# API-202B Empirical Methods II

# Session #12: Instrumental Variables

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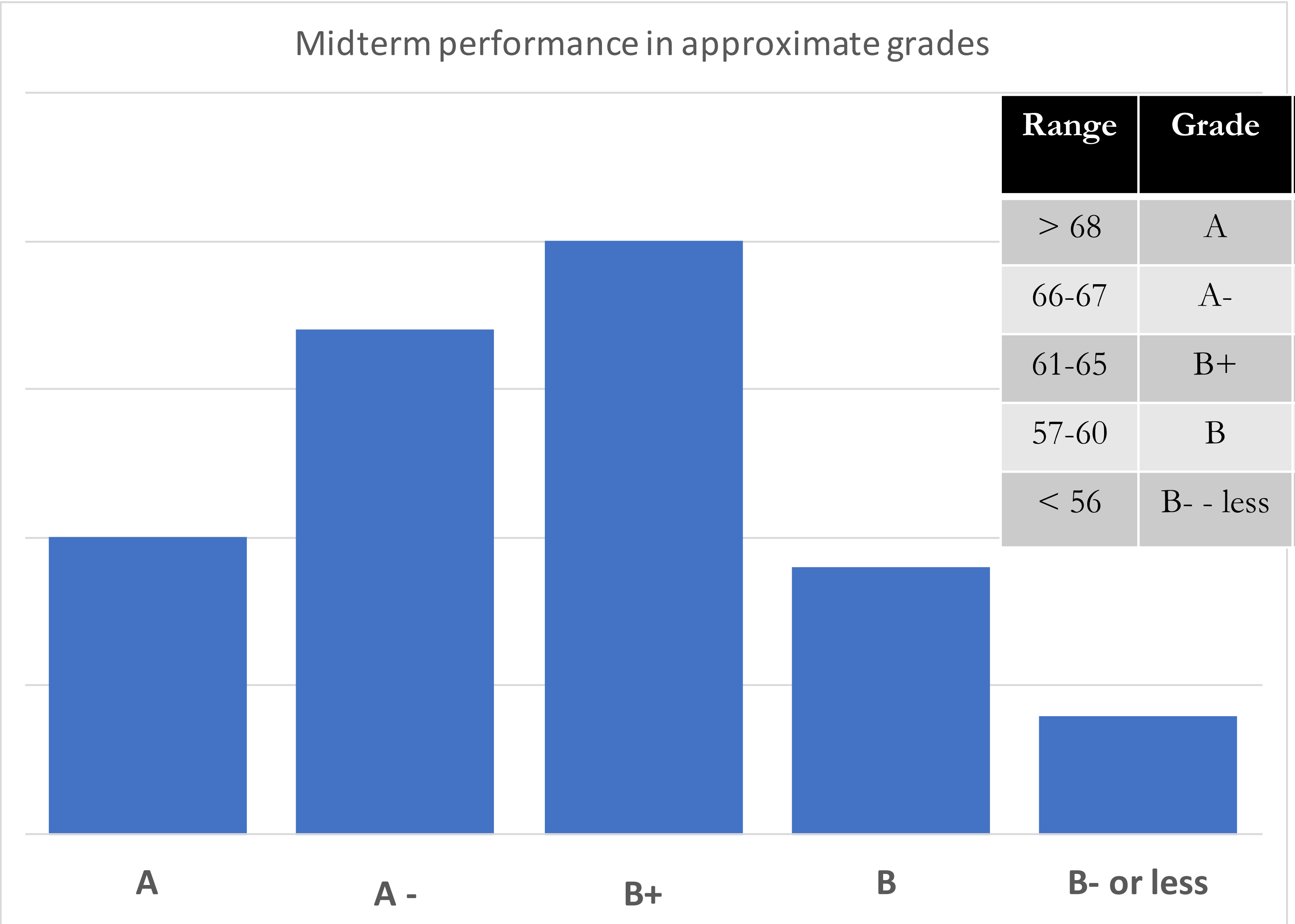
# Strong midterm performance!




| Range | Grade | (%) Actual | (% ) Recom |
|---|---|---|---|
| > 68 | A | 17% | 10% - 15% |
| 66-67 | A- | 28% | 20% - 25% |
| 61-65 | B+ | 33% | 30% - 40% |
| 57-60 | B | 15% | 20% - 25% |
| < 56 | B- - less | 7% | 5% - 10% |

# Strong midterm performance!

| | (1) | (2) |
|---|---|---|
| VARIABLES | midterm | midterm |
| ps1 | -0.101 | 0.211 |
| | (0.570) | (0.411) |
| ps2 | 1.108** | 1.121** |
| | (0.471) | (0.454) |
| comments | 0.134 | 0.184 |
| | (0.135) | (0.115) |
| absences | -0.937 | -1.712 |
| | (1.436) | (1.298) |
| female | 0.781 | 0.752 |
| | (1.260) | (1.159) |
| english | | 0.821 |
| | | (1.684) |
| Constant | 55.39*** | 51.33*** |
| | (4.055) | (3.604) |
| Observations | 60 | 60 |
| R-squared | 0.166 | 0.299 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

# Today's class: Instrumental Variables

## Do Political Protests Matter? Evidence from the Tea Party Movement*

Andreas Madestam, Daniel Shoag, Stan Veuger, David Yanagizawa-Drott

*The Quarterly Journal of Economics*, Volume 128, Issue 4, 1 November 2013, Pages 1633–1685,
https://doi.org/10.1093/qje/qjt021
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**Abstract**

Can protests cause political change, or are they merely symptoms of underlying shifts in policy preferences? We address this question by studying the Tea Party movement in the United States, which rose to prominence through coordinated rallies across the country on Tax Day, April 15, 2009. We exploit variation in rainfall on the day of these rallies as an exogenous source of variation in attendance. We show that good weather at this initial, coordinating event had significant consequences for the subsequent local strength of the movement, increased public support for Tea Party positions, and led to more Republican votes in the 2010 midterm elections. Policy making was also affected, as incumbents responded to large protests in their district by voting more conservatively in Congress. Our estimates suggest significant multiplier effects: an additional protester increased the number of Republican votes by a factor well above 1. Together our results show that protests can build political movements that ultimately affect policy making and that they do so by influencing political views rather than solely through the revelation of existing political preferences. *JEL* Code: D72.

# IV Example: The effects of political protests

- Question: Can political protest affect elections and public policy?
- Explored in a paper by former API-202 instructor Dan Shoag and former HKS professor David Yanagizawa-Drott
- On April 15 2009, Tea Party movement held nation-wide protests
  - Rallies were held in 581 counties, with an average size of 166 protesters (standard deviation of 1,004)
  - Studied if Tea Party protests impacted votes in the 2010 midterm elections and policy-making in the U.S. Congress
- Specifically, authors asked whether size of protests affected how many votes Republican Party candidates got in the elections

# IV Example: The effects of political protests

- The key regression of interest was:

$$rep\_votes = \beta_0 + \beta_1 protesters + u$$

- Each observation is a U.S. county
  - *rep_votes* is the number of Republican U.S. House votes in the county in 2010 (in '000s)
  - *protesters* is the number of Tea Party protesters (in '000s) in the county on the rally day

# IV Example: The effects of political protests

| Table 1. | Rep. Votes, 2010 '000 |
|---|---|
| Number of Protesters, '000 | 27.5 |
| | (4.4) |
| Constant | 10.2 |
| | (1.2) |
| Observations | 2962 |

Robust standard errors in parentheses.

- Interpret the *protesters* coefficient

An additional 1,000 Tea Party protesters in 2009 is associated with 27,500 more votes for Republicans in 2010.

# IV Example: The effects of political protests

- Is the OLS estimate likely to be internally valid?

  No. Many factors are correlated with Tea Party support and Republican vote share, including how conservative a particular area/county is.

- In what direction are the OLS estimates likely biased?

Upwards. Corr(conservative, rally size) > 0 -> Bias > 0

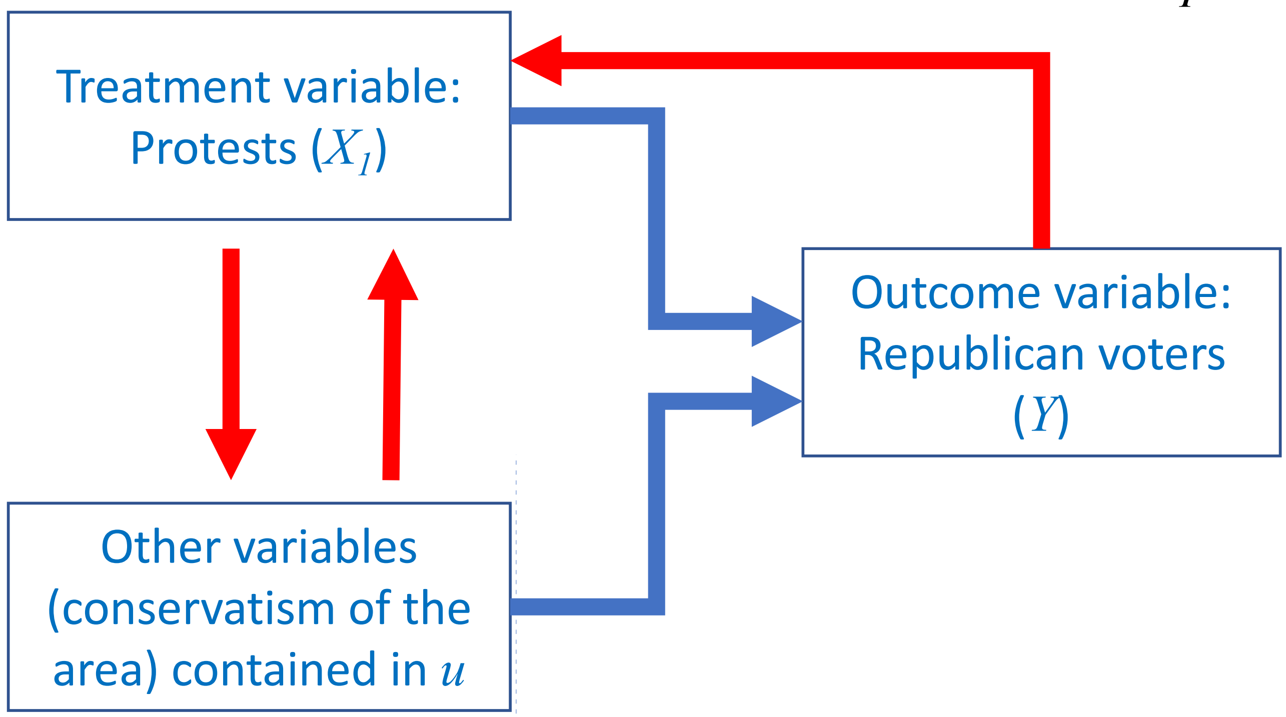
Corr(conservative, R vote numbers) > 0

Likely an overestimate because some of the "effect" of rally size is actually due to prior levels of conservatism.

# Instrumental Variables Introduction: What is the problem we are trying to solve?

**Simultaneous causality:**
$\boldsymbol{X_1}$ plausibly causes $\boldsymbol{Y}$, but plausibly $\boldsymbol{Y}$ can also be a driver of $\boldsymbol{X_1}$

**Endogeneity:**
Explanatory variable is correlated with the error term

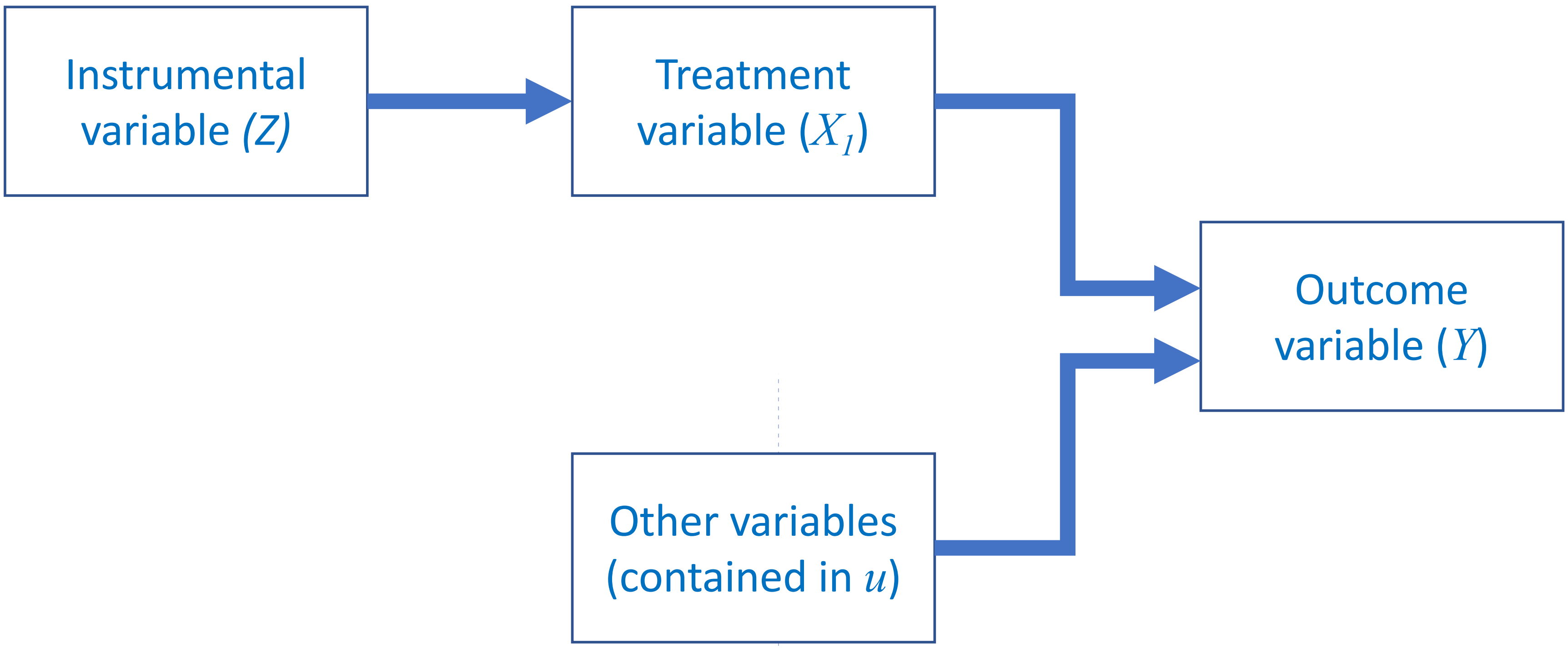


# Instrumental Variables: Introduction

- **Instrumental variables (IV)** estimation uses quasi-random variation in treatment assignment to <u>mimic an experiment</u>
- Ideally, we would like to randomly assign Tea Party protests to certain places with more intensity than others, and measure the difference in outcomes (Republican share of vote in those places, midterms of 2010):
  - What if we find a natural way to randomly assign massive protests to some places, and smaller protests to other places?
- It's a **quasi-experimental** technique (or a "natural experiment")

# Instrumental Variables

- The challenge lies in finding an instrumental variable (Z) that is correlated with X1 (protesters) but uncorrelated with u (everything else potentially causing OVB)




- **Instrumental variables** (**IV**) regression is aimed at breaking $X_1$ into two parts: one that might be correlated with $u$ and another that is not
- The part of $X_1$ that is uncorrelated with $u$ gives an unbiased $\beta_1$ estimate

# IV Example: The effects of political protests

- Authors use rainfall on the day of rally as instrumental variable
  - The variable *rainy_rally* is a dummy variable equal to one if it rained in the county on the rally day (zero otherwise)
- The authors claim that the instrument is valid because rainfall is a random event, <u>as long as the probability of rain in the county is controlled for</u>
- What is it important to control for the probability of rain?

Some people might decide whether to attend or not a rally based on probability of rain, in which case the number of compliers (those who change their behavior depending on the state of the instrumental variable) is lower and the instrument weaker.

- The instrument Z must must satisfy two conditions:

1. **Instrument relevance**: corr $(Z, X_1) \neq 0$. The instrument is correlated with $X_1$, the endogenous (non-random) regressor

2. **Instrument exogeneity (exclusion restriction)** corr $(Z, u) = 0$. If the instrument is correlated with Y, it is only through $X_1$ and not through any other channels

# IV Example: The effects of political protests

Do you think this instrumental variable would be valid?

- Relevance:

  Possibly, because rain could make people less likely to show up to a protest [can check empirically]. In our example, if rain (Z) is a good instrument, it should be correlated with protesters (after controlling for other relevant factors).

- Exogeneity (exclusion restriction):

  In our example, one can plausibly assume that the only way rain on the day of the rally (Z) affects the election outcome (Y) is through its influence on the size of the protests ($X_1$)

  The question is: Other than through the protests themselves, why else would rain on April 15, 2009 affect voting in November 2010?

## IV Steps: Using instrumental variables involve **three different steps**

**Step 1. First stage regression**: test the instrument for **relevance**.

The endogenous regressor X (*protesters*) is regressed on instrument Z (*prob_rain* is the probability of rain):

$$protesters = \beta_0 + \beta_1\, rainy\_rally + \beta_2\, prob\_rain + \varepsilon$$

- Interpret the first stage coefficient on *rainy_rally*. Is the instrument **relevant**?

Yes. On average, rainy protests were 82 protesters smaller than non-rainy protests.

| Table 2. | First Stage |
|---|---|
| Dependent Variables | Number of Protesters, '000 |
| | (1) |
| Number of Protesters, '000 | |
| Rainy Protest | -0.082 |
| | (0.021) |
| Rain probability control | Yes |
| Observations | 2962 |

Standard errors in parentheses.

## IV Steps: Using instrumental variables involve **three different steps**

**Step 2. Reduced form regression**: the outcome Y (*rep_votes*) is regressed on instrument Z (*rainy_rally*):

$$rep\_votes = \beta_0 + \beta_1\, rainy\_rally + \beta_2\, prob\_rain + \varepsilon$$

- Does the instrument affect the outcome of interest? Does rain affect voting patterns?

On average, counties with rainy protests (in April 2009) cast 1,145 fewer votes for Republicans than areas with non-rainy protests.

**Table 2.**

| | **Reduced Form** |
|---|---|
| Dependent Variables | Rep. Votes, 2010 '000 |
| | (2) |
| Number of Protesters, '000 | |
| Rainy Protest | -1.145 |
| | (0.503) |
| Rain probability control | Yes |
| Observations | 2962 |

Standard errors in parentheses.

IV Steps: Using instrumental variables involve **three different steps**

**Step 3. IV estimate or second stage regression**: Run this regression (using Stata's *ivreg2 rep_votes (protesters=rainy rally)*):

$$rep\_votes = \beta_0 + \beta_1 \widehat{protesters} + \beta_2 prob\_rain + \varepsilon$$

| **Table 2.** | **First Stage** | **Reduced Form** | **IV/2SLS** |
|---|---|---|---|
| Dependent Variables | Number of Protesters, '000 | Rep. Votes, 2010 '000 | Rep. Votes, 2010 '000 |
| | (1) | (2) | (3) |
| Number of Protesters, '000 | | | 13.90 |
| | | | (6.73) |
| Rainy Protest | -0.082 | -1.145 | |
| | (0.021) | (0.503) | |
| Rain probability control | Yes | Yes | Yes |
| Observations | 2962 | 2962 | 2962 |

Standard errors in parentheses.

# IV Example: The effects of political protests

- Interpret the IV (2SLS) coefficient on protesters

  Each additional Tea Party protester is associated with 13.9 additional votes for Republicans.

- Do you notice a relationship between the three coefficients?¡

  B_IV = B_ReducedForm / B_FirstStage

  $$13.9 \text{ GOP votes/protester} = \frac{1.145 \text{ GOP votes in rainy rallies}}{0.080 \text{ protesters in rainy rallies}}$$

More intuitively:

13.9 votes/protester * 0.8 protester/rally = 1.145 votes in places with rainy rallies

- Is that coefficient causal? Is the instrument exogenous? Is there another channel through which rain on April 15, 2009 could have affected election results in November 2010?

  Once you control for the probability of rain in a county, it seems safe to assume that actual rain on the day of the protest are indeed exogenous.

# Other IV examples

(always look for instrumental variable (Z), the "treatment" (X), and the outcome (Y)

- Settlers mortality rates in the colonies (Z) has been used as instrument for institutions (X), to study if institutions (X) have a positive impact on income per capita (Y) (Acemoglu-Robinson)
- Vietnam-era draft lottery numbers (Z) have been used as an instrument for military service (X) to ask whether military service (X) affects labor market earnings (Y) (Angrist)
- Cuban immigrants coming to Miami on Mariel lift-boat (Z) have been used as an instrument for the impact of immigration (X) on the equilibrium salaries of domestic workers (Y) (Borjas, Clemens, and Pritchett – not together!)
- Major discoveries of oil and gas (Z) have been used as an instrument for the share of natural resources in exports (X), in studying how higher natural resources impact the diversification of the non/resource export basket (Bahar, Santos)

# Takeaways

- Instrumental variables are useful when we do not have a randomized experiment, but nature or public policy has caused two similar groups of individuals to be treated differently
- Finding a good instrument is hard!
    - Many fail the exogeneity test
    - An instrumental variables regression can adjust for imperfect compliance to the treatment in a randomized experiment
- Thinking about external validity:
    - Estimates generated from instrumental variables are based on the individuals whose behavior is affected by the instrument
    - Thus, people refer to instrumental variable estimates as local average treatment effects (or LATE)
    - This is because the estimates are average effects for a subset (i.e. local part) of the population

# Vocabulary

- Instrumental variable
- Quasi experiments or natural experiment
- Instrument relevance
- Instrument exogeneity
- First stage regression
- Reduced form regression
- Second stage regression

# Bonus slides – Estimation with IV

- We want to measure the effect of $X_1$ on Y controlling for $X_2$, using Z as an instrument for $X_1$, i.e., estimate $\beta_1$ from $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + u$, using Z as an instrument for $X_1$.
- Suppose for now that we have such a Z. How can we use Z to estimate $\beta_1$?
- The standard econometric method for estimating the effect of X on Y using an Instrumental Variable (IV) approach is called "***Two-Stage Least Squares (2SLS)***". It is called "Two-Stage" because it involves two stages (actually two regressions).

***First Stage:*** Isolate the part of *X* that is uncorrelated with *u* by running the regression:

$X_1 = \delta_0 + \delta_1 Z + \delta_2 X_2 + \delta_3 X_3 + \eta$

and get predicted values for $X_1$. Call these predicted values $\hat{X}_1$.

Note that if *Z* is uncorrelated with *u*, then $\hat{X}_1$ is uncorrelated with *u*.

***Second Stage:*** Replace $X_1$ with $\hat{X}_1$ in the regression of interest by running the regression:

$Y = \alpha_0 + \alpha_1 \hat{X}_1 + \alpha_2 X_2 + \alpha_3 X_3 + \nu$

If Z is a valid instrument then $\hat{\alpha}_1$ is an unbiased estimator of the effect of $X_1$ on Y.

# Bonus Slides – Estimation with IV

- Can you test the validity of the instruments?
  - **Relevance**: This assumption can be tested by examining the first stage regression. Stock and Watson suggest using a rule of thumb indicating that if the F test for the joint significance of the instruments is greater than 10, then the instrument is relevant. If not, the instrument is weak. Weak instruments can be problematic.
  - **Exogeneity**: This assumption needs to be assessed conceptually. While there are statistical tests (called overidentifying tests) to test this assumption, they give us limited information that is applicable only when the number of instruments is greater than the number of endogenous variables (See Stock and Watson).
- Note that you can have more than one instrument. This method works just as described above, but you need each instrument to comply with the two conditions, and in the first stage you would include all the instruments as explanatory variables.
- Most statistical packages, including Stata, do both stages together. If you do them separately there is a problem with the standard errors.
- IV estimates can be interpreted as the effect of X on Y for those whose treatment status was changed by the instrument. IV estimates measure ***marginal effects***.