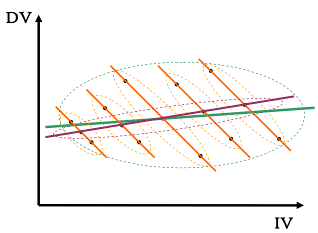
Special topics

Fixed effects

- When trying to compare apples with apples, we worry about the numerous potential differences on confounding variables
- If differences on confounding variables are stable over time, we can eliminate bias from them by only analyzing variation within the same unit over time
  - E.g., breast-feeding study (unit is woman)
  - E.g., currency unions and euro (unit is country)
- To only analyze variation within the same unit over time, we use fixed effects
  - Stata commands `areg` and `xtreg`
  - Equivalent to adding indicator (or dummy variables) variables for units
  - Equivalent to between subjects design (as opposed to within subjects)

Intra- or Inter-country Variation?

(animated slide, see summary on next slide)



[illegible]

[illegible]

(or)

[illegible]
reg [DV] [IV]

Intra- or Inter-country Variation?

Aggregate Panel Variation

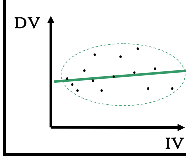
reg [DV] [IV]

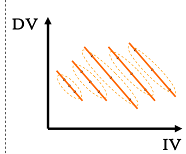
Fixed effects (fe)
Intra-Country Variation

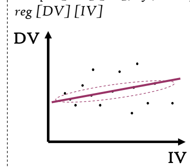
xtreg [DV] [IV], fe
(or)
areg [DV] [IV], a(country)

Between effects (be)
Inter-Country Variation

xtreg [DV] [IV], be
(or)
collapse [DV] [IV], by(country)
reg [DV] [IV]







Fixed effects

- Problems
  - Throws away potentially relevant variation (alternative: random effects)
  - Variation over time may be primarily from random measurement error (e.g., unions and wages)
  - Unusual factors may drive changes in explanatory variables over time and also influence the dependent variable (e.g., currency unions)

Interactions

Interactions

- Interactions test whether the combination of variables affects the outcome differently than the sum of the main (or individual) effects.
- Examples
  - Interaction between adding sugar to coffee and stirring the coffee. Neither of the two individual variables has much effect on sweetness but a combination of the two does.
  - Interaction between smoking and inhaling asbestos fibres: Both raise lung carcinoma risk, but exposure to asbestos multiplies the cancer risk in smokers and non-smokers. Both risk factors were not shown to be additive – a clear indication of interaction
- Example from problem set: how would we test whether defendants are sentenced to death more frequently when their victims are both *white* **and** *strangers* than you would expect from the coefficients on white victim and on victim stranger

Interactions

```
. g wvXvs = wv* vs
. reg death bd yv ac fv v2 ms wv vs wvXvs
--------------------------------------------------
 death |      Coef.   Std. Err.      t    P>|t|
-------+------------------------------------------
 (omitted)
    wv |   .0985493   .1873771     0.53   0.600
    vs |   .1076086   .2004193     0.54   0.593
 wvXvs |   .3303334   .2299526     1.44   0.154
 _cons |   .0558568   .2150039     0.26   0.796
--------------------------------------------------
```

•To interpret interactions, substitute the appropriate values for each variable

•E.g., what's the effect for

```
•                            .099 wv+.108 vs+.330 wvXvs
•White, non-stranger:     .099(1)+.108(0)+.330(1)*(0) = .099
•White,        stranger:  .099(1)+.108(1)+.330(1)*(1) = .537
•Black, non-stranger:     .099(0)+.108(0)+.330(0)*(0) =  comparison
•Black,        stranger:  .099(0)+.108(1)+.330(1)*(0) = .108
```

Interactions

```
. tab wv vs, sum(death)

Means, Standard Deviations and Frequencies of death

           |          vs
        wv |         0          1 |     Total
-----------+----------------------+----------
         0 | .16666667  .28571429 | .23076923
           | .38924947  .46880723 | .42966892
           |        12         14 |        26
-----------+----------------------+----------
         1 | .40540541  .75675676 | .58108108
           | .49774265  .43495884 |  .4967499
           |        37         37 |        74
-----------+----------------------+----------
     Total | .34693878  .62745098 |       .49
           | .48092881  .48829435 | .50241839
           |        49         51 |       100
```

Importance of a variable

Death penalty example

```
. sum death bd- yv

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
       death |       100         .49    .5024184          0          1
          bd |       100         .53    .5016136          0          1
          wv |       100         .74     .440844          0          1
          ac |       100    .4366667     .225705          0          1
          fv |       100         .31    .4648232          0          1
-------------+--------------------------------------------------------
          vs |       100         .51    .5024184          0          1
          v2 |       100         .14    .3487351          0          1
          ms |       100         .12    .3265986          0          1
          yv |       100         .08    .2726599          0          1
```

Death penalty example

```
. reg death bd-yv , beta
------------------------------------------------
 death |      Coef.   Std. Err. P>|t|       Beta
-------+----------------------------------------
    bd |  -.0869168   .1102374  0.432  -.0867775
    wv |   .3052246   .1207463  0.013   .2678175
    ac |   .4071931   .2228501  0.071   .1829263
    fv |   .0790273   .1061283  0.458   .0731138
    vs |   .3563889    .101464  0.001   .3563889
    v2 |   .0499414   .1394044  0.721   .0346649
    ms |   .2836468   .1517671  0.065   .1843855
    yv |    .050356   .1773002  0.777    .027328
 _cons |  -.1189227   .1782999  0.506          .
------------------------------------------------
```

Importance of a variable

- Three potential answers
  - Theoretical importance
  - Level importance
  - Dispersion importance

Importance of a variable

- Theoretical importance
  - Theoretical importance = Regression coefficient (b)
  - To compare explanatory variables, put them on the same scale
    - E.g., vary between 0 and 1

Importance of a variable

- Level importance: most important in particular times and places
  - E.g., did the economy or presidential popularity matter more in congressional races in 2006?
  - Level importance= $b_j * x_j$

Importance of a variable

- Dispersion importance: what explains the variance on the dependent variable
  - E.g., given that the GOP won in this particular election, why did some people vote for them and others against?
  - Dispersion importance =
    - Standardized coefficients, or alternatively
    - Regression coefficient times standard deviation of explanatory variable
    - In bivariate case, correlation

Which to use?

- Depends on the research question
  - Usually theoretical importance
  - Sometimes level importance
  - Dispersion importance not usually relevant

Partial residual scatter plots

Partial residual scatter plots

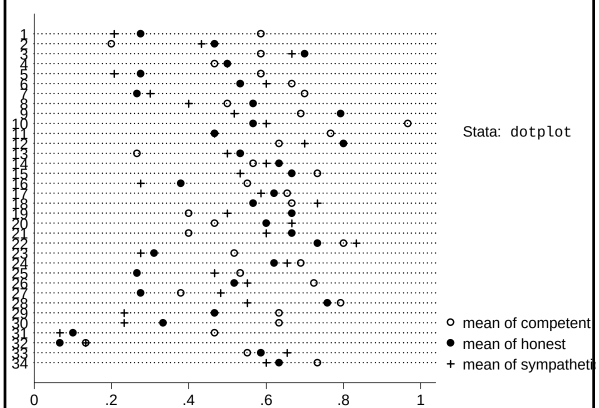
- Importance of plotting your data
- Importance of controls
- How do you plot your data after you've adjusted it for control variables?
- Example: inferences about candidates in Mexico from faces

Greatest competence disparity: pairing 10

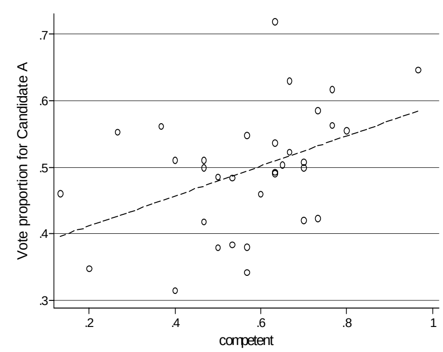
A

B

- Gubernatorial race
- A more competent
- Who won?
  - A by 65%



Stata: `dotplot`



Regression

```
      Source |       SS       df       MS              Number of obs =      33
-------------+------------------------------           F(  3,    29) =    4.16
       Model |  .082003892     3  .027334631           Prob > F      =  0.0144
    Residual |  .190333473    29  .006563223           R-squared     =  0.3011
-------------+------------------------------           Adj R-squared =  0.2288
       Total |  .272337365    32  .008510543           Root MSE      =  .08101

------------------------------------------------------------------------------
      vote_a |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   competent |   .1669117   .0863812     1.93   0.063    -.0097577     .343581
   incumbent |   .0110896   .0310549     0.36   0.724    -.0524248     .074604
     party_a |   .2116774   .1098925     1.93   0.064     -.013078    .4364327
       _cons |   .2859541   .0635944     4.50   0.000     .1558889    .4160194
------------------------------------------------------------------------------
```

- vote_a is vote share for Candidate A
- incumbent is a dummy variable for whether the party currently holds the office
- party_a is the vote share for the party of Candidate A in the previous election

- We want to create a scatter plot of vote_a by competent controlling for incumbent and party_a

Calculating partial residuals

First run your regression with all the relevant variables
`. reg vote_a competent incumbent party_a`

```
------------------------------
      vote_a |      Coef.
-------------+----------------
   competent |   .1669117
   incumbent |   .0110896
     party a |   .2116774
```

To calculate the residual for the full model, use
`. predict e, res`
(This creates a new variable "e", which equals to the residual.)

Here, however, we want to generate the residual controlling <u>only</u> for some variables. To do this, we could manually predict vote_a based only on incumbent and party_a:
`. g y_hat = (0)*.167+ incumbent*.011 + party_a*.212`

We can then generate the partial residual
`. g partial_e = vote_a – y_hat`

Instead, can use the Stata adjust
`. adjust competent = 0, by(incumbent party_a) gen(y_hat)`
`. g partial_e = vote_a – y_hat`

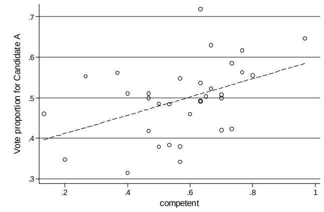
Calculating partial residuals

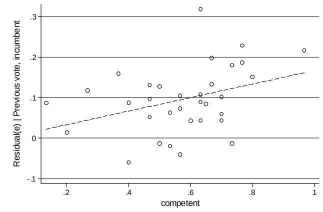
- Regression of the partial residual on competent. (Should not necessarily give you the same coefficient estimate because competent is not residualized.)

```
. reg partial_e competent
      Source |       SS       df       MS              Number of obs =      33
-------------+------------------------------           F(  1,    31) =    4.52
       Model |  .027767147     1  .027767147           Prob > F      =  0.0415
    Residual |  .190333468    31  .006139789           R-squared     =  0.1273
-------------+------------------------------           Adj R-squared =  0.0992
       Total |  .218100616    32  .006815644           Root MSE      =  .07836

------------------------------------------------------------------------------
           e |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   competent |   .1669117    .078487     2.13   0.042     .0068364     .326987
       _cons |  -7.25e-09   .0470166    -0.00   1.000    -.0958909    .0958909
------------------------------------------------------------------------------
```

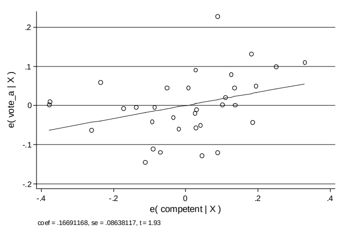
- Compare scatter plot (top) with residual scatter plot (bottom)
- Residual plots especially important if results change when adding controls





Avplot & cprplot

- You can also use `avplot` to generate residual scatter plots
- After you run your regression use the following command
  - `avplot competent`
- Unlike the method above, `avplot` also conditions (residualizes) your explanatory variable
- Good for detecting outliers
- Bad for detecting functional form
- For functional form, use `cprplot`, which does not residualize the explanatory variable



Imputing missing data (on controls

Imputing missing data

- Variables often have missing data
- Sources of missing data
- Missing data
  - May reduce estimate precision (wider confidence intervals b/c smaller sample)
  - May bias estimates if data is not missing a random
- To rescue data with missing cases on control variables: impute using other variables
- Imputing data can
  - Increase sample size and so increase precision of estimates
  - Reduce bias if data is not missing at random

Imputation example

- Car ownership in 1948
- Say that some percentage of sample forgot to answer a question about whether they own a car
- The data set contains variables that predict car ownership: family_income, family_size, rural, urban, employed

Stata imputation command

- `impute depvar varlist [weight] [if exp] [in range], generate(newvar1)`
  - depvar is the variable whose missing values are to be imputed.
  - varlist is the list of variables on which the imputations are to be based
  - newvar1 is the new variable to contain the imputations
- Example
  - `impute own_car family_income family_size rural suburban employed, g(i_own_car)`

Rules about imputing

- Before you estimate a regression model, use the summary command to check for missing data
- Before you impute, check that relevant variables actually predict the variable with missing values (use regression or other estimator)
- Don't use your studies' dependent variable or key explanatory variable to make the imputation's (exceptions)
  - Use demographic variables
  - Use variables exogenous to the dependent variable or key explanatory variables
- Don't impute missing values on your studies' dependent variable or key explanatory variable (exceptions)
- Always note whether imputation changed results
- If too much data is missing, imputation won't help