Problem Set 1

Francisco Brady

16 Sep 2024

#### 1. The purpose of this question is to help you build familiarity with likelihood functions. You may want to use a spreadsheet to help you perform some of the calculations, as it allows you to write an equation in which the unknown is a reference to another cell. Then you can easily change the value of that cell to get different solutions to the equation.

Let’s suppose that we are using a logit to model the probability that a randomly selected voter supports Kamala Harris.

##### a) This function produces a value that falls between 0 and 1. Now let the parameter take on the following values: -3, -1, 0, 1, 3. Calculate for each value of . What do you notice?

. clear  
  
. input theta  
  
 theta  
 1. -3  
 2. -1  
 3. 0  
 4. 1  
 5. 3  
 6. end  
  
.   
. gen prob\_h = exp(theta) / (1 + exp(theta))  
  
.   
. list  
  
 ┌──────────────────┐  
 │ theta prob\_h │  
 ├──────────────────┤  
 1. │ -3 .0474259 │  
 2. │ -1 .2689414 │  
 3. │ 0 .5 │  
 4. │ 1 .7310586 │  
 5. │ 3 .9525741 │  
 └──────────────────┘

Pr(H) is increasing as the value of increases.

##### b) Now suppose that you randomly select three voters and observe: H, H, and T, where T means voting for someone else. The joint probability of this set outcomes is:

Note that the third term on the right hand side can be simplified if we rewrite the 1 as and perform the subtraction.

Again, let the parameter take on the values of -3, -1, 0, 1, 3. This is where using a spreadsheet will really save some time. What are the associated joint probabilities?

. gen prob\_hht = (exp(theta) / (1 + exp(theta))) \* ///  
> (exp(theta) / (1 + exp(theta))) \* ( 1 / (1 + exp(theta)))  
  
. list  
  
 ┌─────────────────────────────┐  
 │ theta prob\_h prob\_hht │  
 ├─────────────────────────────┤  
 1. │ -3 .0474259 .0021425 │  
 2. │ -1 .2689414 .0528771 │  
 3. │ 0 .5 .125 │  
 4. │ 1 .7310586 .1437348 │  
 5. │ 3 .9525741 .0430341 │  
 └─────────────────────────────┘

##### c) Since a likelihood function is proportional to the probability of observing given , we can write the above as a likelihood function.

Try to find the value of that maximizes the expression. What is the value of associated with this value of ? Does this make sense?

. \* create data   
. clear   
  
. set obs 2001  
Number of observations (\_N) was 0, now 2,001.  
  
. gen theta = .  
(2,001 missing values generated)  
  
. local i = 1  
  
. qui forvalues value = -10(0.01)10 {

. gen prob\_h = exp(theta) / (1 + exp(theta))  
  
. gen prob\_hht = (exp(theta) / (1 + exp(theta))) \* ///  
> (exp(theta) / (1 + exp(theta))) \* ( 1 / (1 + exp(theta)))

. summarize prob\_hht  
  
 Variable │ Obs Mean Std. dev. Min Max  
─────────────┼─────────────────────────────────────────────────────────  
 prob\_hht │ 2,001 .0249852 .0433062 2.06e-09 .1481477  
  
. list theta prob\_h prob\_hht if prob\_hht == r(max)  
  
 ┌─────────────────────────────┐  
 │ theta prob\_h prob\_hht │  
 ├─────────────────────────────┤  
1070. │ .69 .6659669 .1481477 │  
 └─────────────────────────────┘

The largest value of the expression is around .148, which occurs when is set to around .69. This value is similar in expectation to the proportion of the sample that voted for H, so this makes sense.

##### d) If we take the log of both sides of the above, we get the following:

Find the value of that maximizes this new equation. Hint: do the calculations inside the parentheses and then take the natural log. What insights do you draw from your answer?

. gen log\_likelihood = ln(prob\_hht)  
  
. summarize log\_likelihood  
  
 Variable │ Obs Mean Std. dev. Min Max  
─────────────┼─────────────────────────────────────────────────────────  
log\_likeli~d │ 2,001 -7.750353 4.943863 -20.00014 -1.909546  
  
. list theta prob\_h prob\_hht log\_likelihood if log\_likelihood == r(max)  
  
 ┌─────────────────────────────────────────┐  
 │ theta prob\_h prob\_hht log\_lik~d │  
 ├─────────────────────────────────────────┤  
1070. │ .69 .6659669 .1481477 -1.909546 │  
 └─────────────────────────────────────────┘

This is consistent with the results above. The that maximizes the log-likelihood function is around .69, the same as with the likelihood function.

##### e) All of this assumes that is the same for all individuals. It’s more likely that different people with different characteristics will have different probabilities of voting H. Let’s assume we measure some characteristic for each person. We now can model the parameter as . Re-write the log likelihood function with this change. Note: normally, we would include an intercept as well, so that , but let’s keep it simpler for now and ignore the intercept.

The new log-likelihood function would be:

##### f) Suppose that the value of in each case respectively (in order) is 6, 3, 4. Find the value of that produces the highest value of the log likelihood function.

. gen beta\_i = theta  
  
. gen betai\_xi = ln(exp(beta\_i \* 6) / (1 + exp(beta\_i \* 6))) + ///  
> ln(exp(beta\_i \* 3) / (1 + exp(beta\_i \* 3))) + ///  
> ln( 1 / (1 + exp(beta\_i \* 4)))  
  
. \*list  
. summarize betai\_xi  
  
 Variable │ Obs Mean Std. dev. Min Max  
─────────────┼─────────────────────────────────────────────────────────  
 betai\_xi │ 2,001 -32.5779 23.61235 -90 -1.868102  
  
. list beta\_i prob\_h prob\_hht log\_likelihood betai\_xi if betai\_xi == r(max)  
  
 ┌──────────────────────────────────────────────────────┐  
 │ beta\_i prob\_h prob\_hht log\_lik~d betai\_xi │  
 ├──────────────────────────────────────────────────────┤  
1018. │ .17 .5423979 .1346245 -2.005266 -1.868102 │  
 └──────────────────────────────────────────────────────┘

The value of that maximizes the log-likelihood function is .17.

##### g) Given this value of , what is the probability that the first voter, with = 6, will vote H? The second voter?

To find this, we can evaluate the log-likelihood for and plugging in . Then we put those values into the standard normal distribution function to get the probability.

. disp "Pr(H|x=6) = " exp(.17 \* 6) / (1 + exp(.17 \* 6))   
Pr(H|x=6) = .7349726  
  
. disp "Pr(H|x=3) = " exp(.17 \* 3) / (1 + exp(.17 \* 3))  
Pr(H|x=3) = .62480647

So the probability that a person with will vote H is .735 and the probability that a person with will vote for H is .625.

#### 2. Use the GSS2014subset dataset for this question. The dependent variable is abany, where 1 indicates the respondent believes a pregnant woman should be able to obtain a legal abortion if she wants, for any reason, and 0 indicates otherwise.

The independent variables are: age, the respondent’s age in years; childs, the number of children a respondent has; educ, the respondent’s education in years; polviews, the respondent’s score on the 7-point ideology scale in which higher values mean a person is more conservative; and relpersn, a four-point scale in which higher values mean the person is *more* religious.

Note: R users likely will want to convert the variables that are in the factor class to numeric class using as numeric from the sjlabelled library so that they start at 0 post-conversion (see help document). The regular as.numeric function will create variables that start at 1.

##### a) Estimate a probit model using the above-mentioned variables. Report the results and describe the basic substantive findings – the effect of each independent variable and its statistical significance – as best you can without calculating any predicted values or marginal effects.

. use GSS2014subset, clear  
  
. probit abany age childs educ polviews relpersn  
  
Iteration 0: Log likelihood = -1084.8368   
Iteration 1: Log likelihood = -909.52299   
Iteration 2: Log likelihood = -908.95059   
Iteration 3: Log likelihood = -908.95042   
Iteration 4: Log likelihood = -908.95042   
  
Probit regression Number of obs = 1,575  
 LR chi2(5) = 351.77  
 Prob > chi2 = 0.0000  
Log likelihood = -908.95042 Pseudo R2 = 0.1621  
  
─────────────┬────────────────────────────────────────────────────────────────  
 abany │ Coefficient Std. err. z P>|z| [95% conf. interval]  
─────────────┼────────────────────────────────────────────────────────────────  
 age │ .0019953 .0021531 0.93 0.354 -.0022246 .0062152  
 childs │ -.0465874 .0232186 -2.01 0.045 -.092095 -.0010798  
 educ │ .0945726 .0120598 7.84 0.000 .0709358 .1182094  
 polviews │ -.2348614 .0251512 -9.34 0.000 -.2841568 -.185566  
 relpersn │ -.3304787 .0368112 -8.98 0.000 -.4026273 -.2583302  
 \_cons │ -.2199313 .2089871 -1.05 0.293 -.6295384 .1896758  
─────────────┴────────────────────────────────────────────────────────────────

* Education has a positive and significant association with support for legal abortion
* A higher score on the political ideology index (polviews) is associated with lower support for abortion.
* A higher value on the relpersn scale, which indicates a more religious person, is significant and associated with lower support for abortion
* Number of children is weakly significantly associated with lower support for abortion
* Age is not significantly related to support for abortion.

##### b) By hand, calculate the probability that a person supports an unrestricted right to legal abortion if that person is 35 years old, has two children, has 16 years of education, is a 3 on the ideology scale (starting at 0), and is a 2 on relpersn.

Using the coefficients from the probit regression output and the values above:

To get the predicted probability, evaluate using the standard normal distribution:

. disp normal(0.095565)  
.53806697

Which tells us that the predicted probability that a person with these characteristics voted for Harris is ~.462.

##### c) Now suppose instead the person is 65 years old and is a 5 on the ideology scale. What is the change in the predicted probability of a support for unrestricted abortion rights?

To get the predicted probability, evaluate using the standard normal distribution:

. disp normal(-0.505495)  
.3066056

Which gives .306. Taking the difference between the two:

Changing the characteristics of a person to age 65 and increasing their score on the ideology scale (to more conservative) decreases their probability of voting Harris by .156.

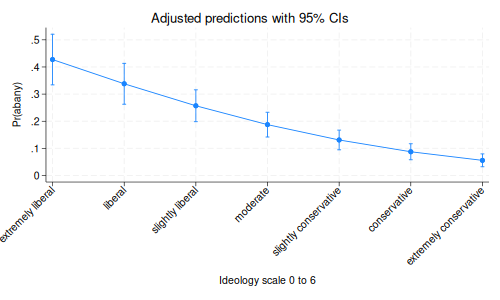
##### d) Using your software, find the predicted probability that a person supports unrestricted abortion rights when all independent variables are set to their medians in the estimation sample. In Stata, this means using the predict’ command with the (medians) all option. In R, use the predictions function from the marginaleffects package, which can also be set to use medians from the estimation sample.

. margins, predict() at((median) \_all)  
  
Adjusted predictions Number of obs = 1,575  
Model VCE: OIM  
  
Expression: Pr(abany), predict()  
At: age = 49 (median)  
 childs = 2 (median)  
 educ = 14 (median)  
 polviews = 3 (median)  
 relpersn = 2 (median)  
  
─────────────┬────────────────────────────────────────────────────────────────  
 │ Delta-method  
 │ Margin std. err. z P>|z| [95% conf. interval]  
─────────────┼────────────────────────────────────────────────────────────────  
 \_cons │ .398643 .0150546 26.48 0.000 .3691366 .4281494  
─────────────┴────────────────────────────────────────────────────────────────

The command outputs a predicted probability of .398.

##### e) Using your software, set age to 40, childs to 4, educ to 12, relpersn to 3, and let polviews vary from 0 to 6 in increments of 1. Find the predicted probability the person supports unrestricted abortion rights as polviews changes. Then make the marginsplot.

. margins, predict() at(age=40 childs=4 educ=12 relpersn=3 polviews=(0(1)6))  
  
Adjusted predictions Number of obs = 1,575  
Model VCE: OIM  
  
Expression: Pr(abany), predict()  
1.\_at: age = 40  
 childs = 4  
 educ = 12  
 polviews = 0  
 relpersn = 3  
2.\_at: age = 40  
 childs = 4  
 educ = 12  
 polviews = 1  
 relpersn = 3  
3.\_at: age = 40  
 childs = 4  
 educ = 12  
 polviews = 2  
 relpersn = 3  
4.\_at: age = 40  
 childs = 4  
 educ = 12  
 polviews = 3  
 relpersn = 3  
5.\_at: age = 40  
 childs = 4  
 educ = 12  
 polviews = 4  
 relpersn = 3  
6.\_at: age = 40  
 childs = 4  
 educ = 12  
 polviews = 5  
 relpersn = 3  
7.\_at: age = 40  
 childs = 4  
 educ = 12  
 polviews = 6  
 relpersn = 3  
  
─────────────┬────────────────────────────────────────────────────────────────  
 │ Delta-method  
 │ Margin std. err. z P>|z| [95% conf. interval]  
─────────────┼────────────────────────────────────────────────────────────────  
 \_at │  
 1 │ .4273858 .0476563 8.97 0.000 .3339812 .5207905  
 2 │ .338012 .038465 8.79 0.000 .2626219 .413402  
 3 │ .2569567 .0299834 8.57 0.000 .1981903 .3157231  
 4 │ .1873732 .0232907 8.04 0.000 .1417242 .2330222  
 5 │ .1308294 .0185277 7.06 0.000 .0945157 .1671431  
 6 │ .0873365 .0150468 5.80 0.000 .0578454 .1168276  
 7 │ .0556697 .0121057 4.60 0.000 .0319429 .0793964  
─────────────┴────────────────────────────────────────────────────────────────  
  
. qui marginsplot, xlabel(, angle(45))  
  
. graph export marginsplot.png, width(500) replace  
file marginsplot.png saved as PNG format



Margins Plot

##### f) What is the average marginal effect of the variable relpersn?

. margins, dydx(relpersn)   
  
Average marginal effects Number of obs = 1,575  
Model VCE: OIM  
  
Expression: Pr(abany), predict()  
dy/dx wrt: relpersn  
  
─────────────┬────────────────────────────────────────────────────────────────  
 │ Delta-method  
 │ dy/dx std. err. z P>|z| [95% conf. interval]  
─────────────┼────────────────────────────────────────────────────────────────  
 relpersn │ -.1084659 .0111446 -9.73 0.000 -.1303089 -.0866229  
─────────────┴────────────────────────────────────────────────────────────────

On average, the marginal effect of a one-unit change in relpersn decreases the probability of a person supporting abortion for any reason by about .108.

##### g) Re-estimate the model as a logit model. Using your software, find the predicted probability that a person supports an unrestricted right to legal abortion if that person is 35 years old, has two children, has 16 years of education, is a 3 on the ideology scale, and is a 2 on relpersn. Compare this to your answer in part (b).

. logit abany age childs educ polviews relpersn  
  
Iteration 0: Log likelihood = -1084.8368   
Iteration 1: Log likelihood = -909.83588   
Iteration 2: Log likelihood = -908.38496   
Iteration 3: Log likelihood = -908.38171   
Iteration 4: Log likelihood = -908.38171   
  
Logistic regression Number of obs = 1,575  
 LR chi2(5) = 352.91  
 Prob > chi2 = 0.0000  
Log likelihood = -908.38171 Pseudo R2 = 0.1627  
  
─────────────┬────────────────────────────────────────────────────────────────  
 abany │ Coefficient Std. err. z P>|z| [95% conf. interval]  
─────────────┼────────────────────────────────────────────────────────────────  
 age │ .0032095 .0035707 0.90 0.369 -.003789 .010208  
 childs │ -.0777166 .0396353 -1.96 0.050 -.1554004 -.0000328  
 educ │ .1608781 .0206356 7.80 0.000 .1204331 .2013231  
 polviews │ -.3923856 .0426454 -9.20 0.000 -.4759691 -.3088022  
 relpersn │ -.5444682 .0618463 -8.80 0.000 -.6656848 -.4232517  
 \_cons │ -.4228543 .3492259 -1.21 0.226 -1.107325 .261616  
─────────────┴────────────────────────────────────────────────────────────────  
  
. margins, predict() at(age=35 childs=2 educ=16 polviews=3 relpersn=2)  
  
Adjusted predictions Number of obs = 1,575  
Model VCE: OIM  
  
Expression: Pr(abany), predict()  
At: age = 35  
 childs = 2  
 educ = 16  
 polviews = 3  
 relpersn = 2  
  
─────────────┬────────────────────────────────────────────────────────────────  
 │ Delta-method  
 │ Margin std. err. z P>|z| [95% conf. interval]  
─────────────┼────────────────────────────────────────────────────────────────  
 \_cons │ .4605824 .0242907 18.96 0.000 .4129735 .5081913  
─────────────┴────────────────────────────────────────────────────────────────

The predicted probability in (b) was .462, the predicted probability using the logit command is .460. They are similar.

##### h) Now run the model as a logistic regression that produces odds ratios for coefficients. Compare the coefficients to the logit model that you just ran, explaining how they have the same substantive meaning.

. logistic abany age childs educ polviews relpersn  
  
Logistic regression Number of obs = 1,575  
 LR chi2(5) = 352.91  
 Prob > chi2 = 0.0000  
Log likelihood = -908.38171 Pseudo R2 = 0.1627  
  
─────────────┬────────────────────────────────────────────────────────────────  
 abany │ Odds ratio Std. err. z P>|z| [95% conf. interval]  
─────────────┼────────────────────────────────────────────────────────────────  
 age │ 1.003215 .0035822 0.90 0.369 .9962182 1.01026  
 childs │ .9252266 .0366716 -1.96 0.050 .8560723 .9999672  
 educ │ 1.174542 .0242374 7.80 0.000 1.127985 1.22302  
 polviews │ .6754436 .0288046 -9.20 0.000 .6212827 .734326  
 relpersn │ .5801502 .0358801 -8.80 0.000 .5139215 .6549138  
 \_cons │ .6551741 .2288038 -1.21 0.226 .3304419 1.299028  
─────────────┴────────────────────────────────────────────────────────────────  
Note: \_cons estimates baseline odds.

The logit command coefficients reflect the change in log odds for a one unit change in the independent variable. To generate the odds ratio from the odds ratio from logit output you need to exponentiate the coefficient. Using the coefficient on age:

. disp exp(.0032095)  
1.0032147

Which is the output from the logistic regression.

#### 3. For this question, use the dataset anes2020subset. The dependent variable is DiversityGood, which provides an ordinal set of responses to the following question: “Does the increasing number of people of many different races and ethnic groups in the United States make this country a better place to live, a worse place to live, or does it make no difference?” The responses are recorded as “worse,” “makes no difference,” or “better.”

The independent variables of interest are: KnowsImmigrant, a dichotomous variable that indicates whether the respondent knows someone who is an immigrant to the US (1=yes); LGBTfriends, a dichotomous variable that indicates whether the respondent has LGBT friends (1=yes); ICEtherm, a feeling thermometer score (0-100) for the U.S. Immigration and Customs Enforcement (ICE) agency; Ideology, the respondent’s placement on a seven-point (0-6) scale in which higher values mean more conservative political beliefs; WhitesTherm, the respondent’s feeling thermometer score (0-100) for white people.

##### (a) Estimate an ordered probit model. Report the results and describe the basic substantive findings, including statistical significance, without calculating predicted or marginal effects.

. use anes2020subset, clear  
  
. oprobit DiversityGood KnowsImmigrant LGBTfriends ICEtherm Ideology WhitesTherm  
  
Iteration 0: Log likelihood = -5069.8804   
Iteration 1: Log likelihood = -4455.9097   
Iteration 2: Log likelihood = -4452.6072   
Iteration 3: Log likelihood = -4452.607   
  
Ordered probit regression Number of obs = 5,855  
 LR chi2(5) = 1234.55  
 Prob > chi2 = 0.0000  
Log likelihood = -4452.607 Pseudo R2 = 0.1218  
  
───────────────┬────────────────────────────────────────────────────────────────  
 DiversityGood │ Coefficient Std. err. z P>|z| [95% conf. interval]  
───────────────┼────────────────────────────────────────────────────────────────  
KnowsImmigrant │ .3305089 .0351652 9.40 0.000 .2615864 .3994314  
 LGBTfriends │ .1840994 .034816 5.29 0.000 .1158612 .2523375  
 ICEtherm │ -.0073763 .0006913 -10.67 0.000 -.0087313 -.0060213  
 Ideology │ -.2275441 .0124519 -18.27 0.000 -.2519494 -.2031388  
 WhitesTherm │ .0062016 .0008351 7.43 0.000 .0045648 .0078384  
───────────────┼────────────────────────────────────────────────────────────────  
 /cut1 │ -1.991851 .0764543 -2.141699 -1.842004  
 /cut2 │ -.5120719 .07273 -.6546201 -.3695236  
───────────────┴────────────────────────────────────────────────────────────────

Note: R users should first convert Ideology to a numeric variable (see help document). Also, it may also be easier for later – in parts (e) and (f) – to deal with the dichotomous variables if they are converted to numeric.

* Going from not knowing an immigrant to knowing an immigrant is positive and significantly associated with a higher/more positive response to the “DiversityGood” question.
* Going from having no LGBT friends to having LGBT friends is positive and significantly associated with a higher/more positive response to the “DiversityGood” question.
* An increase in the positive feelings for ICE is negative and significantly associated with a lower/less positive response to the “DiversityGood” question.
* An increase in ideology score is negative and significantly associated with a lower/less positive response to the “DiversityGood” question.
* An increase in the Whites thermometer is positive and significantly associated with a higher/more positive response to the “DiversityGood” question.

##### (b) By hand, calculate the value of for a person who does not know an immigrant, who does not have LGBT friends, whose feeling thermometer score for ICE is 55, who is a 4 (“slightly conservative”) on the ideology scale, and whose feeling thermometer score for white people is 75.

Using the coefficients from the model:

So for this scenario is: -.8507529

##### (c) Put the value you calculated for at the center of a standard normal (z) distribution (i.e. it has a z-score of 0; the standard deviation is already 1). Then, what would be the corresponding z scores for the 2 cut points? What proportion of the area is below cut1? What proportion of area is above cut2? What proportion is between cut1 and cut2?

We get the values of the two cut points from the model:

To find the corresponding z-scores:

So the proportion of the area that is below cut1 is around .127.

The proportion of the area that is above cut2 is .

Using both, the proportion of the area between cut1 and cut2 is:  
$ .63257497 - 12691455 = .50566545$

##### (d) What if, instead, the person does know an immigrant? How do the predictions change?

Note: keep all other variables at the same values.

If the person knows an immigrant, the calculation changes:

If the scenario changes to where a person knows an immigrant, the calculation changes to -.520.

##### (e) Now use Stata or R. If a person has the median value (in the estimation sample) for all independent variables, with what predicted probabilities does that person give each respective response?

For R users: if the dichotomous variables are left as factors, you will need to follow code examples from the help document for specifying factor variable values.

. margins, predict() at((median) \_all)  
  
Adjusted predictions Number of obs = 5,855  
Model VCE: OIM  
  
1.\_predict: Pr(DiversityGood==0), predict(pr outcome(0))  
2.\_predict: Pr(DiversityGood==1), predict(pr outcome(1))  
3.\_predict: Pr(DiversityGood==2), predict(pr outcome(2))  
  
At: KnowsImmigrant = 1 (median)  
 LGBTfriends = 1 (median)  
 ICEtherm = 50 (median)  
 Ideology = 3 (median)  
 WhitesTherm = 70 (median)  
  
─────────────┬────────────────────────────────────────────────────────────────  
 │ Delta-method  
 │ Margin std. err. z P>|z| [95% conf. interval]  
─────────────┼────────────────────────────────────────────────────────────────  
 \_predict │  
 1 │ .0294375 .0022068 13.34 0.000 .0251123 .0337628  
 2 │ .3117055 .0075575 41.24 0.000 .2968931 .3265179  
 3 │ .658857 .0084535 77.94 0.000 .6422884 .6754256  
─────────────┴────────────────────────────────────────────────────────────────

According to the output, at the median values for all independent variables, the predicted probability that a person responds:

* “worse” is .029
* “makes no difference” is .311
* “better” is .659

##### (f) Again, use your software. For a person with the median values for all independent variables in the estimation sample, what is the predicted effect of a 2-point increase in Ideology on the probability of each answer?

Setting Ideology to it’s median value (3), and increasing it to 5, while keeping all other independent variables the same.

. margins, predict() at(Ideology=(3 5) (median))  
  
Predictive margins Number of obs = 5,855  
Model VCE: OIM  
  
1.\_predict: Pr(DiversityGood==0), predict(pr outcome(0))  
2.\_predict: Pr(DiversityGood==1), predict(pr outcome(1))  
3.\_predict: Pr(DiversityGood==2), predict(pr outcome(2))  
  
1.\_at: Ideology = 3  
2.\_at: Ideology = 5  
  
─────────────┬────────────────────────────────────────────────────────────────  
 │ Delta-method  
 │ Margin std. err. z P>|z| [95% conf. interval]  
─────────────┼────────────────────────────────────────────────────────────────  
\_predict#\_at │  
 1 1 │ .048569 .0027479 17.68 0.000 .0431833 .0539547  
 1 2 │ .1101682 .005661 19.46 0.000 .0990728 .1212635  
 2 1 │ .3527509 .0063461 55.59 0.000 .3403128 .3651889  
 2 2 │ .4626993 .0092142 50.22 0.000 .4446399 .4807587  
 3 1 │ .5986801 .0065563 91.31 0.000 .5858301 .6115302  
 3 2 │ .4271325 .0109962 38.84 0.000 .4055804 .4486847  
─────────────┴────────────────────────────────────────────────────────────────

* The probability of answering “worse” changes from .048569 to .1101682, an increase of .0615992.
* The probability of answering “makes no difference” changes from .3527509 to .4626993, an increase of .1099484.
* The probability of answering “better” changes from .5986801 to .4271325, a decrease of .1715476.