<u>Executive Summary for Lecture Set #3</u>

This set of slides considers the most important question for our course: how can we circumvent the problem of OVB to achieve causal estimates? We will advocate for a method used in the sciences: randomized control trials, because it provides us with a "counterfactual" point of comparison.

<u>Lesson #1:</u> Recall our simple, bivariate regression where X represents a dummy variable equal to one if data was collected after some change we enacted (like a new advertising program), and zero if the data was collected before this program was enacted, and Y represents weekly profits:

$$Y = b_0 + b_1 X$$

We know that b_1 shows us the average change in weekly profits during the "post" period relative to the "pre" period, but does b_1 also represent a "causal" change? We argue that it ***<u>does not</u>***, because we don't know the "counterfactual" in this case: the change in weekly profits that would have occurred in the absence of the new advertising program.

<u>Lesson #2:</u> A "causal" estimate shows us the difference between the change that occurs after we enact some change (like a new advertising program) and the change that *<u>would have occurred if we had never enacted this change</u>*. This latter change is known as the ***<u>counterfactual</u>***, and it can never be inferred from a simple regression.

<u>Lesson #3:</u> How do we fix this problem? We do it in three steps:

Step #1: We create two groups: (1) a "treatment" group that receives some change of interest to us (like a new advertising program) and (2) a "control" group that does not receive this change.

Step #2: We collect data on Y for both groups in two different periods: (1) the period before the change is enacted (which we call the "pre" period, for short) and (2) the period after the change is enacted (which we call the "post" period, for short).

Step #3: We compute the change in Y for the treatment group, and compare it to the change in Y for the control group. We call this the ***<u>"Difference-in-Differences" estimate</u>*** because it compares the difference in Y for the treatment group to the difference in Y for the control group. Using "T" and "C" superscripts to represent the treatment group and control group, respectively, our estimate is:

$$Difference - in - Differences = (Y^T_{Post} - Y^T_{Pre}) - (Y^C_{Post} - Y^C_{Pre})$$

What's the intuition here? There are two major components:

(i) $(Y^T_{Post} - Y^T_{Pre})$ shows us the average change in Y for the treatment group.
(ii) $(Y^C_{Post} - Y^C_{Pre})$ shows us the average change in Y for the control group.

<u>Case #1:</u> Suppose that our advertising campaign is successful for the treatment group, while the control group is unaffected, then (i) will be large and positive, while (ii) close to zero. This will create a positive D-i-D estimate, which matches our intuition about the ad campaign being good.

<u>Case #2:</u> Suppose that our advertising campaign is not successful for the treatment group, while the control group is unaffected, then both (i) and (ii) will be close to zero. This will create a zero D-i-D estimate, which matches our intuition about the ad campaign being ineffectual.

We'll discuss some other cases in class, but this is the basic intuition. Next, we'll discuss how regressions fit into this type of an analysis