Presenting Substantive Results in Meaningful Ways

Week 6
POLS 8830: Advanced Quantitative Methods

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No worries mate!
We are still significant!
Our "p values" are good!
Pvalue
0,001
0,005
0,007
www.biocomicals.com

‘Normal’ Research in Political Science Today

1. Research as quest for significance
2. Overload reader with information
   - Create a giant table of numbers
   - Apply stars generously
3. Eschew ‘better’ ways of presenting results for fear of violating orthodox teachings

Problem 1: Significance(?) Testing

What? Treating classic null hypothesis significance testing as if it were Bayesian

Why? A willful ignorance or intentional amnesia of what classic hypothesis testing actually does

- Read Gill (1999) for more info.

Problem 2: Stargazing vs Substance

What? Presentation of results that focuses on (arbitrary) statistical significance rather than substantive importance

Why? Laziness? Ignorance? Lack of anything substantively meaningful to talk about?

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Why? Laziness? Ignorance? Lack of anything substantively meaningful to talk about?

Note. The tongue-in-cheek naming of our preferred output function.

Problem 3: Orthodoxy vs Evolution

What? A failure to utilize modern technology to improve the presentation of statistical results

Why? Constraints due to 1920s technology became ingrained in our culture and maintained without logical or mathematical reason

Advantages of Graphs

- Increased aesthetic appeal
- Provide clear comparisons
- Are more intuitive to interpret than tables
- Allow the reader to make an informed decision on the data
- Can show confidence measures more intuitively than tables

Advantages of Tables

- Precision (maybe?)

Plots and Graphs Can Replace Nearly Any Table

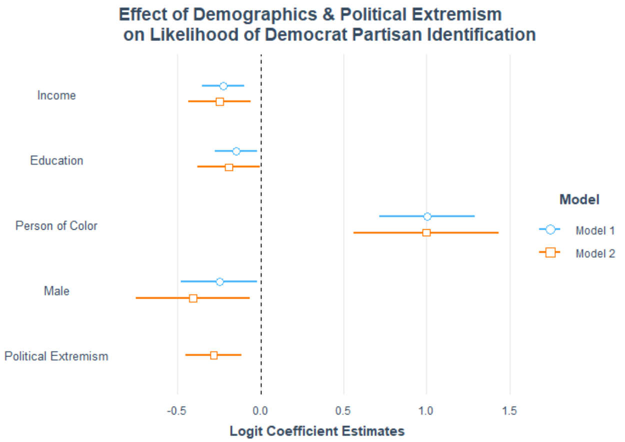
- As the Kastellec and Leoni article illustrates, in just about any circumstance in which we might want a table, we can instead use a graph or plot
- What are the trade offs?
- Compare the following visuals

Option 1

Table: Effect of Demographics and Political Extremism on Likelihood of Democrat Partisan Identification.

Income	-0.196^{***}	-0.217^{**}
	(0.057)	(0.085)
Education	-0.165^{**}	-0.216^{**}
	(0.072)	(0.107)
Person of Color	1.002^{***}	0.999^{***}
	(0.147)	(0.223)
Male	-0.249^{**}	-0.407^{**}
	(0.117)	(0.174)
Political Extremism		-0.300^{***}
		(0.092)
Constant	1.240^{***}	2.166^{***}
	(0.226)	(0.381)
Observations	1,316	630
Log Likelihood	−847.830	−391.977
Wald χ^2	88.837 ***	61.728 ***
P.R.E.	0.093	0.083
Note:	*p<0.1; **p<0.05; ***p<0.01	

Option 2

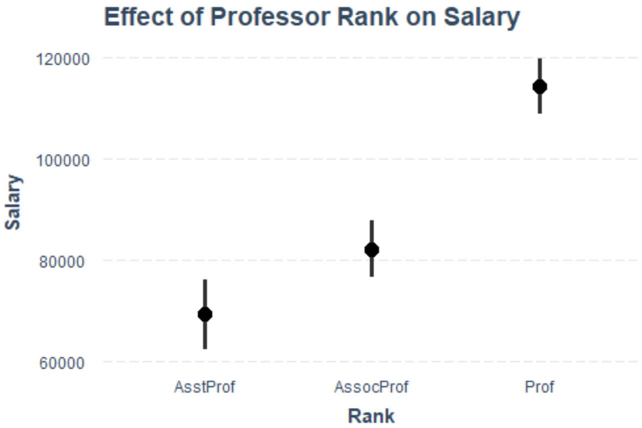

Effect of Demographics & Political Extremism
on Likelihood of Democrat Partisan Identification
Income
Education
Person of Color
Male
Political Extremism
-0.5
0.0
0.5
1.0
1.5
Logit Coefficient Estimates
Model
Model 1
Model 2

Another Example: Option 1

Table: Effect of Title, Tenure, and Gender on Professor's Salaries

	OLS	*GLM*
Associate Professor	12,907.590***	12,907.590***
	(2,240.184)	(2,240.184)
Full Professor	45,066.000***	45,066.000***
	(3,325.489)	(3,325.489)
Discipline	14,417.630***	14,417.630***
	(2,334.130)	(2,334.130)
Years Since PhD	535.058*	535.058*
	(319.678)	(319.678)
Years of Service	−489.516	−489.516
	(313.939)	(313.939)
Male	4,783.493*	4,783.493*
	(2,456.576)	(2,456.576)
Constant	65,955.230***	65,955.230***
	(2,953.152)	(2,953.152)
Observations	397	397
R^2	0.455	
Adjusted R^2	0.446	
Log Likelihood		−4,539.913
Akaike Inf. Crit.		9,093.826
Residual Std. Error	22,538.650 (df = 390)	
F Statistic	54.195*** (df = 6; 390)	
Note:		*p<0.1; **p<0.05; ***p<0.01

Another Example: Option 2



Interaction Terms

- The use of interaction terms in applied political science research is quite common
- Unfortunately, the misuse of interaction terms is nearly as common
  - What is an interaction (or multiplicative term)? And how to we properly model it?
  - How do we interpret the results?
  - According to Brambor, Clark, and Golder what are some of the most common problems?

Interaction Terms

- Key points to remember:
  1. Include all constitutive terms
  2. Do not incorrectly interpret constitutive terms
  3. Calculate and present meaning quantities of interest

Interaction Terms

- Often we have hypotheses that involve a conditional relationship between two independent variables and the dependent variable
- However, when modeling this we must model the two constitutive terms in addition to the interactions term
- E.g. $y = X_1\beta_1 + X_2\beta_2 + X_1X_2\beta_3 + \epsilon$
- NOT
- $y = X_1X_2\beta_* + \epsilon$

Interaction Terms

- Given the correct specification:
- $y = X_1\beta_1 + X_2\beta_2 + X_1X_2\beta_3 + \epsilon$
- We must remember that we cannot interpret the coefficient on the constitutive terms as unconditional effect
- In the above example, we cannot interpret β_1 as the effect of X_1 on y, rather we can only interpret it as the effect of X_1 on y when $X_2 = 0$

Interaction Terms

- In R, this is specified as:

$$\text{glm}(\text{DV} \sim \text{IV1} * \text{IV2}, \ldots)$$

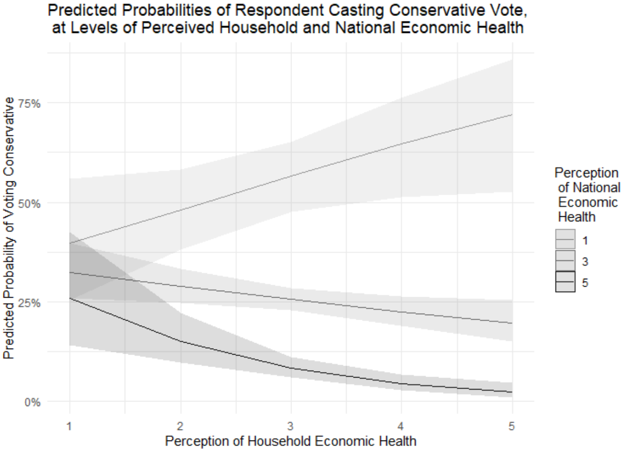
not

$$\text{glm}(\text{DV} \sim \text{IV1} : \text{IV2}, \ldots)$$

Interaction Terms

- The best way to present meaningful quantities of interest from interactive models is through graphs
- This requires you to go beyond the built in point-and-click approaches in R
- However, a number of individuals have made it relatively easy to do so

Graphing Interaction Terms: An Example



Graphing Interaction Terms

- R has multiple packages for plotting interaction terms
- `ggplot2`, `jtools`, `sjplot`, `margins`, etc.
- Most are simplifications and/or direct implementations of `ggplot`
- `margins` seeks to emulate the `marginsplot` command from STATA

Predicted Probabilities

- Allows us to generate numerical estimates of the probability that $y = 1$ holding the other variables constant
  - We can then adjust the variable of interest across various levels and observe the corresponding change in the predicted probability
- Advantage of Predicted Probabilities
  - Flexibility to calculate ANY desired effect for a single independent variable
- Disadvantage
  - Somewhat more complicated to calculate

Margins: Introduction

- From the STATA documentation
  - "The margins command estimates margins of responses for specified values of covariates and presents the results as a table."
  - "Capabilities include estimated marginal means, least-squares means, average and conditional marginal and partial effects (which may be reported as derivatives or as elasticities), average and conditional adjusted predictions, and predictive margins."
- the `margins` implementation in R seeks to mirror these functions and are, largely, calculated identically

Margins: Introduction

- From the margins (R) documentation
  - "These tools provide ways of obtaining common quantities of interest from regression-type models. margins provides "marginal effects" summaries of models and prediction provides unit-specific and sample average predictions from models. ... **margins therefore provides ways of calculating the marginal effects of variables to make these models more interpretable**"

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- Predictive margins rely on the `prediction` package in R

Margins: Procedure

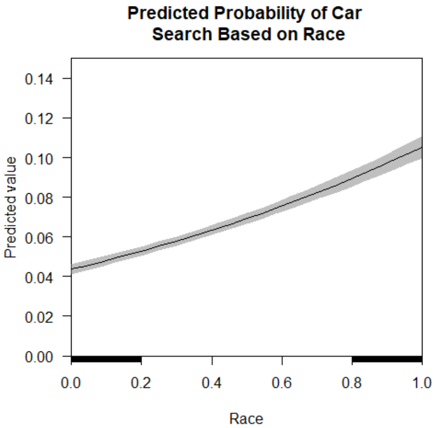
- The general syntax is:
- model_object $<-$ glm(IV1 $+$ IV2 $\ldots$)
  - Basic glm/lm estimation
- `margins(model_object)`
- A large number of options from this basic syntax

Margins: Key Options

- The most important options (functionally) are:
- `margins(model_object, ...`
  - `variables = c("IV1", "IV2")`
    - `variables` tell `margins` which covariates to vary when calculating marginal effect/predicted probabilities, all others are held at their means
  - `at = list(IV1=#:#)`
    - Specifying the covariate values at which to calculate the marginal effects/predicted probabilities
    - Where # are lower and upper bounds - generally the limits of the IV

Margins: Plotting

- Key command for graphs is `cplot()`
- `cplot(model object, x="IV", ...)`
  - Where `x="IV"` sets the x axis as the covariate's influence you want to plot

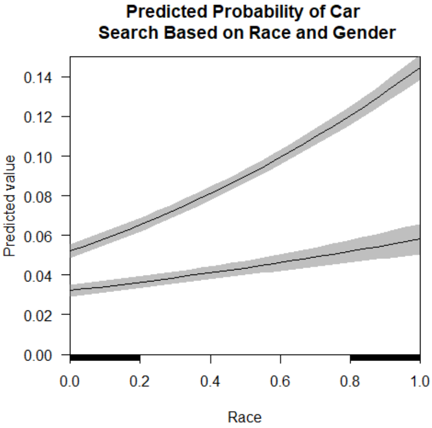


Margins: Plotting

- Plotting interactions is a bit more complex
- Need to subset the data and combine the plots with `draw = "add"`
    - object1<-cplot(model_object, x="IV1", **data=df[df[["IV2"]]==0,]**)
    - object2<-cplot(model_object, x="IV1", **data=df[df[["IV2"]]==1,]**, draw = "add")

Margins: Plotting

- Which yields:

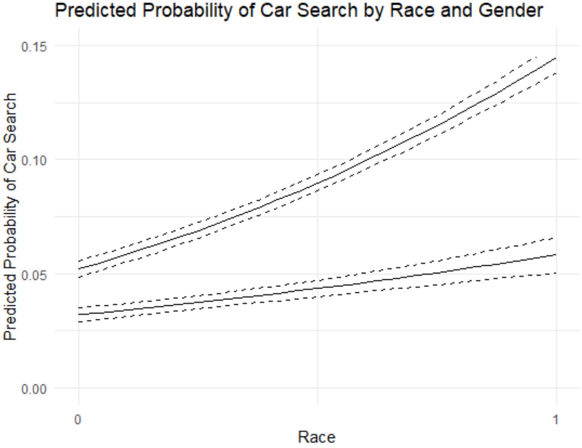


- Note: See the tutorial for the full code

Margins: Plotting

- A more flexible, and better looking option is to use the predictions from the `cplot` command to build a ggplot object
  - cd1<-cplot(model_object, x="IV1", data=df[mStops[["IV2"]]==0,])
  - cd2<-cplot(model_object, x="IV1", data=df[mStops[["IV2"]]==1,])
  - ggplot(cd1, aes(x = xvals)) +
    geom_line(aes(y = yvals)) +
    geom_line(aes(y = upper), linetype = 2) +
    geom_line(aes(y = lower), linetype = 2) +
    geom_line(data=cd2, aes(y=yvals)) +
    geom_line(data=cd2, aes(y=upper), linetype = 2) +
    geom_line(data=cd2, aes(y=lower), linetype = 2)

Margins: Plotting



Predicted Probabilties: Conclusion

- There are a ton of different options for graphs in R, especially with interactions and predicted probabilities - more than can be covered here
- Look at the tutorial for some options
- See `https://cran.r-project.org/web/packages/margins/vignettes/Introduction.html` for a full discussion of the `margins` package