14.75: Leaders and Democratic Institutions

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Do Leaders Matter?

One view about leaders:

> *"The historians, from an old habit of acknowledging divine intervention in human affairs, look for the cause of events in the expression of the will of someone endowed with power, but that supposition is not confirmed either by reason or by experience."*

– Leo Tolstoy

Another view:

> *"There is no number two, three, or four... There is only a number one: that's me and I do not share my decisions."*

– Felix Houphouet-Boigny, President of Cote D'Ivoire (1960-1993)

Who is right?And when do leaders matter?

Do Leaders Matter?

- Why might leaders (Presidents, Prime Ministers, etc) matter for economic outcomes (e.g. economic growth)?
- Why might they not?
- How do we empirically study whether political leader matter?
- As with any empirical study, we need three things:
  - An outcome variable (e.g. economic growth). This is called the *dependent variable*.
  - An explanatory variable (e.g. leader identity). This is called the *independent variable*.
  - Variation in the explanatory variable. If you had the same leader forever, you'd never be able to see if changing leaders affected anything.

Understanding variation

- Much of what we'll study in empirical papers is about finding good variation in the explanatory variable.
    - E.g., we need to know why leaders are changing.
    - For example, Presidents are more likely to lose elections when the economy is doing badly.
    - So you're more likely to change Presidents when the economy is doing badly than when the economy is doing well.
    - What could happen if you just looked at changes in economic growth depending on whether the President was re-elected?

Variation in Leaders

- We'll study examine two empirical papers that investigate these questions:
  - Paper 1: Jones and Olken (2009): "Hit or Miss? The Effect of Assassinations on Institutions and War"
  - Paper 2: Jones and Olken (2005): "Do Leaders Matter? National Leadership and Growth Since World War II"
- The key idea of both of these papers is that they try to identify clean (or "exogenous") variation in who the leader is; that is, variation that is as if it was a random experiment.
- These are often called "natural experiments."
- Let's see how this works.

Why Study Assassinations

- The idea of the paper is assassination attempts provide something like a randomized experiment in changing the leader: failed assassinations are a control group for successful assassinations
  - e.g., compare the assassination of JFK to the assassination attempt on Ronald Reagan. Bullet killed JFK but missed Reagan's heart by inches.
- We'll come back to whether this is a good idea in a minute

How to Study Assassinations

- To see whether changing the leader matters, we look at assassination attempt i and estimate the following regression:

$$y_i = \beta SUCCESS_i + \varepsilon_i$$

  - y_i is:the outcome variable (e.g., change in democracy levels from year before assassination attempt to 5 years after attempt)
  - $SUCCESS_i$ is: a dummy variable: $= 1$ if leader killed and $= 0$ if survives
  - ε_i is: an error term.
  - β is: the average impact of a successful assassination on y

- In this simple regression $\hat{\beta}$ is just the difference in y_i between when the attempt succeeds and when it fails, i.e.

$$\hat{\beta} = \mathbf{E}\left[y \mid SUCCESS = 1\right] - \mathbf{E}\left[y \mid SUCCESS = 0\right]$$

The identifying assumption in theory

$$y_i = \beta SUCCESS_i + \varepsilon_i$$

- The key assumption in any regression like this is that ε and $SUCCESS$ are uncorrelated
- Why is this?
- Suppose we calculated

$$\hat{\beta} = \mathbf{E}\left[y \mid SUCCESS = 1\right] - \mathbf{E}\left[y \mid SUCCESS = 0\right]$$

  Substituting in that $y_i = \beta SUCCESS_i + \varepsilon_i$ yields

$$\hat{\beta} = \beta + \mathbf{E}\left[\varepsilon \mid SUCCESS = 1\right] - \mathbf{E}\left[\varepsilon \mid SUCCESS = 0\right]$$

- Thus we required that $\mathbf{E}\left[\varepsilon \mid SUCCESS = 1\right] = \mathbf{E}\left[\varepsilon \mid SUCCESS = 0\right]$, i.e. that ε is uncorrelated with $SUCCESS$

The identifying assumption in practice

$$y_i = \beta SUCCESS_i + \varepsilon_i$$

- Suppose that y is a variable that captures "became a democracy between the year before assassination attempt and after assassination attempt".
- What does it mean that ε and $SUCCESS$ are uncorrelated in this context?
- Answer:
    - It means that assassination attempts not more likely to succeed if the country was going to become democratic anyway
- For example, on the eve of the Iraq war, the U.S. tried to assassinate Saddam Hussein. Suppose all the cases were like that. Would that be a problem?
- Suppose that the U.S. tried really, really hard to assassinate Saddam Hussein because they knew they were going to go to war to remove him if they failed? Would that be a problem?

$$y_i = \beta SUCCESS_i + \varepsilon_i$$

- How would we that ε and $SUCCESS$ are uncorrelated?
- Answer: we can't ever check it directly. It is an assumption.
- But we can try to think of other things that it might imply. In particular, we can check that other things we might think are correlated with y_i are uncorrelated with $SUCCESS_i$

Control variables

$$y_i = \beta SUCCESS_i + \varepsilon_i$$

- We saw that assassination attempts using guns are more likely succeed than those using bombs
- Guns require a more dedicated assassin, since you're more likely to get caught firing a gun than planting a bomb
- So maybe guns are more likely to be used when it's more likely that there would be a democratization anyway. Would this be a problem?
- If so, we can control for guns:

$$y_i = \beta SUCCESS_i + \gamma GUN + \varepsilon_i$$

- Now the assumption is that ε is uncorrelated with $SUCCESS$, once we condition on whether there was a gun or not.
  - E.g., we compare the impact of successes with guns to failures with guns, and the impact of successes without guns to failures without guns

What control variables do and don't solve

- In cases like this one – where we think we have really isolated the source of the problem (guns are more likely to succeed and may be correlated with y_i) – control variables help

- But in general there is no substitute for a good research design that creates variation that is pseudo-random – i.e., you know where your variation is coming from and can assess the identification assumption that it is uncorrelated with your outcome, based on first principles

- For example:
  - Suppose we compared years with successful assassinations to all other years in all countries
  - Is this a good idea? Why or why not?

OK, so what is the answer?

- We restrict our attention to "serious assassination attempts" where the gun was fired, bomb exploded, etc
- Regress

$$y_i = \beta SUCCESS_i + \gamma WEAPON_i + \varepsilon_i$$

where $WEAPON_i$ are several dummy variables for different weapon types
- Examine change in whether a country is democratic or not
  - POLITY dataset classifies all countries since 1875 as autocracies (0) or democracies (1)
  - Look for any change, and change in positive direction
  - Archigos dataset looks at leader transitions, and classifies them as regular (elections) or irregular (coups). Look at percent over next 20 years that are regular.
- Examine changes in conflict
  - Conflicts with > 1000 deaths per year (COW dataset)
  - Conflicts with > 1000 deaths per year 25-1000 deaths per year (PRIO)

Wait, how do I know if the difference is meaningful?

- We are estimating

$$y_i = \beta SUCCESS_i + \gamma WEAPON_i + \varepsilon_i$$

- In addition to estimating $\hat{\beta}$, we also need to know how precise our estimate of $\hat{\beta}$ is
- So we also calculate the *standard error* of $\hat{\beta}$, denoted σ. What is this?
- Definition: the standard error of $\hat{\beta}$ is the standard deviation of our estimate of $\hat{\beta}$ around the true value β.
  - That is, suppose we re-ran the world 100 times and collected the data each time. The standard error of $\hat{\beta}$ captures the standard deviation of our estimate of $\hat{\beta}$ across those 100 iterations
- Example from sampling:
  - Suppose there are 300 million people in the US. We randomly sample 1000 of them and run a regression.
  - Standard errors says: how much would $\hat{\beta}$ change if we repeatedly drew different 1000 person random samples.

Standard errors and hypothesis testing

- How is this related to a confidence interval?
- A standard error (σ) is the standard deviation of our estimate of $\hat{\beta}$
- Define the true value of β as β^*
- The standard error means that $\hat{\beta}$ is distributed as a Normal variable with mean β^* and standard deviation σ

Distribution of

$\hat{\beta}$

- Suppose we have a normal distribution (draw on board) centered around $\hat{\beta}$ with standard error σ.
- Where is the true β?

Hypothesis testing

- A statistical test takes the following form:
  - Suppose that I have a null hypothesis that $\beta = \beta_0$.
  - Can I reject that null hypothesis?
  - How do I test this? I say: If the truth was that $\beta = \beta_0$, and the standard error is σ, then I know the likely distributions of $\hat{\beta}$ I would estimate given β_0.
  - If the $\hat{\beta}$ I estimate looks very unlikely to occur under the null β_0, I say that $\hat{\beta}$ is *statistically significantly different from* β_0.
  - Usually we test the null that $\beta_0 = 0$. In this case if we can reject that $\hat{\beta} = 0$, we just say that $\hat{\beta}$ *statistically significant*.
  - We define the probability that $\beta^* = \beta_0$ given our estimate $\hat{\beta}$ as the significance level. Conventionally we use 5% threshold, but sometimes 1% or 10%.
  - So "statistically significant at 5% level" means that we the probability of that $\beta^* = 0$ given our estimate $\hat{\beta}$ is less than or equal to 5%.
- In most cases, we can reject at the 5% level if $\left|\hat{\beta}\right| > 1.96\sigma$ and we can reject at the 10% level if $\left|\hat{\beta}\right| > 1.65\sigma$

Confidence intervals

- Suppose we have a normal distribution (draw on board) centered around β_0 with standard error σ.
- What do p values look like?

Confidence interval

- A confidence interval is the range of null hypotheses that we cannot reject at the 5% level
- Usually, this is

$$\left[\hat{\beta} - 1.96\sigma, \hat{\beta} + 1.96\sigma\right]$$

- So $\hat{\beta}$ is statistically significant at the 5% level if 0 is outside the 5% confidence interval

Now we are finally ready to look at the answer

- Regress

$$y_i = \beta SUCCESS_i + \gamma WEAPON_i + \varepsilon_i$$

  where $WEAPON_i$ are several dummy variables for different weapon types

- Examine change in whether a country is democratic or not
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Interpretation

- What do the assassination results tell us about the impact of leaders?

What about economic activity?

- Unfortunately, economic growth data only start in 1950, and for most countries, it only starts in 1960 or 1970.
- There are not enough assassination attempts during that period (especially in autocratic regimes) to really be of much use
- So here we use a different approach: we consider deaths of leaders either in accidents or by natural causes.
- Why not use other types of deaths?

Methodology

- Methodology:
    - Compare economic growth rates 5 years before the death of the leader with 5 years after
    - Ask: in general, are the changes in growth rates over the 5-5 year intervals when leaders die larger than what would be predicted by random chance?
- Findings:
    - Leaders matter
    - But only in autocracies, not democracies
    - Random leader changes affect inflation
- What does this imply?
- Why might leaders not matter in democracies?

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