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Generalized ordered logit/partial proportional odds models for ordinal dependent variables

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Abstract. This article describes the gologit2 program for generalized ordered logit models. gologit2 is inspired by Vincent Fu's gologit routine (*Stata Technical Bulletin Reprints* 8: 160–164) and is backward compatible with it but offers several additional powerful options. A major strength of gologit2 is that it can fit three special cases of the generalized model: the proportional odds/parallel-lines model, the partial proportional odds model, and the logistic regression model. Hence, gologit2 can fit models that are less restrictive than the parallel-lines models fitted by ologit (whose assumptions are often violated) but more parsimonious and interpretable than those fitted by a nonordinal method, such as multinomial logistic regression (i.e., mlogit). Other key advantages of gologit2 include support for linear constraints, survey data estimation, and the computation of estimated probabilities via the predict command.

Keywords: st0097, gologit2, gologit, logistic regression, ordinal regression, proportional odds, partial proportional odds, generalized ordered logit model, parallel-lines model

1 Introduction

gologit2 is a user-written program that fits generalized ordered logit models for ordinal dependent variables. The actual values taken on by the dependent variable are irrelevant except that larger values are assumed to correspond to "higher" outcomes.

A major strength of gologit2 is that it can also fit three special cases of the generalized model: the *proportional odds/parallel-lines model*, the *partial proportional odds model*, and the *logistic regression model*. Hence, gologit2 can fit models that are less restrictive than the parallel-lines models fitted by ologit (whose assumptions are often violated) but more parsimonious and interpretable than those fitted by a nonordinal method, such as multinomial logistic regression (i.e., mlogit). The autofit option greatly simplifies the process of identifying partial proportional odds models that fit the data, whereas the pl (parallel lines) and npl (nonparallel lines) options can be used when users want greater control over the final model specification.

An alternative but equivalent parameterization of the model that has appeared in the literature is reported when the gamma option is selected. Other key advantages of gologit2 include support for linear constraints (making it possible to use gologit2 for constrained logistic regression), survey data (`svy`) estimation, and the computation of estimated probabilities via the `predict` command.

`gologit2` is inspired by Vincent Fu's (1998) `gologit` program and is backward compatible with it but offers several additional powerful options. `gologit2` was written for Stata 8.2; however, its `svy` features work with files that were `svyset` in Stata 9 if you are using Stata 9. Support for Stata 9's new features is currently under development.

2 The generalized ordered logit (gologit) model

As Fu (1998) notes, researchers have given the generalized ordered logit (`gologit`) model brief attention (e.g., Clogg and Shihadeh 1994) but have generally passed over it in favor of the parallel-lines model. The `gologit` model can be written as[1]

$$P(Y_i > j) = g(X\beta_j) = \frac{\exp(\alpha_j + X_i\beta_j)}{1 + \{\exp(\alpha_j + X_i\beta_j)\}}, \quad j = 1, 2, \ldots, M-1$$

where M is the number of categories of the ordinal dependent variable. From the above, it can be determined that the probabilities that Y will take on each of the values 1, …, M are equal to

$$\begin{aligned} P(Y_i = 1) &= 1 - g(X_i\beta_1) \\ P(Y_i = j) &= g(X_i\beta_{j-1}) - g(X_i\beta_j) \quad j = 2, \ldots, M-1 \\ P(Y_i = M) &= g(X_i\beta_{M-1}) \end{aligned}$$

Some well-known models are special cases of the `gologit` model. When $M = 2$, the `gologit` model is equivalent to the logistic regression model. When $M > 2$, the `gologit` model becomes equivalent to a series of binary logistic regressions where categories of the dependent variable are combined; e.g., if $M = 4$, then for $J = 1$ category 1 is contrasted with categories 2, 3, and 4; for $J = 2$ the contrast is between categories 1 and 2 versus 3 and 4; and for $J = 3$, it is categories 1, 2, and 3 versus category 4.

The parallel-lines model fitted by `ologit` is also a special case of the `gologit` model. The parallel-lines model can be written as

$$P(Y_i > j) = g(X\beta) = \frac{\exp(\alpha_j + X_i\beta)}{1 + \{\exp(\alpha_j + X_i\beta)\}}, \quad j = 1, 2, \ldots, M-1$$

The formulas for the parallel-lines model and `gologit` model are the same, except that in the parallel-lines model the β's (but not the α's) are the same for all values of j. (Also, `ologit` uses an equivalent parameterization of the model; instead of α's there are cutpoints, which equal the negatives of the α's.)

1. An advantage of writing the model this way is that it facilitates comparisons among the `logit`, `ologit`, and `gologit` models and makes parameter interpretation easier. The model could also be written in terms of the cumulative distribution function: $P(Y_i \leq j) = 1 - g(X\beta_j) = F(X\beta_j)$.

This requirement that the β's be the same for each value of j has been called various names. In Stata, Wolfe and Gould's (1998) `omodel` command calls it the *proportional odds* assumption. Long and Freese's `brant` command refers to the *parallel regressions* assumption. Both SPSS's `PLUM` command (Norusis 2005) and SAS's `PROC LOGISTIC` (SAS Institute Inc. 2004) provide tests of what they call the *parallel-lines* assumption. Because only the α's differ across values of j, the $M-1$ regression lines are all parallel. For consistency with other major statistical packages, `gologit2` uses the terminology *parallel lines*, but others may use different but equivalent phrasings.

A key problem with the parallel-lines model is that its assumptions are often violated; it is common for one or more β's to differ across values of j; i.e., the parallel-lines model is overly restrictive. Unfortunately, common solutions often go too far in the other direction, estimating far more parameters than is really necessary. Another special case of the `gologit` model overcomes these limitations. In the partial proportional odds model, some of the β coefficients can be the same for all values of j, while others can differ. For example, in the following expression, the β's for $X1$ and $X2$ are the same for all values of j but the β's for $X3$ are free to differ.

$$P(Y_i > j) = \frac{\exp(\alpha_j X1_i\beta1 + X2_i\beta2 + X3_i\beta3_j)}{1+\{\exp(\alpha_j + X1_i\beta1 + X2_i\beta2 + X3_i\beta3_j)\}}, \quad j = 1, 2, \ldots, M-1$$

Fu's 1998 program, `gologit` 1.0, was the first Stata routine that could fit the generalized ordered logit model. However, it can fit only the least constrained version of the `gologit` model; i.e., it cannot fit the special case of the parallel-lines model or the partial proportional odds model. `gologit2` overcomes these limitations and adds several other features that make model estimation easier and more powerful.

3 Examples

A series of examples will help to illustrate the utility of partial proportional odds models and the other capabilities of the `gologit2` program.

3.1 Example 1: Parallel-lines assumption violated

Long and Freese (2006) present data from the 1977/1989 General Social Survey. Respondents are asked to evaluate the following statement: "A working mother can establish just as warm and secure a relationship with her child as a mother who does not work." Responses were coded as 1 = Strongly Disagree (`1SD`), 2 = Disagree (`2D`), 3 = Agree (`3A`), and 4 = Strongly Agree (`4SA`). Explanatory variables are `yr89` (survey year; 0 = 1977, 1 = 1989), `male` (0 = female, 1 = male), `white` (0 = nonwhite, 1 = white), `age` (measured in years), `ed` (years of education), and `prst` (occupational prestige scale). `ologit` yields the following results:

```
. use http://www.indiana.edu/~jslsoc/stata/spex_data/ordwarm2
(77 & 89 General Social Survey)

. ologit warm yr89 male white age ed prst, nolog

Ordered logistic regression                       Number of obs   =       2293
                                                  LR chi2(6)      =     301.72
                                                  Prob > chi2     =     0.0000
Log likelihood = -2844.9123                       Pseudo R2       =     0.0504

------------------------------------------------------------------------------
        warm |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        yr89 |   .5239025   .0798988     6.56   0.000     .3673037    .6805013
        male |  -.7332997   .0784827    -9.34   0.000    -.8871229   -.5794766
       white |  -.3911595   .1183808    -3.30   0.001    -.6231815   -.1591374
         age |  -.0216655   .0024683    -8.78   0.000    -.0265032   -.0168278
          ed |   .0671728    .015975     4.20   0.000     .0358624    .0984831
        prst |   .0060727   .0032929     1.84   0.065    -.0003813    .0125267
-------------+----------------------------------------------------------------
       /cut1 |  -2.465362   .2389126                     -2.933622   -1.997102
       /cut2 |   -.630904   .2333155                     -1.088194    -.173614
       /cut3 |   1.261854   .2340179                      .8031873    1.720521
------------------------------------------------------------------------------
```

These results are relatively straightforward, intuitive, and easy to interpret. People tended to be more supportive of working mothers in 1989 than in 1977. Males, whites, and older people tended to be less supportive of working mothers, whereas better-educated people and people with higher occupational prestige were more supportive.

But although the results may be straightforward, intuitive, and easy to interpret, are they correct? Are the assumptions of the parallel-lines model met? The `brant` command (part of Long and Freese's `spost` routines) provides both a global test of whether any variable violates the parallel-lines assumption, as well as tests of the assumption for each variable separately.

```
. brant

Brant Test of Parallel Regression Assumption

    Variable |      chi2   p>chi2    df
-------------+--------------------------
         All |     49.18    0.000    12
-------------+--------------------------
        yr89 |     13.01    0.001     2
        male |     22.24    0.000     2
       white |      1.27    0.531     2
         age |      7.38    0.025     2
          ed |      4.31    0.116     2
        prst |      4.33    0.115     2
----------------------------------------

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

The Brant test shows that the assumptions of the parallel-lines model are violated, but the main problems seem to be with the variables `yr89` and `male`. By adding the `detail` option to the `brant` command, we get a clearer idea of how assumptions are violated.

```
. brant, detail
Estimated coefficients from j-1 binary regressions
              y>1          y>2          y>3
 yr89     .9647422    .56540626    .31907316
 male   -.30536425   -.69054232   -1.0837888
white   -.55265759   -.31427081   -.39299842
  age    -.0164704   -.02533448   -.01859051
   ed    .10479624    .05285265    .05755466
 prst   -.00141118    .00953216    .00553043
_cons    1.8584045    .73032873   -1.0245168
Brant Test of Parallel Regression Assumption
```

Variable	chi2	p>chi2	df
All	49.18	0.000	12
yr89	13.01	0.001	2
male	22.24	0.000	2
white	1.27	0.531	2
age	7.38	0.025	2
ed	4.31	0.116	2
prst	4.33	0.115	2

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

This output is a series of binary logistic regressions. First, it is category 1 versus categories 2, 3, and 4; then categories 1 and 2 versus 3 and 4; and then categories 1, 2, and 3 versus 4. If the parallel-lines assumptions were not violated, all these coefficients (except the intercepts) would be the same across equations except for sampling variability. Instead, we see that the coefficients for `yr89` and `male` differ greatly across regressions, while the coefficients for other variables also differ but much more modestly.

Given that the assumptions of the parallel-lines model are violated, what should be done about it? One perhaps common practice is to go ahead and use the model anyway, which as we will see can lead to incorrect, incomplete, or misleading results. Another option is to use a nonordinal alternative, such as the multinomial logistic regression model fitted by `mlogit`. We will not talk about this model in depth, except to note that it has far more parameters than the parallel-lines model (in this case, there are three coefficients for every explanatory variable, instead of only one), and hence its interpretation is not as simple or straightforward.

Fu's (1998) original `gologit` program offers an ordinal alternative in which the parallel-lines assumption is not violated. By default, `gologit2` provides almost identical output to that of `gologit`:

```
. gologit2 warm yr89 male white age ed prst

Generalized Ordered Logit Estimates               Number of obs   =       2293
                                                  LR chi2(18)     =     350.92
                                                  Prob > chi2     =     0.0000
Log likelihood =  -2820.311                       Pseudo R2       =     0.0586

------------------------------------------------------------------------------
        warm |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
1SD          |
        yr89 |     .95575   .1547185     6.18   0.000     .6525074    1.258993
        male |  -.3009776   .1287712    -2.34   0.019    -.5533645   -.0485906
       white |  -.5287268   .2278446    -2.32   0.020    -.9752941   -.0821595
         age |  -.0163486   .0039508    -4.14   0.000    -.0240921   -.0086051
          ed |   .1032469   .0247377     4.17   0.000     .0547619     .151732
        prst |  -.0016912   .0055997    -0.30   0.763    -.0126665     .009284
       _cons |   1.856951   .3872576     4.80   0.000      1.09794    2.615962
-------------+----------------------------------------------------------------
2D           |
        yr89 |   .5363707   .0919074     5.84   0.000     .3562355     .716506
        male |   -.717995   .0894852    -8.02   0.000    -.8933827   -.5426072
       white |   -.349234   .1391882    -2.51   0.012    -.6220379     -.07643
         age |  -.0249764   .0028053    -8.90   0.000    -.0304747   -.0194782
          ed |   .0558691   .0183654     3.04   0.002     .0198737    .0918646
        prst |   .0098476   .0038216     2.58   0.010     .0023575    .0173377
       _cons |   .7198119    .265235     2.71   0.007     .1999609    1.239663
-------------+----------------------------------------------------------------
3A           |
        yr89 |   .3312184   .1127882     2.94   0.003     .1101577    .5522792
        male |  -1.085618   .1217755    -8.91   0.000    -1.324294   -.8469423
       white |  -.3775375   .1568429    -2.41   0.016     -.684944    -.070131
         age |  -.0186902   .0037291    -5.01   0.000     -.025999   -.0113814
          ed |   .0566852   .0251836     2.25   0.024     .0073263    .1060441
        prst |   .0049225   .0048543     1.01   0.311    -.0045918    .0144368
       _cons |  -1.002225   .3446354    -2.91   0.004    -1.677698   -.3267523
------------------------------------------------------------------------------
```

The default `gologit2` results are similar to the series of binary logistic regressions estimated by the `brant` command and can be interpreted the same way: i.e., the first panel contrasts category 1 with categories 2, 3, and 4; the second panel contrasts categories 1 and 2 with categories 3 and 4; and the third panel contrasts categories 1, 2, and 3 with category 4.[2] Hence, positive coefficients indicate that higher values on the explanatory variable make it more likely that the respondent will be in a higher category of Y than the current one, whereas negative coefficients indicate that higher values on the explanatory variable increase the likelihood of being in the current or a lower category.

The main problem with the `mlogit` and the default `gologit`/`gologit2` models is that they include many more parameters than `ologit`—possibly many more than is necessary. These methods free *all* variables from the parallel-lines constraint, even

2. Put another way, the jth panel gives results that are equivalent to those of a logistic regression in which categories 1 through j have been recoded to 0 and categories $j+1$ through M have been recoded to 1. The simultaneous estimation of all equations causes results to differ slightly from when each equation is estimated separately. When interpreting results for each panel, remember that the current category of Y, as well as the lower-coded categories, are serving as the reference group.

though the assumption may be violated only by *one or a few* of them. `gologit2` can overcome this limitation by fitting partial proportional odds models, where the parallel-lines constraint is relaxed only for those variables where it is not justified. This task is most easily done with the `autofit` option. We will analyze different parts of the `gologit2` output to explain what is going on.

```
. gologit2 warm yr89 male white age ed prst, autofit lrforce
------------------------------------------------------------------------------
Testing parallel-lines assumption using the .05 level of significance...
Step  1:  Constraints for parallel lines imposed for white (P Value = 0.7136)
Step  2:  Constraints for parallel lines imposed for ed (P Value = 0.1589)
Step  3:  Constraints for parallel lines imposed for prst (P Value = 0.2046)
Step  4:  Constraints for parallel lines imposed for age (P Value = 0.0743)
Step  5:  Constraints for parallel lines are not imposed for
          yr89 (P Value = 0.00093)
          male (P Value = 0.00002)
Wald test of parallel-lines assumption for the final model:
 ( 1)  [1SD]white - [2D]white = 0
 ( 2)  [1SD]ed - [2D]ed = 0
 ( 3)  [1SD]prst - [2D]prst = 0
 ( 4)  [1SD]age - [2D]age = 0
 ( 5)  [1SD]white - [3A]white = 0
 ( 6)  [1SD]ed - [3A]ed = 0
 ( 7)  [1SD]prst - [3A]prst = 0
 ( 8)  [1SD]age - [3A]age = 0
           chi2(  8) =   12.80
         Prob > chi2 =    0.1190
An insignificant test statistic indicates that the final model
does not violate the proportional odds/parallel-lines assumption
If you refit this exact same model with gologit2, instead
of autofit, you can save time by using the parameter
pl(white ed prst age)
------------------------------------------------------------------------------
```

When `autofit` is specified, `gologit2` goes through an iterative process. First, it fits a totally unconstrained model, the same model as the original `gologit`. It then does a series of Wald tests on each variable to see whether its coefficients differ across equations, e.g., whether the variable meets the parallel-lines assumption. If the Wald test is statistically insignificant for one or more variables, the variable with the least significant value on the Wald test is constrained to have equal effects across equations. The model is then refitted with constraints, and the process is repeated until there are no more variables that meet the parallel-lines assumption. A global Wald test is then done of the final model with constraints versus the original unconstrained model; a statistically insignificant test value indicates that the final model does not violate the parallel-lines assumption. As the global Wald test shows, eight constraints have been imposed in the final model, corresponding to four variables' being constrained to have their effects meet the parallel-lines assumption.

Here is the rest of the output. Stata normally reports Wald statistics when constraints are imposed in a model, but the `lrforce` parameter causes a likelihood-ratio (LR) chi-squared for the model to be reported instead.

```
Generalized Ordered Logit Estimates               Number of obs   =       2293
                                                  LR chi2(10)     =     338.30
                                                  Prob > chi2     =     0.0000
Log likelihood = -2826.6182                       Pseudo R2       =     0.0565
 ( 1)  [1SD]white - [2D]white = 0
 ( 2)  [1SD]ed - [2D]ed = 0
 ( 3)  [1SD]prst - [2D]prst = 0
 ( 4)  [1SD]age - [2D]age = 0
 ( 5)  [2D]white - [3A]white = 0
 ( 6)  [2D]ed - [3A]ed = 0
 ( 7)  [2D]prst - [3A]prst = 0
 ( 8)  [2D]age - [3A]age = 0
```

warm	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1SD						
yr89	.98368	.1530091	6.43	0.000	.6837876	1.283572
male	-.3328209	.1275129	-2.61	0.009	-.5827417	-.0829002
white	-.3832583	.1184635	-3.24	0.001	-.6154424	-.1510742
age	-.0216325	.0024751	-8.74	0.000	-.0264835	-.0167814
ed	.0670703	.0161311	4.16	0.000	.0354539	.0986866
prst	.0059146	.0033158	1.78	0.074	-.0005843	.0124135
_cons	2.12173	.2467146	8.60	0.000	1.638178	2.605282
2D						
yr89	.534369	.0913937	5.85	0.000	.3552406	.7134974
male	-.6932772	.0885898	-7.83	0.000	-.8669099	-.5196444
white	-.3832583	.1184635	-3.24	0.001	-.6154424	-.1510742
age	-.0216325	.0024751	-8.74	0.000	-.0264835	-.0167814
ed	.0670703	.0161311	4.16	0.000	.0354539	.0986866
prst	.0059146	.0033158	1.78	0.074	-.0005843	.0124135
_cons	.6021625	.2358361	2.55	0.011	.1399323	1.064393
3A						
yr89	.3258098	.1125481	2.89	0.004	.1052197	.5464
male	-1.097615	.1214597	-9.04	0.000	-1.335671	-.8595579
white	-.3832583	.1184635	-3.24	0.001	-.6154424	-.1510742
age	-.0216325	.0024751	-8.74	0.000	-.0264835	-.0167814
ed	.0670703	.0161311	4.16	0.000	.0354539	.0986866
prst	.0059146	.0033158	1.78	0.074	-.0005843	.0124135
_cons	-1.048137	.2393568	-4.38	0.000	-1.517268	-.5790061

At first glance, this model might not appear to be any more parsimonious than the original `gologit2` model, but note that the parameter estimates for the constrained variables `white`, `age`, `ed`, and `prst` are the same in all three panels. Hence, only 10 unique β coefficients need to be examined, compared with the 18 produced by `mlogit` and the original `gologit`.

This model is only slightly more difficult to interpret than the earlier parallel-lines model, and it provides insights that were obscured before. Effects of the constrained variables (`white`, `age`, `ed`, and `prst`) can be interpreted much the same as they were previously. For `yr89` and `male`, the differences from before are largely a matter of degree. People became more supportive of working mothers across time, but the greatest effect of time was to push people away from the most extremely negative attitudes. For gender, men were less supportive of working mothers than were women, but men were especially unlikely to have strongly favorable attitudes. Hence, the strongest effects of both gender and time were found with the most extreme attitudes.

With the partial proportional odds model fitted by `gologit2`, the effects of the variables that meet the parallel-lines assumption are easily interpretable (you interpret them the same way as you do in `ologit`). For other variables, examining the pattern of coefficients reveals insights that would be obscured or distorted if a parallel-lines model were fitted instead. An `mlogit` or `gologit` 1.0 analysis might lead to conclusions similar to those of `gologit2`, but there would be many more parameters to look at, and the increased number of parameters could cause some effects to become statistically insignificant.

Although convenient, the `autofit` option should be used with caution. `autofit` basically uses a backward stepwise selection procedure, starting with the least parsimonious model and gradually imposing constraints. As such, it has many of the same strengths and weaknesses as backward stepwise regression. Researchers may have little theory as to which variables will violate the parallel-lines assumptions. The `autofit` option therefore provides an empirical means of identifying where assumptions may be violated. At the same time, like other stepwise procedures, `autofit` can capitalize on chance, i.e., just by chance alone some variables may appear to violate the parallel-lines assumption when in reality they do not.

Ideally, theory should be used when testing violations of assumptions. But when theory is lacking, another approach is to use more stringent significance levels when testing. Since several tests are being conducted, researchers may wish to specify a more stringent significance level, e.g., .01, or else do something like a Bonferroni or Šidák adjustment. By default, `autofit` uses the .05 level of significance, but this level can be changed; e.g., you can specify `autofit(.01)`. Sample size may also be a factor when choosing a significance level; e.g., in a very large sample, even substantively trivial violations of the parallel-lines assumption can be statistically significant. In the above example, the parallel-lines constraints for `yr89` and `male` would be rejected even at the .001 level of significance, suggesting that we can have confidence in the final model.

As always, when choosing a significance level, the costs of Type I versus Type II error need to be considered. A key advantage of `gologit2` is that it gives the researcher greater flexibility in choosing between Type I and Type II error; i.e., the researcher is not forced to choose only between a model where all parameters are constrained versus one with no constraints.

Later, I provide examples of alternatives to `autofit` that the researcher may wish to use. These options allow for a more theory-based model selection and/or alternative statistical tests for violations of assumptions.

3.2 Example 2: The alternative gamma parameterization

Peterson and Harrell (1990) and Lall et al. (2002) present an equivalent parameterization of the gologit model, called the *unconstrained partial proportional odds model*.[3] Under the Peterson–Harrell parameterization, each explanatory variable has

- one β coefficient and
- $M - 2$ γ coefficients, where M = the number of categories in the Y variable and the γ coefficients represent deviations from proportionality.

The gamma option of gologit2 (abbreviated g) presents this parameterization.

```
. gologit2 warm yr89 male white age ed prst, autofit lrforce gamma
```
(*output omitted*)

```
Alternative parameterization: Gammas are deviations from proportionality
```

warm	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Beta						
yr89	.98368	.1530091	6.43	0.000	.6837876	1.283572
male	-.3328209	.1275129	-2.61	0.009	-.5827417	-.0829002
white	-.3832583	.1184635	-3.24	0.001	-.6154424	-.1510742
age	-.0216325	.0024751	-8.74	0.000	-.0264835	-.0167814
ed	.0670703	.0161311	4.16	0.000	.0354539	.0986866
prst	.0059146	.0033158	1.78	0.074	-.0005843	.0124135
Gamma_2						
yr89	-.449311	.1465627	-3.07	0.002	-.7365686	-.1620533
male	-.3604562	.1233732	-2.92	0.003	-.6022633	-.1186492
Gamma_3						
yr89	-.6578702	.1768034	-3.72	0.000	-1.004399	-.3113418
male	-.7647937	.1631536	-4.69	0.000	-1.084569	-.4450186
Alpha						
_cons_1	2.12173	.2467146	8.60	0.000	1.638178	2.605282
_cons_2	.6021625	.2358361	2.55	0.011	.1399323	1.064393
_cons_3	-1.048137	.2393568	-4.38	0.000	-1.517268	-.5790061

The relationship between the two parameterizations is straightforward. The coefficients for the first equation in the default parameterization correspond to the β's in the γ parameterization. Gamma_2 parameters = equation 2 − equation 1 parameters, and Gamma_3 parameters = equation 3 − equation 1 parameters. For example, in the "Agree" panel for the default parameterization, the coefficient for yr89 is .3258098, and in the "Strongly Disagree" panel, it is .98368. Gamma_3 for yr89 therefore equals $.3258098 - .98368 = -.6578702$. You see Gammas only for variables that are *not* constrained to meet the parallel-lines assumption, because the Gammas that are not reported all equal 0.

3. As the name implies, there is also a constrained partial proportional odds model, but the constraints are generally specified by the researcher based on prior knowledge or beliefs. I am aware of no software that will actually estimate the constraints.

There are several advantages to the γ parameterization:

- It is consistent with other published research.
- It has a more parsimonious layout—you do not keep seeing the same parameters over and over that have been constrained to be equal.
- It provides another way of understanding the parallel-lines assumption. If the Gammas for a variable all equal 0, the assumption is met for that variable, and if all the Gammas equal 0 you have `ologit`'s parallel-lines model.
- By examining the Gammas you can better pinpoint where assumptions are being violated. Normally, all the $M - 2$ Gammas for a variable are either free or else constrained to equal zero, but by using the `constraints()` option (see example 8 below) you can deal with Gammas individually.

3.3 Example 3: svy estimation

The Stata 8 *Survey Data Reference Manual* presents an example where `svyologit` is used for an analysis of the Second National Health and Nutrition Examination Survey (NHANES II) dataset. The variable `health` contains self-reported health status, where 1 = poor, 2 = fair, 3 = average, 4 = good, and 5 = excellent. `gologit2` can analyze survey data by including the `svy` parameter. Data must be `svyset` first. The original example includes variables for age and age^2. To make the results a little more interpretable, I have created centered age (`c_age`) and centered age^2 (`c_age2`). This approach does not change the model selected or the model fit. The `lrforce` option has no effect when doing `svy` estimation since LR chi-squared tests are not appropriate in such cases.

```
. use http://www.stata-press.com/data/r8/nhanes2f
. quietly sum age, meanonly
. gen c_age = age - r(mean)
. gen c_age2=c_age^2
. gologit2 health female black c_age c_age2, svy auto
------------------------------------------------------------------------------
Testing parallel-lines assumption using the .05 level of significance...
Step  1:  Constraints for parallel lines imposed for black (P Value = 0.2310)
Step  2:  Constraints for parallel lines are not imposed for
          female (P Value = 0.00280)
          c_age (P Value = 0.00000)
          c_age2 (P Value = 0.00004)
Wald test of parallel-lines assumption for the final model:
Adjusted Wald test
 ( 1)  [poor]black - [fair]black = 0
 ( 2)  [poor]black - [average]black = 0
 ( 3)  [poor]black - [good]black = 0
       F(  3,    29) =    1.52
            Prob > F =    0.2310
```

```
An insignificant test statistic indicates that the final model
does not violate the proportional odds/parallel-lines assumption

If you refit this exact same model with gologit2, instead
of autofit, you can save time by using the parameter

pl(black)
------------------------------------------------------------------------------

Generalized Ordered Logit Estimates

pweight:  finalwgt                                Number of obs    =     10335
Strata:   stratid                                 Number of strata =        31
PSU:      psuid                                   Number of PSUs   =        62
                                                  Population size  = 1.170e+08
                                                  F(  13,      19)  =     52.24
                                                  Prob > F         =    0.0000

 ( 1)  [poor]black - [fair]black = 0
 ( 2)  [fair]black - [average]black = 0
 ( 3)  [average]black - [good]black = 0
------------------------------------------------------------------------------
      health |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
poor         |
      female |   .1681817   .1034177     1.63   0.114    -.0427401    .3791034
       black |  -1.008808   .0836513   -12.06   0.000    -1.179416   -.8382006
       c_age |  -.0617038    .003537   -17.45   0.000    -.0689175    -.05449
      c_age2 |   .0006893   .0003049     2.26   0.031     .0000674    .0013111
       _cons |   2.962162   .1373065    21.57   0.000     2.682124     3.2422
-------------+----------------------------------------------------------------
fair         |
      female |  -.1545385   .0680284    -2.27   0.030    -.2932834   -.0157937
       black |  -1.008808   .0836513   -12.06   0.000    -1.179416   -.8382006
       c_age |  -.0525504    .002082   -25.24   0.000    -.0567966   -.0483042
      c_age2 |   -.000028   .0001237    -0.23   0.822    -.0002802    .0002242
       _cons |   1.718909   .0765319    22.46   0.000     1.562821    1.874997
-------------+----------------------------------------------------------------
average      |
      female |  -.1576817   .0596012    -2.65   0.013     -.279239   -.0361243
       black |  -1.008808   .0836513   -12.06   0.000    -1.179416   -.8382006
       c_age |  -.0409575   .0017576   -23.30   0.000    -.0445422   -.0373728
      c_age2 |   8.91e-06   .0000882     0.10   0.920     -.000171    .0001889
       _cons |   .1705633   .0534477     3.19   0.003     .0615559    .2795707
-------------+----------------------------------------------------------------
good         |
      female |  -.2133394   .0636419    -3.35   0.002    -.3431379   -.0835408
       black |  -1.008808   .0836513   -12.06   0.000    -1.179416   -.8382006
       c_age |  -.0356466   .0020002   -17.82   0.000     -.039726   -.0315672
      c_age2 |  -.0004546   .0001311    -3.47   0.002    -.0007221   -.0001872
       _cons |  -.9136692   .0574078   -15.92   0.000    -1.030753   -.7965852
------------------------------------------------------------------------------
```

Here only one variable, `black`, meets the parallel-lines assumption. Blacks tend to report worse health than do whites. For females, the pattern is more complicated. They are less likely to report poor health than are males (see the positive female coefficient in the poor panel), but they are also less likely to report higher levels of health (see the negative female coefficients in the other panels); i.e., women tend to be less at the extremes of health than men. Such a pattern would be obscured in a parallel-lines model. The effect of age is more extreme on lower levels of health.

3.4 Example 4: gologit 1.0 compatibility

Some postestimation commands—specifically, the `spost` routines of Long and Freese (2006)—currently work with the original `gologit` but not `gologit2`. Long and Freese plan to support `gologit2`. For now, you can use the `v1` parameter to make the stored results from `gologit2` compatible with `gologit` 1.0. (This work-around, however, may make the results incompatible with postestimation routines written for `gologit2`.) Using the working mother's data again, we run the following:

```
. use http://www.indiana.edu/~jslsoc/stata/spex_data/ordwarm2
(77 & 89 General Social Survey)
. * Use the v1 option to save internally stored results in gologit 1.0 format
. quietly gologit2 warm yr89 male white age ed prst, pl(yr89 male) lrf v1
. * Use spost routines.  Get predicted probability for a 30 year old
. * average white woman in 1989
. prvalue, x(male=0 yr89=1 age=30) rest(mean)
gologit: Predictions for warm
Confidence intervals by delta method
                                95% Conf. Interval
  Pr(y=1SD|x):        0.0473   [ 0.0366,    0.0580]
  Pr(y=2D|x):         0.1699   [ 0.1456,    0.1943]
  Pr(y=3A|x):         0.4487   [ 0.4176,    0.4798]
  Pr(y=4SA|x):        0.3340   [ 0.2939,    0.3741]
         yr89       male      white        age         ed       prst
x=          1          0   .8765809         30  12.218055  39.585259
. * Now do 70 year old average black male in 1977
. prvalue, x(male=1 yr89=0 age=70) rest(mean)
gologit: Predictions for warm
Confidence intervals by delta method
                                95% Conf. Interval
  Pr(y=1SD|x):        0.2565   [ 0.2111,    0.3018]
  Pr(y=2D|x):         0.4699   [ 0.4278,    0.5121]
  Pr(y=3A|x):         0.2093   [ 0.1765,    0.2420]
  Pr(y=4SA|x):        0.0644   [ 0.0486,    0.0801]
         yr89       male      white        age         ed       prst
x=          0          1   .8765809         70  12.218055  39.585259
```

These "representative" cases show us that a 30-year-old average white woman in 1989 was much more supportive of working mothers than a 70-year-old average black male in 1977. Various other `spost` routines that work with the original `gologit` (not all do) can also be used, e.g., `prtab`.

3.5 Example 5: The predict command

In addition to the standard options (`xb`, `stdp`, `stddp`), the `predict` command supports the `pr` option (abbreviated `p`) for predicted probabilities; `pr` is the default option if nothing is specified. For example,

```
. quietly gologit2 warm yr89 male white age ed prst, pl(yr89 male) lrf
. predict p1 p2 p3 p4
(option p assumed; predicted probabilities)
```

```
. list p1 p2 p3 p4 in 1/10
```

	p1	p2	p3	p4
1.	.1083968	.2843347	.4195861	.1876824
2.	.2057451	.4859219	.236662	.0716709
3.	.1120911	.3004282	.4181407	.16934
4.	.2099544	.4283575	.2636952	.0979929
5.	.1407257	.3221328	.3887267	.1484148
6.	.2279584	.3338488	.3237104	.1144824
7.	.1652819	.3070716	.3804251	.1472214
8.	.1100771	.3058248	.4105159	.1735823
9.	.0930135	.2593877	.4754793	.1721194
10.	.1997068	.3816947	.3235006	.095098

3.6 Example 6: Alternatives to autofit

The `autofit` option provides a convenient means for fitting models that do not violate the parallel-lines assumption, but there are other ways that fitting can be done as well. Rather than use `autofit`, you can use the `pl` and `npl` parameters to specify which variables are or are not constrained to meet the parallel-lines assumption. (`pl` without parameters will produce the same results as `ologit`, whereas `npl` without parameters is the default and produces the same results as the original `gologit`.) You may want to do this because:

- You have more control over model specification and testing.
- If you prefer, you can use LR, Bayesian information criterion, or Akaike information criterion tests. rather than Wald chi-squared tests when deciding on constraints.
- You have specific hypotheses you want to test about which variables do and do not meet the parallel-lines assumption.

The `store()` option will cause the command `estimates store` to be run at the end of the job, making it slightly easier to do LR chi-squared contrasts. For example, here is how you could use LR chi-squared tests to test the model produced by `autofit`.[4]

```
. * Least constrained model - same as the original gologit
. quietly gologit2 warm yr89 male white age ed prst, store(gologit)
. * Partial Proportional Odds Model, fitted using autofit
. quietly gologit2 warm yr89 male white age ed prst, store(gologit2) autofit
. * ologit clone
. quietly gologit2 warm yr89 male white age ed prst, store(ologit) pl
. * Confirm that ologit is too restrictive
. lrtest ologit gologit
Likelihood-ratio test                                 LR chi2(12) =     49.20
(Assumption: ologit nested in gologit)                Prob > chi2 =    0.0000
```

4. The SPSS `PLUM` test of parallel lines produces results that are identical to the LR contrast between the `ologit` and unconstrained `gologit` models.

```
. * Confirm that partial proportional odds is not too restrictive
. lrtest gologit gologit2
Likelihood-ratio test                                 LR chi2(8)  =     12.61
(Assumption: gologit2 nested in gologit)              Prob > chi2 =    0.1258
```

3.7 Example 7: Constrained logistic regression

As noted before, the logistic regression model fitted by `logit` is a special case of the `gologit` model. However, the `logit` command, unlike `gologit2`, does not currently allow for constrained estimation, such as constraining two variables to have equal effects. `gologit2`'s `store()` option also makes it easier to store results from constrained and unconstrained models and then contrast them. Here is an example:

```
. use http://www.indiana.edu/~jslsoc/stata/spex_data/ordwarm2
(77 & 89 General Social Survey)
. recode warm (1 2  = 0)(3 4 = 1), gen(agree)
(2293 differences between warm and agree)
. * Estimate logistic regression model using logit command
. logit agree yr89 male white age ed prst, nolog
Logistic regression                               Number of obs   =       2293
                                                  LR chi2(6)      =     251.23
                                                  Prob > chi2     =     0.0000
Log likelihood = -1449.7863                       Pseudo R2       =     0.0797

------------------------------------------------------------------------------
       agree |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        yr89 |   .5654063   .0928433     6.09   0.000     .3834368    .7473757
        male |  -.6905423   .0898786    -7.68   0.000    -.8667012   -.5143834
       white |  -.3142708   .1405978    -2.24   0.025    -.5898374   -.0387042
         age |  -.0253345   .0028644    -8.84   0.000    -.0309486   -.0197203
          ed |   .0528527   .0184571     2.86   0.004     .0166774    .0890279
        prst |   .0095322   .0038184     2.50   0.013     .0020482    .0170162
       _cons |   .7303287    .269163     2.71   0.007      .202779    1.257878
------------------------------------------------------------------------------
. * Equivalent model fitted by gologit2
. gologit2 agree yr89 male white age ed prst, lrf store(unconstrained)
Generalized Ordered Logit Estimates               Number of obs   =       2293
                                                  LR chi2(6)      =     251.23
                                                  Prob > chi2     =     0.0000
Log likelihood = -1449.7863                       Pseudo R2       =     0.0797

------------------------------------------------------------------------------
       agree |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        yr89 |   .5654063   .0928433     6.09   0.000     .3834368    .7473758
        male |  -.6905423   .0898786    -7.68   0.000    -.8667012   -.5143834
       white |  -.3142708   .1405978    -2.24   0.025    -.5898374   -.0387042
         age |  -.0253345   .0028644    -8.84   0.000    -.0309486   -.0197203
          ed |   .0528527   .0184571     2.86   0.004     .0166774    .0890279
        prst |   .0095322   .0038184     2.50   0.013     .0020482    .0170162
       _cons |   .7303288    .269163     2.71   0.007     .2027789    1.257879
------------------------------------------------------------------------------
```

```
. * Constrain the effects of male and white to be equal
. constraint 1 male = white

. * Estimate the constrained model
. gologit2 agree yr89 male white age ed prst, lrf store(constrained) c(1)

Generalized Ordered Logit Estimates               Number of obs   =       2293
                                                  LR chi2(5)      =     246.28
                                                  Prob > chi2     =     0.0000
Log likelihood = -1452.2601                       Pseudo R2       =     0.0782

 ( 1)  [0]male - [0]white = 0

------------------------------------------------------------------------------
       agree |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        yr89 |   .5608948   .0927087     6.05   0.000     .3791892    .7426005
        male |  -.5819469   .0755686    -7.70   0.000    -.7300587   -.4338351
       white |  -.5819469   .0755686    -7.70   0.000    -.7300587   -.4338351
         age |  -.0247219   .0028436    -8.69   0.000    -.0302952   -.0191486
          ed |   .0551505   .0183781     3.00   0.003     .0191301     .091171
        prst |   .0097573   .0038138     2.56   0.011     .0022824    .0172322
       _cons |   .8530839   .2635373     3.24   0.001     .3365604    1.369608
------------------------------------------------------------------------------

. * Test the equality constraint
. lrtest constrained unconstrained

Likelihood-ratio test                                 LR chi2(1)  =      4.95
(Assumption: constrained nested in unconstrained)     Prob > chi2 =    0.0261
```

The significant LR chi-squared value means that we should reject the hypothesis that the effects of gender and race are equal.

3.8 Example 8: A detailed replication and extension of published work

Lall and colleagues (2002) examined the relationship between subjective impressions of health with smoking and heart problems. The dependent variable, `hstatus`, is measured on a four-point scale with categories 4 = poor, 3 = fair, 2 = good, and 1 = excellent. The independent variables are `heart` (0 = did not suffer from heart attack, 1 = did suffer from heart attack) and `smoke` (0 = does not smoke, 1 = does smoke). Table 1 is a reproduction of Lall's table 5.

(*Continued on next page*)

Table 1: Log odds ratios for unconstrained partial proportional odds model

Variable			(Good, fair, poor) vs excellent		(Fair, poor) vs (excellent, good)		Poor vs (excellent, good, fair)	
	ln(O.R.)	s.e. ln(O.R.)	ln(O.R.)	s.e. ln(O.R.)	ln(O.R.)	s.e. ln(O.R.)	ln(O.R.)	s.e. ln(O.R.)
	Constant component of log odds ratio across cut-off points		*Increment at cut-off points*					
Suffered from a heart attack (yes/no)?	1.023	0.0554	—	—	—	—	—	—
Do you smoke (yes/no)?	0.1218	0.059	0		0.00822	(0.0628)	0.3382	(0.1006)
			Log odds ratios at cut-off points					
Do you smoke (yes/no)?	—	—	0.1218	(0.059)	0.1300	(0.0991)	0.4600	(0.1281)

Reprinted from Lall et al. (2002).

In the parameterization of the partial proportional odds model used in their paper, each X has a β coefficient associated with it (called the *constant component* in the table). Also, each X can have $M - 2$ γ coefficients (labeled in the table as the "Increment at cut-off points"), where $M =$ the number of categories for Y and the Gammas represent deviations from proportionality. If the Gammas for a variable are all 0, the variable meets the parallel-lines assumption. In the above example, there are Gammas for smoke but not heart, meaning that heart is constrained to meet the parallel-lines assumption but smoking is not. In effect, then, a test of the parallel-lines assumption for a variable is a test of whether its Gammas equal zero.

The parameterization used by Lall can be produced by using `gologit2`'s `gamma` option (with minor differences probably reflecting differences in the software and estimation methods used; Lall used weighted least squares with SAS 6.2 for Windows 95, whereas `gologit2` uses maximum likelihood estimation with Stata 8.2 or later). Further, by using the `autofit` option, we can see whether we come up with the same final model that they do.

```
. use http://www.nd.edu/~rwilliam/gologit2/lall, clear
(Lall et al, 2002, Statistical Methods in Medical Research, p. 58)
. * Confirm that ologit's assumptions are violated. Contrast ologit (constrained)
. * and gologit (unconstrained)
. quietly gologit2 hstatus heart smoke, npl lrf store(unconstrained)
. quietly gologit2 hstatus heart smoke, pl lrf store(constrained)
. lrtest unconstrained constrained
Likelihood-ratio test                                 LR chi2(4)  =     15.11
(Assumption: constrained nested in unconstrained)     Prob > chi2 =    0.0045
. * Now use autofit to fit partial proportional odds model
. gologit2 hstatus heart smoke, auto gamma lrf
------------------------------------------------------------------------------
Testing parallel-lines assumption using the .05 level of significance...
Step  1:  Constraints for parallel lines imposed for heart (P Value = 0.7444)
Step  2:  Constraints for parallel lines are not imposed for
          smoke (P Value = 0.00044)
Wald test of parallel-lines assumption for the final model:
 ( 1)  [Excellent]heart - [Good]heart = 0
 ( 2)  [Excellent]heart - [Fair]heart = 0
           chi2(  2) =    0.59
         Prob > chi2 =    0.7444
An insignificant test statistic indicates that the final model
does not violate the proportional odds/parallel-lines assumption
If you refit this exact same model with gologit2, instead
of autofit, you can save time by using the parameter
pl(heart)
------------------------------------------------------------------------------
```

```
Generalized Ordered Logit Estimates              Number of obs   =      12535
                                                  LR chi2(4)      =     373.10
                                                  Prob > chi2     =     0.0000
Log likelihood = -14664.661                       Pseudo R2       =     0.0126
 ( 1)  [Excellent]heart - [Good]heart = 0
 ( 2)  [Good]heart - [Fair]heart = 0

------------------------------------------------------------------------------
     hstatus |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Excellent    |
       heart |   1.025339   .0551397    18.60   0.000     .9172672    1.133411
       smoke |    .127191   .0590098     2.16   0.031     .0115339    .2428482
       _cons |   1.303032   .0251244    51.86   0.000     1.253789    1.352275
-------------+----------------------------------------------------------------
Good         |
       heart |   1.025339   .0551397    18.60   0.000     .9172672    1.133411
       smoke |   .1283844   .0488556     2.63   0.009     .0326292    .2241396
       _cons |  -.8967713   .0226262   -39.63   0.000    -.9411177   -.8524248
-------------+----------------------------------------------------------------
Fair         |
       heart |   1.025339   .0551397    18.60   0.000     .9172672    1.133411
       smoke |   .4581369   .0894379     5.12   0.000     .2828418     .633432
       _cons |  -3.082652   .0463864   -66.46   0.000    -3.173568   -2.991737
------------------------------------------------------------------------------

Alternative parameterization: Gammas are deviations from proportionality
------------------------------------------------------------------------------
     hstatus |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Beta         |
       heart |   1.025339   .0551397    18.60   0.000     .9172672    1.133411
       smoke |    .127191   .0590098     2.16   0.031     .0115339    .2428482
-------------+----------------------------------------------------------------
Gamma_2      |
       smoke |   .0011933   .0629692     0.02   0.985    -.1222239    .1246106
-------------+----------------------------------------------------------------
Gamma_3      |
       smoke |   .3309459    .100827     3.28   0.001     .1333287    .5285631
-------------+----------------------------------------------------------------
Alpha        |
     _cons_1 |   1.303032   .0251244    51.86   0.000     1.253789    1.352275
     _cons_2 |  -.8967713   .0226262   -39.63   0.000    -.9411177   -.8524248
     _cons_3 |  -3.082652   .0463864   -66.46   0.000    -3.173568   -2.991737
------------------------------------------------------------------------------
```

Using either parameterization, the results suggest that those who have had heart attacks tend to report worse health. The same assertion is true for smokers, but smokers are especially likely to report themselves as being in poor health as opposed to fair, good, or excellent health.

The use of the `autofit` parameter confirms Lall's choice of models; i.e., `autofit` produces the same partial proportional odds model that he and his colleagues reported. But, if we wanted to just trust him, we could have fitted the same model by using the `pl` or `npl` parameters. The following two commands will each produce the same results in this case:

```
. gologit2 hstatus heart smoke, pl(heart) gamma lrf
. gologit2 hstatus heart smoke, npl(smoke) gamma lrf
```

However, it is possible to produce an even more parsimonious model than the one reported by Lall and replicated by `autofit`. By starting with an unconstrained model, the γ parameterization helps identify at a glance the potential problems in a model. For example, with the Lall data,

```
. gologit2 hstatus heart smoke, lrf npl gamma
Generalized Ordered Logit Estimates               Number of obs   =      12535
                                                  LR chi2(6)      =     373.70
                                                  Prob > chi2     =     0.0000
Log likelihood = -14664.362                       Pseudo R2       =     0.0126
  (output omitted)
Alternative parameterization: Gammas are deviations from proportionality
```

hstatus	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Beta						
heart	1.046722	.1023646	10.23	0.000	.8460913	1.247353
smoke	.1274032	.0590163	2.16	0.031	.0117334	.2430729
Gamma_2						
heart	-.0109007	.100116	-0.11	0.913	-.2071244	.185323
smoke	.0012914	.0629834	0.02	0.984	-.1221537	.1247365
Gamma_3						
heart	-.0821184	.1328688	-0.62	0.537	-.3425365	.1782996
smoke	.3305576	.1007839	3.28	0.001	.1330249	.5280903
Alpha						
_cons_1	1.302031	.0254276	51.21	0.000	1.252194	1.351868
_cons_2	-.8973008	.0228198	-39.32	0.000	-.9420269	-.8525748
_cons_3	-3.069089	.0494071	-62.12	0.000	-3.165925	-2.972252

We see that only `Gamma_3` for smoke significantly differs from 0. Ergo, we could use the `constraints()` option to specify an even more parsimonious model:

```
. constraint 1 [#1=#2]:smoke
. gologit2 hstatus heart smoke, lrf gamma pl(heart) constraints(1)
Generalized Ordered Logit Estimates               Number of obs   =      12535
                                                  LR chi2(3)      =     373.10
                                                  Prob > chi2     =     0.0000
Log likelihood = -14664.661                       Pseudo R2       =     0.0126
 ( 1)  [Excellent]smoke - [Good]smoke = 0
 ( 2)  [Excellent]heart - [Good]heart = 0
 ( 3)  [Good]heart - [Fair]heart = 0
```

hstatus	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Excellent						
heart	1.025334	.055139	18.60	0.000	.9172638	1.133405
smoke	.1279526	.0432192	2.96	0.003	.0432446	.2126606
_cons	1.3029	.024137	53.98	0.000	1.255592	1.350208

Good						
heart	1.025334	.055139	18.60	0.000	.9172638	1.133405
smoke	.1279526	.0432192	2.96	0.003	.0432446	.2126606
_cons	-.8966838	.0221497	-40.48	0.000	-.9400964	-.8532712
Fair						
heart	1.025334	.055139	18.60	0.000	.9172638	1.133405
smoke	.4578386	.0880417	5.20	0.000	.28528	.6303971
_cons	-3.082591	.046273	-66.62	0.000	-3.173284	-2.991898

Alternative parameterization: Gammas are deviations from proportionality

hstatus	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Beta						
heart	1.025334	.055139	18.60	0.000	.9172638	1.133405
smoke	.1279526	.0432192	2.96	0.003	.0432446	.2126606
Gamma_2						
smoke	-2.50e-16	.	.	.	.	.
Gamma_3						
smoke	.329886	.0838936	3.93	0.000	.1654577	.4943144
Alpha						
_cons_1	1.3029	.024137	53.98	0.000	1.255592	1.350208
_cons_2	-.8966838	.0221497	-40.48	0.000	-.9400964	-.8532712
_cons_3	-3.082591	.046273	-66.62	0.000	-3.173284	-2.991898

`gologit2` is not smart enough to know that `Gamma_2` should not be in there (`gologit2` knows to omit `Gamma_2` when `pl`, `npl`, or `autofit` has forced the parameter to be 0, but not when the `constraints()` option has been used), but this matter is one of aesthetics; everything is being done correctly. The fit for this model is virtually identical to the fit of the model that included `Gamma_2` (LR chi2 = 373.10 in both), so we conclude that this more parsimonious parameterization is justified. Hence, although the assumptions of the two-parameter parallel-lines model fitted by `ologit` are violated by these data, we can get a model that fits whose assumptions are not violated simply by allowing one γ parameter to differ from 0.

4 The gologit2 command

4.1 Syntax

`gologit2` supports many standard Stata options, which work the same way as they do with other Stata commands. Several other options are unique to or fine-tuned for `gologit2`. The complete syntax is

`gologit2` *depvar* [*indepvars*] [*if*] [*in*] [*weight*] [`,` `lrforce`
[`pl` | `pl(`*varlist*`)` | `npl` | `npl(`*varlist*`)` | `autofit` | `autofit(`*alpha*`)`] `gamma` `nolabel`
`store(`*name*`)` `constraints(`*clist*`)` `robust` `cluster(`*varname*`)` `level(`#`)`
`score(`*newvarlist* | `stub*)` `or` `log` `v1` `svy` *svy_options* *maximize_options*]

4.2 Options unique to or fine-tuned for gologit2

`lrforce` forces Stata to report an LR statistic under certain conditions when it ordinarily would not. Some types of constraints can make an LR chi-squared test invalid. Hence, to be safe, Stata reports a Wald statistic whenever constraints are used. But LR statistics should be correct for the types of constraints imposed by the `pl`, `npl`, and `autofit` options. The `lrforce` option will be ignored when robust standard errors are specified either directly or indirectly, e.g., via use of the `robust` or `svy` options. Use this option with caution if you specify other constraints since these may make an LR chi-squared statistic inappropriate.

`pl`, `pl(`*varlist*`)`, `npl`, `npl(`*varlist*`)`, `autofit`, and `autofit(`*alpha*`)` provide alternative means for imposing or relaxing the parallel-lines assumption. Only one may be specified at a time.

`pl` specified without parameters constrains all independent variables to meet the parallel-lines assumption. It will produce results that are equivalent to those of `ologit`.

`pl(`*varlist*`)` constrains the specified explanatory variables to meet the parallel-lines assumption. All other variable effects need not meet the assumption. The variables specified must be a subset of the explanatory variables.

`npl` specified without parameters relaxes the parallel-lines assumption for all explanatory variables. This is the default option and presents results equivalent to those of the original `gologit`.

`npl(`*varlist*`)` frees the specified explanatory variables from meeting the parallel-lines assumption. All other explanatory variables are constrained to meet the assumption. The variables specified must be a subset of the explanatory variables.

`autofit` uses an iterative process to identify the partial proportional odds model that best fits the data. If `autofit` is specified without parameters, the .05 level of significance is used. This option can take some time to run because several models may need to be fitted. The use of `autofit` is highly recommended but other options provide more control over the final model if the user wants it.

`autofit(`*alpha*`)` lets the user specify the significance level *alpha* to be used by `autofit`. *alpha* must be greater than 0 and less than 1, e.g., `autofit(.01)`. The higher *alpha* is, the easier it is to reject the parallel-lines assumption, and the less parsimonious the model will tend to be.

`gamma` displays an alternative but equivalent parameterization of the partial proportional odds model used by Peterson and Harrell (1990) and Lall et al. (2002). Under this parameterization, there is one β coefficient and $M-2$ γ coefficients for each explanatory variable, where $M =$ the number of categories for Y. The Gammas indicate the extent to which the parallel-lines assumption is violated by the variable; i.e., when the Gammas do not significantly differ from 0 the parallel-lines assumption is met.

Advantages of this parameterization include its being more parsimonious than the default layout. Also, by examining the test statistics for the Gammas, you can see where parallel-lines assumptions are being violated.

`nolabel` causes the equations to be named `eq1`, `eq2`, etc. The default is to use the first 32 characters of the value labels and/or the values of Y as the equation labels. Some characters cannot be used in equation names, e.g., the period (`.`), the dollar sign (`$`), and the colon (`:`), and will be replaced with the underscore (`_`) character. The default behavior works well when the value labels are short and descriptive. It may not work well when value labels are long and/or include characters that must be changed to underscores. If the output looks unattractive and/or you are getting strange errors, try changing the value labels of Y or else use the `nolabel` option.

`store(`*name*`)` causes the command **`estimates store`** *name* to be executed when `gologit2` finishes. This option is useful for when you wish to fit a series of models and want to save the results.

`constraints(`*clist*`)` specifies linear constraints to be applied during estimation. Constraints are defined with the `constraint` command. `constraints(1)` specifies that the model is to be constrained according to constraint 1; `constraints(1-4)` specifies constraints 1–4; `constraints(1-4,8)` specifies 1–4 and 8. Remember that the `pl`, `npl`, and `autofit` options work by generating across-equation constraints, which may affect how any additional constraints should be specified. When using the `constraint` command, refer to equations by their equation number—`#1`, `#2`, etc.

`or` reports the estimated coefficients transformed to relative odds ratios, i.e., `exp(b)` rather than `b`; see [R] **ologit** for a description of this concept. Options `rrr`, `eform`, `hr`, and `irr` produce identical results (labeled differently) and can also be used.

`log` displays the iteration log. By default, it is suppressed.

`v1` causes `gologit2` to return results in a format that is consistent with `gologit` 1.0. This option may be useful or necessary for postestimation commands that were written specifically for `gologit` (in particular, some versions of the Long and Freese `spost` commands support `gologit` but not `gologit2`). However, postestimation commands written for `gologit2` may not work correctly if `v1` is specified.

`svy` indicates that `gologit2` is to pick up the svy settings set by `svyset` and use the robust variance estimator. Thus this option requires the data to be `svyset`; see [SVY] **svyset**. When using `svy` estimation, `if` or `in` restrictions often will not produce correct variance estimates for subpopulations. To compute estimates for subpopulations, use the `subpop()` option. If `svy` has not been specified, use of other `svy`-related options (e.g., `subpop()`, `deff`, `meff`) will produce an error.

4.3 Other standard Stata options supported by gologit2

`robust cluster(`*varname*`) level(`*#*`) score(`*newvarlist*`|stub*)`

4.4 Other standard svy-related options supported by gologit2

`subpop nosvyadjust prob ci deff deft meff meft`

4.5 Options available when replaying results

`gamma store or level prob ci deff deft`

`prob`, `ci`, `deff`, and `deft` are available only when `svy` estimation has been used.

4.6 Options available for the predict command

`xb stdp stddp p`

`p` gives the predicted probability. You specify one new variable with `xb`, `stdp`, and `stddp` and specify either one or M new variables with `p`. These statistics are available both in and out of sample; type `predict` ... `if e(sample)` if wanted only for the estimation sample.

5 Support for gologit2

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