Economics 402: Method of Economic Investigation
Lent Term 2009
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Exercise 2: Experimental and Non-Experimental Evaluations of Domestic Violence Arrests

Domestic violence is a very serious problem all over the world. There has been an increasing trend to arresting individuals after they commit an assault on an intimate partner based on the evidence from the Minnesota Domestic Violence Experiment, so you can see how public policy can be greatly influenced by social science. This exercise reviews some of the concept we covered in class. You are also asked to use the data provided (in STATA format) to supplement your answers. The commands you need to perform any analysis in STATA are provided with the question.

Two papers are referenced and may be of help when working through the exercise:

- Angrist (2006) "Instrumental variables methods in experimental criminological research: what, why, and how" *Journal of Experimental Criminology* 2:1-22

- Iyengar (2009) "Does the Certainty of Arrest Reduce Domestic Violence? Evidence from Mandatory and Recommended Arrest Laws" *Journal of Public Economics Vol 93 pp.85-98*

QUESTION 1. ISSUES OF COMPLIANCE

In general in the MDVE, officers deviated for a variety of reasons some of which were correlated with the behavior of the subjects and some of which were not.

A. In the example of the MDVE, the treatment effect differed for a variety of reasons including that police simply forgot to bring the color-coded note pad. If this was the *only* form of bias, would the treatment effect as measured by TOT be biased by imperfect compliance? Show this algebraically and then interpret your results

B. Using the data you were provided: determine the compliance rates in the experiment. You can do this by using the command:

tab t_random t_final, row

What does this indicate about the fraction of the sample that was compliers, always-takers, and never-takers?

C. The researchers in the MDVE kept track of *why* they may have given a different treatment than was assigned. To see these reasons, look at the variable *reason2*. You can do this by typing:

tab reason2

Given the *full* set of reasons for non-compliance, in what direction would you expect a simple OLS estimate of the difference in outcomes by the treatment delivered to be biased?

QUESTION 2. MEASURING TREATMENT EFFECTS

In class we discussed the Angrist (2006) paper which analyzes the Minnesota Domestic Violence Experiment (MDVE) in a Instrumental Variable framework. While in general we want to estimate the average treatment effect, ATE = $E(Y_{1i} \mid T_i =1) - E(Y_{0i} \mid T_i =1)$, sometimes compliance is an issue. As a result, instead of ATE, experimental studies may focus on the intent to treat outcomes, ITT = $E(Y_{1i} \mid T_i =1) - E(Y_{0i} \mid T_i =1)$. This is because looking only at what treatment as actually delivered, the treatment on the treated or TOT = $E(Y_{1i} – Y_{0i} \mid R_i =1)$, can be biased by selection. We discussed why in this context, another useful estimate of the treatment effect may be the *local average treatment effect* or LATE = $E(Y_{1i} – Y_{0i} \mid R_{1i} > R_{0i})$.

A. Show that in general, with non-compliance, ITT will be smaller than the true ATE. What is the intuition behind this (HINT: Think about when ITT and ATE will be equal)

B. In general, TOT and LATE will not be the same. This is because TOT is a weighted average of two effects: one on always-takers and one on compliers. Show that this is the case.

C. In question 1 you showed that in the MDVE, there was mostly only one-sided non-compliance. If this was true, how does LATE relate to TOT in this case?

QUESTION 3. REPLICATING ANGRIST'S RESULTS
To get used to working with your data and interpreting Stata output, please replicate the results found in Angrist. Don't worry if your estimates are not exactly the same as those presented in the paper (they won't be for complicated reasons related to simulated outcomes that are done slightly differently in this data than in the data in the paper).
A. Begin with the "Reduced Form" estimate of the assigned treatment on the probability an individual reoffends. You can do this with the command
regress reoffend1 coddle_assigned
What is your estimate? Explain why this estimate can be interpreted as the ITT.

B. Now add some covariates. You can do this by the command
regress reoffend1 coddle_assigned y82 q1 q2 q3 nonwhite mixed anyweapon s_influence
Does your point estimate change much ? Why not?
What happens to the R-Squared? Why is this important?

C. Estimate the OLS treatment effect. You can do this with the command
regress reoffend2 coddle_received
How does this compare to the estimates in A? Is this the true treatment effect? Why or Why not?
[NOTE: You are using a different outcome variable here (reoffend2) because issues related to the outcome simulation. Don't worry about that and just pretend as if this is the same variable as in A and D]

D. Estimate the IV treatment effect. You can do this with the command
regress reoffend1 (coddle_received = coddle_assigned)
What type of treatment effect does the instrumental variables approach recover? Why?

E. Compute the mean reoffense rate. You can do this with the command
sum reoffend1
From this compute the percent change in recidivism rates for the various estimates ITT, OLS (TOT + Selection bias), and LATE presented in class. Is the relationship between the estimates as you predicted? Why or why not?

QUESTION 4. INTERPRETING THE RESULTS

The MDVE found convincing evidence that individuals who are arrested after they commit domestic violence are less like to reoffend after arrest. Many advocates and policy makers were concerned about police not arresting frequently enough, many states passed so called “Mandatory Arrest Laws” which required the police to arrest an offender when a domestic violence incident was reported. In my paper (Iyengar, 2009), I show that in states that passed these laws, domestic violence actually went up after the laws were passed.

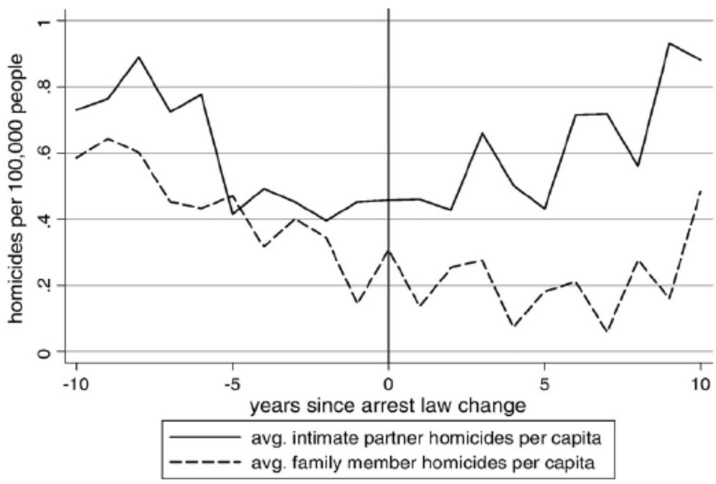

Fig. 1. Intimate partner and familial homicide rates in mandatory arrest law states. Notes: Means based on author's own calculations using Supplementary Homicide Reports 1976–2003. Intimate partner homicides include homicides of husbands, wives, ex-husbands, ex-wives, common-law husbands and common-law wives. Mandatory arrest states are defined as states where officers have no discretion as to whether or not to make a warrentless arrest when an intimate partner offense is reported.

This exercise helps understand why experimental results *may not* be translated correctly into public policy.

A. Consider first the initial experiment: Someone reported a crime and *then* a police unit dispatched would apply a randomly assigned treatment. This meant that the treatment effect measured Pr(Reoffend | Arrest & Report). Does a law which mandates the police arrest replicate this experimental setting? Why or why not.

B. Iyengar (2009) uses a ‘natural experiment’ to measure the causal effect of mandatory arrest laws on domestic violence. The variation comes from the fact that some states passed mandatory arrest laws (treatment group) and some states did not (control group) and thus some individuals were ‘as if’ randomly assigned to treatment. What assumption is necessary for this to be a ‘quasi’ experiment? [HINT: Think about what the source of variation is and how that is related to unobserved factors] What evidence could Iyengar provide to support this assumption?

C. Figure 1 above shows that while intimate partner violence went up in states with mandatory arrest laws, family violence (i.e. child abuse) went down after the laws were passed. The paper also notes that while intimate partner violence is most often reported by the victim, child abuse is typically reported by outside third parties (like doctors or teachers). Why does this help explain why the results in family violence more closely mirror those of the experiment while the results in intimate partner violence do not?