# WWS 509 Generalized Linear Models: Precept 7 Poisson Models with Extra Variation

Kristin E. Bietsch

Office of Population Research, Princeton University

### November 2012

## Introducing the Data

This data looks at number of volunteer experiences in the past year. Control variables include race, gender, education, and income. Do not cite!

## Extra Poisson Variation

## Zero Inflated Poisson

- 2. Zero Inflated Poisson is divided into two analyses: finding the \_\_\_\_\_ and those that follow the Poisson distribution.
- 3. You need to tell Stata which \_\_\_\_\_\_ to use to predict the count and the "always zeros"

1. Sometimes in count data, you have many more zeros than the model

(a) You do not have to use the same variables if you think they aren't predictive of those who never do something and of those who might do something and how often they will do it.

## Interpreting Results

- 1. Why did I rename two of the variables?
- 2. The mean number of volunteer experiences in the past year is 0.36, and they variance is 0.86. What does this tell us?
- 3. Looking at the Poisson regression, does this model fit the data?
  - (a) How do you know?
  - (b) What does the line "di invchi2tail" mean?
  - (c) In this model, how much larger is the variance than the mean?
  - (d) How would you adjust your standard errors to account for extra variation using the above number?
- 4. What am I doing in the second regression?
  - (a) Has the significance levels of any variables changed?
  - (b) What is different in this model from the previous model?
  - (c) What is the same?
  - (d) What are some assumptions about error in this model?
- 5. Now looking at the negative binomial regression, what does alpha tell us?
  - (a) Compare the coefficients for the variables in the 3 models. What do you think?
- 6. Now look at the last model, which kind of model am I using?
  - (a) Are these coefficients similar to the first three models?
  - (b) What do the bottom set of coefficients represent? The top?

WWS509 Precept 7 K.Bietsch

- (c) Looking at the bottom set of numbers, are any significant in determining who will be in the "always zero" class?
- (d) Now looking at the top set of numbers, what can you tell me about predicting the number of volunteer experiences?

## **Appendices**

## Stata Output

```
. rename gender female
```

- . rename race nonwhite
- . drop if educate==.
  (9 observations deleted)
- . drop if income==.
  (951 observations deleted)
- . summarize volteer

Variable	Obs	Mean	Std. Dev.	Min	Max
volteer	1944	.3605967	.928261	0	9

- . di r(Var)
- .8616684

```
*********************
```

. glm volteer female nonwhite educate income, family(poisson)

```
Iteration 0: log likelihood = -1787.7576
Iteration 1: log likelihood = -1686.0444
Iteration 2: log likelihood = -1685.4303
Iteration 3: log likelihood = -1685.4299
Iteration 4: log likelihood = -1685.4299
```

```
      Generalized linear models
      No. of obs = 1944

      Optimization : ML
      Residual df = 1939

      Scale parameter = 1
      1

      Deviance = 2465.513855
      (1/df) Deviance = 1.271539
```

WWS509	Precept 7	K.Bietsch

= 4349.349483 (1/df) Pearson = 2.243089 Pearson

Variance function: V(u) = u[Poisson] Link function : g(u) = ln(u)[Log]

AIC = 1.739125 Log likelihood = -1685.429933BIC = -12217.57

		MIO				
volteer	Coef.	Std. Err.	z	P> z	[95% Conf.	Interval]
female	.2613218	.077849	3.36	0.001	.1087407	.413903
nonwhite	2803773	.1083786	-2.59	0.010	4927954	0679592
educate	.1028018	.0144317	7.12	0.000	.0745161	.1310875
income	.0568278	.0156635	3.63	0.000	.0261278	.0875278
_cons	-3.158302	.2447916	-12.90	0.000	-3.638084	-2.678519

. di invchi2tail(1939,0.05) 2042.5553

. \*

. glm volteer female nonwhite educate income, family(poisson) scale(x2)

Iteration 0: log likelihood = -1787.7576 Iteration 1:  $\log likelihood = -1686.0444$ Iteration 2: log likelihood = -1685.4303 Iteration 3: log likelihood = -1685.4299 Iteration 4: log likelihood = -1685.4299

No. of obs = 1944 Generalized linear models Residual df = Optimization : ML 1939 Scale parameter = Deviance = 2465.513855 (1/df) Deviance = 1.271539 Pearson = 4349.349483 (1/df) Pearson = 2.243089 [Poisson] Variance function: V(u) = u

Link function : g(u) = ln(u)[Log]

= 1.739125 AIC Log likelihood = -1685.429933BIC = -12217.57

\_\_\_\_\_\_ 

MIO

WWS509 Precept 7 K.Bietsch

	volteer	Coef.	Std. Err.		P> z		Interval]
-	female   nonwhite   educate   income   cons		.1165939 .162318 .0216143 .0234592 .3666231	2.24 -1.73 4.76 2.42 -8.61	0.025 0.084 0.000 0.015 0.000	.03280195985148 .0604385 .0108486 -3.87687	.4898418 .0377601 .1451652 .102807

(Standard errors scaled using square root of Pearson X2-based dispersion.)

. \*

. nbreg volteer female nonwhite educate income

#### Fitting Poisson model:

Iteration 0: log likelihood = -1685.4301
Iteration 1: log likelihood = -1685.4299

#### Fitting constant-only model:

Iteration 0: log likelihood = -1529.4738
Iteration 1: log likelihood = -1478.209
Iteration 2: log likelihood = -1441.165
Iteration 3: log likelihood = -1441.1354
Iteration 4: log likelihood = -1441.1354

#### Fitting full model:

Iteration 0: log likelihood = -1421.3272
Iteration 1: log likelihood = -1419.7876
Iteration 2: log likelihood = -1419.7818
Iteration 3: log likelihood = -1419.7818

Negative binomial regression 
Number of obs = 1944 
LR chi2(4) = 42.71 
Dispersion = mean 
Prob > chi2 = 0.0000 
Log likelihood = -1419.7818 
Pseudo R2 = 0.0148

volteer | Coef. Std. Err. z P>|z| [95% Conf. Interval]

female | .2844083 .1240645 2.29 0.022 .0412463 .5275702

nonwhite | -.3110729 .1622372 -1.92 0.055 -.629052 .0069063

educate | .1119953 .0242689 4.61 0.000 .064429 .1595615

income | .051931 .0224104 2.32 0.020 .0080075 .0958545

WWS509 Precept 7 K.Bietsch

					-3.986067	
	1.362715	.0979507			1.170735	1.554695
	3.906786					4.733642
Likelihood-rat	tio test of a	lpha=0: c	hibar2(01)	= 531	.30 Prob>=chib	par2 = 0.000

. \*

. zip volteer female nonwhite educate income, inflate(female nonwhite educate income)

## Fitting constant-only model:

Iteration 0: log likelihood = -1688.6627
Iteration 1: log likelihood = -1476.8738
Iteration 2: log likelihood = -1444.8905
Iteration 3: log likelihood = -1441.6992
Iteration 4: log likelihood = -1441.6908
Iteration 5: log likelihood = -1441.6908

#### Fitting full model:

Iteration 0: log likelihood = -1441.6908
Iteration 1: log likelihood = -1433.2457
Iteration 2: log likelihood = -1433.0106
Iteration 3: log likelihood = -1433.0101
Iteration 4: log likelihood = -1433.0101

Zero-inflated Poisson regression	Number of obs		1944 376
	Nonzero obs	=	
	Zero obs	=	1568
Inflation model = logit	LR chi2(4)	=	17.36
Log likelihood = -1433.01	Prob > chi2	=	0.0016

volteer	Coef.	Std. Err.	z	P> z		Interval]
volteer						
female	.1400743	.1068452	1.31	0.190	0693386	.3494871
nonwhite	1001711	.1532696	-0.65	0.513	400574	.2002317
educate	.0595475	.0217629	2.74	0.006	.016893	.102202
income	.0413874	.0227047	1.82	0.068	003113	.0858878
_cons	-1.033588	.3601695	-2.87	0.004	-1.739508	3276692

WWS509		Precept 7			K.Bietsch	
inflate						
female	1849913	.1477324	-1.25	0.210	4745414	.1045589
nonwhite $ $	.2341655	.2002978	1.17	0.242	158411	.626742
educate	0650641	.0286693	-2.27	0.023	1212549	0088734
income	0164052	.0295685	-0.55	0.579	0743584	.041548
_cons	2.152383	.4718441	4.56	0.000	1.227585	3.07718