Lecture 9: Empirical Methods in Corporate Finance II

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Roadmap

1. Introduction
2. Instrumental Variables
3. Panel Data Methods
4. Difference in Differences Estimator
5. Conclusion

Motivation

- Last time we talked about a simple method for studying empirical relationships between variables in corporate finance: OLS and regression analysis generally.
- Endogeneity is a problem that's pervasive throughout economics though, that plagues our regression estimates with asymptotic bias.
- Is there any hope for statistical analysis in economics?

Motivation

- Yes!
- Before you can find the remedy, you need to ask the questions: what variable is endogenous? Why? What are the implications with regard to bias?
- What are the alternative hypotheses, about which one should be concerned?

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General setting

- A common way to deal with endogeneity.
- Say that we're considering a framework of

$$y_i = \beta_0 + \beta_1 x_{1,i} + ... + \beta_M x_{M,i} + u_i \tag{1}$$

where $Cov(x_{k,i}, u_i) \neq 0$ for some $k \in \{1, 2, ..., M\}$.

- Generally means that all of our coefficient estimates will be biased.
- Unless $x_{k,i}$ happens to be uncorrelated with the other regressors.

General setting

- An instrumental variable (denoted z_i) for $x_{k,i}$ satisfies two conditions

  (1) Relevance condition.

  (2) Exclusion condition.

Relevance Condition

- Requires that the partial correlation between the instrument and endogenous variable not be zero.
- Means formally that the coefficient γ in the regression

$$x_{k,i} = \alpha_0 + \alpha_1 x_{1,i} + ... + \alpha_{k-1} x_{k-1,i} + \alpha_{k+1} x_{k+1,i} + ... + \alpha_M x_{M,i} + \gamma z_i + v_i$$

be non-zero.

- Says that the endogenous variable and the instrument are correlated after netting-out the effects of all other exogenous variables.

Exclusion Condition

- Says that z_i's only influence on the outcome variable of interest is through the endogenous regressor.
- That is: $Cov(z_i, u_i) = 0$ where u_i is the residual from (1) above.
- What does it mean if this condition is not satisfied?
- Would mean that the instrument is also endogenous! This is the same problem that we're trying to fix.

Multiple variables

- One can use multiple instruments for an endogenous variable.
- Both conditions need to be satisfied for each instrument though.
- Relevance condition can be done with joint test of statistical significance.
- May also have multiple endogenous variables.
- In this case, need at least as many instruments as we have endogenous variables.

Examples in corporate finance

- Bennedsen et al. (2007): does replacing an outgoing CEO with a family member hurt firm performance in family firms?
- CEO succession is likely correlated with things that affect performance also.
- E.g. non-family CEO may come in during bad times, family CEO during good times.
- Need exogenous variation in the CEO succession decision.
- They use gender of the first-born child of a departing CEO.
- Show that CEOs with boy-first families are significantly more likely to appoint a family CEO.
- Gender is a biological thing, likely uncorrelated with the firm's performance.

Estimation

- Common approach is to use two-stage least squares (2SLS).
- **1st stage:** regress the endogenous variable ($x_{k,i}$) on the exogenous variables and instruments. Gives fitted values $\hat{x}_{k,i}$: those predicted by the regression.

$$\hat{x}_{k,i} = \hat{\alpha}_0 + \hat{\alpha}_1 x_{1,i} + ... + \hat{\alpha}_{k-1} x_{k-1,i} + \hat{\alpha}_{k+1} x_{k+1,i} + ... + \hat{\alpha}_M x_{M,i} + \hat{\gamma} z_i$$

- **2nd stage:** use the fitted values ($\hat{x}_{k,i}$) to stand-in for the endogenous variable ($x_{k,i}$) in the regression of y_i (outcome) on all the right-side variables.

$$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_{1,i} + ... + \hat{\beta}_k \hat{x}_{k,i} + ... \hat{\beta}_M x_{M,i}$$

Estimation

- The residual in the first stage contains all the junk that's correlated with the outcome variable.
- We disregard that and just keep the exogenous component, (since recall z_i is doesn't affect the outcome variable directly).
- The idea is that the fitted values $\hat{x}_{k,i}$ contain only variation in the endogenous variable that is exogenous to the regression system.
- We've removed the "evil" endogenous part.
- The regression coefficient will be consistent.
- Introduces more noise into the estimation though: need to correct the standard error estimates.

Estimation

- Easy to run two stage least squares in Stata.

- If we're dealing with a model

$$y_i = \beta x_i + u_i$$

where z_i is an instrument for x_i then use the Stata command

```
ivregress 2sls y (x = z)
```

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Panel setup

- A panel dataset for firms follows the same firm for multiple periods of time.
- Are there unobservable attributes at the firm-level that are time-invariant?
- We could control for these with fixed effects.

Fixed effects

- A fixed effects panel regression takes the form

$$y_{it} = \beta x_{it} + \alpha_i + u_{it}$$

  where parameter α_i is a firm-specific, unobservable and time-invariant fixed effect.

- We can't observe this fixed effect.

- I.e. it's likely an omitted variable (absorbed into the residual term).

- That is: there might be omitted variables that are correlated with the firm itself.

- So how is it helpful conceptually?

Least Squares with Dummy Variables

- Why don't we just use a dummy for each firm (each i)?
- Run the following regression

$$y_{it} = \beta x_{it} + \sum_{j=1}^{N} \alpha_j d_j + u_{it}$$

where $d_j = 1$ if $j = i$ and 0 otherwise.

- In Stata, use the command

```
xi: regress y x i.firm
```

Demeaning

- Another approach is to demean the variables across time.

- Consider

$$y_{it} - \bar{y}_i = \beta(x_{it} - \bar{x}_i) + (u_{it} - \bar{u}_{it})$$
$$\tilde{y}_{it} = \beta \tilde{x}_{it} + \tilde{u}_{it}$$

  where notice that the mean variables (with bars over the top) are firm-dependent (note $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{it}$).

- Why does this work? Because α_i is time invariant — its mean is the same as itself. Drops-out in the differencing.

- In Stata, use the command

```
xtreg y x, fe
```

  should offer the same results as the dummy approach.

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Treatment Effects

- Difference in differences is a method used to estimate the impact of a treatment effect.
- Recall that simply taking a difference in the averages for treated and untreated samples leads to a selection bias term.
- The key is to take another difference!

Treatment Effects

- Consider a two-period example.
- In 1987 Arizona passed anti-takerover legislation, while Connecticut had not.
- Assume we have data pre and post reform: start of 1986 and end of 1987.
- Arizona firms are the treatment group and Connecticut firms are the control group.

Treatment Effects

- The regression model for the DD estimator is given by

$$y = \beta_0 + \beta_1 d \times p + \beta_2 d + \beta_3 p + u$$

  where

  - d is the treatment assignment variable equal to 1 if an Arizona firm and 0 if a Connecticut firm.
  - p is the post-treatment indicator equal to 1 if datum is from 1987 (post-reform) and 0 if from 1986 (pre-reform).

- β_2 captures differences across the two states, while β_3 captures differences across time.

- β_1 is our object of interest here: how did the policy change affect the Arizona firms?

Treatment Effects

- What are the possible combinations of outcomes?
  - $(d = 0) \wedge (p = 0) \Rightarrow y = \beta_0 + u$.
  - $(d = 1) \wedge (p = 0) \Rightarrow y = \beta_0 + \beta_2 + u$.
  - $(d = 0) \wedge (p = 1) \Rightarrow y = \beta_0 + \beta_3 + u$.
  - $(d = 1) \wedge (p = 1) \Rightarrow y = \beta_0 + \beta_1 + \beta_2 + \beta_3 + u$.

where $\wedge$ is shorthand for "and".

Treatment Effects

- Assume that $\mathbb{E}[u|p,d] = 0$: that is, the expectation of the residual is zero, irrespective of the values of d and p.

- Conditional expectations are all given then by
  - $\mathbb{E}[y|d=0,p=0] = \beta_0$
  - $\mathbb{E}[y|d=1,p=0] = \beta_0 + \beta_2$
  - $\mathbb{E}[y|d=0,p=1] = \beta_0 + \beta_3$
  - $\mathbb{E}[y|d=1,p=1] = \beta_0 + \beta_1 + \beta_2 + \beta_3$

- So our DD estimator is given by

$$(\mathbb{E}[y|d=1,p=1] - \mathbb{E}[y|d=0,p=1])$$
$$-(\mathbb{E}[y|d=1,p=0] - \mathbb{E}[y|d=0,p=0]) = (\beta_1+\beta_2) - (\beta_2) = \beta_1$$

Treatment Effects

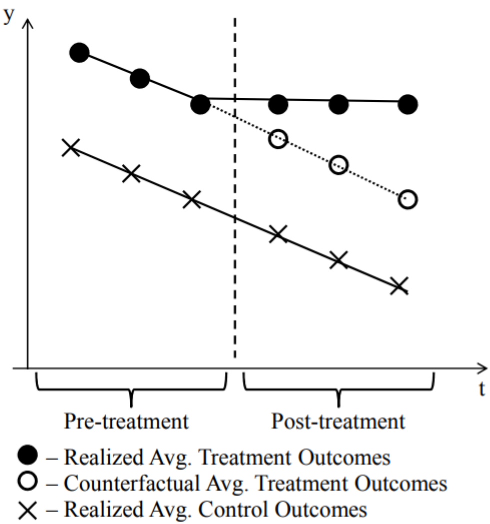
- Approximate this difference using sample averages!

Identifying assumption

- For this to work, we need the parallel trends assumption to hold.
- Means that the time-trend the two groups would have followed would be the same in the absence of the treatment.
- In the counter-factual, the trend would have been the same for the treatment and control groups.
- Then we can attribute the difference to the treatment effect.

Identifying assumption

Figure 1: **Difference-in-Differences Intuition**



Identifying assumption: robustness tests

- We don't observe the counterfactual outcome for the treatment group.
- Test: repeat the DD estimation for previous years (where the treatment was not present).
- Estimated treatment effect should be no different from zero statistically.
- Other tests possible as well.

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Summary

- Linear regressions are easy to implement in Stata and can be very informative.
- Selection bias and endogeneity bias can be issues though.
- To deal with endogeneity: IV or panel regressions are two possible tools for fixing the issue.
- Difference in difference regressions can be used to identify treatment effects under some fairly strong assumptions.