**Day 2 Exercise – Randomization and IV**
**Ghana Microfinance Experimental Evaluation**

This exercise looks at the analysis of randomized impact evaluations where compliance is imperfect (i.e., where some eligible individuals choose not to participate). We use the data set discussed in the morning session, taken from the evaluation of the Credit with Education program in Ghana conducted by Freedom from Hunger.

## 1. Was the randomization successful?

If villages were chosen randomly, mean characteristics should be the same in the treatment and control groups for all variables. With a small sample size though, this may not hold in practice. Compare the means of program and control villages in the baseline data (i.e., before the program began). Two simple ways to do this is are follows:

```
. graph bar momage if wave==0, over(programvillage)
. reg momage programvillage if wave==0
```

The regression coefficient tells you the difference between the two groups and gives you t-test of whether it is significantly different from zero.

| | Is there a significant difference between program and control villages? (Y/N) | If so, is the variable higher or lower in program villages (+/-) |
|---|---|---|
| momage | | |
| momschool | | |
| numchildren | | |
| capital | | |
| profit | | |
| logprofit | | |
| hungrymonths | | |
| haz | | |
| whz | | |

## 2. Who joins the program?

What characteristics are associated with joining the CWE program? To investigate this question you should limit attention to the baseline data from 1993 – before mother and child characteristics are 'contaminated' by the program itself. You'll also want to restrict attention to the program villages (where women were eligible to join). The variable measuring the choice to join the program is signedup. Thus you might estimate

```
. gen capitalsq = capital^2
. reg signedup momage momschool capital capitalsq if
wave==0 & programvillage==1
```

How would you describe the relationship between socio-economic status and program participation?

## 3. What are the causal effects of the program?

**3a.** To get familiar with the outcomes, graph the mean profit and WHZ for each of the following groups: ineligible vs. eligible women in the follow-up survey and participants vs. non-participants in the program villages in the follow-up survey.

```
. graph bar profit if wave==1, over(Z)
. graph bar profit if wave==1 & Z==1, over(T)
```

If you want to do something fancier, you can compare the whole distribution of the outcome variable across two groups using a kernel density:

```
. twoway (kdensity logprofit if T==0 & Z==1)(kdensity
logprofit if T==1), legend(lab(1 "declined") lab(2
"treated"))
```

**3b.** In the morning we discussed various measures and definitions of impacts or treatment effects. Consider the following 5 outcomes of interest in the microfinance program and estimate these various measures of impact.

Naïve OLS refers to the coefficient on T from a simple regression such as

```
. reg profit T if wave==1
```

ITT is the intent-to-treat effect. It measures the mean difference between eligible and ineligible villages.

```
. reg profit Z if wave==1
```

ATT is the average treatment for the treated, or the instrumental variables estimate of the local average treatment effect.

```
. ivreg profit (T=Z) if wave==1
```

Estmate these regression to fill in the boxes below. You may want to add stars to denote statistical significance at the 10% (*), 5% (**) and 1% (***) levels.

| | Col. 1 | Col. 2 | Col. 3 |
|---|---|---|---|
| | Naïve OLS | ITT Effect | ATT |
| `profit` | | | |
| `logprofit` | | | |
| `hungrymonths` | | | |
| `haz` | | | |
| `whz` | | | |

*Thanks to Christopher Dunford of Freedom from Hunger for granting permission to use the data for this exercise.