EPE - Lecture 5
Placebo Tests and Power Analysis for Natural Experiments and Observational Studies

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In a nutshell

In this lecture, we are going to study how to test for the validity and estimate the power of observational studies and natural experiments.

Key Idea of Placebo Tests

We are going to estimate the effect of a treatment whose effect should be zero if our method is valid. If the outcome is a pre-treatment outcome, we can use the standard error of the estimator to gauge sampling noise ex ante.

Why Power Analysis for Natural Experiments?

- It seems that natural experiments should not be subject to a power analysis since there are not many decisions that we can make to alter their design, contrary to RCTs for which we fine tune sample size, proportion of participants and type of design
- Actually, there are decisions we can take regarding natural experiments:
  1. Stop a project before collecting costly outcome data from administrations
  2. Decide to collect more data by accessing new sources
  3. Choose among different methods based on estimates of sampling noise (along with placebo tests)
  4. It is also extremely healthy to try to guess the effect of the treatment ex ante and how much power you have to detect it with your method. It looks like a pre-analysis plan, and minimizes the risks for specification searches.

The Methods Covered

- Natural Experiments
- Observational Methods

Outline

DID and the Parallel Trends Assumption

The crucial assumption for the validity of DID is the Parallel Trends Assumption (PTA)

DID: Parallel trends among groups defined by D_i

DID-IV: Parallel trends among groups defined by Z_i

Key Idea to Test the PTA

With two years (BB and B) (or more) of pre-treatment data and knowledge of D_i (or Z_i) we can test the PTA by estimating the effect of a placebo (fake) treatment given on year B to the group with $D_i = 1$ (or $Z_i = 1$).

Placebo Test with DID: Illustration

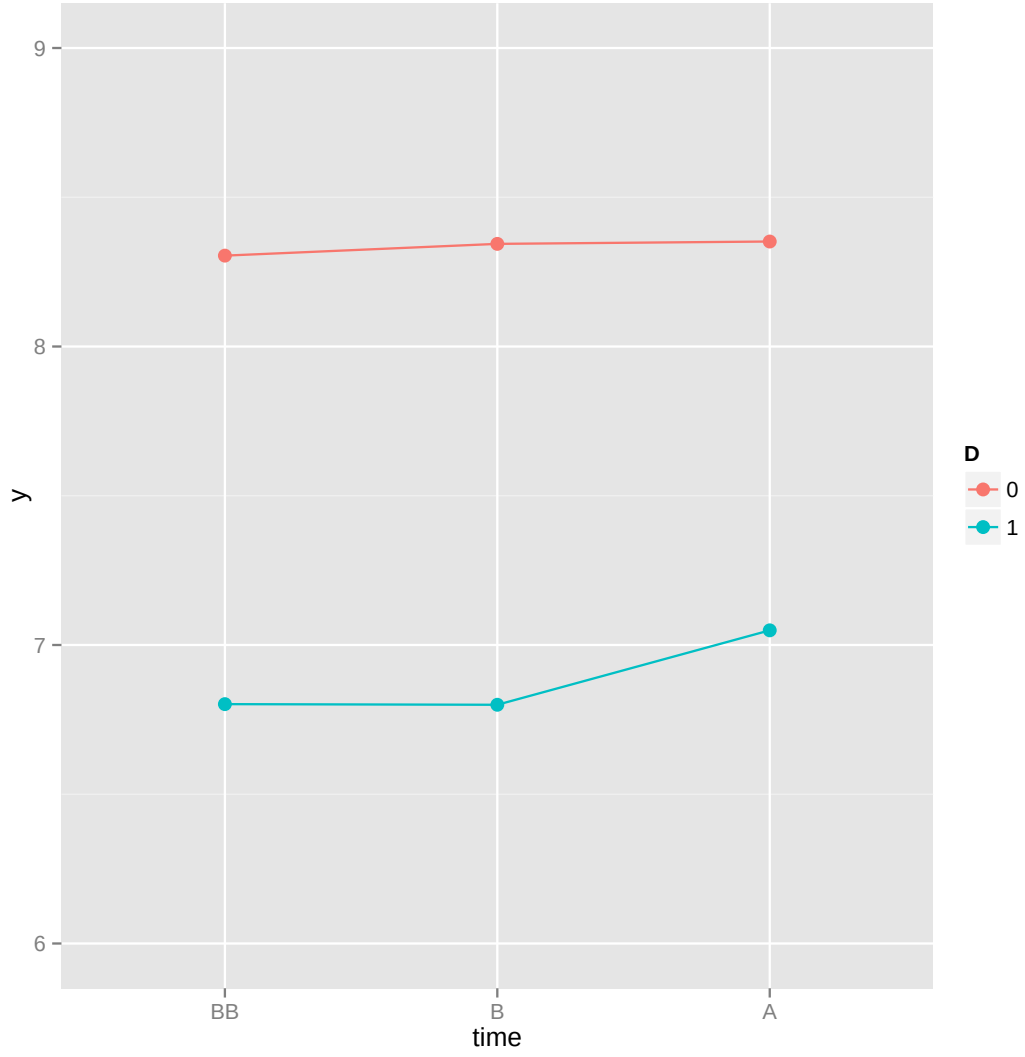


Figure: Outcomes Over Time in the Treated and Control Group

Placebo Test With DID: Illustration

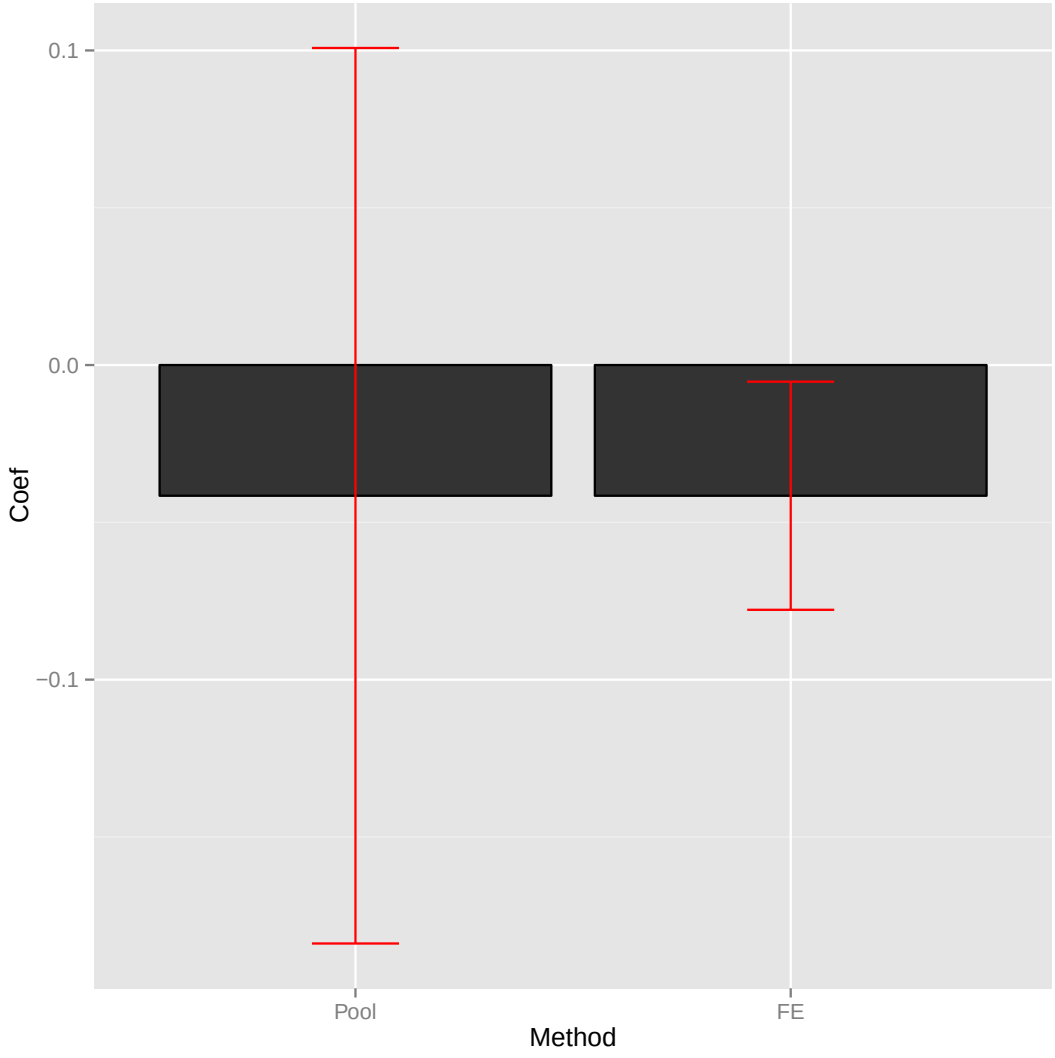


Figure: Placebo Test with DID

Power Analysis With DID: Illustration

95% Sampling Noise with our sample size is estimated using the standard error of the estimated coefficient:

Pooling: Estimated: 0.2847, Truth: 0.2325

Fixed Effects: 0.0725, Truth: 0.0921

Placebo Test with DID-IV: Illustration

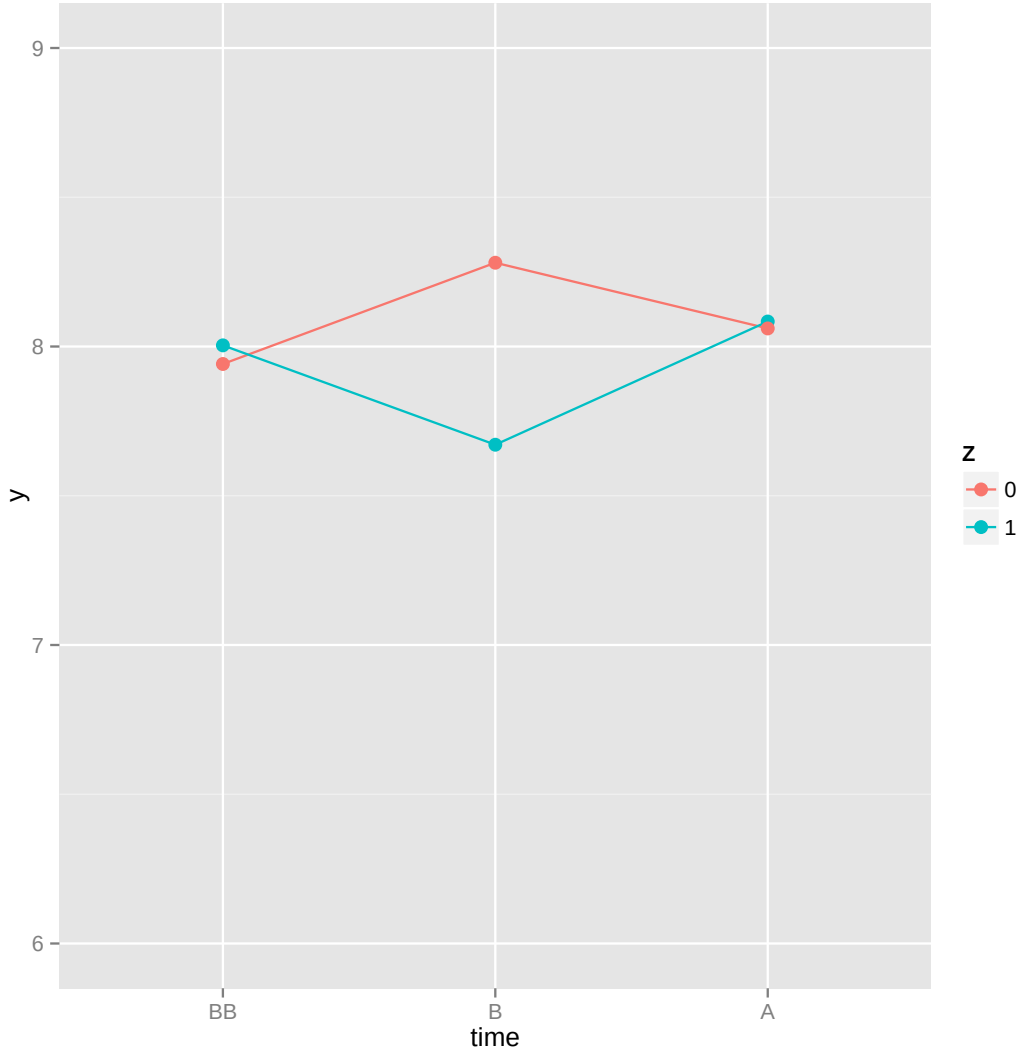


Figure: Outcomes Over Time

DID - Wait For It - IV

I'm not going to complete the calculations in the application since it requires estimates of clustered standard errors. We will come back to that issue in the next Lecture.

RDD and the Continuity of Expected Outcomes

The crucial assumption for the validity of RDD is the Continuity of Expected Outcomes at the threshold. There are two tests of this assumption:

1. Continuity of pre-treatment covariates
2. Continuity of density of the running variable

Testing the Continuity of Pre-Treatment Covariates: Key idea

Pre-treatment covariates should be continuous at the threshold.

Testing the Continuity of Pre-Treatment Covariates In Practice

1. Estimate placebo effect with RDD-LLR
2. Estimate sampling noise
3. Is the placebo effect precisely around zero?

RDD LLR

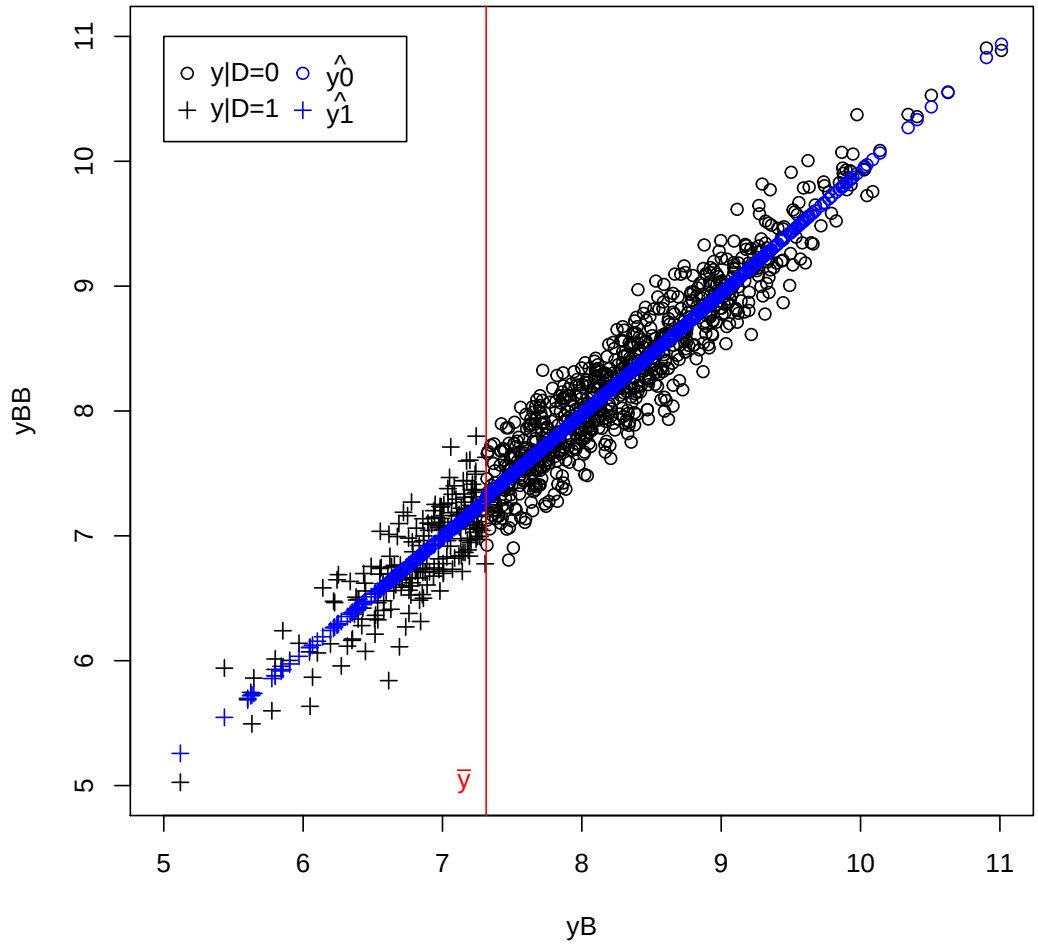


Figure: Placebo test with RDD LLR

Continuity of Pre-Treatment Outcomes: Illustration

- The estimated value of TT(z) on y_i^{BB} by simplified LLR is -0.0136
- The estimated 99% sampling noise is: 0.1972
- The true sampling noise is 0.34

Testing the Continuity of the Density of the Running Variable: Key Idea

McCrary (2008): The distribution of observations should be continuous around the threshold, unless one side of the threshold is more attractive and people can move around it.

Testing the Continuity of the Density of the Running Variable: In Practice

1. Estimate the density on each side of the threshold
2. Estimate the sampling noise around this estimator

Problem In Practice

Usual (kernel) density estimators are lame when used only on one side. Solution: use Local Linear Density (LLD) estimator

1. Estimate an undersmoothed histogram at regularly spaced points
2. Use LLR to smooth the histogram

Estimation and Inferende In Practice

I have not had the time to code it. Everything is in McCray (2008):

- Practical estimation procedure
- Binwidth and bandwidth choice (RoT)
- Estimation of Sampling Noise

IV and Independence

The crucial assumption for the validity of IV is the Independence of potential outcomes from the instrument. We can test this assumption by looking at whether the IV is correlated with pre-treatment outcomes. This test is easily implemented using the reduced form (OLS) or the structural form (2SLS).

Testing Independence: Illustration

- The estimated value of LATE on y_i^{BB} by simplified 2SLS is -0.134
- The estimated 99% sampling noise is: 0.966
- The true sampling noise is 1

Outline

Placebo Tests for Observational Methods: Key Idea

Imbens and Wooldridge (2009): conditional on covariates, we should observe

1. No effect of eligibility on eligible non applicants
2. No effect on pre-treatment covariates

Eligibility and Eligible Non Applicants (ENPs)

$$\mathbb{E}[\mathbb{E}[Y_i|E_i = 1, D_i = 0, X_i] - \mathbb{E}[Y_i|E_i = 0, X_i]|E_i = 1] = 0$$

Testing Conditional Independence under Sharp Eligibility: Illustration

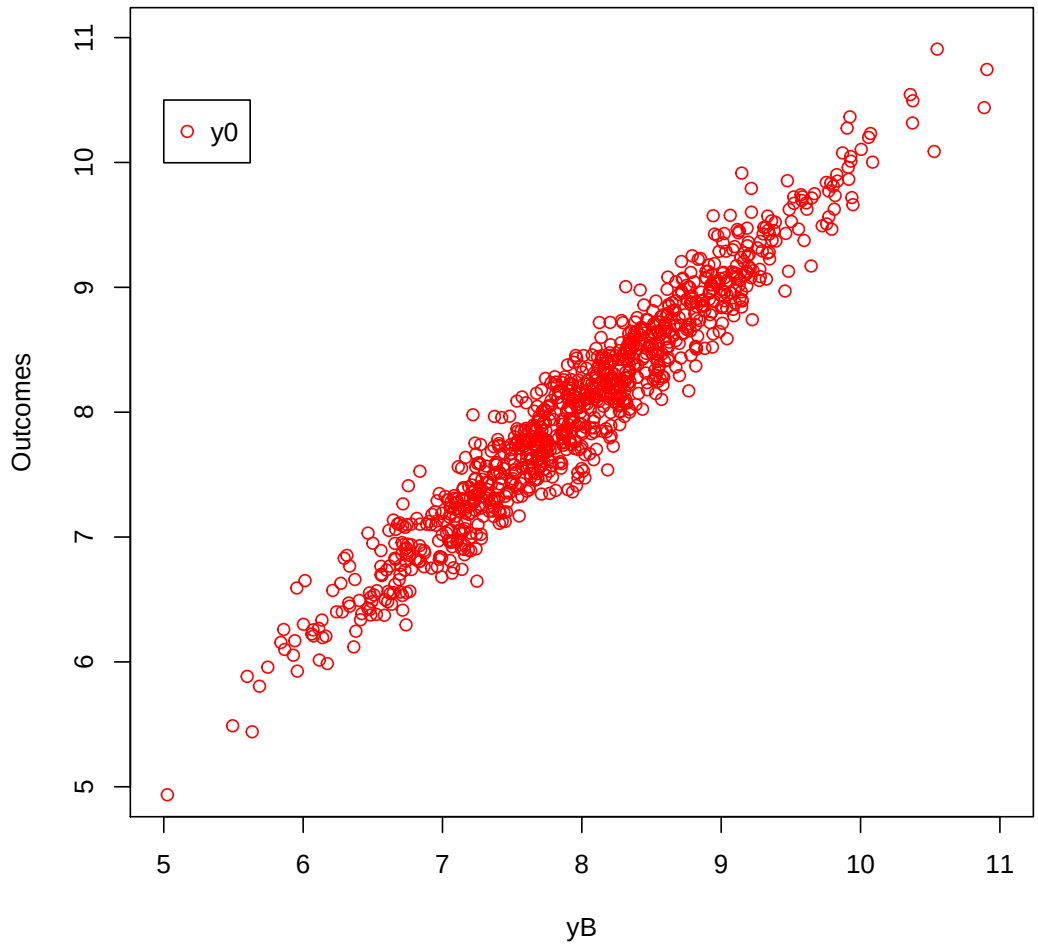
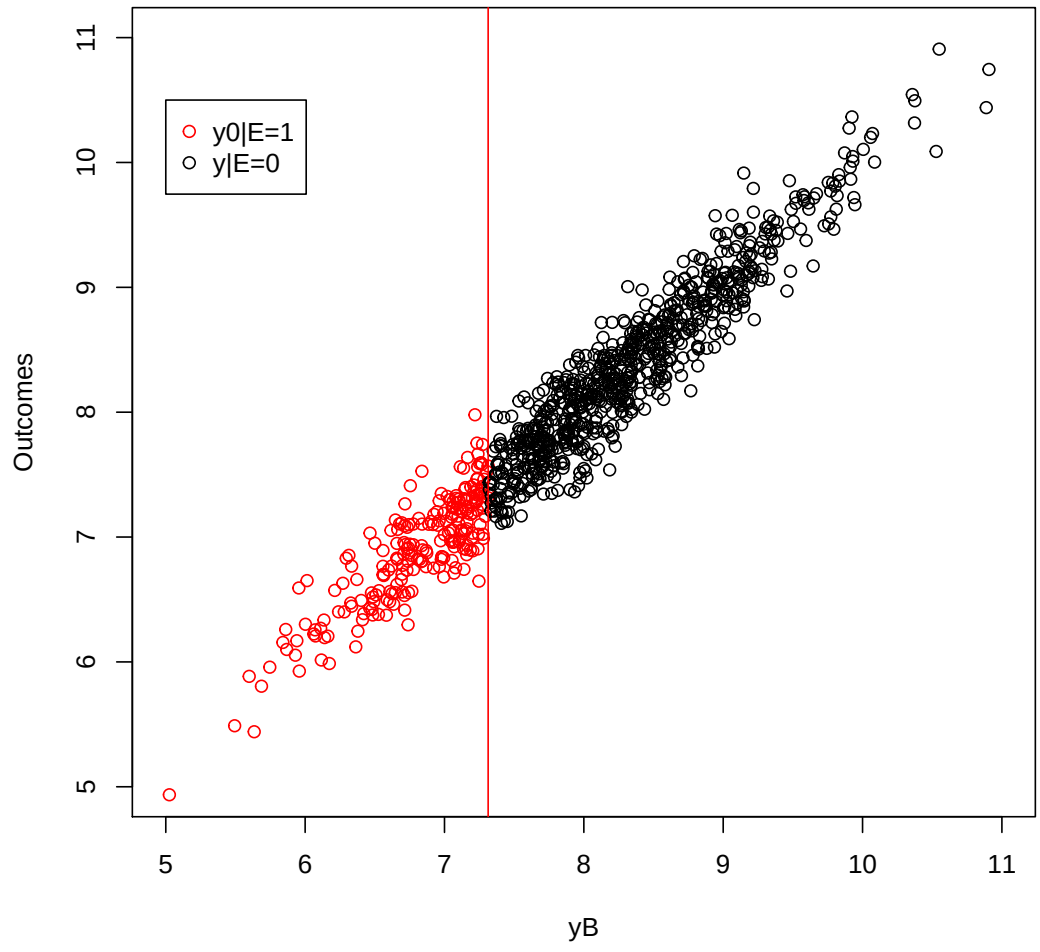


Figure: Randomization After Self-Selection

Testing Conditional Independence under Sharp Eligibility: Illustration



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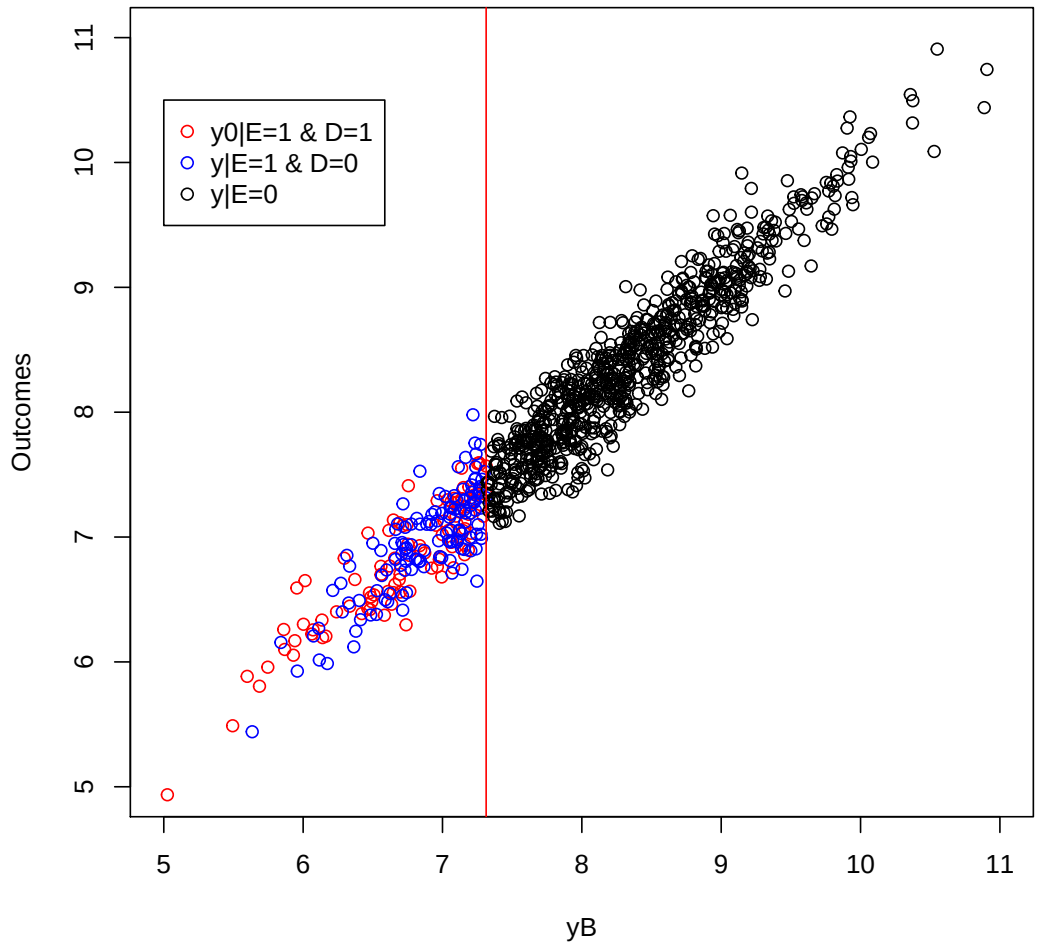

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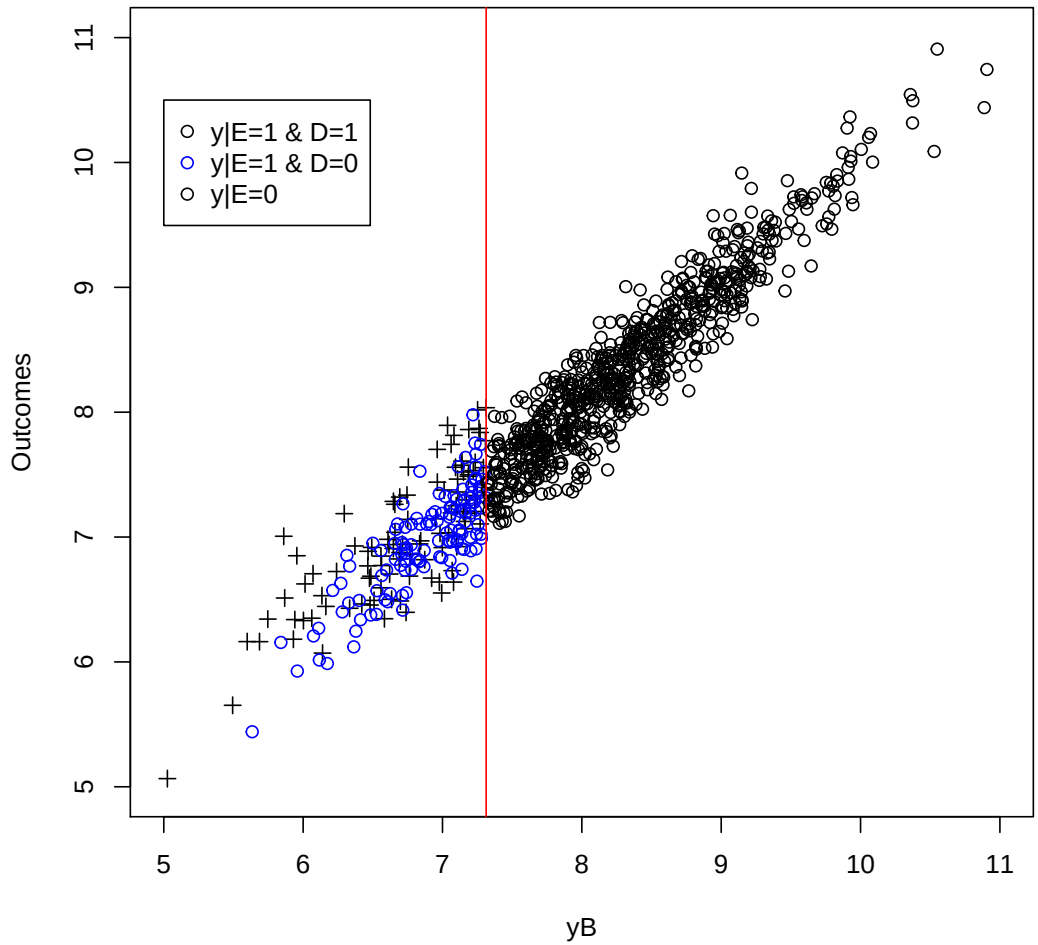

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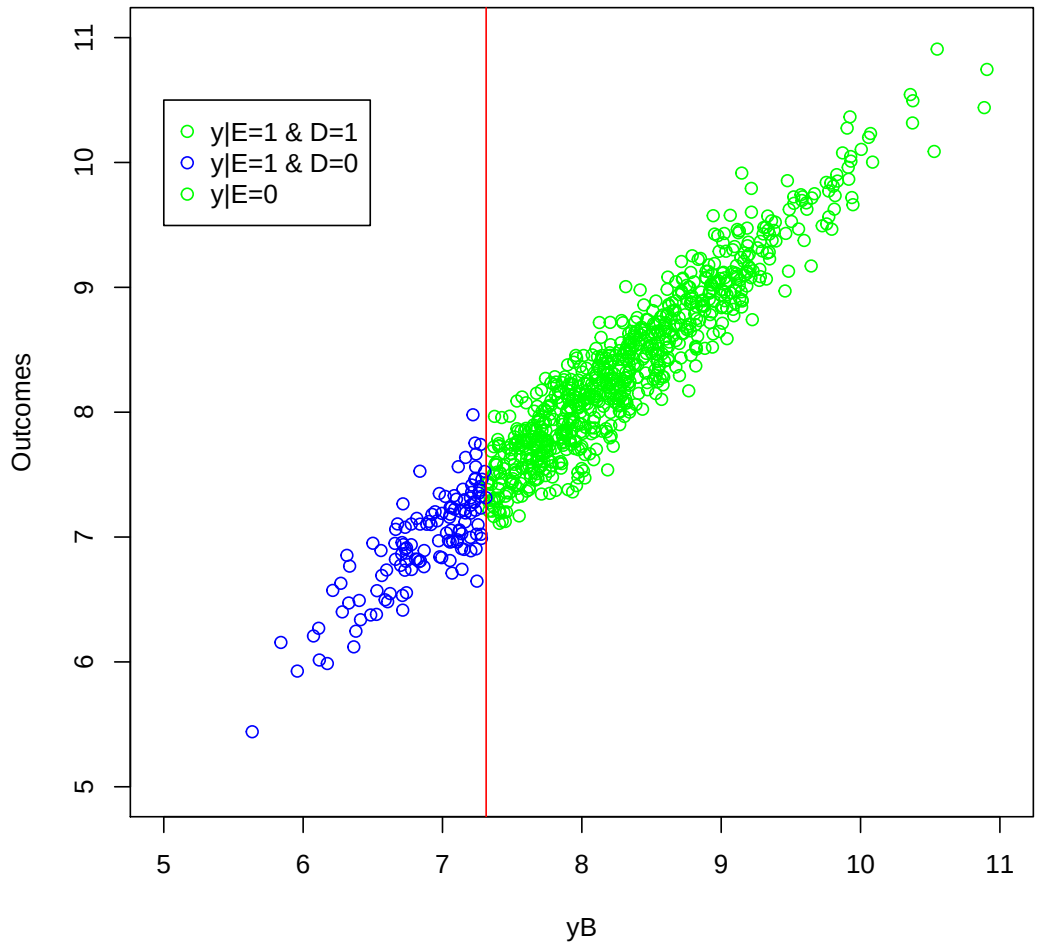


Figure: Randomization After Self-Selection

```r
yB.E <- (yB - mean(yB[Ds == 0 & E == 1])) * E
ols.direct <- lm(y[Ds != 1] ~ yB[Ds != 1] + E[Ds != 1] + yB
ww.ols.direct <- ols.direct$coef[[3]]
```

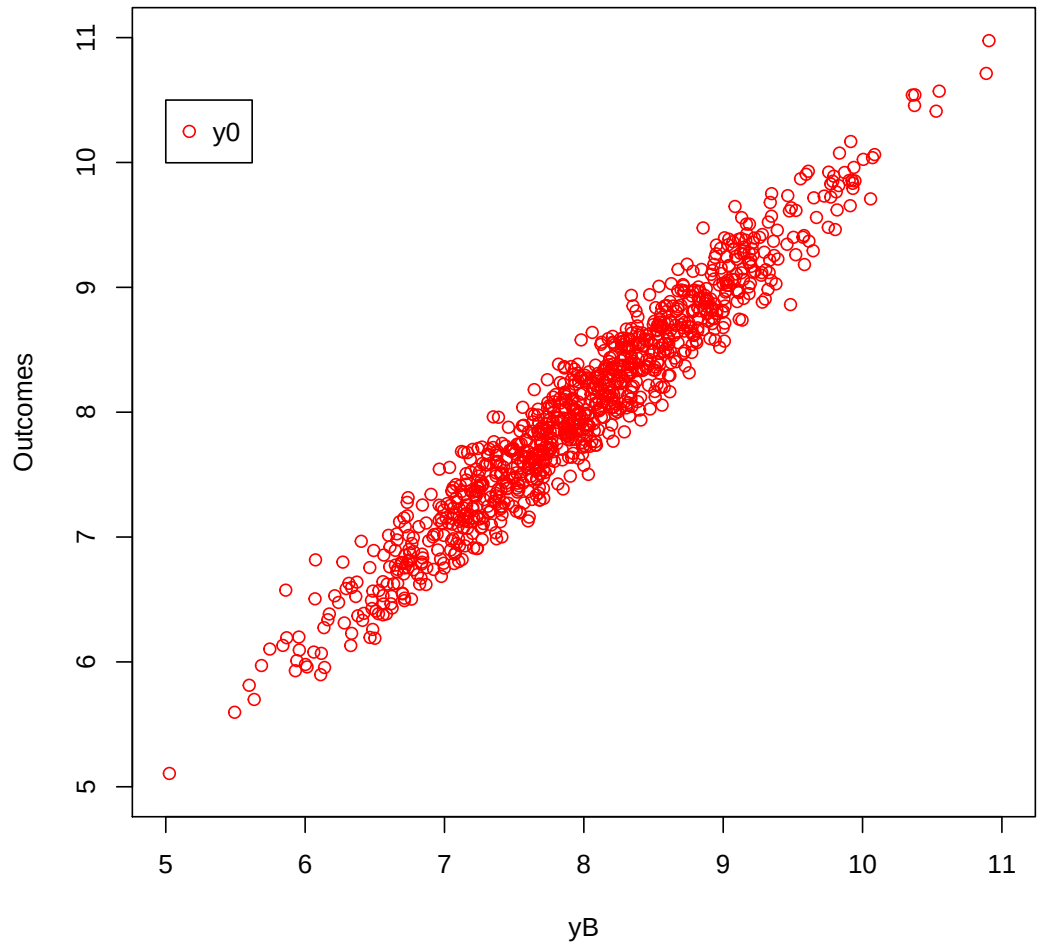
Testing Conditional Independence under Sharp Eligibility: Illustration

- The estimated value of the effect of E_i on ENPs by OLS conditioning on y_i^B is 0.0029
- The estimated 99% sampling noise is: 0.1434

Problem: common support

When eligibility is sharp, we do not have common support and we have to rely on the funcitonal form as well.

Testing Conditional Independence under Fuzzy Eligibility: Illustration



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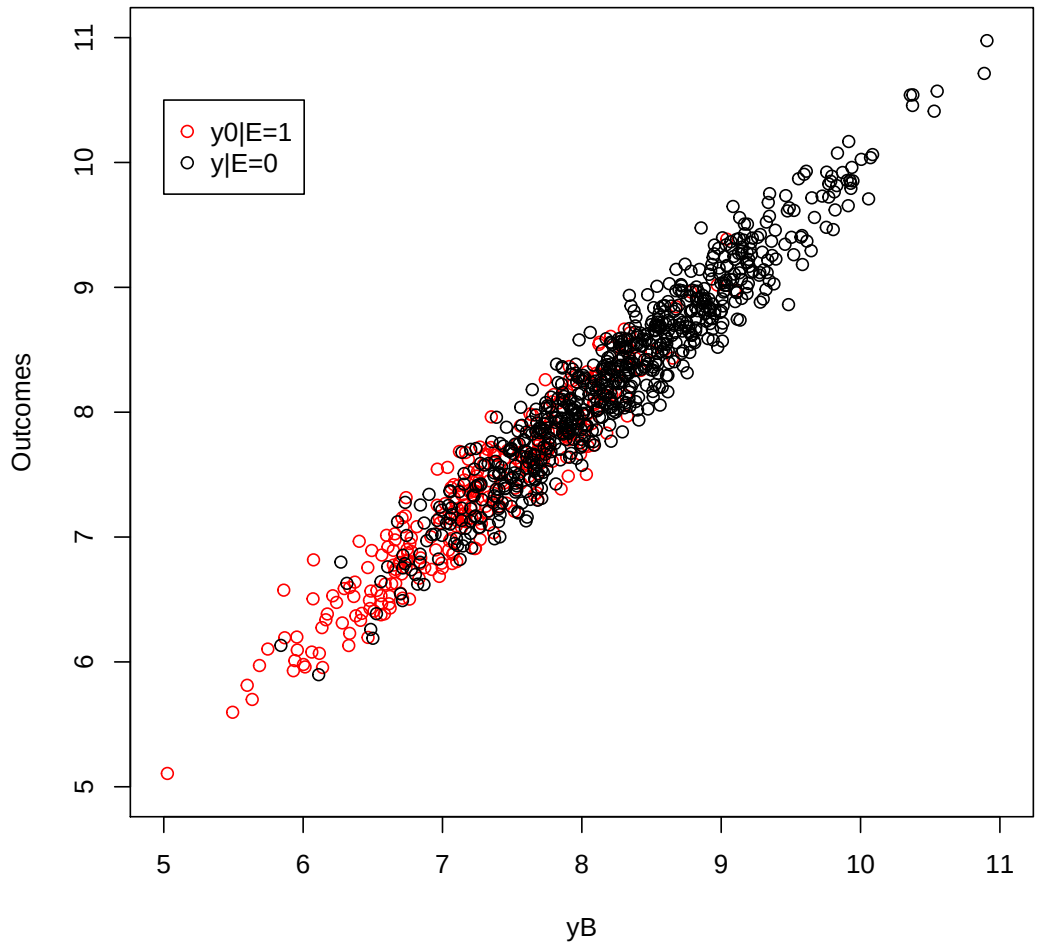

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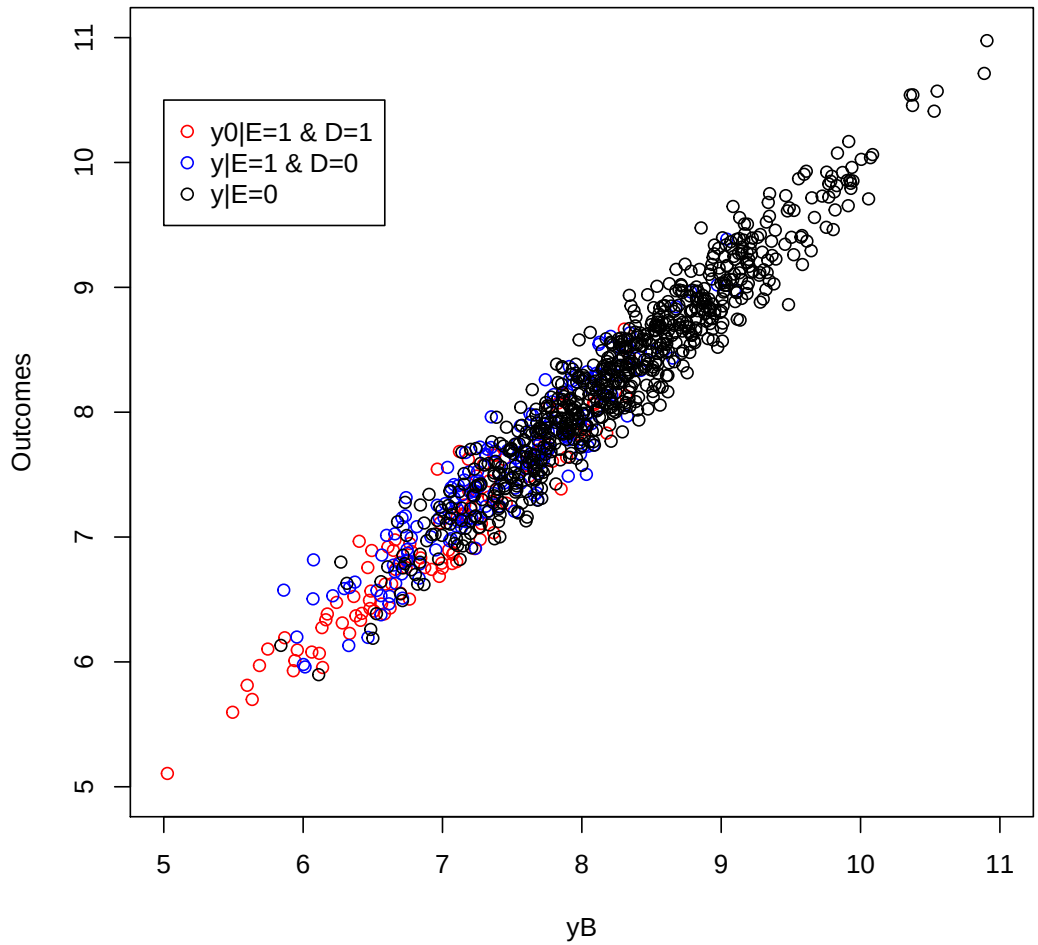

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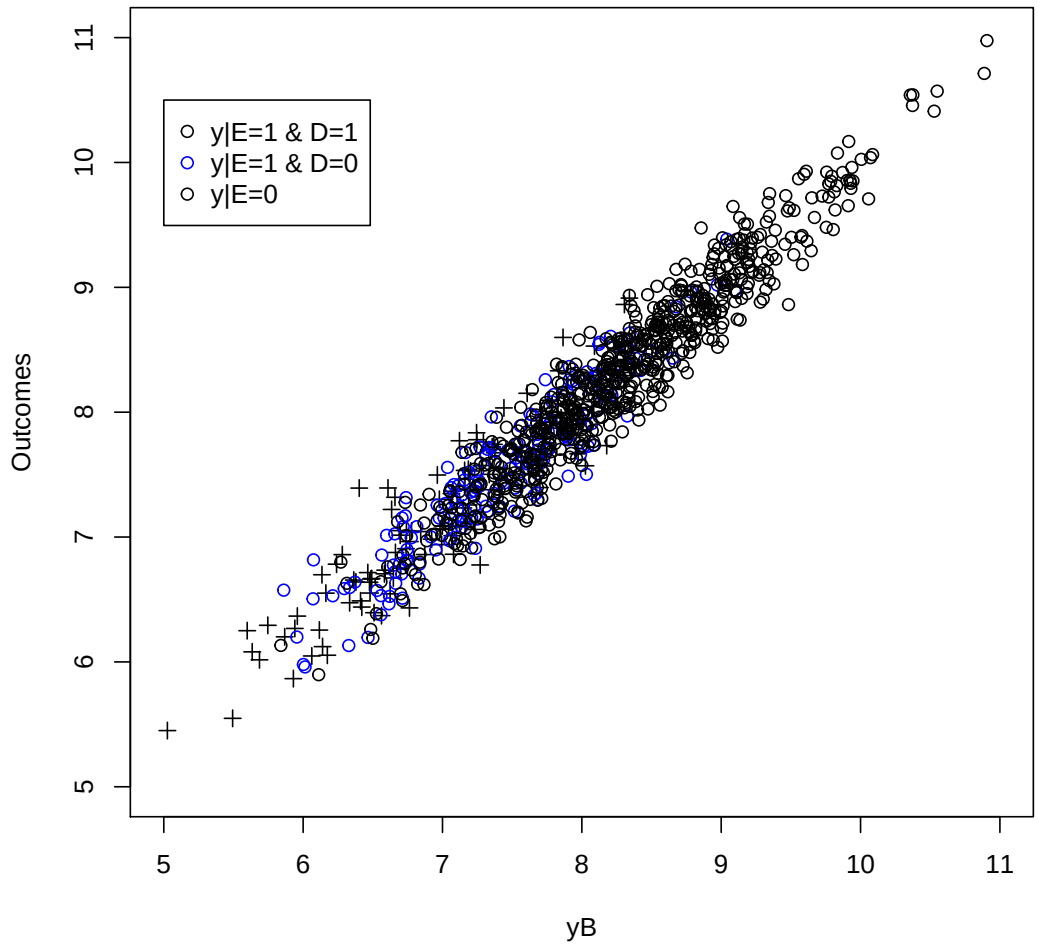

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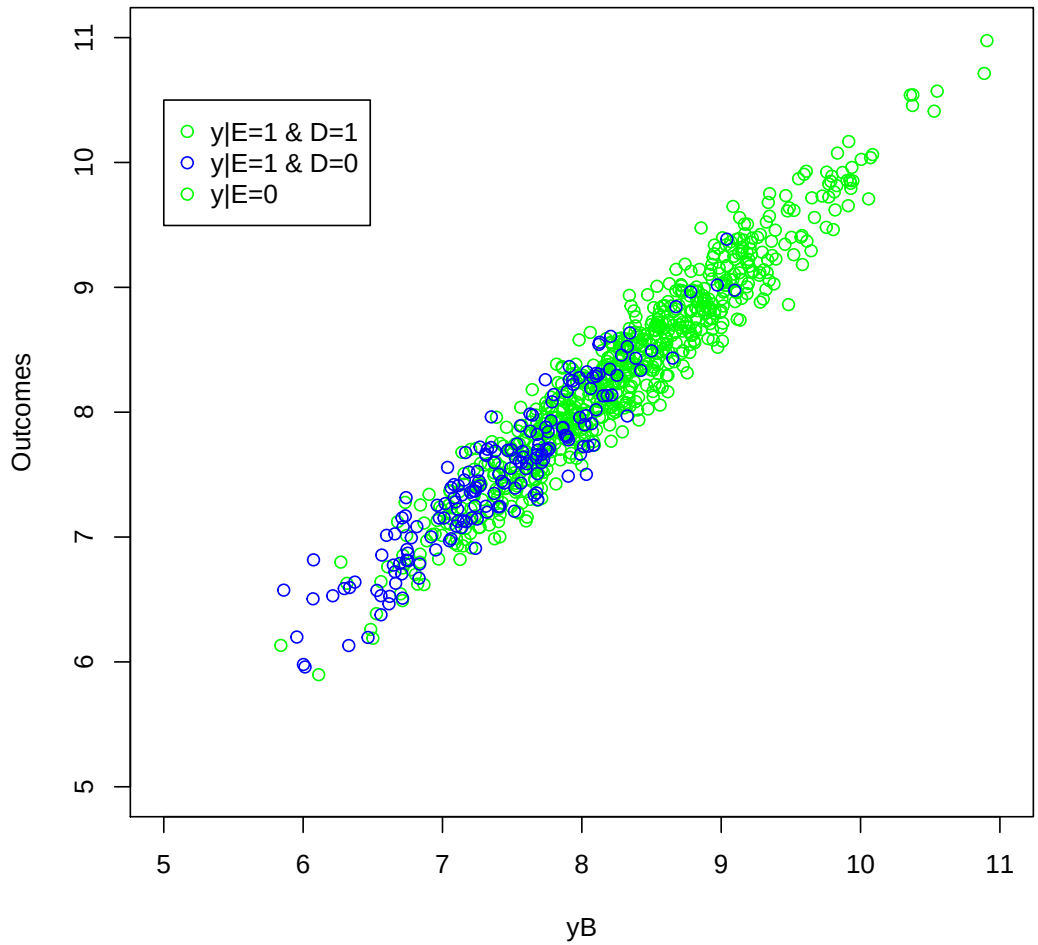

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```

Testing Conditional Independence under Fuzzy Eligibility: Illustration

- The estimated value of the effect of E_i on ENPs by OLS conditioning on y_i^B is 0.0402
- The estimated 99% sampling noise is: 0.105

Testing Conditional Independence Using Pre-Treatment Outcomes: Key Idea

Conditional on X_i, the treatment should have no effect on pre-treatment outcomes

Testing Conditional Independence Using Pre-Treatment Outcomes: Problem (1)

- Problem: what if pre-treatment outcomes are in X_i?
- Imbens and Wooldridge suggest to lag pre-treatment outcomes: condition on y_i^{BB} to estimate the placebo effect on y_i^B

Testing Conditional Independence Using Pre-Treatment Outcomes: Problem (2)

- Is Imbens and Wooldridge's suggestion such a great idea?
- Not so sure: last shocks matter a lot for selection and are in y_i^B and not in y_i^{BB}
- We might reject a perfectly valid estimator

Testing Conditional Independence Using Pre-Treatment Outcomes: Sylvain's Suggestion

- Condition on y_i^B and look at effect on y_i^{BB}
- Advantage: might do that progressively as you move further away in the past
- Problem: smaller power as older shocks should matter less for selection

```r
yB.Ds <- (yB - mean(yB[Ds == 1])) * Ds
yBB.Ds <- (yBB - mean(yBB[Ds == 1])) * Ds
placebo.IW <- lm(yB[E == 1] ~ yBB[E == 1] + Ds[E == 1] + yB
placebo.sylvain <- lm(yBB[E == 1] ~ yB[E == 1] + Ds[E == 1
```

Testing Conditional Independence with Pre-Treatment Outcomes: Illustration

- The estimated value of the effect of D_i on y_i^B by OLS conditioning on y_i^{BB} is -0.1542
- The estimated 99% sampling noise is: 0.2492
- The estimated value of the effect of D_i on y_i^{BB} by OLS conditioning on y_i^B is 0.0421
- The estimated 99% sampling noise is: 0.2974