Exercise: Understanding Potential Outcomes

1. We are going to generate simulated data on a population of 1,000 people. Specifically, create a variable x that randomly assigns these people to be male or female (50:50). *Hint: In R, try rbinom and in Stata, try rbinomial.*

2. Now we are going to simulate the potential outcomes - a measure of attitudes - *if our units were not treated* (y_0) for our population. Create another variable of random normally-distributed values with mean of 5 and standard deviation of 1. *Hint: In R, try rnorm and in Stata, try rnormal.*

3. One problem with observational data is that potential outcomes are often correlated with other variables such as gender. Perhaps women are simply more conservative, for example. Adjust your value of y_0 to add 1 (one) for all units who are male.

4. Now simulate potential outcomes *if the units receive treatment* (y_1) for all units. Define a *constant* treatment effect of $c = 2$ and create another variable $y_1 = y_0 + c$.

5. To compare our two sets of potential outcomes, plot two density charts on the same figure - one for y_0 and one for y_1.

6. Next, let us assume a specific **Treatment Assignment Mechanism** where men are more likely than women to receive treatment. This requires a few steps:

   a. First, we need to generate some noise so treatment is not simply identical to gender. Create a random uniform variable u that can take on values between 0 and 1 for all our units. *Hint: In R, try $runif$ and in Stata, try $runiform$.*
   b. Second, let's combine this with a function of gender: $z = 0.5x + u$
   c. Third, we can make a treatment variable D to assign binary treatment values of 0 or 1:

$$D = \begin{cases} 1 \text{ if } z > 0.75 \\ 0 \text{ if } z <= 0.75 \end{cases}$$

7. To show that gender (x) and treatment (D) are related, calculate the correlation between x and D.

8. What is the average of the *real* indvidual treatment effects based on all the potential outcomes, $E(y_1 - y_0)$?

9. The Fundamental Problem of Causal Inference is that we *cannot* calculate (8.) above. Instead, we only observe one value: y_{obs}. Create a new variable y_{obs} which equals y_1 if $D = 1$ but which equals y_0 if $D = 0$.

10. Based on the observable data, run the basic regression of treatment (D) on observable outcomes (y_{obs}). Interpret the result. Is this an accurate estimate of the treatment effect that we assumed at the start?

11. Re-run all your code above but this time with $c = 0$ so we are assuming **NO** treatment effect. Run the regression in (10.) again - what is the result?

12. To see why, let's plot two density charts on the same figure - one for the distribution of observable y_{obs} for the treated group ($y_{obs}|D == 1$) and one for the distribution of observable y_{obs} for the control group ($y_{obs}|D == 0$).

13. Run your code again for $c = 0$, but this time assume a larger population of $N = 1,000,000$. Does that solve the problem?

14. For $c = 0$, run the regression of treatment on observable outcomes, but this time controlling for gender.