Ordered logistic regression interpretation

The interpretation of coefficients in ordinal logistic regression depends on the software used. This FAQ page focuses on the interpretation of stata and R coefficients, but the results are generalized to SPSS and Mplus. The parameterization of SAS is different from the others. Definition First, let's establish a notation for ordinal logistic regression and review the concepts. $Y let's make it an ordinal result in the <a0></a0>J<a2></a2> category. Next, the <a0></a0>Y<a2></a2> <a3></a3><a5></a5> is the cumulative probability of less than or less than a certain category, <a2></a2>,<a3></a3><a5></a5><a5></a5>. the probability of a $P $P(Y-le-J $j) less than or below a certain category is not defined. Alternatively$P you can write a file (Y >j) to 1 - P(Y .le j). Log-odds, also known as logits, are called logits. It can be defined as a beta_ beta_ beta_ beta_ ,j1 x_1 x_p>>$j>$j $j>$j>$j>$j>$j $j>$j>$j>$j>$logit beta_ $logit $log Predictive variables for J-1 and . . . . Due to parallel line assumptions, the cut is different for each category, but the slope is constant between the categories. How stata and R parameterize the ordinal regression model of stata and R (porr $logit x_p beta_ beta_{1}x_1 beta_) in the above equation. . . . . beta_i eta_i x_p eta_ eta_{1}x_1 beta_ The coefficients (pards) of the parent's education remain the same across the two categories, even though we have three categories, because of the assumption of a parallel line. $logit The two equations, Pard, x_1 1, and Pard, are the following equations: <a0></a0><a1></a x_1 eta_{1} beta_1><a2></a2><a3></a3><a5></a5><a5></a5><a5></a5></a5><a5></a5> <a5></a5> <a5></a5><a5></a5><a5></a5><a5></a5></a1><a2></a2><a3></a3><a4></a4></a5> <a5></a5><a5></a5><a5></a5><a5></a5><a5></a5></a1><a2></a2><a4></a5><a5></a5><a5></a5><a5></a5><a5></a5><a5><&amp eta_{1} x_1 x_1; beta_ allows you to clearly logit apply i.pared <.. >Ordined Logistic Regression Obs , 400 LR chi2(1) , 18.41 Prob > chi2 , 0.0000 Log Likelihood, -361.39515 Pseudo R2 , 0.0248 Applied-- [95% Conf. Interval] -------------+-- 1.pared .1.127491 .2634324 4.28 0.0001.643809 -------------+-- /cut1 , .3768424 .1103421 .1605758 .593109 /cut2 2.451855 .1825628 2.094039 2.809672 -- To perform the same analysis on r R, more steps are required. First load the following libraries: Libraries (External) Libraries (MASS) Now read the data and perform analysis using pollr: dat <- read.dta (.dta) m <- pollr (Apply-Pard, data-dat) Summary (m) The short output looks like this: Coefficient: Value Std. Error t value is 1.127 0.2634 4.28 Intercept: Value Std. Error t-values are unlikely to be .3768 0.1103 3.4152 somely likely to be 2.4519 0.1826 13.4302 The output for students attended by their parents shows in college Log odds (some or more likely) that are unlikely to apply to college are actually lower than students thy parents did not attend college. $logit beta_i eta_i you don't have a defined <a0></a0>beta_i $j<a2></a2> <a3></a3><a5></a5><a5></a5><a5></a5><a5></a5><a5></a5><a5></a5><a5></a5><a5></a5><a5></a5></a5 Therefore, the formula for the first and second categories is as follows: <a0></a0><a x_1 x_1 1></a1><a2></a2><a3></a3><a4></a4><a5></a5><a5></a5><a5></a5><a5></a5><a5></a5></Calculates pard odds for each application level, using the properties of $log(b)-log(a)-log(b/a) <a0></a0><a1></a x_1 1><a2></a2><a3></a3><a4></a4><a5></a5><a5><x_1/a5><a5></a5><a5></a5><a5></a5><a5></a5></a5 & exp(0.377)/x_1 exp(1.13)x_1) & exp(0.377 x_1 x_1) & & exp(2.45 x_1)/exp(1.13) You can calculate the odds ratio of the pard for each application level from the odds for each level of the x_1.0) and exp(2.45) . . . . <a0></a0><a1></a1><a2></a2><a3></a3><a4></a4><a5></a5><a5></a5><a5></a5></a1><a2></a2><a4></a4><a5></a5><a5></a5> <a5>& 1/exp(1.13) & & &x_1 x_1 x_1 x_1 exp(1.13) & 1/exp(1.13) & & $J exp(-1.13) x_1 x_1 x_1 x_1 This means that it is the same as the probability that it is likely to be applied ($j is 2 dollars). Interpretation of odds ratio The assumption of proportional odds is not just that the odds are the same, but the assumption that the odds ratio is the same between categories. These odds ratios can be derived by exponentialing the coefficientsmetric), but the interpretation is a bit unexpected. A factor of –eta_{1} represents a one-unit change in log odds that applies to students ed who went to college by their parents and parents who did not eta_{1} x_1 x_1 $logit. It simply exponentizes both sides of this equation and uses the property $log(b)-log(a) - log(b/a) <a0></a0>P<a1></a1><a2></a2><a3></a3><a4></a4><a5></a5><a5></a5><a5></a5></a1><a2></a2><a3></a4><a5></a5><a5><x_1 Make an assumption based on the proportional odds, assuming that you are exp (-eta_{1} x_1 x_1), and that you can make assumptions based on the proportional odds. p_1 <a0><x_1 x_1 x_1 p_1/a0> <a1></a1> <a2></a2><a3></a3><a4></a4><a5></a5><a5></a5><a5></a5> <a2></a2><a3></a3><a5></a5> <a5></a5><a5></a5></a5 the p_0/ (1-p_0 p_1 eta_{1} p_0 p_0) odds ratio is defined as <a0></a0><a1></a p_1 1><a2></a2><a3></a3><a5></a5><a5></a5></a5><a5></a5><a5></a5></a5> <a5></a5> <a5></a5><a5></a5> <a x_1 x_1 x_1 As you see in the output, this is not really what you get from Stata and R! To get the odds ratio in Stata, add an option or use the ologit command. ologit applies i.pared, or <.. Omit the output.. > Logistic Regression Obs - 400 LR chi2(1) - 18.41 prob > chi2 - 0.0000 log-likelihood - -361.39515 Pseudo R2 - 0.0248 -- Apply - Odds Ratio St. Error z P>> [95% Conf. Interval] -------------+-- 1.pared .087899 .8134527 4.28 0.000 1.842591 5.174843 -------------+-- /cut1 3768424 .1103421 .1605758 .593109 /cut2 .2.451855 .1825628 2.094039 2.809672 --: Estimates are converted only in the first equation. To find the odds ratio for R R, simply exponentize the coefficients or even odds. The following code uses cbind to combine the odds ratio with the confidence interval: First, save the confidence interval to the object ci, (ci <-confint(m)) 2.5 % 97.5 % 0.6131222 1.6478130 Combine the conversion of the ci object with coef(m), exponentize the value, and then exponentialize the value (cbind() coef(m)t(ci)) 2.5 % 97.5 % is 3.087899 1.846187 5.195605 In our example, $exp(-1.127) But this doesn't correspond to the odds ratio from the output! $exp(-&p_1 p_1 p_0 p_0 p_1 p_1 p_0 p_0 eta_{1} $exp eta_{1}{1} eta_{1} gt;>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>><>>>>>>>>&gt This suggests that students thy parents who did not go to college are less likely to apply to students who did not go to college. Another way to see the odds ratio doubleIt can be logically confusing. You want to interpret the probability of applying to a university. You can manipulate the original odds ratio a little eta_{1}: & p_1 / (1-p_1 p_1 p_0 p_0 p_1 p_1 p_0 p_0) &/frac(1-p_0)/p_0(1-p_1 p_1 p_1)/p_0 & & & & .frac&P (Y >j > x>0)/P(Y > le j > x)/P eta_{1}{1}(Y .le eta_{1} $exp j . . . . You can interpret the probability greater than the $j.th category by indexing the odds of frac>j > x > 1)/P(Y > j > j >0)/P(Y>$j le j In this example, the value of $exp is 3.086 times that of students 3.086, which is a very likely (some or less likely) parent to apply compared to the student 3.086. The result here is in agreement with our intuition because it removes the double nega. As a general rule, it is easier to interpret the odds ratio of $x_ $x $x 1 $x However, doing so $P the interpretation of the result by including Y >j in the numerator. To verify that the odds ratio of 3.08 can be interpreted in two ways to verify the interpretation of both the odds ratio using the prediction probability, derive them from the predicted probability in both Stata and $j R. Stata following the Orogit command, run the margin using the category predictors, and predict the prediction probability for each predicted value at each level of the result. Margin-adjusted Adjusted Forecasts obs : 400 Model VCE : OIM 1._predict: Pr(pr output(0)) 2._predict: Pr(pr output(1)) 3._predict 3._predict Prediction (pr output(2) -- 95% Conf. Intervals] ---------------+-- _predict .---------------+-- _predict ,1 0 ,5931113 .0266289 22.27 0.000 .5409196 .645303 1 1 .32068 .0532744 6.02 0.000 .2162641 .4250959 2 0 3.69 0.000 .2806789 .3744926 2 1 631 .5345907 3 0 0 .079303 .0133296 5.95 0.000 .0531774 .1054286 3 1 2100931 . 0424965 4.94 0.000 .1268015 .2933847 -- x_1 $x After storing the pollr object in the R object m, pass this object and the dataset.The level that is parded by the prediction function. For the predicted probability, specify the type: p. newdat <- data.frame(pared_c(0,1)) type-p)) unlikly something likely very likely 1 0.5931114 0.3275856 0.07930294 2 0.3206801 0. 4692269 0.21009300 Each row represents the first level ($x_ $x 1 And each column represents $j . . . . Interaction 1 The First Interaction Is for Students Who Did Not End College, The Odds of Being Unlyly Versus Somewhere or Very Likely (i.e., Less Likely) to Apply Is 3.08 Times That To verify this interaction, we arbitrally calculate the odds rutio for the first level of apply we know by the professional odds assembly is an exhibition to the odds rasio for the second level of apply. Since we are looking at pared , 0 vs. pared, 1 for $P (x_1 Y . . . . 1 x_1-x $p $p) (1-p_0 p_0) / (1 p_1-p_0 p_1) 0.593) 0.321 / (1-0.321) The interpretation of the students of the second university is the interpretation of that second university if it is very unlikely (i.e., more likely) is 3.08 times that of the student 3.08 times 3.08 times that of the student 2 parents did not go to college. Here, we're looking at $P(Y > 1 & x_1>x)/P(Y -le 1 > x_1>x) You can then apply the following values: .P(Y>1 >x_1 >1) >0.469+0.210 >0.679>>>x_1>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>&gt Similarly, the $P(Y>1 > x_1 x 0), 0.328+0.0 x_1 79, 0.407) x_1 x_1 . . . . /P(Y>1 > x_1 > 0) /P(Y >le 1 > x_1>0) The odds ratio of both the interpretations of 7/0.593 is the same as the output of Stata and R. . . . . In general, it is easier to exponentize the coefficients themselves rather than negative values because they are output directly from Stata and R(pollr) in order to obtain the odds ratio. Researchers then need to decide which of the two interpretations to use: if the parents did not attend college, the probability of applying is 3.08 times that of the students 3.08 times that of the students hether the parents went to college. If your parents are college students, the probability of applying is 3.08 times that of students thy parents did not go to college. The second interpretation is simple, avoiding double negation. See Builder, C.R., Luhan, T.M. (2014) R. Analysis Hall/CRC of Category Data by Chapman and Hall/CRC.