Extending OLS: Fixed Effects, Controls, and Interactions

POSC 3410 – Quantitative Methods in Political Science

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Goal for Today

Add some wrinkles to the OLS regression framework.

Introduction

By this point, I think you could be doing your own research.

- You know what variables are.
- You know how to describe them.
- You know how to propose an explanation for variations in them.
- You know how to set up a research design to test an argument.
- You even know how to interpret a regression coefficient!

Limitations in Bivariate Regression

However, simple bivariate OLS is never enough.

- Variables of interest in political science are rarely interval.
- Bivariate regression does not control for confounders.

This lecture will deal with those topics accordingly.

R Packages We'll Be Using

```r
library(tidyverse)
library(stevemisc)
library(stevedata) # ?election_turnout, ?anes_prochoice
library(stargazer)

election_turnout %>%
  mutate(south = ifelse(region == "South", 1, 0)) -> election_turnout
```

Dummy Variables as Predictors

Dummy variables are everywhere in political science.

- They play an important role in “fixed effects” regression.
- Sometimes we’re just interested in the effect of “one thing”.

Swing States and Voter Turnout

Return to our education and turnout example: what if we're just interested in the effect of a state being a "swing state?"

- We'll follow 538's coding of "swing states": CO, FL, IA, MI, MN, NV, NH, NC, OH, PA, VA, and WI
- When $x = 0$, we have the y-intercept.

R Code

```r
M1 <- lm(turnoutho ~ ss, data=election_turnout)

# need stargazer and broom packages

M1df <- broom::tidy(M1)

stargazer(M1, style="ajps",
          omit.stat=c("F","rsq","ser"), header=FALSE,
          dep.var.labels.include = FALSE,
          covariate.labels=c("Swing State"),
          title="The Effect of Being a Swing State on Voter Turnout, 2016")
```

Table 1: The Effect of Being a Swing State on Voter Turnout, 2016

Swing State	7.371^{***}
	(1.747)
Constant	59.087^{***}
	(0.847)
N	51
Adj. R-squared	0.252

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$

Swing States and Voter Turnout

- The estimated turnout in safe states is 59.09%
- The estimated turnout in swing states is 66.46%
- The “swing state” effect is an estimated 7.37% (s.e.: 1.75).
- t-statistic: 7.37/1.75 = 4.22

We can rule out, with high confidence, an argument that being a “swing state” has no effect on voter turnout.

- Our findings suggest a precise positive effect.

What About Regional Variation?

Southern states tend to have lower turnout, for any number of reasons.

- Most Southern states are safe states.
- Southern states also tend to have poorer citizens, which raise costs of voting.
- A few have larger minority populations and a gross past/recent history of votings rights restrictions.

Let's first unpack regional variation by looking at the effect of the South relative to non-Southern states on voter turnout.

Table 2: The Effect of Being a Southern State on Voter Turnout, 2016

South	-3.465^{*}
	(1.768)
Constant	61.976^{***}
	(1.020)
N	51
Adj. R-squared	0.054

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$

Southern States and Voter Turnout

- The estimated turnout in non-Southern states is 61.98%
- The estimated turnout in Southern states is 58.51%
- The “South” effect is an estimated -3.46% (s.e.: 1.77).
- *t*-statistic: -3.46/1.77 = -1.96

We can rule out, with high confidence, an argument that being a Southern state has no effect on voter turnout.

- Our findings suggest a precise negative effect.
- However, don’t confuse this for a large effect. The difference is an estimated 3%.
  - This amounts to about half a standard deviation change across *y*.

Fixed Effects and Voter Turnout

Obviously, this last regression isn't that informative.

- It also problematically treats non-Southern states as homogenous.
- A meager R^2 suggests that.

We can specify other regions as "fixed effects".

- These treat predictors as a series of dummy variables for each value of *x*.
- One predictor (or group) is left out as "baseline category".
  - Otherwise, we'd have no *y*-intercept.

Table 3: The Effect of State Regions on Voter Turnout, 2016

Northeast	6.099**
	(2.351)
Midwest	4.805**
	(2.151)
West	0.404
	(2.102)
Constant	58.512***
	(1.383)
N	51
Adj. R-squared	0.131

***$p < .01$; **$p < .05$; *$p < .1$

Region Fixed Effects and Voter Turnout

How to interpret this regression:

- All coefficients communicate the effect of that region versus the baseline category.
    - This is the South in our example.
- Estimated turnout in the South is 58.51%.
- Turnout in the Northeast is discernibly higher than the South (t = 2.59)
- Turnout in the Midwest is discernibly higher than the South (t = 2.23).
- We cannot estimate a difference between the South and West (t = 0.19)

Notice the coefficient for the West is positive, but probability of observing it if there's no actual difference between South and West is 0.42. Kinda probable.

Multiple Regression

Your previous example is basically an applied **multiple regression**.

- However, it lacks control variables.

Multiple regression produces **partial regression coefficients**.

Multiple Regression

Let's return to our state voter turnout example. Let:

- x_1: % of citizens in state having a college diploma.
- x_2: states in the South.
- x_3: state is a swing state.

Important: we do this to "control" for potential confounders.

The Rationale

Assume you are proposing a novel argument that state-level education explains voter turnout. I might argue for omitted variable bias on these grounds:

- The "South" effect depresses state-level education and voter turnout.
- The "swing state" effect may explain state-level education (roll with it...) and increases voter turnout.

In other words, I contend your argument linking education (*x*) to voter turnout (*y*) is spurious to these other factors (*z*).

- That's why you "control." Not to soak up variation but to test for effect of potential confounders.

Table 4: A Simple Model of Voter Turnout, 2016

% College Diploma	0.384^{***}
	(0.111)
South	-1.940
	(1.415)
Swing State	7.008^{***}
	(1.546)
Constant	48.479^{***}
	(3.468)
N	51
Adj. R-squared	0.420

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$

Multiple Regression

- Estimated turnout for 1) a state not in the South that's 2) not a swing state and in which 3) no one graduated from college: 48.48%
    - This seems reasonable, but recall the minimum on this variable is WV (19.2%).
    - This parameter is effectively useless.
- The partial regression coefficient for % college diploma: 0.38 (t = 3.47).
- The partial regression coefficient for the South is insignificant.
    - Conceivable explanation: education levels have a more precise effect and muddy the estimated negative effect of the South.
- The estimated effect of being a "swing state" is to increase voter turnout by an estimated 7.01% (t = 4.53)

Interactive Effects

Multiple regression is linear and additive.

- However, some effects (say: x_1) may depend on the value of some other variable (say: x_2).

In regression, we call this an **interactive effect**.

A Real World Example

Consider this argument from Zaller (1992):

- Democrats are weakly more pro-choice than Republicans.
- However, the difference is very stark among the politically aware.

Let's use 2012 ANES data to evaluate whether there's something to this.

Our Data

IVs: Party ID, political knowledge, interaction between both

- Party ID: (0 = Dem, 1 = Independent, 2 = GOP)
- Political knowledge: does respondent know who Speaker of the House is?

Only 40% of respondents (n= 5,914) in the 2012 ANES data knew who the Speaker of the House was.

Our Data

DV: latent pro-choice score via graded response model of favor/oppose/neither abortion if:

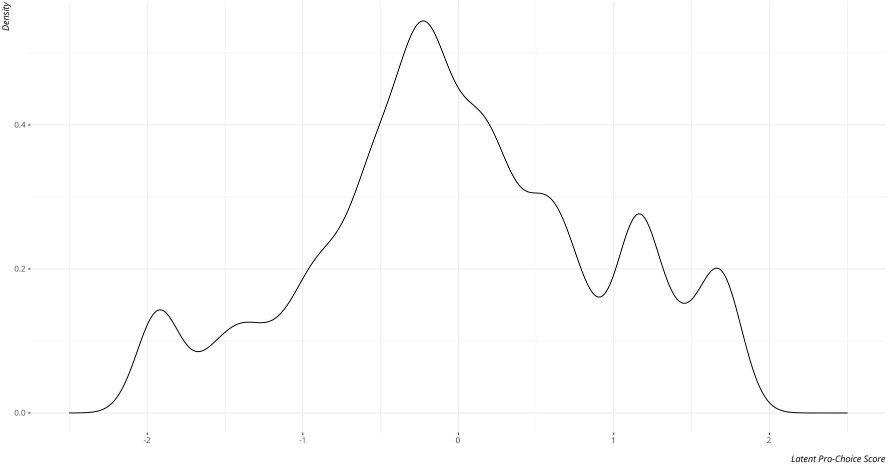
- non-fatal health risk to woman
- fatal health risk to woman
- woman pregnant via incest
- woman pregnant via rape
- birth defect cases
- financial hardship cases
- woman wants to select child gender
- it's woman's choice.

Emerging estimate has a mean of zero and standard deviation of one.

- Higher values = more "pro-choice."

Density Plot of Latent Pro-Choice Score (ANES, 2012)

The data were generated from a graded response model to have an approximate mean of 0 and standard deviation of 1.



Data: ANES (2012). Data available as anes_prochoice in stevedata. Github: svmiller/stevedata

Interactive Effects

Our regression formula would look like this:

$$\hat{y} = \hat{a} + \hat{b_1}(x_1) + \hat{b_2}(x_2) + \hat{b_3}(x_1 * x_2)$$

where:

- $\hat{y}$ = estimated pro-choice scale score.
- x_1 = partisanship (0 = Dems, 1 = Ind., 2 = GOP).
- x_2 = political knowledge (0 = doesn't know Speaker, 1 = knows Speaker).
- $x_1 * x_2$ = product of the two variables.

A Caution About Constituent Terms

Be careful with interpreting regression coefficients for constituent terms of an interaction.

- The regression coefficient for party ID is effect of party ID when political knowledge = 0.
- The political knowledge coefficient is effect of knowledge when party ID variable = 0 (i.e. among Democrats).

R Code

```r
M5 <- lm(lchoice ~ pid*knowspeaker, data=anes_prochoice)
M5df <- broom::tidy(M5)

library(stargazer)
stargazer(M5, style="ajps",
          omit.stat=c("F","rsq","ser"), header=FALSE,
          dep.var.labels.include = FALSE,
          covariate.labels=c("Party ID (D to R)", "Political Knowledge",
                             "Party ID*Political Knowledge"),
          title="A Simple Interaction Between Partisanship and
          Political Knowledge on Pro-Choice Attitudes (ANES, 2012)")
```

Table 5: A Simple Interaction Between Partisanship and Political Knowledge on Pro-Choice Attitudes (ANES, 2012)

Party ID (D to R)	-0.237^{***}
	(0.020)
Political Knowledge	0.414^{***}
	(0.036)
Party ID*Political Knowledge	-0.184^{***}
	(0.031)
Constant	0.099^{***}
	(0.022)
N	5196
Adj. R-squared	0.091

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$

Interactive Effects

How to interpret Table 5:

- Our estimate of pro-choice scores is 0.099 for low-knowledge Democrats.
- $\hat{b_1}$, $\hat{b_2}$, and $\hat{b_3}$ are all statistically significant.
- When x_1 and $x_2 = 1$, subtract -0.184 from $\hat{y}$.
- Political knowledge leads to higher pro-choice scores *among Democrats*.

Interactive Effects

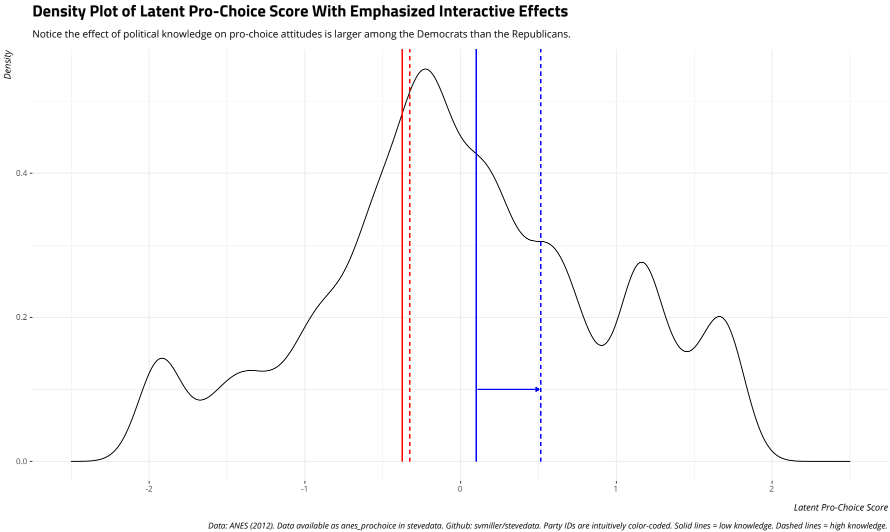
Here's what this does for Democrats:

- $\hat{y}$ for low-knowledge Democrats: 0.099.
- $\hat{y}$ for high-knowledge Democrats: 0.513.

What this does for Republicans is arguably more interesting.

- $\hat{y}$ for low-knowledge Republicans: -0.374.
- $\hat{y}$ for high-knowledge Republicans: -0.328.

You see a huge effect of political knowledge on Democrats and, perhaps, no large (or even discernible) effect on Republicans.


Density Plot of Latent Pro-Choice Score With Emphasized Interactive Effects
Notice the effect of political knowledge on pro-choice attitudes is larger among the Democrats than the Republicans.
Density
0.4
0.2
0.0
-2
-1
0
1
2
Latent Pro-Choice Score
Data: ANES (2012). Data available as anes_prochoice in stevedata. Github: svmiller/stevedata. Party IDs are intuitively color-coded. Solid lines = low knowledge. Dashed lines = high knowledge.

Conclusion

This chapter is the culmination of everything discussed previously.

- It's basically what quantitative political science is.

Regrettably, we can only use OLS for interval-level dependent variables.

- We rarely have that.
- Next, we'll discuss what to do with non-normal responses.

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