Homework 9
QMB 3200: Advanced and Quantitative Methods
Fall 2019

Poisson Regression Analysis

Submitted to
Dr. Jim Dewey
Florida Polytechnic University

Submitted by
Luiz Gustavo Fagundes Malpele
Department of Data Science
Florida Polytechnic University

November 28th, 2019

1. Robust-Poisson regression model selection:

In order to find the best Poisson regression model that measured the effects of supplement on days, two variables were created which were created which were supXweight, that measured the interaction of weight with the supplement, and supXfemale, that measured the interaction of supplement and female variables.

Five different regression models were created so it would be possible to establish a comparison through the RMSE value of these model which are:

1. Robust-Poisson regression of female, supplement, and weight on days;
2. Robust-Poisson regression of female, supplement, supXweight and weight on days;
3. Robust-Poisson regression of female, supplement, supXfemale and weight on days;
4. Robust-Poisson regression of i.female, i.supplement, i.supXfemale, c.supXweight and c.weight on days;
5. Robust-Poisson regression of i.female, i.supplement, i.supXfemale, c.supXweight on days.

After running all regression and comparing, it was possible to compare the RMSE value which are below. From the following the table (1), it is possible to check that models 4 and 5 reached the lowest RMSE values, but both still close. So, the next step to choose which model to proceed with is to analyze if there is any statistically insignificant variable present on them.

RMSE value comparison for 5 different Poisson regression models (1)

Variable	Obs	Mean	Std. Dev.	Min	Max
sqres1	60	.6730404	1.283789	1.82e-16	6.005032
sqres2	60	.6656469	1.224504	3.05e-16	5.395259
sqres3	60	.6206649	1.052345	2.70e-16	4.400746
sqres4	60	.5963178	1.013113	4.93e-16	4.339605
sqres5	60	.5998339	1.015574	4.93e-16	4.373257

After running all regression and comparing, it was possible to compare the RMSE value which are below. From the following the table (1), it is possible to check that models 4 and 5 reached the lowest RMSE values, but both still close. So, the next step to choose which model to proceed with is to analyze if there is any statistically insignificant variable present on them.

The Poisson regression below refers to model 4, which account for all variables available for the analysis, but it is necessary to check the statistical significance of the variables and to do so, the Chi-Square test will be used.

Regression of cold, female, supplement, supXweight, supXfemale on days (2)

```
. poisson days i.female i.supplement i.supXfemale c.supXweight c.weight, robust

Iteration 0:   log pseudolikelihood = -210.16873
Iteration 1:   log pseudolikelihood = -210.16862
Iteration 2:   log pseudolikelihood = -210.16862

Poisson regression                              Number of obs     =         60
                                                Wald chi2(5)      =       8.33
                                                Prob > chi2       =     0.1389
Log pseudolikelihood = -210.16862               Pseudo R2         =     0.0710
```

days	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.female	-.303716	.476637	-0.64	0.524	-1.237907	.6304754
1.supplement	-1.75855	2.321738	-0.76	0.449	-6.309073	2.791973
1.supXfemale	.5604808	.8441554	0.66	0.507	-1.094033	2.214995
supXweight	.0048173	.0126236	0.38	0.703	-.0199245	.029559
weight	-.0011699	.0073747	-0.16	0.874	-.0156239	.0132842
_cons	1.988694	1.316029	1.51	0.131	-.5906754	4.568063

The p-values for supplement ($\widehat{\beta_1}$), weight ($\widehat{\beta_5}$), and supXweight ($\widehat{\beta_4}$) are the 3 above 0.05, but since these variables is a high degree of correlation between these three variables as they are being multiplied, the Chi-Square test is the most appropriate to measure the statistical significance of them:

Chi-Square tests to evaluate the statistical significance of supXweight, supplement and weight (3)

```
 ( 1)  [days]1.supplement = 0
 ( 2)  [days]weight = 0

           chi2(  2) =    0.68
         Prob > chi2 =    0.7124
```

```
 ( 1)  [days]1.supplement = 0
 ( 2)  [days]supXweight = 0

           chi2(  2) =    5.93
         Prob > chi2 =    0.0515
```

```
 ( 1)  [days]1.supplement = 0
 ( 2)  [days]supXweight = 0
 ( 3)  [days]weight = 0

           chi2(  3) =    5.97
         Prob > chi2 =    0.1130
```

While conducing these tests, there is strong enough evidence to say that the combination of supplement and supXweight have a higher degree statistical significance to the Poisson Regression model, while compared to the other combination, this one has a p-value of 0.0515 which is approximately the same as 0.05.

Regression of cold, female, supplement, supXweight, supXfemale on days (4)

```
Iteration 0:   log pseudolikelihood = -71.301641
Iteration 1:   log pseudolikelihood = -61.151587
Iteration 2:   log pseudolikelihood = -60.952759
Iteration 3:   log pseudolikelihood = -60.930133
Iteration 4:   log pseudolikelihood = -60.924935
Iteration 5:   log pseudolikelihood = -60.923834
Iteration 6:   log pseudolikelihood = -60.923638
Iteration 7:   log pseudolikelihood = -60.923617
Iteration 8:   log pseudolikelihood = -60.923613

Poisson regression                              Number of obs     =         60
                                                Wald chi2(4)      =          .
                                                Prob > chi2       =          .
Log pseudolikelihood = -60.923613               Pseudo R2         =     0.7307
```

days	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.cold	19.3437	.0962442	200.99	0.000	19.15506	19.53233
1.female	.0783132	.0552752	1.42	0.157	-.0300243	.1866507
1.supplement	-.709851	.3748833	-1.89	0.058	-1.444609	.0249068
1.supXfemale	.3023291	.1508405	2.00	0.045	.0066872	.5979709
supXweight	.0023576	.0020215	1.17	0.244	-.0016045	.0063197
_cons	-17.25292	.1372267	-125.73	0.000	-17.52188	-16.98396

This Poisson regression model does not accounts for the value of c.weight, has the highest Pseudo R2 value between the previously tested models and the second lowest RMSE, the RMSE is close to the RMSE of the model including the weight variable. While testing for the combination of coefficients, we have that:

Chi-Square tests to evaluate the statistical significance of supXweight, supplement , supXfemale and female (5)

```
 ( 1)  [days]1.female = 0
 ( 2)  [days]1.supplement = 0

           chi2(  2) =    6.14
         Prob > chi2 =    0.0464
```

```
 ( 1)  [days]1.female = 0
 ( 2)  [days]1.supplement = 0
 ( 3)  [days]1.supXfemale = 0

           chi2(  3) =    9.37
         Prob > chi2 =    0.0248
```

```
 ( 1)  [days]1.supplement = 0
 ( 2)  [days]supXweight = 0

           chi2(  2) =   12.46
         Prob > chi2 =    0.0020
```

While using the Chi-Square test to evaluate the combination of different variable to test for their significance, it can be concluded that there is strong enough evidence to reject the null hypothesis that at least one variable of each combination is different from zero, since the three p-values are respectively 0.0464, 0.0248, and 0.0020, and the three p-values < α (0.05).

In conclusion the selected Robust-Regression model is the th model: Robust-Poisson regression of i.female, i.supplement, i.supXfemale, c.supXweight and c.weight on days.

2. Marginal effects of gender and weight

Marginal effect of change in each variable on cold daration (6)

```
Average marginal effects                        Number of obs     =         60
Model VCE     : Robust

Expression    : Predicted number of events, predict()
dy/dx w.r.t. : 1.cold 1.female 1.supplement 1.supXfemale supXweight weight
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.cold	7.745808	.7337234	10.56	0.000	6.307737	9.183879
1.female	.1862122	.4001226	0.47	0.642	-.5980137	.9704382
1.supplement	-3.059245	1.906369	-1.60	0.109	-6.795661	.6771699
1.supXfemale	1.481691	.8819499	1.68	0.093	-.2468989	3.210281
supXweight	.0113994	.0101861	1.12	0.263	-.0085651	.0313638
weight	-.0021259	.0062972	-0.34	0.736	-.0144681	.0102164

Note: dy/dx for factor levels is the discrete change from the base level.

For the sake of this specific analysis, the variable weight was also included. The table above shows the marginal effect of each variable on cold duration, in other words, how unit-change on X_i impacts the cold duration.

The table indicate that if the subject's gender is female, the cold duration will be 0.186 day longer and that supplement's effect will be lower, 1.48 days more than if the subject was a man. Furthermore, the marginal effects also extend to weight which indicate that the supplement is more effective in lower weighted subjects, since the supXweight variable has a positive value (0.0114) which higher than the weight variable (-0.0021).

3. Models comparison

Regression of cold, female, supplement, supXweight, supXfemale on days (8)

```
Iteration 0:   log pseudolikelihood = -71.301641
Iteration 1:   log pseudolikelihood = -61.151587
Iteration 2:   log pseudolikelihood = -60.952759
Iteration 3:   log pseudolikelihood = -60.930133
Iteration 4:   log pseudolikelihood = -60.924935
Iteration 5:   log pseudolikelihood = -60.923834
Iteration 6:   log pseudolikelihood = -60.923638
Iteration 7:   log pseudolikelihood = -60.923617
Iteration 8:   log pseudolikelihood = -60.923613

Poisson regression                              Number of obs     =         60
                                                Wald chi2(4)      =          .
                                                Prob > chi2       =          .
Log pseudolikelihood = -60.923613               Pseudo R2         =     0.7307
```

days	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.cold	19.3437	.0962442	200.99	0.000	19.15506	19.53233
1.female	.0783132	.0552752	1.42	0.157	-.0300243	.1866507
1.supplement	-.709851	.3748833	-1.89	0.058	-1.444609	.0249068
1.supXfemale	.3023291	.1508405	2.00	0.045	.0066872	.5979709
supXweight	.0023576	.0020215	1.17	0.244	-.0016045	.0063197
_cons	-17.25292	.1372267	-125.73	0.000	-17.52188	-16.98396

Regression of cold duration on female, supplement, femXsup, weight, and squared weight variables (9)

Source	SS	df	MS
Model	31.4209757	5	6.28419514
Residual	30.0456909	24	1.25190379
Total	61.4666667	29	2.11954023

Number of obs	=	30
F(5, 24)	=	5.02
Prob > F	=	0.0027
R-squared	=	0.5112
Adj R-squared	=	0.4094
Root MSE	=	1.1189

days	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
female	-.0960073	.8776852	-0.11	0.914	-1.90746	1.715446
supplement	-2.168236	.5781803	-3.75	0.001	-3.361541	-.9749306
femXsup	1.929918	.9194998	2.10	0.047	.0321637	3.827672
weight	-.1333561	.0589879	-2.26	0.033	-.2551012	-.011611
sqweight	.0003956	.0001674	2.36	0.027	.00005	.0007411
_cons	19.10933	5.288807	3.61	0.001	8.193769	30.02489

The Poisson-robust regression model provides a best fit for the prediction line of cold duration, the Poisson model is more appropriate for a dataset that involves rate data, for this research the effect of a supplement on cold duration was being measured. Therefore, since the subject of study is a time interval (cold duration), the Poisson regression is more suitable to do it, since it has been made within a fixed period of time.

Furthermore, it can be said that the Poisson model is statistically more significant as the Pseudo R2 is 42.93% higher than the R-Squared value of the Linear Regression model. The Linear Regression accounts account for some issues for this analysis that does not occur with the Poisson regression model, it can give a negative prediction depending on the X_i values, and if the log transformation model was attempted, the ln (0) is undefined, and since most variables are discrete, this would be a problem.

In conclusion, taking into consideration that counts have been made within a fixed period of time, since the experiment evaluated cold duration during the period of 2 months, the most defensible model is the Poisson as it has the best fit according the experiment variables and conditions, and it also a better R-Squared value (even though it is a Pseudo-R2).

Appendix A: Do-file-for-Homework 9

```
/* QMB 3200 Regression Example Work */

clear

cd "C:\Users\luizg\Desktop\Stata"

import delimited "C:\Users\luizg\Desktop\Stata\supplement (2).csv"

// Variable creation
gen supXweight = supplement * weight
gen supXfemale = supplement * female

// Poisson regression model
poisson days cold female supplement weight, robust
estimate store model1
predict pred1

//RMSE value of the model
gen sqres1=(days-pred1)^2

//Repetition of the processes mentioned above for another 4 different models
poisson days cold female supplement weight supXweight, robust
estimate store model2
predict pred2
gen sqres2=(days-pred2)^2
poisson days cold female supplement weight supXfemale, robust
estimate store model3
predict pred3
gen sqres3=(days-pred3)^2
```

```
poisson days i.cold i.female i.supplement i.supXfemale c.weight c.supXweight, robust

estimate store model4

predict pred4

gen sqres4=(days-pred4)^2

poisson days i.cold i.female i.supplement i.supXfemale c.supXweight, robust

estimate store model5

predict pred5

gen sqres5=(days-pred5)^2


//RMSE Comparison

sum sqres*


//Chi-Square Hypothesis Testing

poisson days i.cold i.female i.supplement i.supXfemale c.weight c.supXweight, robust

testparm i.supplement supXweight

testparm i.supplement weight supXweight

testparm i.supplement weight


testparm i.female i.supplement i.supXfemale

testparm i.female i.supXfemale

testparm i.female supplement


poisson days i.cold i.female i.supplement i.supXfemale c.supXweight, robust

testparm i.supplement supXweight

testparm i.female i.supplement i.supXfemale

testparm i.female i.supXfemale

testparm i.female supplement


//Marginal effect of each variable on cold duration

poisson days i.cold i.female i.supplement i.supXfemale c.supXweight c.weight, robust
```

```
margins, dydx(*) post

STOP

log close
```

Appendix B :Do-file-for-Homework 9

```
  ___  ____  ____  ____  ____ (R)
 /__    /   ____/   /   ____/
___/   /   /___/   /   /___/   16.0   Copyright 1985-2019 StataCorp LLC
  Statistics/Data Analysis            StataCorp
                                      4905 Lakeway Drive
                                      College Station, Texas 77845 USA
                                      800-STATA-PC        http://www.stata.com
                                      979-696-4600        stata@stata.com
                                      979-696-4601 (fax)

Single-user Stata license expires 16 Mar 2020:
       Serial number:  301609236389
         Licensed to:  Luiz Gustavo Fagundes Malpele
                       Florida Polytechnic University

Notes:
      1.  Unicode is supported; see help unicode_advice.

. do "C:\Users\luizg\AppData\Local\Temp\STD28f0_000000.tmp"

. /* QMB 3200 Regression Example Work */
.
. clear

.
. cd "C:\Users\luizg\Desktop\Stata"
C:\Users\luizg\Desktop\Stata

.
. import delimited "C:\Users\luizg\Desktop\Stata\supplement (2).csv"
(6 vars, 60 obs)
```

```
.
. // Variable creation
. gen supXweight = supplement * weight

. gen supXfemale = supplement * female


.
. // Poisson regression model
. poisson days cold female supplement weight, robust

Iteration 0:   log pseudolikelihood = -71.577617
Iteration 1:   log pseudolikelihood = -61.415315
Iteration 2:   log pseudolikelihood =  -61.23925
Iteration 3:   log pseudolikelihood = -61.216872
Iteration 4:   log pseudolikelihood = -61.212233
Iteration 5:   log pseudolikelihood = -61.211246
Iteration 6:   log pseudolikelihood = -61.211023
Iteration 7:   log pseudolikelihood = -61.210967
Iteration 8:   log pseudolikelihood = -61.210957
Iteration 9:   log pseudolikelihood = -61.210955

Poisson regression                              Number of obs     =         60
                                                Wald chi2(4)      =  635911.70
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -61.210955               Pseudo R2         =     0.7294

------------------------------------------------------------------------------
             |               Robust
        days |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        cold |   19.97145   .0352608   566.39   0.000     19.90234    20.04056
      female |   .1776382   .0952762     1.86   0.062    -.0090997    .3643761
```

```
  supplement |  -.1897913   .0649447    -2.92   0.003    -.3170806   -.0625021
      weight |   .0007159   .0014076     0.51   0.611     -.002043    .0034748
       _cons |  -18.03518    .255191   -70.67   0.000    -18.53534   -17.53501
------------------------------------------------------------------------------

. estimate store model1

. predict pred1
(option n assumed; predicted number of events)

.
. //RMSE value of the model
. gen sqres1=(days-pred1)^2

.
. //Repetition of the processes mentioned above for another 4 different models
. poisson days cold female supplement weight supXweight, robust

Iteration 0:   log pseudolikelihood = -71.550479
Iteration 1:   log pseudolikelihood = -61.388552
Iteration 2:   log pseudolikelihood = -61.211133
Iteration 3:   log pseudolikelihood = -61.188743
Iteration 4:   log pseudolikelihood = -61.184081
Iteration 5:   log pseudolikelihood =  -61.18309
Iteration 6:   log pseudolikelihood = -61.182867
Iteration 7:   log pseudolikelihood = -61.182812
Iteration 8:   log pseudolikelihood = -61.182801
Iteration 9:   log pseudolikelihood = -61.182799

Poisson regression                              Number of obs     =         60
                                                Wald chi2(5)      =  623439.71
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -61.182799               Pseudo R2         =     0.7295
```

```
------------------------------------------------------------------------------
             |               Robust
        days |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        cold |   19.72195   .0348164   566.46   0.000     19.65372    19.79019
      female |     .17949   .0975865     1.84   0.066     -.011776     .370756
  supplement |  -.0352196   .3267364    -0.11   0.914    -.6756111     .605172
      weight |    .001042   .0014831     0.70   0.482    -.0018647    .0039487
  supXweight |  -.0009785   .0020819    -0.47   0.638    -.0050589     .003102
       _cons |  -17.83661   .2676687   -66.64   0.000    -18.36123   -17.31198
------------------------------------------------------------------------------

. estimate store model2

. predict pred2
(option n assumed; predicted number of events)

. gen sqres2=(days-pred2)^2

. poisson days cold female supplement weight supXfemale, robust

Iteration 0:   log pseudolikelihood = -71.381109
Iteration 1:   log pseudolikelihood =  -61.22312
Iteration 2:   log pseudolikelihood = -61.036445
Iteration 3:   log pseudolikelihood = -61.013969
Iteration 4:   log pseudolikelihood = -61.009126
Iteration 5:   log pseudolikelihood = -61.008109
Iteration 6:   log pseudolikelihood = -61.007882
Iteration 7:   log pseudolikelihood = -61.007827
Iteration 8:   log pseudolikelihood = -61.007815
Iteration 9:   log pseudolikelihood = -61.007813
```

```
Poisson regression                              Number of obs     =         60
                                                Wald chi2(4)      =          .
                                                Prob > chi2       =          .
Log pseudolikelihood = -61.007813               Pseudo R2         =     0.7303

------------------------------------------------------------------------------
             |               Robust
        days |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        cold |   19.72065   .0333885   590.64   0.000     19.65521    19.78609
      female |   .1097792   .1008707     1.09   0.276    -.0879237    .3074821
  supplement |  -.2747057   .0885343    -3.10   0.002    -.4482298   -.1011816
      weight |   .0005466   .0014818     0.37   0.712    -.0023577    .0034508
  supXfemale |   .1780059   .1222578     1.46   0.145    -.0616149    .4176267
       _cons |  -17.72799   .2723251   -65.10   0.000    -18.26173   -17.19424
------------------------------------------------------------------------------

. estimate store model3

. predict pred3
(option n assumed; predicted number of events)

. gen sqres3=(days-pred3)^2

. poisson days i.cold i.female i.supplement i.supXfemale c.weight c.supXweight,
robust

Iteration 0:   log pseudolikelihood = -71.291964
Iteration 1:   log pseudolikelihood = -61.143836
Iteration 2:   log pseudolikelihood = -60.944193
Iteration 3:   log pseudolikelihood = -60.921564
Iteration 4:   log pseudolikelihood = -60.916351
Iteration 5:   log pseudolikelihood = -60.915251
Iteration 6:   log pseudolikelihood = -60.915054
```

```
Iteration 7:   log pseudolikelihood = -60.915033
Iteration 8:   log pseudolikelihood = -60.915029

Poisson regression                                Number of obs     =         60
                                                  Wald chi2(6)      =   43423.31
                                                  Prob > chi2       =     0.0000
Log pseudolikelihood = -60.915029                 Pseudo R2         =     0.7307

------------------------------------------------------------------------------
             |               Robust
        days |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      1.cold |   19.34352   .0962226   201.03   0.000     19.15493    19.53211
    1.female |   .0472468   .1011591     0.47   0.640    -.1510214     .245515
1.supplement |  -.8066765   .4650756    -1.73   0.083    -1.718208    .1048551
 1.supXfemale |   .3333956   .1730048     1.93   0.054    -.0056876    .6724789
      weight |  -.0005405   .0016033    -0.34   0.736    -.0036829     .002602
  supXweight |    .002898   .0025802     1.12   0.261     -.002159     .007955
       _cons |  -17.15592   .2976164   -57.64   0.000    -17.73923    -16.5726
------------------------------------------------------------------------------

. estimate store model4

. predict pred4
(option n assumed; predicted number of events)

. gen sqres4=(days-pred4)^2

. poisson days i.cold i.female i.supplement i.supXfemale c.supXweight, robust

Iteration 0:   log pseudolikelihood = -71.301641
Iteration 1:   log pseudolikelihood = -61.151587
Iteration 2:   log pseudolikelihood = -60.952759
```

```
Iteration 3:   log pseudolikelihood = -60.930133
Iteration 4:   log pseudolikelihood = -60.924935
Iteration 5:   log pseudolikelihood = -60.923834
Iteration 6:   log pseudolikelihood = -60.923638
Iteration 7:   log pseudolikelihood = -60.923617
Iteration 8:   log pseudolikelihood = -60.923613

Poisson regression                              Number of obs     =         60
                                                Wald chi2(4)      =          .
                                                Prob > chi2       =          .
Log pseudolikelihood = -60.923613               Pseudo R2         =     0.7307

------------------------------------------------------------------------------
             |               Robust
        days |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      1.cold |    19.3437   .0962442   200.99   0.000     19.15506    19.53233
    1.female |   .0783132   .0552752     1.42   0.157    -.0300243    .1866507
1.supplement |   -.709851   .3748833    -1.89   0.058    -1.444609    .0249068
 1.supXfemale |   .3023291   .1508405     2.00   0.045     .0066872    .5979709
  supXweight |   .0023576   .0020215     1.17   0.244    -.0016045    .0063197
       _cons |  -17.25292   .1372267  -125.73   0.000    -17.52188   -16.98396
------------------------------------------------------------------------------

. estimate store model5

. predict pred5
(option n assumed; predicted number of events)

. gen sqres5=(days-pred5)^2

.
. //RMSE Comparison
```

```
. sum sqres*

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
      sqres1 |         60    .6730404    1.283789   1.82e-16   6.005032
      sqres2 |         60    .6656469    1.224504   3.05e-16   5.395259
      sqres3 |         60    .6206649    1.052345   2.70e-16   4.400746
      sqres4 |         60    .5963178    1.013113   4.93e-16   4.339605
      sqres5 |         60    .5998339    1.015574   4.93e-16   4.373257

.
. //Chi-Square Hypothesis Testing
. poisson days i.cold i.female i.supplement i.supXfemale c.weight c.supXweight,
robust

Iteration 0:   log pseudolikelihood = -71.291964
Iteration 1:   log pseudolikelihood = -61.143836
Iteration 2:   log pseudolikelihood = -60.944193
Iteration 3:   log pseudolikelihood = -60.921564
Iteration 4:   log pseudolikelihood = -60.916351
Iteration 5:   log pseudolikelihood = -60.915251
Iteration 6:   log pseudolikelihood = -60.915054
Iteration 7:   log pseudolikelihood = -60.915033
Iteration 8:   log pseudolikelihood = -60.915029

Poisson regression                              Number of obs     =         60
                                                Wald chi2(6)      =   43423.31
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -60.915029               Pseudo R2         =     0.7307

------------------------------------------------------------------------------
             |               Robust
        days |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
```

```
      1.cold |   19.34352   .0962226   201.03   0.000     19.15493    19.53211
    1.female |   .0472468   .1011591     0.47   0.640    -.1510214     .245515
1.supplement |  -.8066765   .4650756    -1.73   0.083    -1.718208    .1048551
1.supXfemale |   .3333956   .1730048     1.93   0.054    -.0056876    .6724789
      weight |  -.0005405   .0016033    -0.34   0.736    -.0036829     .002602
  supXweight |    .002898   .0025802     1.12   0.261     -.002159     .007955
       _cons |  -17.15592   .2976164   -57.64   0.000    -17.73923    -16.5726
------------------------------------------------------------------------------

. testparm i.supplement supXweight

 ( 1)  [days]1.supplement = 0
 ( 2)  [days]supXweight = 0

           chi2(  2) =   12.97
         Prob > chi2 =    0.0015

. testparm i.supplement weight supXweight

 ( 1)  [days]1.supplement = 0
 ( 2)  [days]weight = 0
 ( 3)  [days]supXweight = 0

           chi2(  3) =   12.97
         Prob > chi2 =    0.0047

. testparm i.supplement weight

 ( 1)  [days]1.supplement = 0
 ( 2)  [days]weight = 0

           chi2(  2) =    3.74
         Prob > chi2 =    0.1540
```

```
.
. testparm i.female i.supplement i.supXfemale

 ( 1)  [days]1.female = 0
 ( 2)  [days]1.supplement = 0
 ( 3)  [days]1.supXfemale = 0

           chi2(  3) =    7.88
         Prob > chi2 =    0.0486

. testparm i.female i.supXfemale

 ( 1)  [days]1.female = 0
 ( 2)  [days]1.supXfemale = 0

           chi2(  2) =    7.57
         Prob > chi2 =    0.0227

. testparm i.female supplement

 ( 1)  [days]1.female = 0

           chi2(  1) =    0.22
         Prob > chi2 =    0.6405

.
. poisson days i.cold i.female i.supplement i.supXfemale c.supXweight, robust

Iteration 0:   log pseudolikelihood = -71.301641
Iteration 1:   log pseudolikelihood = -61.151587
Iteration 2:   log pseudolikelihood = -60.952759
Iteration 3:   log pseudolikelihood = -60.930133
```

```
Iteration 4:   log pseudolikelihood = -60.924935
Iteration 5:   log pseudolikelihood = -60.923834
Iteration 6:   log pseudolikelihood = -60.923638
Iteration 7:   log pseudolikelihood = -60.923617
Iteration 8:   log pseudolikelihood = -60.923613

Poisson regression                              Number of obs     =         60
                                                Wald chi2(4)      =          .
                                                Prob > chi2       =          .
Log pseudolikelihood = -60.923613               Pseudo R2         =     0.7307

------------------------------------------------------------------------------
             |               Robust
        days |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      1.cold |    19.3437   .0962442   200.99   0.000     19.15506    19.53233
    1.female |   .0783132   .0552752     1.42   0.157    -.0300243    .1866507
1.supplement |   -.709851   .3748833    -1.89   0.058    -1.444609    .0249068
 1.supXfemale |   .3023291   .1508405     2.00   0.045     .0066872    .5979709
  supXweight |   .0023576   .0020215     1.17   0.244    -.0016045    .0063197
       _cons |  -17.25292   .1372267  -125.73   0.000    -17.52188   -16.98396
------------------------------------------------------------------------------

. testparm i.supplement supXweight

 ( 1)  [days]1.supplement = 0
 ( 2)  [days]supXweight = 0

           chi2(  2) =   12.46
         Prob > chi2 =    0.0020

. testparm i.female i.supplement i.supXfemale
```

```
 ( 1)  [days]1.female = 0
 ( 2)  [days]1.supplement = 0
 ( 3)  [days]1.supXfemale = 0

           chi2(  3) =    9.37
         Prob > chi2 =    0.0248

. testparm i.female i.supXfemale

 ( 1)  [days]1.female = 0
 ( 2)  [days]1.supXfemale = 0

           chi2(  2) =    9.36
         Prob > chi2 =    0.0093

. testparm i.female supplement

 ( 1)  [days]1.female = 0

           chi2(  1) =    2.01
         Prob > chi2 =    0.1565

.
. //Marginal effect of each variable on cold duration
. poisson days i.cold i.female i.supplement i.supXfemale c.supXweight c.weight,
robust

Iteration 0:   log pseudolikelihood = -71.291964
Iteration 1:   log pseudolikelihood = -61.143836
Iteration 2:   log pseudolikelihood = -60.944193
Iteration 3:   log pseudolikelihood = -60.921564
Iteration 4:   log pseudolikelihood = -60.916351
Iteration 5:   log pseudolikelihood = -60.915251
Iteration 6:   log pseudolikelihood = -60.915054
```

```
Iteration 7:   log pseudolikelihood = -60.915033
Iteration 8:   log pseudolikelihood = -60.915029

Poisson regression                              Number of obs     =         60
                                                Wald chi2(6)      =   22345.22
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -60.915029               Pseudo R2         =     0.7307

------------------------------------------------------------------------------
             |               Robust
        days |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      1.cold |   19.34352    .132119   146.41   0.000     19.08457    19.60247
    1.female |   .0472468   .1011591     0.47   0.640    -.1510214     .245515
1.supplement |  -.8066765   .4650756    -1.73   0.083    -1.718208    .1048551
 1.supXfemale |   .3333956   .1730048     1.93   0.054    -.0056876    .6724789
  supXweight |    .002898   .0025802     1.12   0.261     -.002159     .007955
      weight |  -.0005405   .0016033    -0.34   0.736    -.0036829     .002602
       _cons |  -17.15592   .2976164   -57.64   0.000    -17.73923    -16.5726
------------------------------------------------------------------------------

. margins, dydx(*) post

Average marginal effects                        Number of obs     =         60
Model VCE    : Robust

Expression   : Predicted number of events, predict()
dy/dx w.r.t. : 1.cold 1.female 1.supplement 1.supXfemale supXweight weight

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
```

```
      1.cold |   7.745808   .7337234    10.56   0.000     6.307737    9.183879
    1.female |   .1862122   .4001226     0.47   0.642    -.5980137    .9704382
1.supplement |  -3.059245   1.906369    -1.60   0.109    -6.795661    .6771699
1.supXfemale |   1.481691   .8819499     1.68   0.093    -.2468989    3.210281
  supXweight |   .0113994   .0101861     1.12   0.263    -.0085651    .0313638
      weight |  -.0021259   .0062972    -0.34   0.736    -.0144681    .0102164
------------------------------------------------------------------------------
Note: dy/dx for factor levels is the discrete change from the base level.

.
end of do-file

. do "C:\Users\luizg\AppData\Local\Temp\STD28f0_000000.tmp"

.
. log close
no log file open
r(606);

end of do-file

r(606);
```