Week 7

Ordered Dependent Variables

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Clarification

- Last week's notation might have been misleading for the heteroskedastic probit.

$$\text{Var}[\varepsilon]=\sigma^2 = [e^{\gamma Z}]^2$$

So :

$$\sigma = e^{\gamma Z}$$

and the likelihood function is:

$$\text{Ln } L = \sum_{i=1}^{n} y_i \ln\Phi\left(\frac{X\beta}{e^{\gamma Z}}\right) + (1- y_i)\ln\Phi\left(\frac{X\beta}{e^{\gamma Z}}\right)$$

- So far we have looked at continuous and dichotomous dependent variables.

- Continuous data have meaningful and constant distance between units and can theoretically be divided infinitely (e.g. money).

- Now, let's move on to look at another type of dependent variable…ordinal variables.

Ordinality

- Ordinal data can be discrete or grouped continuous.
- Some data can be ordered but should not be.
- Some data are ordered in some situations but not others.
    - Long compares colors on the electromagnetic spectrum to that of buying cars of certain colors.
- Some treat ordered (discrete) variables as if they were continuous (e.g. use OLS).

Ordinality

- Often seen in survey research with the seven point Likert scale.
  - Strongly disagree
  - Disagree
  - Weakly disagree
  - Neutral
  - Weakly disagree
  - Agree
  - Strongly Agree

Using OLS with ordinal data

- Some people use OLS with data with an ordinal outcome.
  - Do'h! OLS results, however, would be misleading.
- OLS assumes that the distance between categories is equal.
  - If this is the case, our estimates of β might be unbiased.
  - But the errors will be heteroskedastic and non-normal.
- If this assumption is not met, then the β estimates will be biased.

Latent variable approach

- Like logit and probit, we can motivate the ordered model via a latent variable approach.

- Suppose the unobservable latent variable y^* varies from $-\infty$ to ∞ and is mapped to an observed variable y_i.

- Then like in previous examples let

$$y^* = X\beta + \varepsilon$$

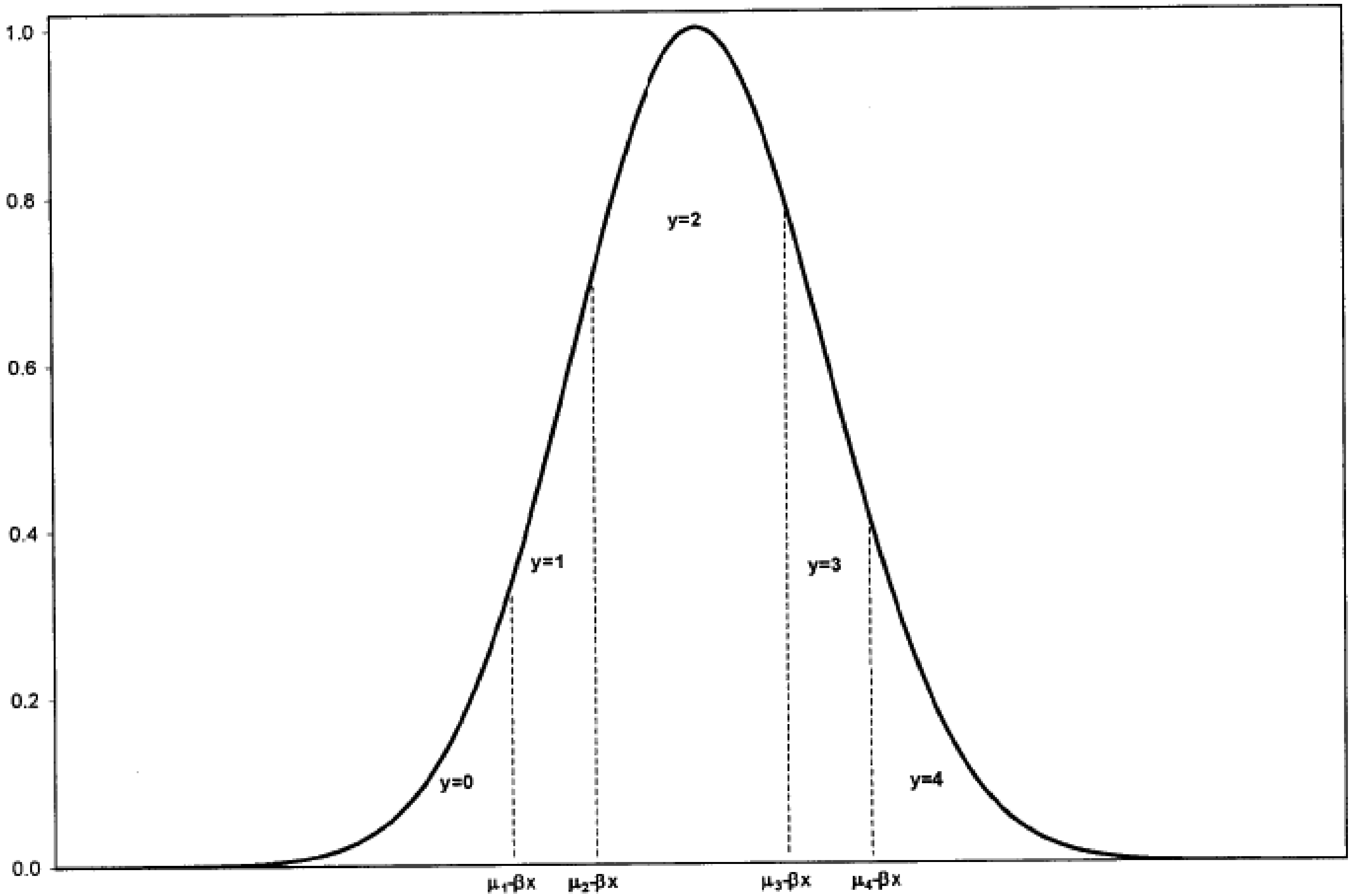
$$y_i = \begin{cases} 0, if\ y^* \ \leq 0 \\ 1, if\ 0 < y^* \ \leq \tau_1 \\ 2, if \tau_1 < \ y^* \ \leq \ \tau_2 \end{cases}$$

$$\begin{cases} 3, if\ \tau_2 < \ y^* \ \leq \ \tau_3 \\ \dots \\ j, if\ \tau_{j-1} \ \leq \ y^* \end{cases}$$

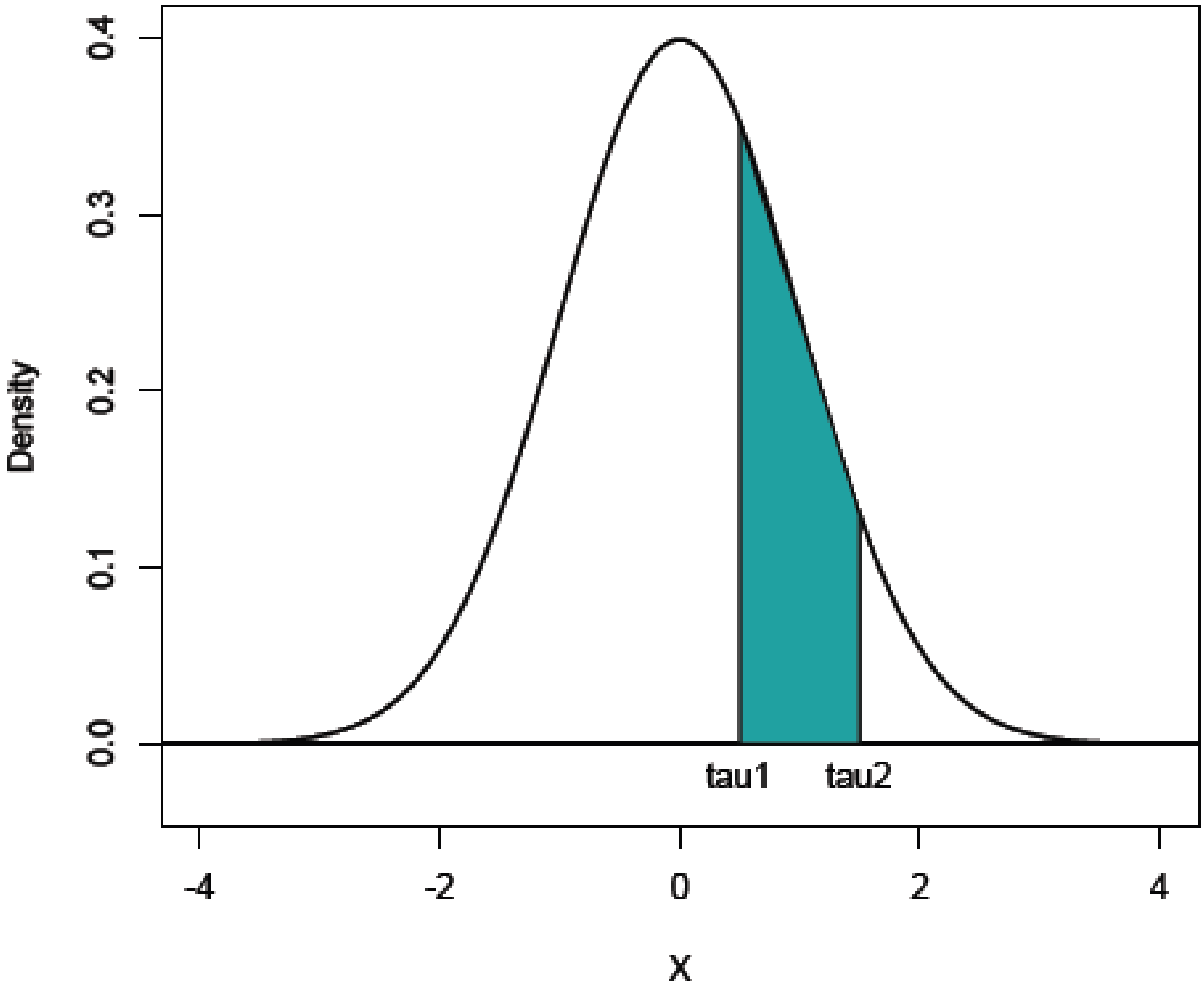
- Crucial to understanding the ordinal regression model (ORM) is τ.

- τ is the threshold or cut-point between categories.

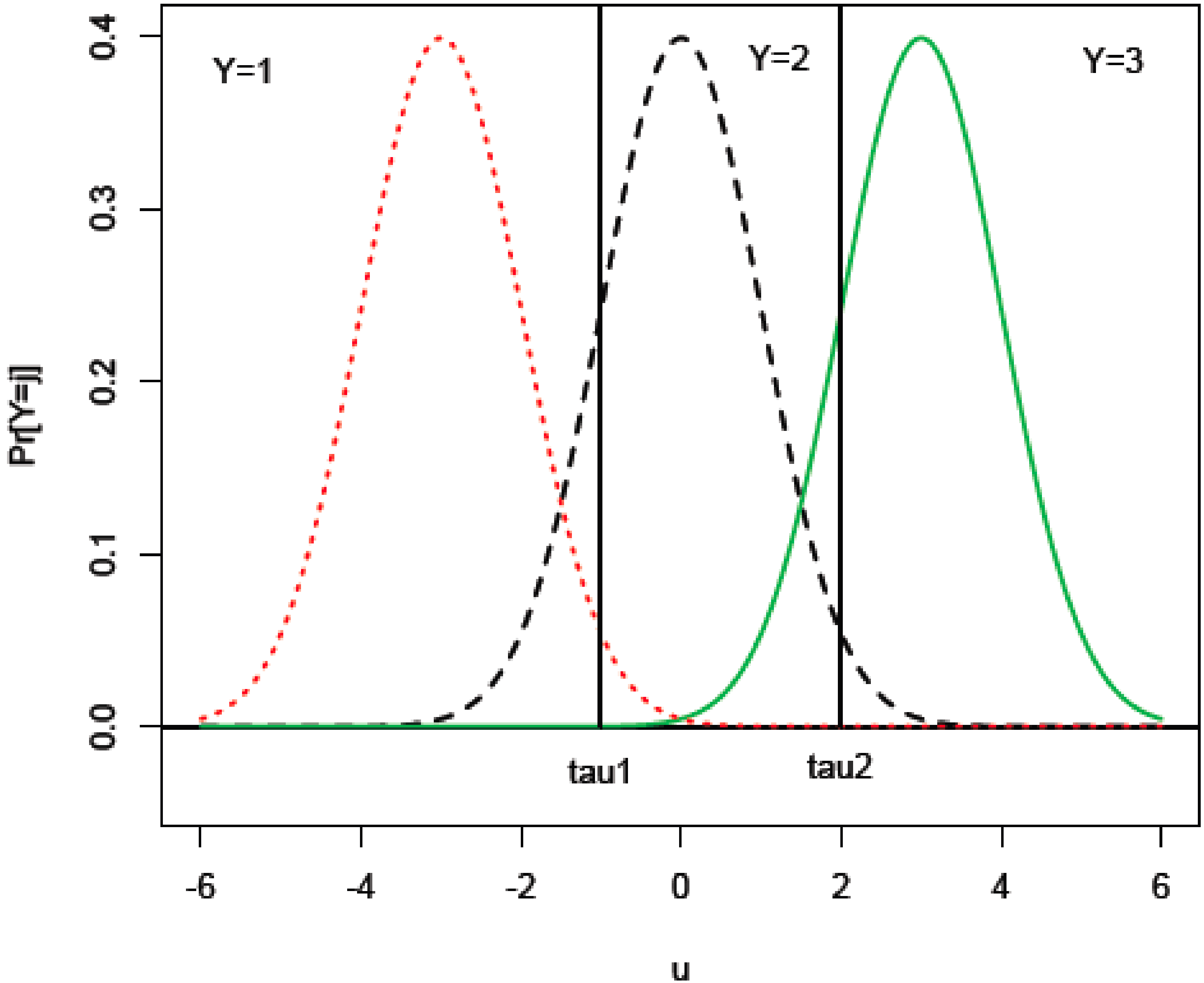
Probabilities and cut-points



- Basically, as Long (1997: 121) puts it: “The probability that a random variable is between two values is the difference between the CDF evaluated at these values.”


0.4
0.3
0.2
0.1
0.0
Density
tau1
tau2
-4
-2
0
2
4
X

So you are basically subtracting one from the others.



- The probability $Y = j$ is given by:

$$Pr(Y = j|\boldsymbol{X}) = F(\tau_j - \boldsymbol{X\beta}) \text{ - } \mathrm{F}(\tau_{j-1} - \boldsymbol{X\beta})$$

- So the probability $Y = 1$ is the area between the two thresholds that delineate $Y = 1$.

$$Pr(Y = j|\boldsymbol{X}) = F(\tau_j - \boldsymbol{X\beta}) \text{ - } F(-\boldsymbol{X\beta})$$

Or for probit models:

$$Pr(Y = j|\boldsymbol{X}) = \Phi(\tau_j - \boldsymbol{X\beta}) \text{ - } \Phi(-\boldsymbol{X\beta})$$

- Given the fact that the ordered probit and logit are extensions of the binary model, estimation is relatively simple.

- Remember our old friend, the probit likelihood function:

$$\mathrm{L}(\beta|Y,X) = \prod_{i=1}^{n}[\Phi(\boldsymbol{X\beta})]^{y_i}[1\text{-}\ \Phi(\boldsymbol{X\beta})]^{1-y_i}$$

and the log likelihood:

$$ln\mathrm{L} = \sum_{i=1}^{n} y_i \ln\Phi(X\beta) + \ (1 \text{ - } y_i)\ln\Phi(X\beta)$$

- We just substitute τ_j in for y_i.

- Therefore for the ordered probit the likelihood is:

$$L(\beta, \tau \mid Y, X) = \prod_{i=1}^{n} \prod_{j=1}^{m} [\Phi(\tau_j - \beta X) - \Phi(\tau_{j-1} - \beta X)]^{\tau ij}$$

- Then we log both sides to get the log likelihood.

$$\ln L(\beta, \tau \mid Y, X) = \sum_{i=1}^{n} \sum_{j=1}^{m} \tau_{ij} \ln[\Phi(\tau_j - \beta X) - \Phi(\tau_{j-1} - \beta X)]$$

Heteroskedastic ordered probit?

- Theoretically, we could also model potential heteroskedasticity by parameterizing the variance σ^2 by parameterizing it as $e^{\gamma Z}$.

- What examples can you think of that could use this?

- Unfortunately, Stata does not currently support an easy pre-baked heteroskedastic ordered probit.

- You could specify your own ML model and do it yourself!

Identification

- Since y* is unobserved, its mean and variance cannot be measured.

- We assume the variance to be 1 for ordered probit and $\pi^2/3$ for logit.

- For identification we need to fix another variable to some arbitrary value.

Identification

- As Long (1997: 123) writes, there are two frequently used assumptions
  - Assume $\tau_1 = 0$
  - Assume $\alpha = 0$
- Different software packages use one or the other.
  - Stata assumes $\alpha = 0$.
- This choice affects the interpretation of the output.
- The predictions, however, stay the same.

Let's look at some real data

- Englehart, Neil A. 2009. "State Capacity, State Failure, and Human Rights." *Journal of Peace Research* 46(2): 163-180.

- As close to Cingranelli and Filippov (2010) that I could find.

- This article looks at how state capacity affects observed levels of human rights.

DV= Political Terror Scale

Level	Description
1	Countries under a secure rule of law, people are not imprisoned for their views, and torture is rare or exceptional. Political murders are extremely rare.
2	There is a limited amount of imprisonment for nonviolent political activity. However, few persons are affected, torture and beatings are exceptional. Political murder is rare.
3	There is extensive political imprisonment, or a recent history of such imprisonment. Execution or other political murders and brutality may be common. Unlimited detention, with or without a trial, for political views is accepted.
4	Civil and political rights violations have expanded to large numbers of the population. Murders, disappearances, and torture are a common part of life. In spite of its generality, on this level terror affects those who interest themselves in politics or ideas.
5	Terror has expanded to the whole population. The leaders of these societies place no limits on the means or thoroughness with which they pursue personal or ideological goals.

- Therefore, when estimating what level of political terror a state will have we use the following:

$$Pr(Y = 1) = \Phi(\tau_1 - X\beta)$$

$$Pr(Y = 2) = \Phi(\tau_2 - X\beta) - \Phi(\tau_1 - X\beta)$$

$$Pr(Y = 3) = \Phi(\tau_3 - X\beta) - \Phi(\tau_2 - X\beta)$$

$$Pr(Y = 4) = \Phi(\tau_4 - X\beta) - \Phi(\tau_3 - X\beta)$$

$$Pr(Y = 5) = 1 - \Phi(\tau_5 - X\beta)$$

- Englehart inverts the PTS scale so that higher scores represent better human rights conditions.

- Independent variables capturing state capacity:
  - Political Risk Service's Law and Order measure
    - Strength and impartiality of legal system/degree to which law is respected and order maintained.
  - Transparency International's Corruption Perceptions Index (CPI)
  - Taxes as a proportion of GDP

Summary data

```
. sum law_order_prs cpi05 taxgdp_best cwardead  iwardead polity2
gdppccus06ln poptot06ln igoprop iccpropt1 ptss2in1

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
law_order_~w |      2552    3.633138    1.549606          0          6
       cpi05 |      1266    4.926619    2.546021          0         10
 taxgdp_best |      4139    .1912724    .0994063   .0003458   .8837426
    cwardead |      7227    503.8608    3329.971          0      80000
    iwardead |      7227     3087.54    22874.13          0     323914
-------------+--------------------------------------------------------
     polity2 |      6008   -.1709387      7.5282        -10         10
gdppccus06ln |      5421    7.430181    1.560977   4.034598   10.87698
  poptot06ln |      6885    15.51374    1.886037   9.888374   20.98267
     igoprop |      6282    1.000449    .4255889   .0200336   2.768744
   iccpropt1 |      7198    .2399278    .4270688          0          1
-------------+--------------------------------------------------------
    ptss2in1 |      3940    3.675127      1.1674          1          5
```

- I replicate the first three columns of Table 1 (Englehart 2009: 172) without including year dummies, then one model with all three IVs.

```
.  ologit ptss2inv law_order_prs cpi05 taxgdp_best cwardead  iwardead polity2 gdp
> pccus06ln poptot06ln igoprop iccpropt1 ptss2in1, robust cluster(banks) nolog


Ordered logistic regression                          Number of obs   =        628
                                                     Wald chi2(11)   =     355.09
                                                     Prob > chi2     =     0.0000
Log pseudolikelihood = -386.39185                    Pseudo R2       =     0.5552

                                  (Std. Err. adjusted for 90 clusters in banks)
------------------------------------------------------------------------------
             |               Robust
    ptss2inv |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
law_order_~w |    .297825   .0886246     3.36   0.001     .1241239    .4715262
       cpi05 |   .1312412   .0915943     1.43   0.152    -.0482803    .3107627
 taxgdp_best |   2.776397    1.48146     1.87   0.061    -.1272105    5.680004
    cwardead |  -.0000168   .0000815    -0.21   0.836    -.0001766    .0001429
    iwardead |  -.0000223   6.56e-06    -3.40   0.001    -.0000351   -9.42e-06
     polity2 |   .0128612    .021753     0.59   0.554    -.0297739    .0554963
gdppccus06ln |   .0712448    .123099     0.58   0.563    -.1700249    .3125144
  poptot06ln |  -.3215179   .1250645    -2.57   0.010    -.5666398   -.0763961
     igoprop |   1.277837   .5276149     2.42   0.015      .243731    2.311943
   iccpropt1 |   .0107571    .268408     0.04   0.968    -.5153129    .5368271
    ptss2in1 |   2.616011   .2158452    12.12   0.000     2.192962    3.039059
-------------+----------------------------------------------------------------
       /cut1 |  -.0540404   2.289588                      -4.54155    4.433469
       /cut2 |   3.954703   2.145507                     -.2504131     8.15982
       /cut3 |   7.712964   2.121039                      3.555804    11.87012
       /cut4 |   11.40724    2.13511                      7.222497    15.59198
```

- Although unsurprisingly these three variables are correlated above .5.

```
. corr law_order_prs  cpi05  taxgdp_best
(obs=934)

             | law_or~w    cpi05 taxgdp~t
-------------+---------------------------
law_order_~w |   1.0000
       cpi05 |   0.7260   1.0000
 taxgdp_best |   0.5593   0.5873   1.0000
```

Differences between OLS and oprobit

```
. estimates table OLS  oprobit, b(%9.3f) t label varwidth(30) equations(1:1)

--------------------------------------------------------
                      Variable |    OLS       oprobit   
-------------------------------+------------------------
#1                             |
                 law and order |     0.094       0.212
                               |      7.05        7.50
        prio civil war deaths  |    -0.000      -0.000
                               |     -2.48       -2.22
 prio international war deaths |    -0.000      -0.000
                               |     -0.33       -0.97
          revised polity score |     0.007       0.019
                               |      2.86        3.36
                  gdppccus06ln |     0.029       0.080
                               |      1.67        2.24
                    poptot06ln |    -0.083      -0.181
                               |     -5.99       -6.11
                       igoprop |     0.100       0.391
                               |      1.57        2.58
                     iccpropt1 |    -0.030      -0.080
                               |     -0.85       -0.98
                      ptss2in1 |     0.703       1.321
                               |     32.81       20.18
                      Constant |     1.736
                               |      6.42
-------------------------------+------------------------
cut1                           |
                      Constant |                -0.149
                               |                 -0.28
-------------------------------+------------------------
cut2                           |
                      Constant |                 1.455
                               |                  2.64
-------------------------------+------------------------
cut3                           |
                      Constant |                 3.293
                               |                  5.75
-------------------------------+------------------------
cut4                           |
                      Constant |                 5.258
                               |                  8.97
--------------------------------------------------------
                                          legend: b/t
```

Comparing ologit and oprobit

```
. estimates table ologit oprobit, b(%9.3f) t label varwidth(30)

--------------------------------------------------------
                      Variable |   ologit      oprobit
-------------------------------+------------------------
ptss2inv                       |
                 prs, 12.02.04 |     0.374       0.212
                               |      7.29        7.50
         prio civil war deaths |    -0.000      -0.000
                               |     -1.68       -2.22
 prio international war deaths |    -0.000      -0.000
                               |     -0.85       -0.97
          revised polity score |     0.034       0.019
                               |      3.37        3.36
                  gdppccus06ln |     0.140       0.080
                               |      2.21        2.24
                    poptot06ln |    -0.325      -0.181
                               |     -6.08       -6.11
                       igoprop |     0.654       0.391
                               |      2.45        2.58
                     iccpropt1 |    -0.121      -0.080
                               |     -0.86       -0.98
                      ptss2in1 |     2.412       1.321
                               |     21.91       20.18
-------------------------------+------------------------
cut1                           |
                      Constant |    -0.379      -0.149
                               |     -0.39       -0.28
-------------------------------+------------------------
cut2                           |
                      Constant |     2.627       1.455
                               |      2.68        2.64
-------------------------------+------------------------
cut3                           |
                      Constant |     5.986       3.293
                               |      5.90        5.75
-------------------------------+------------------------
cut4                           |
                      Constant |     9.542       5.258
                               |      9.24        8.97
--------------------------------------------------------
                                             legend: b/t
```

Can also run Wald tests of coefficients

```
. * Wald test
. oprobit ptss2inv law_order_prs_new cwardead  iwardead polity2 gdppccus06ln ///
>  poptot06ln igoprop iccpropt1 ptss2in1, robust cluster(banks)

Iteration 0:   log pseudolikelihood = -2701.9243
Iteration 1:   log pseudolikelihood = -1487.3775
Iteration 2:   log pseudolikelihood = -1404.0518
Iteration 3:   log pseudolikelihood = -1402.6146
Iteration 4:   log pseudolikelihood = -1402.6129
Iteration 5:   log pseudolikelihood = -1402.6129

Ordered probit regression                         Number of obs   =       1801
                                                  Wald chi2(9)    =     795.83
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -1402.6129                 Pseudo R2       =     0.4809

                                (Std. Err. adjusted for 125 clusters in banks)
------------------------------------------------------------------------------
             |               Robust
    ptss2inv |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
law_order_~w |   .2120258   .0282618     7.50   0.000     .1566337    .2674178
    cwardead |   -.000061   .0000274    -2.22   0.026    -.0001147   -7.22e-06
    iwardead |  -4.59e-06   4.73e-06    -0.97   0.332    -.0000139    4.68e-06
     polity2 |   .0193145   .0057418     3.36   0.001     .0080608    .0305683
gdppccus06ln |     .08046   .0359567     2.24   0.025     .0099861    .1509338
  poptot06ln |  -.1812513   .0296876    -6.11   0.000    -.2394378   -.1230647
     igoprop |   .3910244   .1516026     2.58   0.010     .0938887    .6881601
   iccpropt1 |  -.0799299   .0813197    -0.98   0.326    -.2393136    .0794538
    ptss2in1 |   1.321426   .0654844    20.18   0.000     1.193079    1.449773
-------------+----------------------------------------------------------------
       /cut1 |  -.1489925   .5408084                     -1.208958    .9109725
       /cut2 |   1.455258   .5512756                      .3747777    2.535738
       /cut3 |   3.292576   .5722217                      2.171042     4.41411
       /cut4 |   5.258085   .5860828                      4.109384    6.406786
------------------------------------------------------------------------------

.
.  test law_order_prs

 ( 1)  [ptss2inv]law_order_prs_new = 0

           chi2(  1) =   56.28
         Prob > chi2 =    0.0000
```

And LR tests

```
* LR test
** Unconstrained ***

.oprobit ptss2inv law_order_prs_new cwardead  iwardead polity2 
gdppccus06ln ///
 poptot06ln igoprop iccpropt1 ptss2in1

 estimates store fullmodel

** Constrained **

oprobit ptss2inv  iwardead polity2 gdppccus06ln ///
 poptot06ln igoprop iccpropt1 ptss2in1 if law_~=.

estimates store constmodel



. lrtest fullmodel constmodel

Likelihood-ratio test                                 LR chi2(2)  =     80.95
(Assumption: constmodel nested in fullmodel)          Prob > chi2 =    0.0000
```

Can also run fitstat for more measures of fit

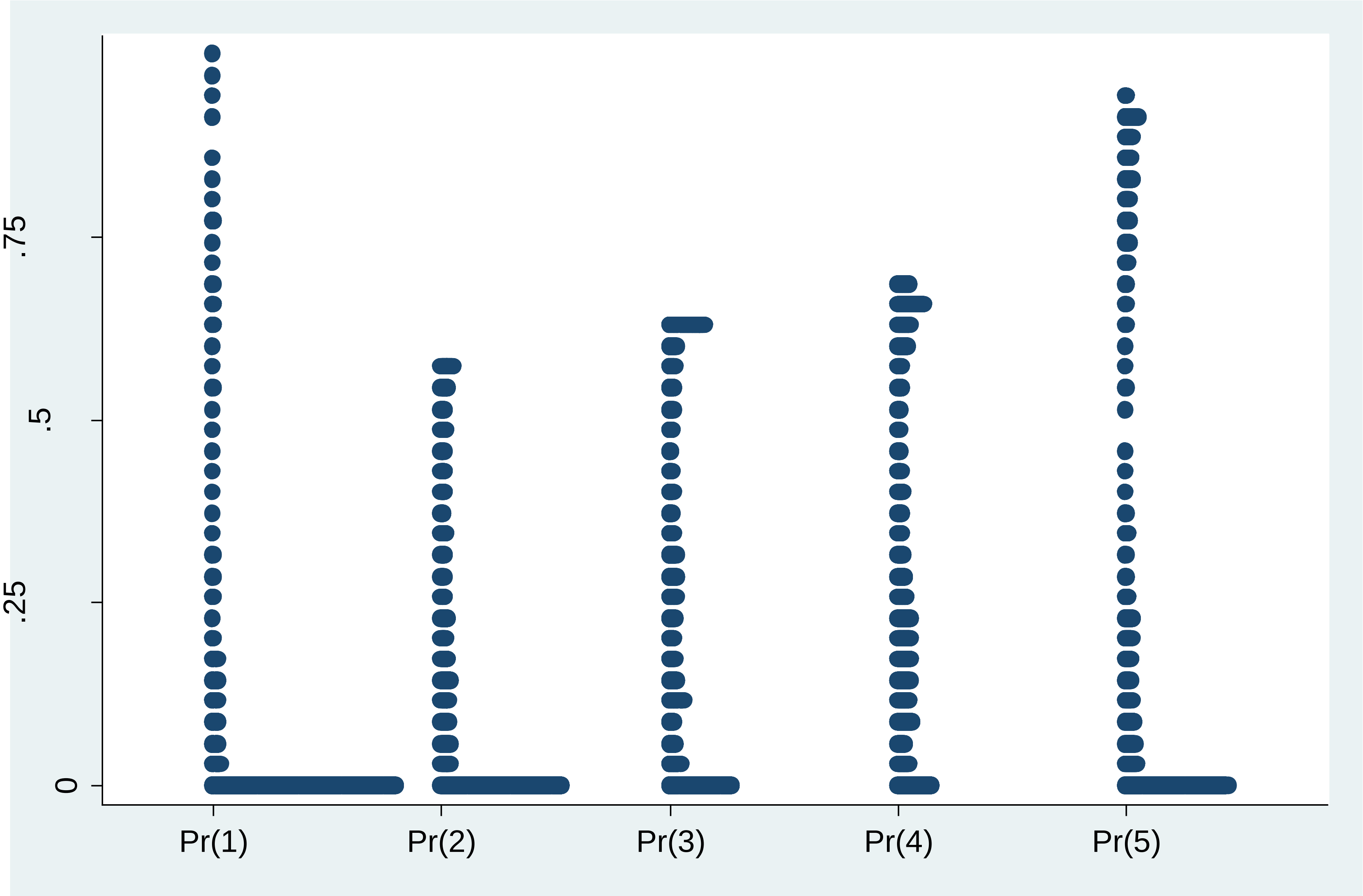
```
.  fitstat

Measures of Fit for oprobit of ptss2inv

Log-Lik Intercept Only:       -2701.924   Log-Lik Full Model:           -1402.613
D(1788):                       2805.226   LR(9):                         2598.623
                                          Prob > LR:                        0.000
McFadden's R2:                    0.481   McFadden's Adj R2:                0.476
ML (Cox-Snell) R2:                0.764   Cragg-Uhler(Nagelkerke) R2:       0.804
McKelvey & Zavoina's R2:          0.815
Variance of y*:                   5.418   Variance of error:                1.000
Count R2:                         0.713   Adj Count R2:                     0.596
AIC:                              1.572   AIC*n:                         2831.226
BIC:                         -10597.796   BIC':                         -2531.158
BIC used by Stata:             2902.675   AIC used by Stata:             2831.226

.
end of do-file
```

Predicted probabilities



Predicted probabilities

```
 use "Englehart_StatesandRights.dta"

oprobit ptss2inv law_order_prs_new cwardead  iwardead polity2 gdppccus06ln ///
 poptot06ln igoprop iccpropt1 ptss2in1, robust cluster(banks)

predict pts1 pts2 pts3 pts4 pts5
label var pts1 "Pr(1)"
label var pts2 "Pr(2)"
label var pts3 "Pr(3)"
label var pts4 "Pr(4)"
label var pts5 "Pr(5)“

dotplot pts1 pts2 pts3 pts4 pts5, ylabel(0(.25).75) ///
    ysize(2.0124) xsize(3.039)
```

Individual predicted probabilities

	Political Terror Scale				
	1	**2**	**3**	**4**	**5**
Mean values (no ICC protocol)	0.0001	0.0184	0.3837	0.5549	0.0429
With ICC ratification	0.0002	0.0223	0.4109	0.5305	0.0361
Autocratic state (Polity=-6; no ICC)	0.0002	0.0269	0.4382	0.5045	0.0302
Democratic state (Polity=6; no ICC)	0.0001	0.0155	0.3594	0.5753	0.0498

Stata commands

```
oprobit ptss2inv law_order_prs_new cwardead  iwardead polity2
gdppccus06ln poptot06ln igoprop iccpropt1 ptss2in1, robust
cluster(banks)

prvalue, x(iccpropt1=0) rest(mean)
prvalue, x(iccpropt1=1) rest(mean)
prvalue, x(polity2=-6 iccpropt1=0) rest(mean) brief
prvalue, x(polity2=6 iccpropt1=0) rest(mean) brief
```

Continuous probabilities

- Like last week, we are interested in trying to understand how an IV affects our DV.

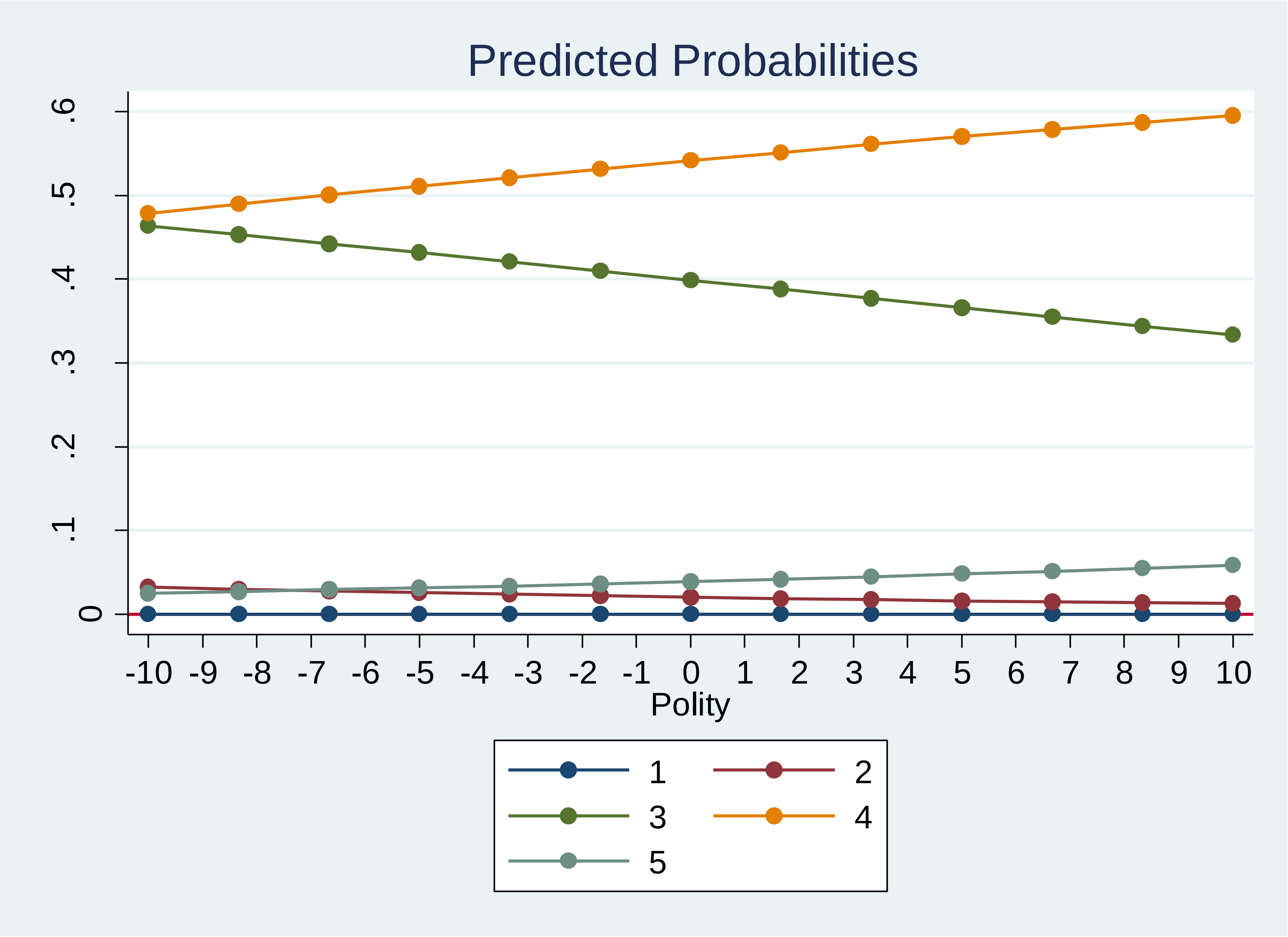
- This is a bit more complicated than with logit or probit, but it is possible.

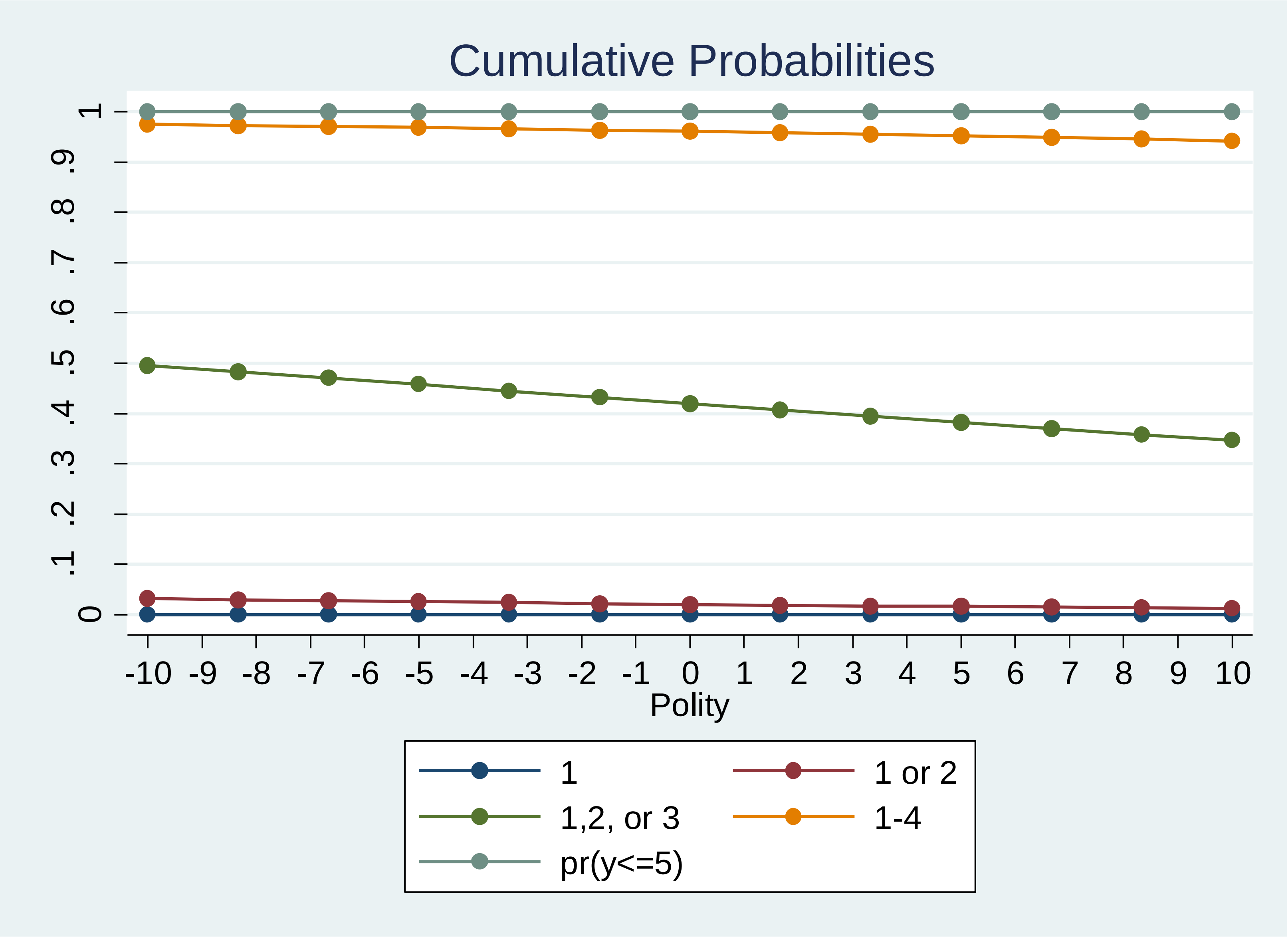
Graphing

```
//  graphing predicted probabilities with -prgen-
prgen polity2, from(-10) to(10) generate(nope) x(iccpropt1=0) ncases(13)
desc nope*
label var nopep1 "1"
label var nopep2 "2"
label var nopep3 "3"
label var nopep4 "4"
label var nopep5 "5"
label var nopes1 "1"
label var nopes2 "1 or 2"
label var nopes3 "1,2, or 3"
label var nopes4 "1-4"

* step 1: graph predicted probabilities
graph twoway connected nopep1 nopep2 nopep3 nopep4 nopep5 nopex, ///
     title("Panel A: Predicted Probabilities") ///
     xtitle("Polity") xlabel(-10(1)10) ylabel(0(.25).50) ///
      ylabel(0(.1).6) yline(0) ///
      ytitle("Pr(Y = j)") name(tmp1, replace)

* step 2: graph cumulative probabilities
graph twoway connected nopes1 nopes2 nopes3 nopes4 nopes5 nopex, ///
    title("Panel B: Cumulative Probabilities") ///
    xtitle("Polity") xlabel(-10(1)10) ylabel(0(.25).50) ///
    yscale(noline) ylabel(0(.1)1) name(tmp2, replace) ///
    ytitle("Pr(Y = j)")
```


Predicted Probabilities
0
.1
.2
.3
.4
.5
.6
-10 -9 -8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8 9 10
Polity
1
2
3
4
5



Cumulative Probabilities
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
-10 -9 -8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8 9 10
Polity
1
1 or 2
1,2, or 3
1-4
pr(y<=5)

- There are a number of other means of interpretation.
  - Marginal effects
  - Discrete change
  - Odds ratios

- See Long (1997: 127-140) and Long and Freese (2006: 202-220).

- However, before we get too carried away with interpreting our results, we need to think about a fundamental assumption of ORM.

- This is that an independent variable (Polity or whatever) has the same effect on all categories of the dependent variable.

Parallel regression assumption

$$\frac{\delta \Pr(Y_i = j)}{\delta X} = \frac{\delta \Pr(Y_i = j')}{\delta X} \; \forall \, j \neq j'$$

Also known as the "proportional odds" assumption

- More simply, for the data above ORM assumes that:

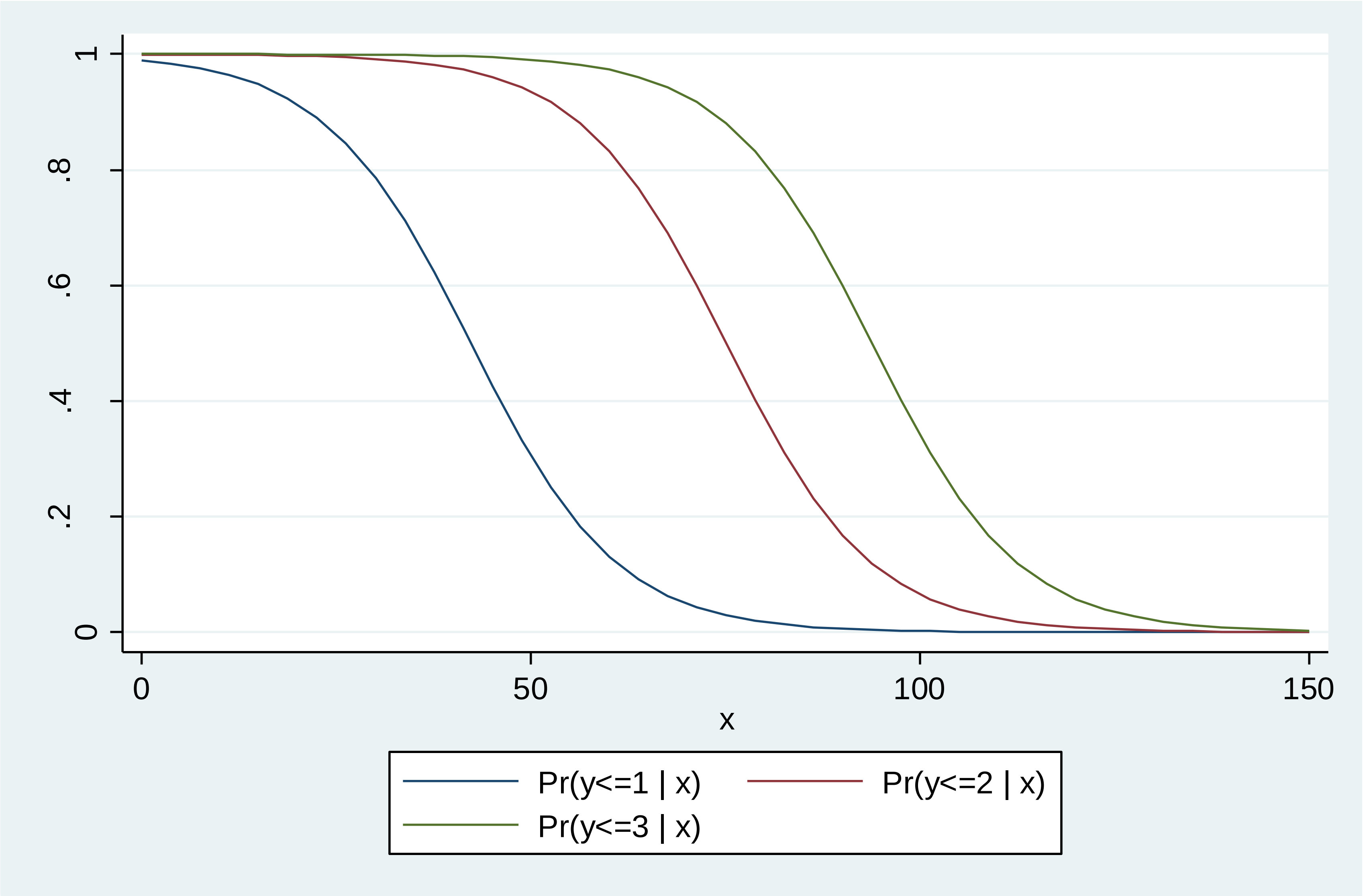
$$\beta_{Polity\ for\ y=1} = \beta_{Polity for\ y=2} = \beta_{Polity for\ y=3} = \beta_{Polity for\ y=4} = \beta_{Polity for\ y=5}$$

- As you can see with the colors example, sometimes they are ordered in some instances and not others.

- Or the Likert scale can be imposing a different ordering than you are theoretically interested in.

  - E.g. the difference between <u>intensity</u> of opinion and <u>direction</u> of opinion.

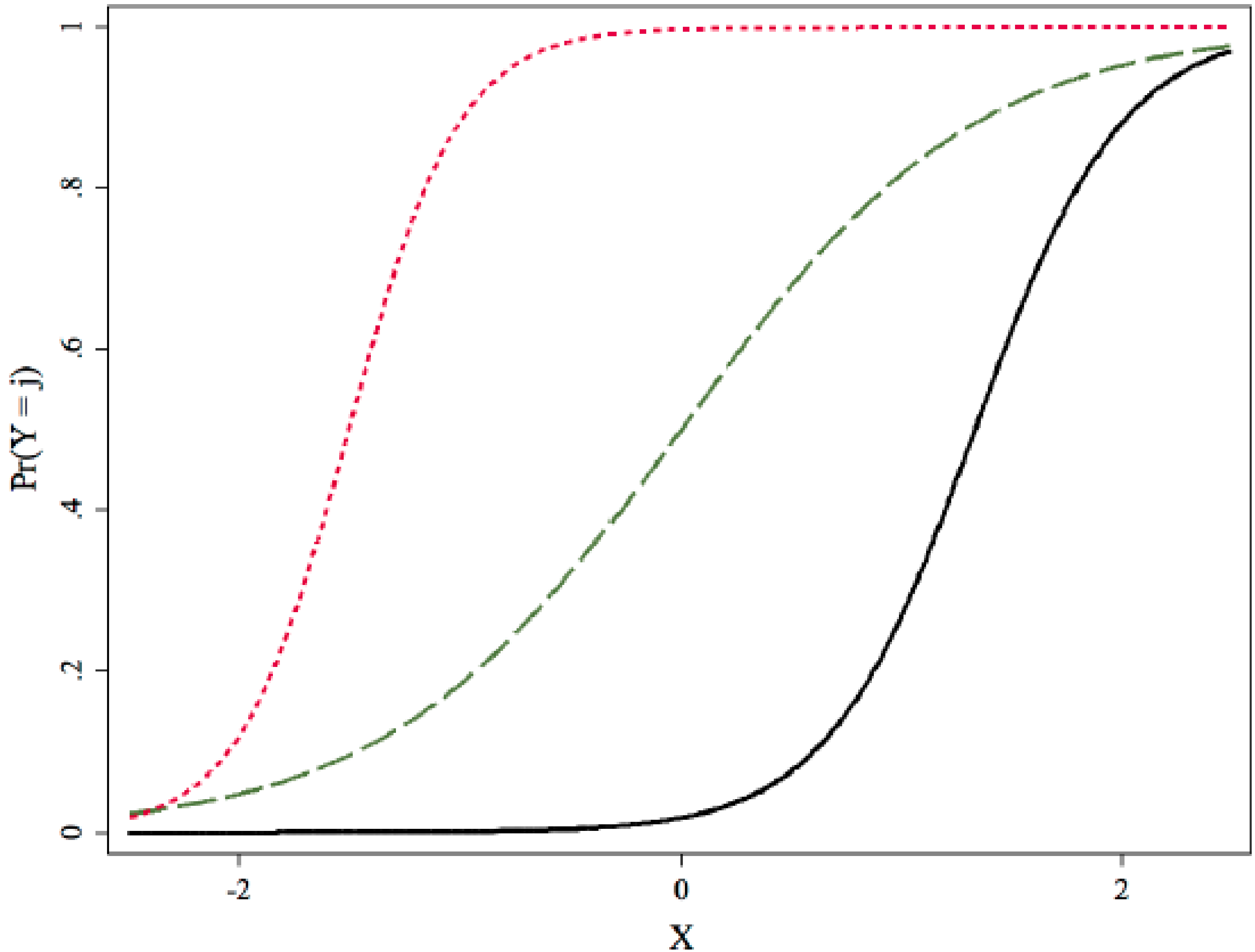
We constrain the slopes to be the same.



Relaxing the Parallel Regression Assumption

$$\frac{\delta \Pr(Y_i = j)}{\delta X} \neq \frac{\delta \Pr(Y_i = j')}{\delta X} \; \forall \, j \neq j'$$

Which allows the slopes to vary across categories.



- We can find out if our data violate the parallel regression assumption in several ways.
  - LR Score test
  - Wald test

LR Score test

```
. omodel logit ptss2inv law_order_prs_new cwardead  iwardead polity2 gdppccus06ln
>  poptot06ln igoprop iccpropt1 ptss2in1


Ordered logit estimates                           Number of obs   =       1801
                                                  LR chi2(9)      =    2634.73
                                                  Prob > chi2     =     0.0000
Log likelihood = -1384.5615                       Pseudo R2       =     0.4876

------------------------------------------------------------------------------
    ptss2inv |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
law_order_~w |   .3744251   .0481613     7.77   0.000     .2800307    .4688195
    cwardead |  -.0001238   .0000357    -3.47   0.001    -.0001938   -.0000538
    iwardead |  -6.92e-06   9.04e-06    -0.77   0.444    -.0000246    .0000108
     polity2 |   .0337874   .0086336     3.91   0.000     .0168659    .0507089
gdppccus06ln |   .1402367   .0505103     2.78   0.005     .0412383    .2392352
  poptot06ln |  -.3250962    .046525    -6.99   0.000    -.4162835   -.2339089
     igoprop |   .6535872   .2332295     2.80   0.005     .1964657    1.110709
   iccpropt1 |  -.1212637   .1191453    -1.02   0.309    -.3547843    .1122568
    ptss2in1 |   2.412143   .0846339    28.50   0.000     2.246264    2.578023
-------------+----------------------------------------------------------------
       _cut1 |  -.3786732   .8287469          (Ancillary parameters)
       _cut2 |   2.627115   .8327884
       _cut3 |    5.98563   .8291999
       _cut4 |   9.542013   .8547224
------------------------------------------------------------------------------

Approximate likelihood-ratio test of proportionality of odds
across response categories:
         chi2(27) =    127.97
       Prob > chi2 =    0.0000
```

Wald Test

```
.  brant, detail

Estimated coefficients from j-1 binary regressions

                         y>1         y>2         y>3         y>4
law_order_prs_new   .33906617   .35936187   .13192648   .44543819
         cwardead  -.00010451  -.00047064   -.0078738   -.0118445
         iwardead  -.00002627   7.324e-06  -.00001431  -3.813e-07
          polity2   .01490471  -.00075719   .03970096   .09356547
      gdppccus06ln   .09945581  -.03174733   .12769929    .4003256
       poptot06ln  -.02282324  -.30841648  -.34625633  -.52781449
          igoprop  -.12972196  -.27735119   .33374152   1.1791421
        iccpropt1  -.63222831  -.16288806   .04867037  -.38133556
         ptss2in1   1.9304874   2.2023459   2.2926375   2.4272291
            _cons  -2.5165771   .01504851  -3.9378484  -9.6694084

Brant Test of Parallel Regression Assumption

    Variable |      chi2   p>chi2    df
-------------+--------------------------
         All |    131.69    0.000    27
-------------+--------------------------
law_order_~w |      8.46    0.037     3
    cwardead |     36.85    0.000     3
    iwardead |      4.36    0.225     3
     polity2 |     14.10    0.003     3
gdppccus06ln |      8.46    0.037     3
  poptot06ln |     10.48    0.015     3
     igoprop |      5.15    0.161     3
   iccpropt1 |      4.88    0.181     3
    ptss2in1 |      3.94    0.268     3
----------------------------------------

A significant test statistic provides evidence that the parallel
regression assumption has been violated.
```

- As you can see from both tests, these data violate the parallel regression assumption, and Englehart should have looked to other methods to estimate his model with.

- We will learn more about such models in two weeks.

- As we have seen the ordinal regression model has some assumptions that our data can easily violate.
- The most notable is the parallel regression assumption.
- This constrains the effect of our IVs to be the same over the range of Y outcomes.
- If this assumption is violated and ORM is used, the results can be biased at best, and nonsensical at worst.

- Let’s turn to another example of ordered probit…Cingranelli and Filippov (2010).

Cingranelli and Fillipov 2010

- Replication data unfortunately not available online.
- Instead of PTS, they use the Cingranelli-Richards (CIRI) human rights data.
- **Physical Integrity Rights Index**
  - This is an additive index constructed from the Torture, Extrajudicial Killing, Political Imprisonment, and Disappearance indicators. It ranges from 0 (no government respect for these four rights) to 8 (full government respect for these four rights).

- Thoughts on this article?
  - Their methods?
  - Their interpretation of the models?

- Let’s discuss with the remaining time the types of interpretation we learned about last week…

- For example, predicted probabilities of our latent DV given a range of an independent variable of interest.