ECON 626: Applied Microeconomics

Lecture 10:

Attrition, Manski Bounds, and Lee Bounds

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Attrition and selection bias

Recall Angrist and Pishke:

"The goal of most empirical economic research is to overcome selection bias, and therefore to say something about the causal effect..."

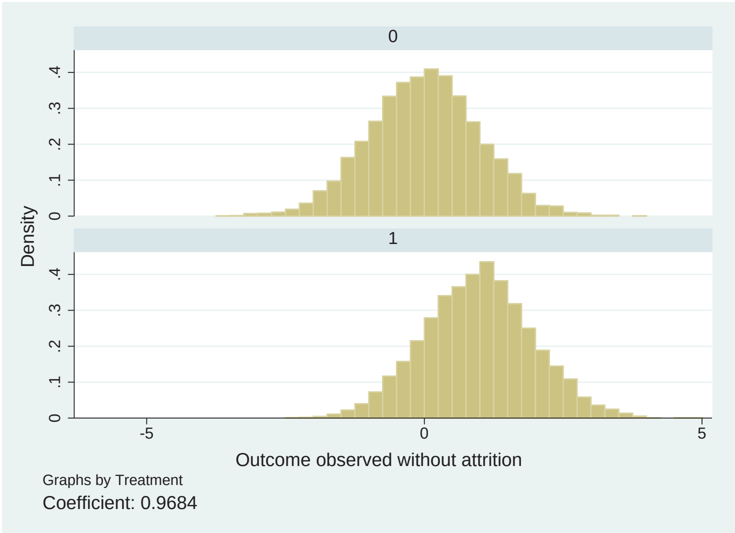
- Motivation 1:
  - We have focused on point estimates in general;
  - We looked at how the relationship between selection on observables and selection on unobservables can influence the point estimate.
  - What about situations in which the structure of the data suggests bounding the treatment effect in an interval?
- Motivation 2:
  - What do we do when an RCT should identify the effect of interest, but there is attrition (missing endline data)?
  - What if that attrition is differential across arms?

Attrition and selection bias

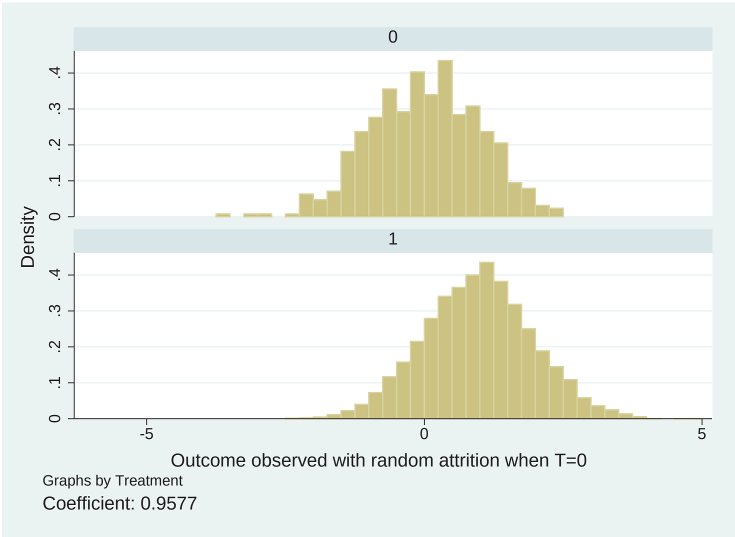
Bounds on treatment effects from randomized trials:

- Horowitz and Manski (2000):
  - Make no assumptions besides bounded support for the outcome.
  - What is the worst-case scenario for missing observations?
  - Replacing missing values with maximum or minimum in the support.
  - The result may be uninformative much of the time, but is at least a benchmark.
- Lee (2005 NBER, 2008 online, 2009 ReStud):
  - Assumption: Monotonicity. “treatment assignment can only affect sample selection in ‘one direction’. ”
  - Bounded support not required.
  - Worst-case scenario for missing obs. is less extreme than above.
  - Throw away highest/lowest values from less-attritted study arm.
  - Identifies the ATE for never-attriters.

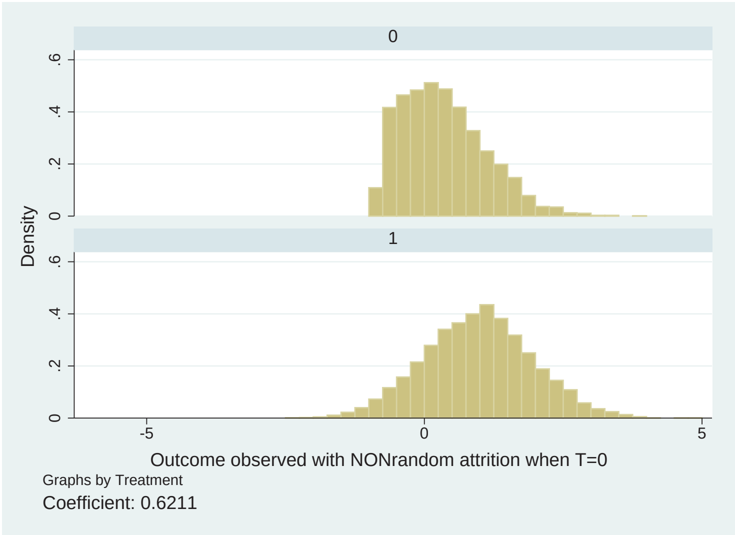
Departure point



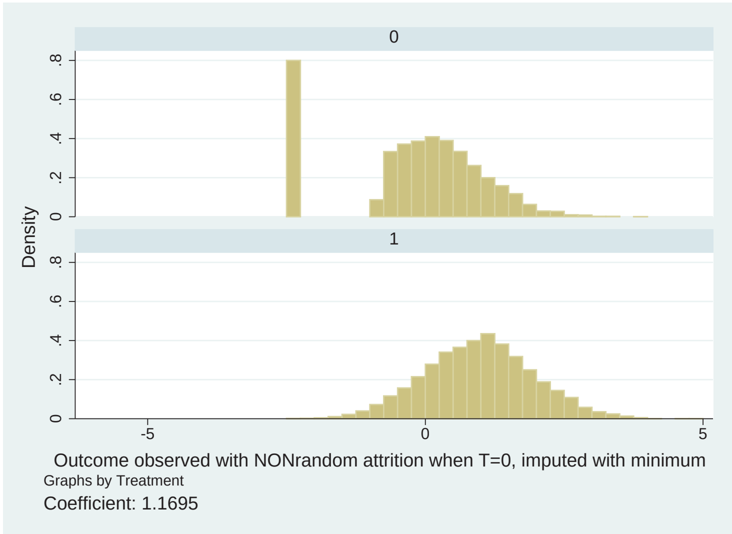
Attrition at random



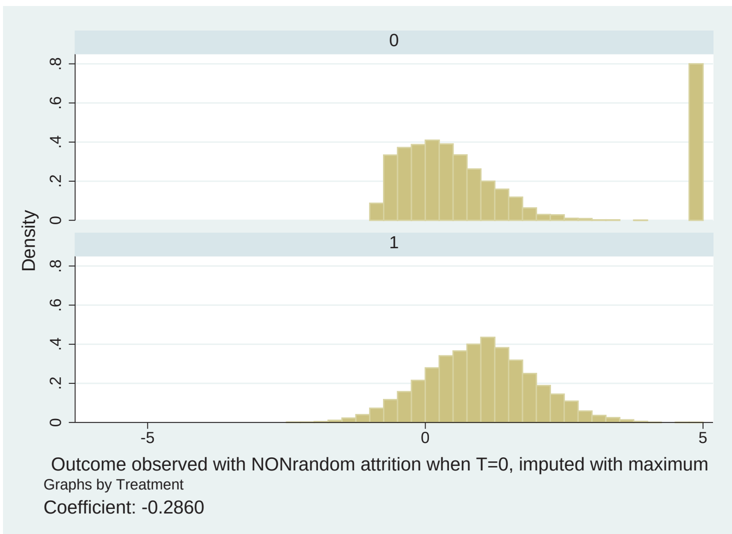
Attrition not at random



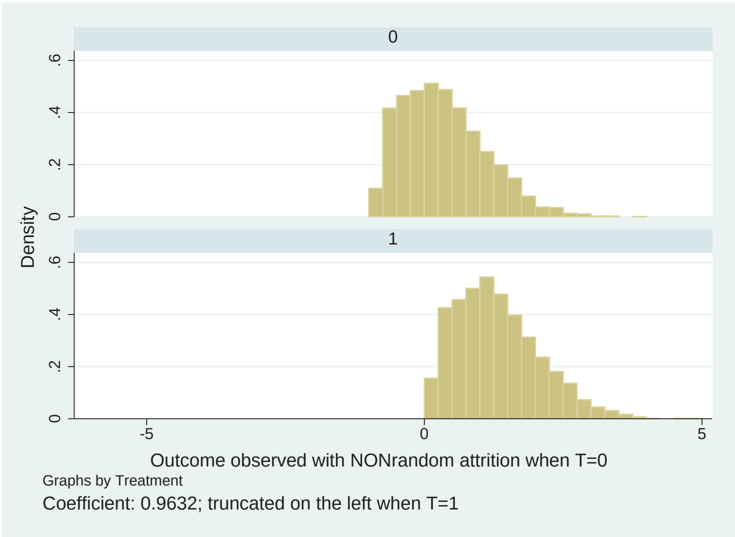
Manski upper bound



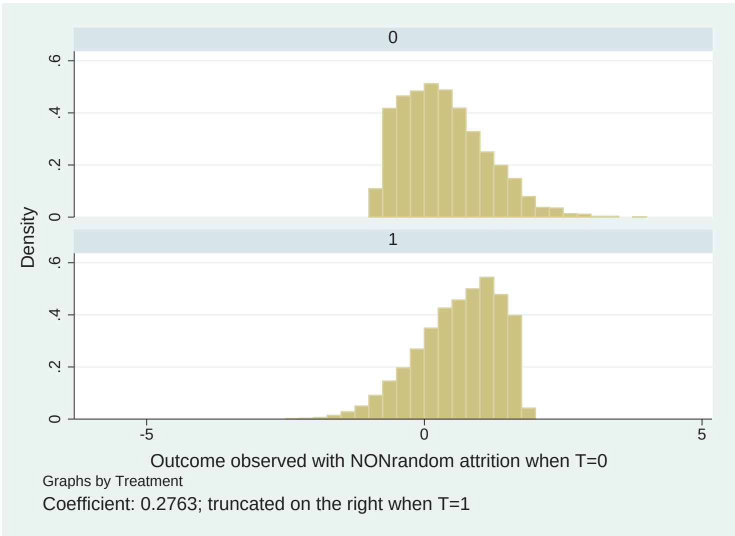
Manski lower bound



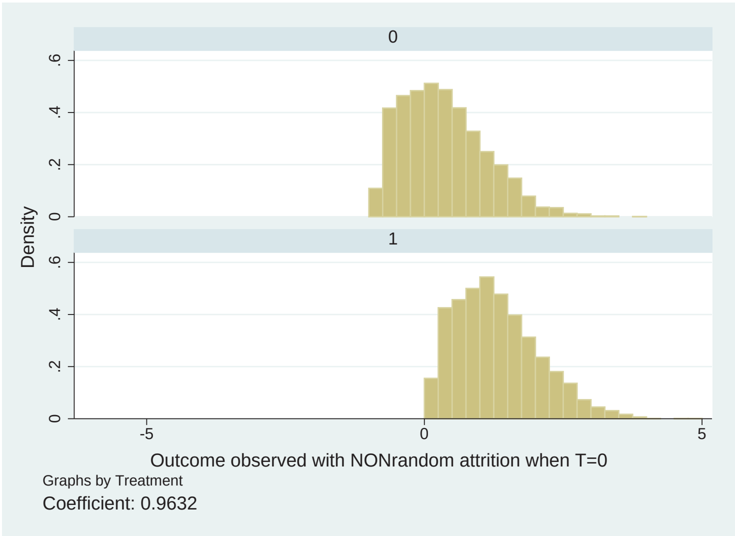
Lee upper bound



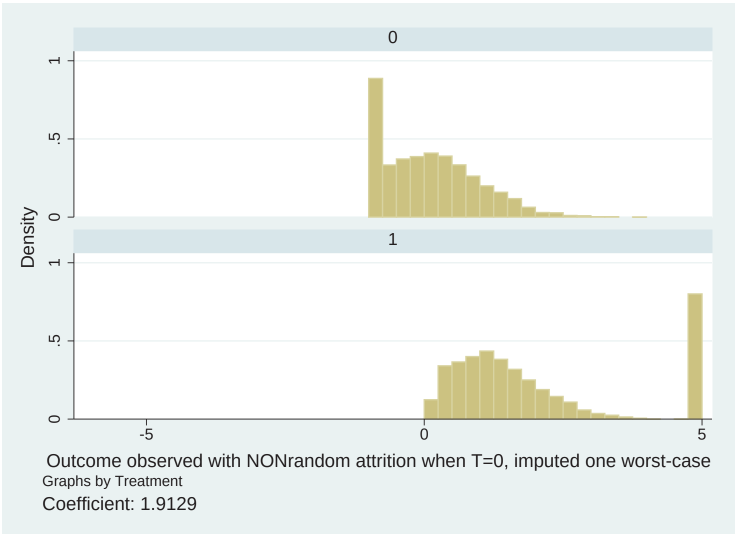
Lee lower bound



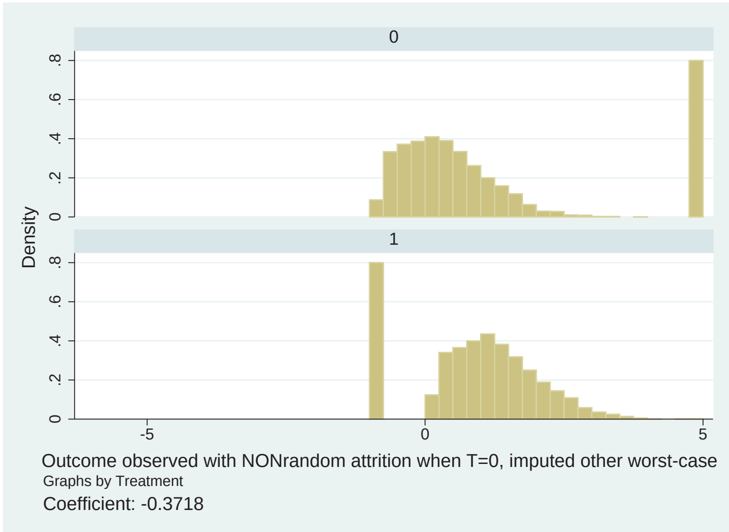
What if same attrition in both groups?



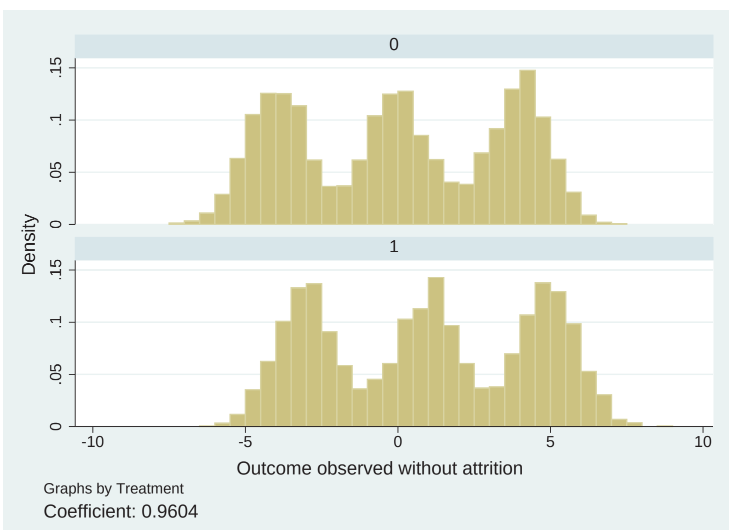
Manski upper bound



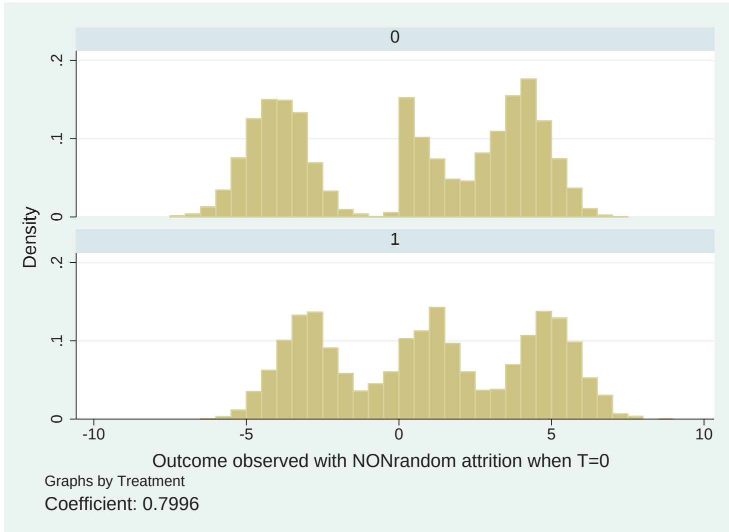
Manski lower bound



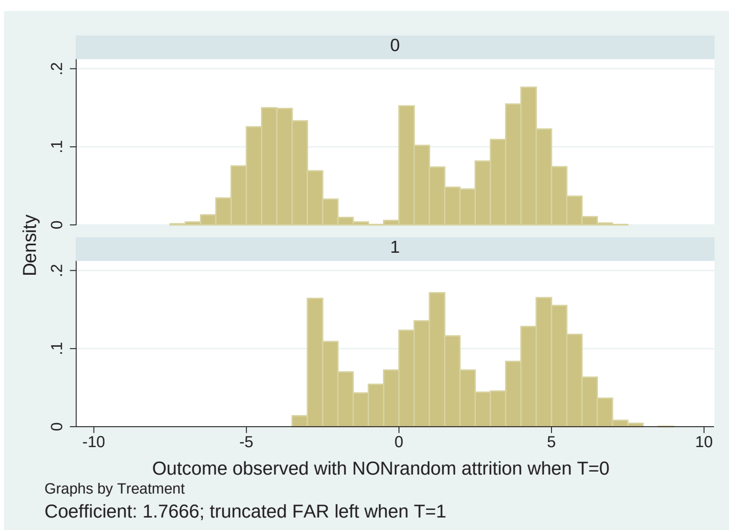
If a control variable predicts outcome...



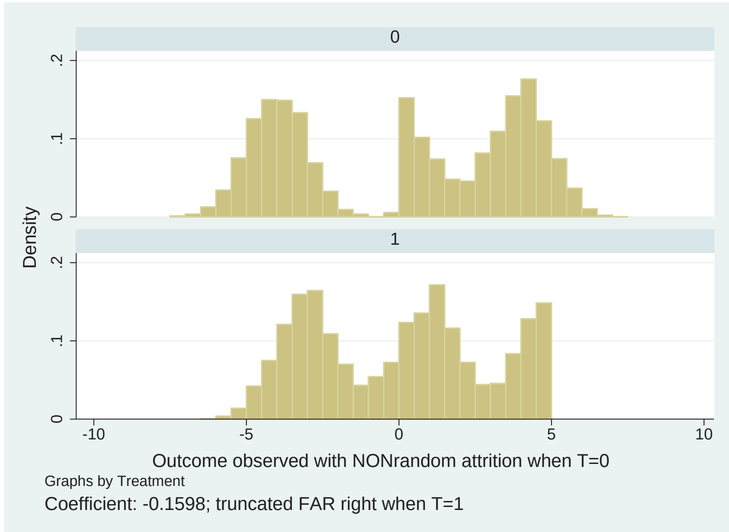
If a control variable predicts outcome... and attrition



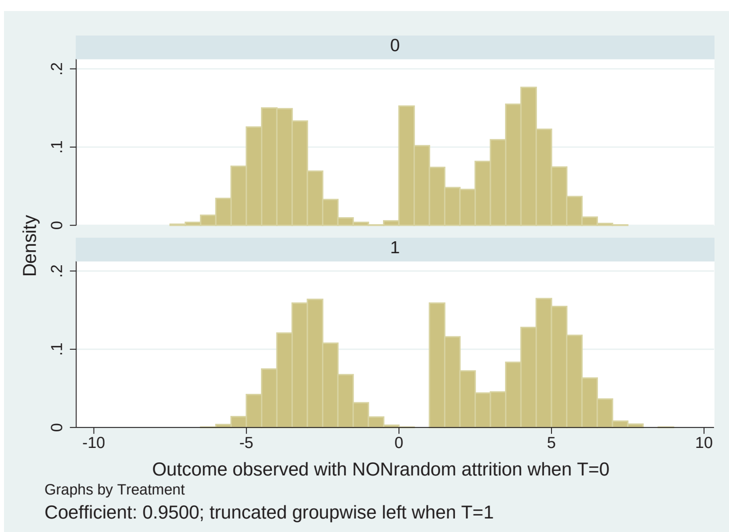
We could ignore it, and compute Lee upper bound



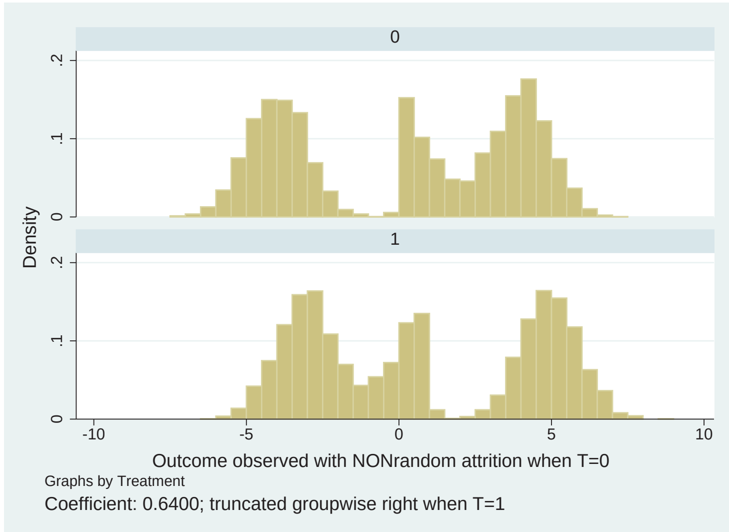
We could ignore it, and compute Lee lower bound



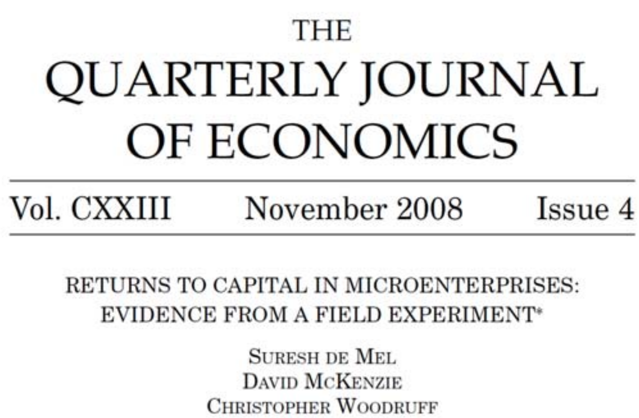
Or use tight Lee upper bound



And tight Lee lower bound



A comment on using these in practice



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RETURNS TO CAPITAL IN MICROENTERPRISES:
EVIDENCE FROM A FIELD EXPERIMENT*

SURESH DE MEL
DAVID MCKENZIE
CHRISTOPHER WOODRUFF

A comment on using these in practice

The attrition rate is thus 11.5% firm-period observations. Comparing firms assigned to treatment and to control, the attrition rate is 14.3% for the control group and 9.6% for the group assigned to treatment.

To examine the robustness of our results to this differential attrition, we use the bounding approach of Lee (2005) to construct upper and lower bounds for the treatment effect. The key identifying assumption required for implementing the Lee (2005) bounds is a monotonicity assumption that treatment assignment affects sample selection only in one direction. In our context, this requires assuming that there are some firms who would have attrited if they had not been assigned to treatment, but that no firm attrits as a result of being assigned to treatment. This seems plausible in our context.

A comment on using these in practice

To construct the Lee (2005) bounds we trim the distribution of profits for the group assigned to treatment by the difference in attrition rates between the two groups as a proportion of the retention rate of the group assigned to treatment. In our application, this requires trimming the upper or lower 5.2% of the real profits distribution for the group assigned to treatment. Doing this then gives a lower bound for the treatment effect of 404 LKR and an upper bound of 754 LKR, compared to the treatment effect of 541 in column (2), Table III. Similarly, the bounds for the return to capital of 5.3% estimated in column (4), Table IV, are 2.6% and 6.7%. The lower bounds occur only if it is the most profitable control firms that attrit. However, a panel regression predicting attrition as a function of the previous period's profit finds no significant effect of having high profits on attrition, and that having the previous period's profit in the bottom 10% lowers the probability of staying in the sample by five percentage points ($p = .054$). Attrition of the least profitable firms from the control sample would lead us to understate the returns, making the upper bounds more relevant. Thus our estimated treatment effects and return to capital appear robust to attrition.

Standard errors

Three components:

- Usual
- Quantile
- Estimation of quantile

Standard errors

For the entire interval, you can do better than:

$$\left[\widehat{\Delta^{LB}} - 1.96\frac{\widehat{\sigma_{LB}}}{\sqrt{n}}, \widehat{\Delta^{UB}} + 1.96\frac{\widehat{\sigma_{UB}}}{\sqrt{n}}\right]$$

Instead (Imbens and Manski 2004), use:

$$\left[\widehat{\Delta^{LB}} - \bar{C}_n\frac{\widehat{\sigma_{LB}}}{\sqrt{n}}, \widehat{\Delta^{UB}} + \bar{C}_n\frac{\widehat{\sigma_{UB}}}{\sqrt{n}}\right]$$

where $\bar{C}_n$ satisfies:

$$\Phi\left(\bar{C}_n + \sqrt{n}\frac{\widehat{\Delta^{UB}} - \widehat{\Delta^{LB}}}{\max(\widehat{\sigma_{LB}}, \widehat{\sigma_{UB}})}\right) - \Phi\left(-\bar{C}_n\right) = 0.95$$