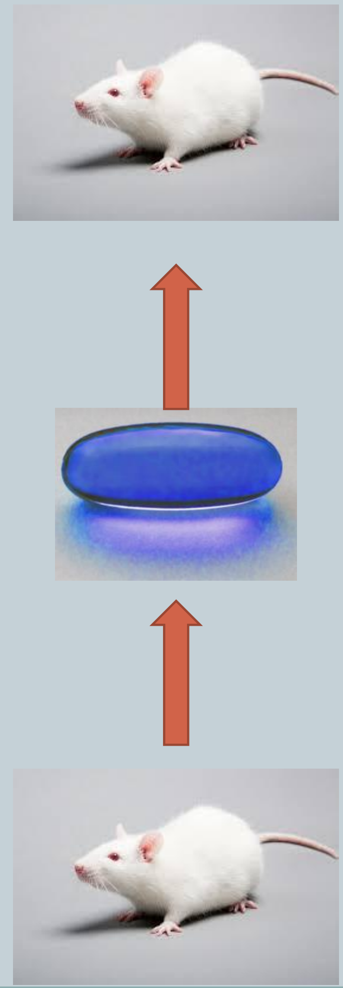
$\boldsymbol{x} =$

$$r_T = f(d = 1, X = x)$$

$$r_C = f(d = 0, X = \boldsymbol{x})$$



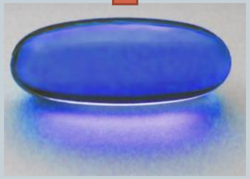
$x =$



$\boldsymbol{x} =$

The only difference

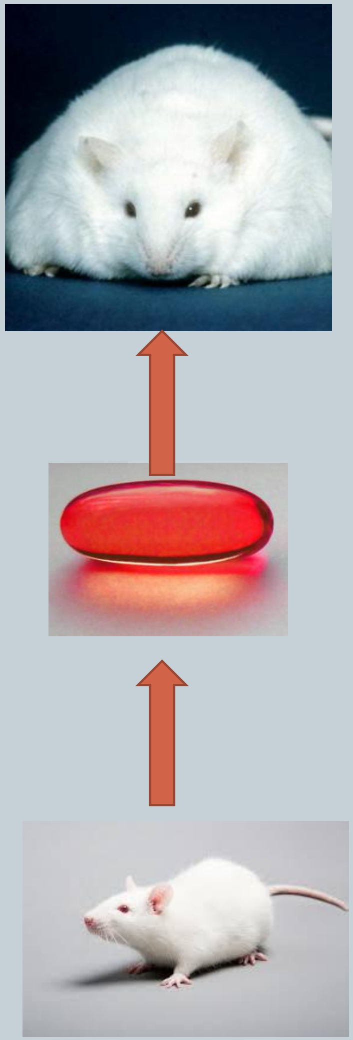
$$r_T = f(d = 1, X = \boldsymbol{x}) \qquad r_C = f(d = 0, X = \boldsymbol{x})$$



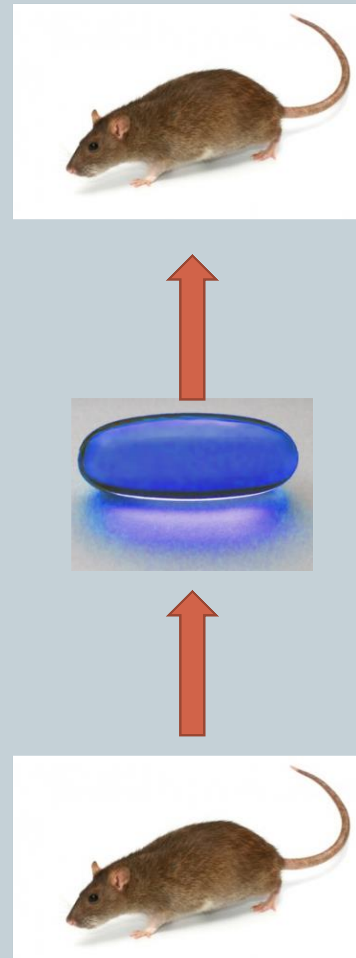
$\boldsymbol{x} =$ 

$\boldsymbol{x} =$

$r_T = f(d = 1, X = x)$ $r_C = f(d = 0, X = x')$

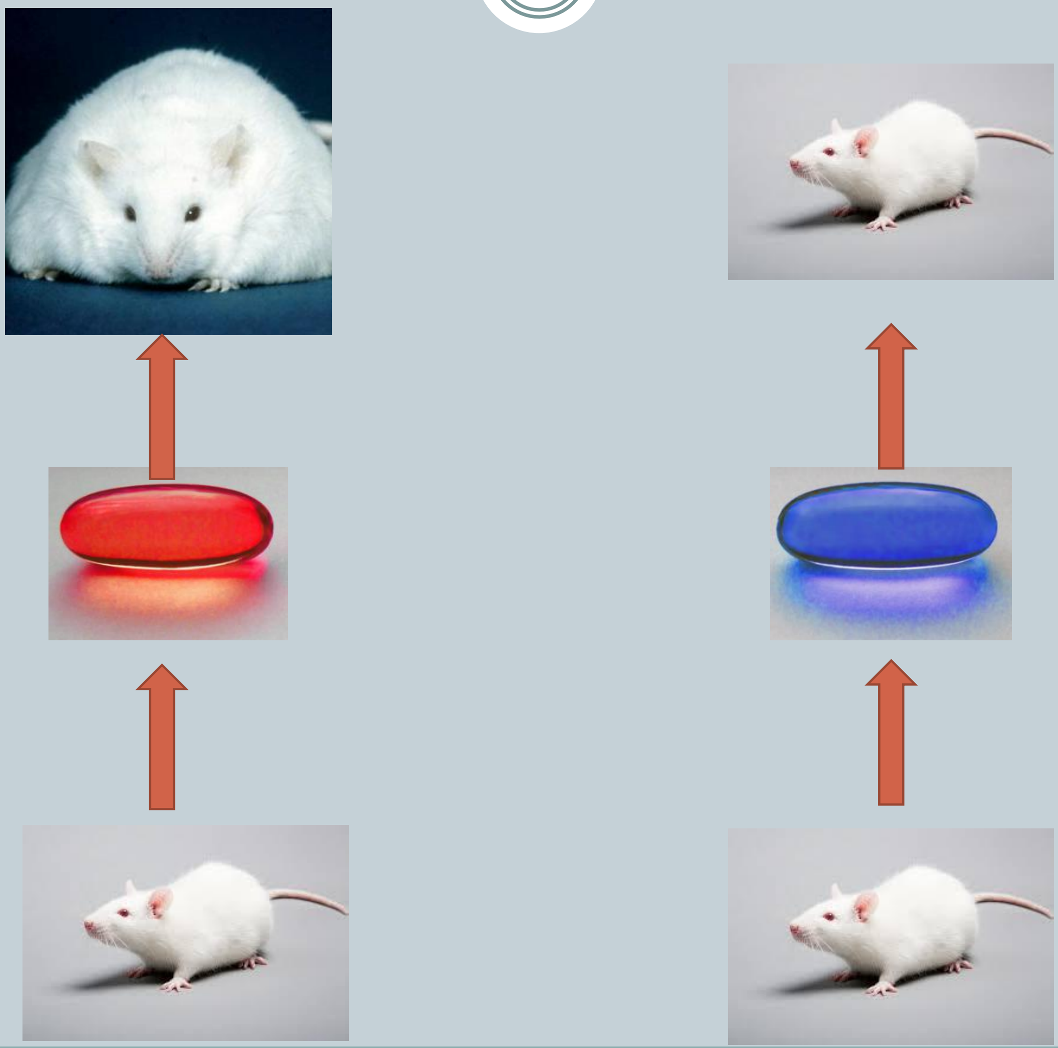


$x =$

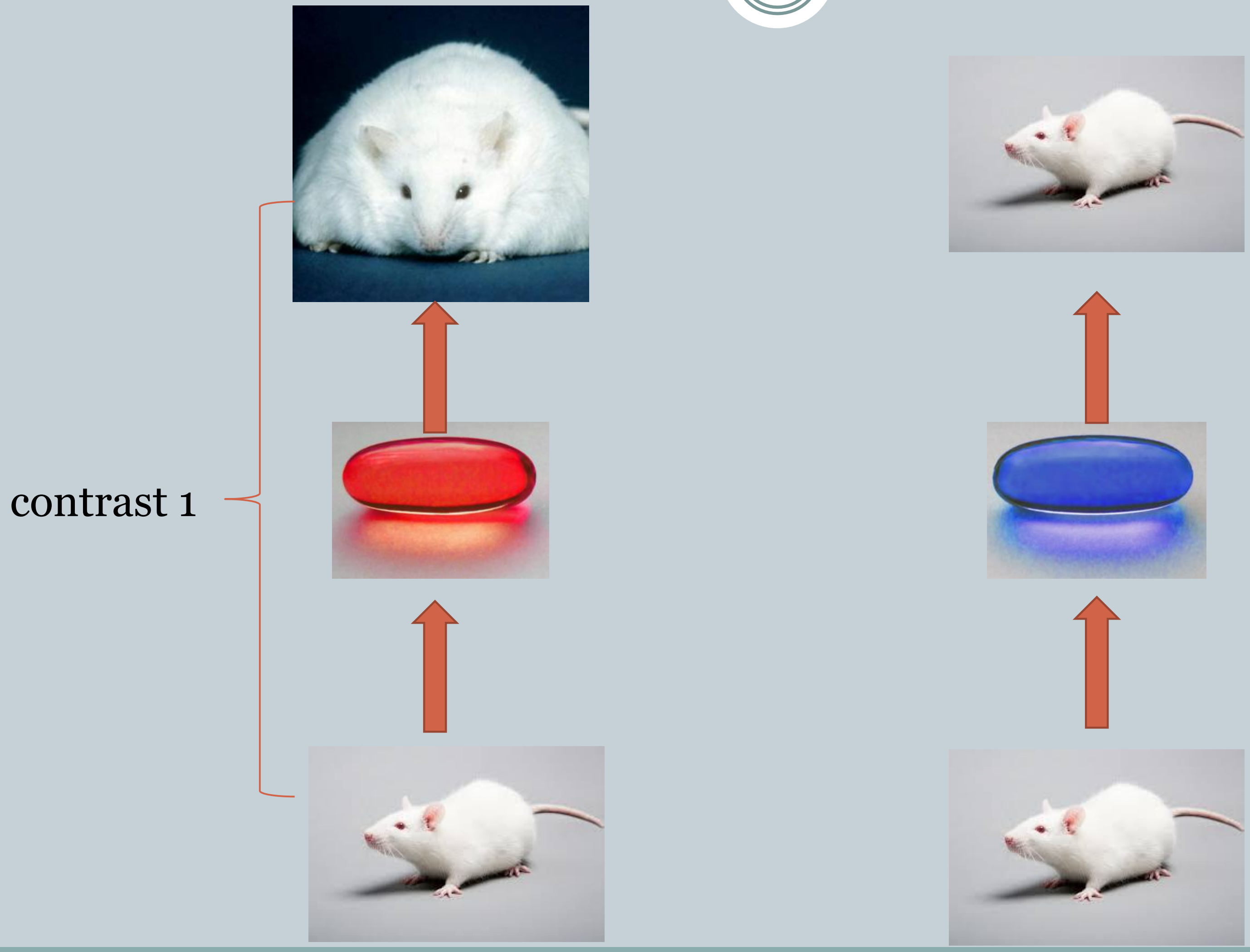


$x' =$

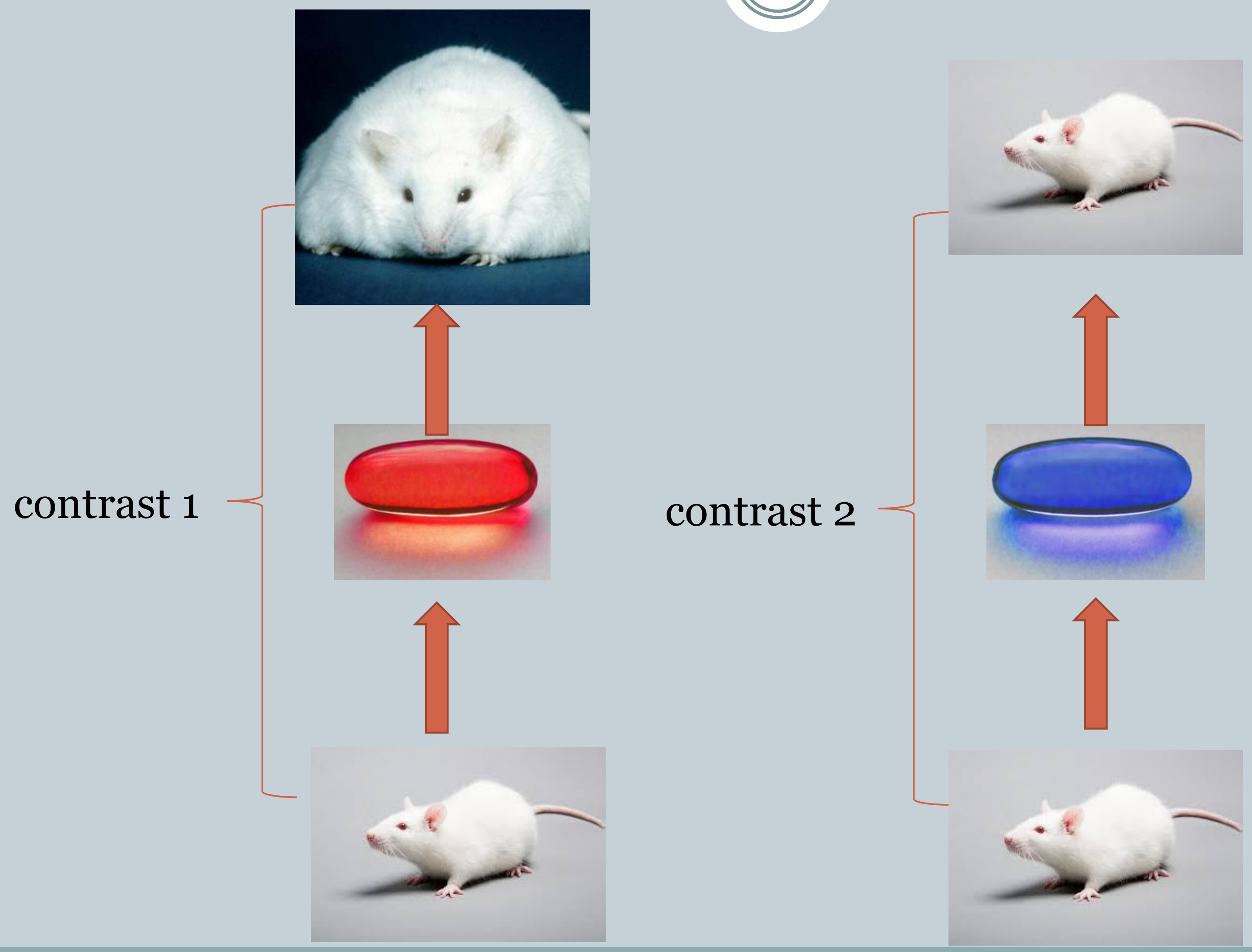
diff-in-diff



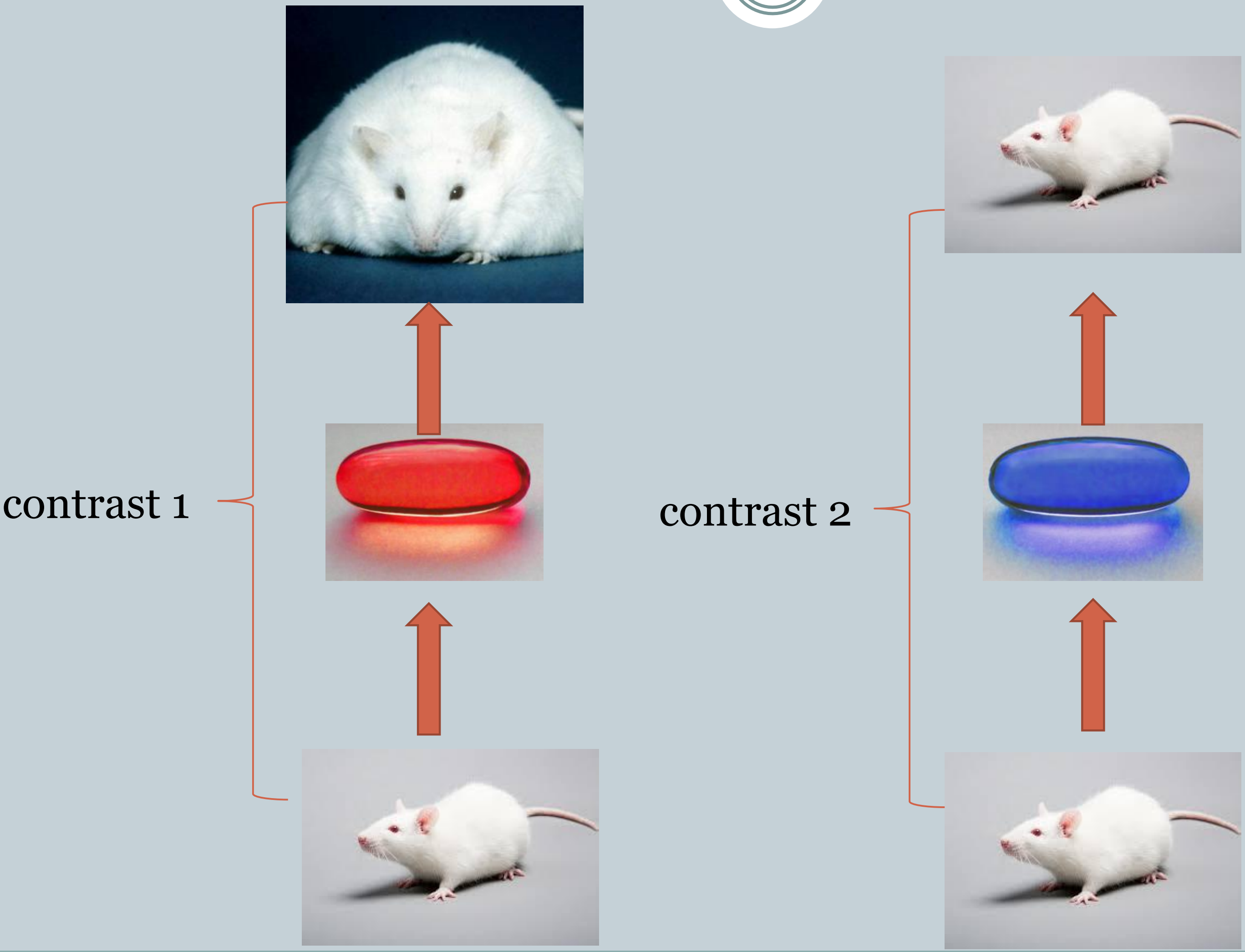
diff-in-diff



diff-in-diff



(contrast 1) – (contrast 2) = difference-in-differences



diff-in-diff

- Takeaway:

diff-in-diff

- Takeaway: difference-in-difference approaches try to reduce the variation in your estimate due to unit-to-unit differences. It does this by focusing on differencing a pre-treatment and post-post measurement.

diff-in-diff

- Takeaway: difference-in-difference approaches try to reduce the variation in your estimate due to unit-to-unit differences. It does this by focusing on differencing a pre-treatment and post-post measurement.
- Keep in mind:

diff-in-diff

- Takeaway: difference-in-difference approaches try to reduce the variation in your estimate due to unit-to-unit differences. It does this by focusing on differencing a pre-treatment and post-post measurement.
- Keep in mind: diff-in-diff is an approach that can often be pared with other aspects of design (e.g., pscore matching, IVs, RCTs).

diff-in-diff

- Takeaway: difference-in-difference approaches try to reduce the variation in your estimate due to unit-to-unit differences. It does this by focusing on differencing a pre-treatment and post-post measurement.
- Keep in mind: diff-in-diff is an approach that can often be pared with other aspects of design (e.g., pscore matching, IVs, RCTs).
- If you have the data available then doing a diff-in-diff is usually a good idea.

diff-in-diff

- Takeaway: difference-in-difference approaches try to reduce the variation in your estimate due to unit-to-unit differences. It does this by focusing on differencing a pre-treatment and post-post measurement.
- Keep in mind: diff-in-diff is an approach that can often be pared with other aspects of design (e.g., pscore matching, IVs, RCTs).
- If you have the data available then doing a diff-in-diff is usually a good idea. (Personally, I’ve never seen a situation where the diff-in-diff was worse.)

fin.

“case-control” studies

case-noncase

- Several different names
- Developed for looking for causes of rare outcomes
- Staple of epi
- Out-of-favor in modern causal inference
- If you're being intellectually lazy then these studies feel a bit similar to what we've been doing.
- The structure of argument is much weaker than what we've been doing.

case-noncase

- Diagram of what we’ve been doing (start with cause and look at an outcome) – swap structure and go backward from outcome to candidate causes.

case-noncase

- Match from Y=1 to Y=0 on all baseline characteristics, POSSIBLY some intermediate variables, but NOT the candidate causal covariates of interest.
- Look for maximal disagreement in candidate causal covariates.
- There are several reasonable critiques (e.g., doesn't look like an RCT). But the most devastating: we may not have the variables we need to answer the question we're asking. It's possible we don't have the correct candidate causal covariate, and we may capture "causal smoke"
- The difference between a scientist and a detective.

fin.