# **Statgraphics** 19°

#### Modeling Zero-Inflated Count

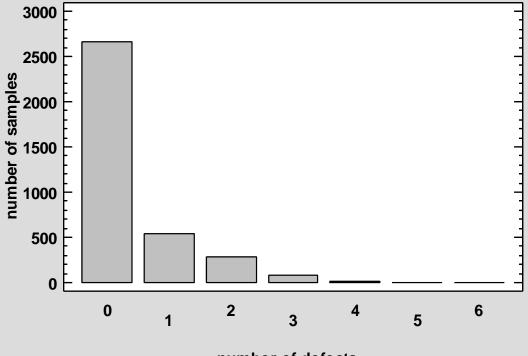
Data

#### **Zero-Inflated Distributions**

- Arise when count data have more zeroes than would be expected from the usual Poisson and negative binomial distributions
- Examples include:
  - Number of days a student is absent from school
  - Number of fish caught by visitors to a state park
  - Number of times a machine fails each month
  - Number of defects in samples from a production line
- Zeroes are often caused by two separate phenomena and are sometimes referred to as "true" zeroes and "excess" zeroes

#### Sample Data (n=3600)

**Barchart for Defects** 



number of defects

#### Zero-Inflated Poisson Distribution

 $p(0) = \alpha + (1 - \alpha)e^{-\lambda}$ 

 $p(y) = (1 - \alpha) \frac{\lambda^{y} e^{-\lambda}}{y!}$ for y > 0

 $\lambda$  = conditional mean (excluding excess zeroes)

**α** = probability of excess zero

## Data Input Dialog Box

Distribution Fitting Defects		ta) Data: Defects (Select:)			×
Sort column n	ames Cancel	Delete	Transform	Help	

## Analysis Options Dialog Box

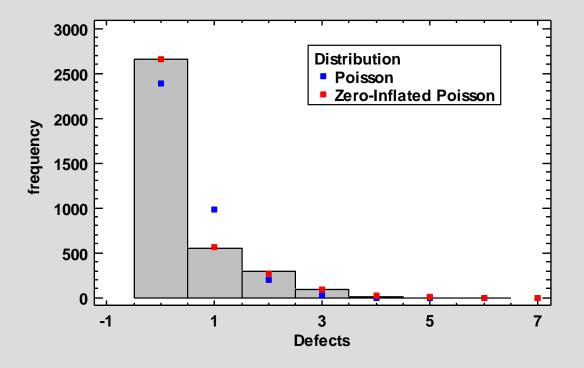
Distribution Fitting Options			×
Distribution			Binomial Trials OK
🗖 Bernoulli	🔲 Exponential (2-parameter)	🗌 Lognormal	Sample Size n:
🔲 Binomial	Exponential Power	Lognormal (3-parameter)	
🔲 Discrete Uniform	🔲 F (Variance Ratio)	Maxwell (2-parameter)	Hypergeometric Trials
🗖 Geometric	Folded Normal	🔲 Noncentral Chi-Square	Sample Size n:
Hypergeometric	🗌 Gamma	Noncentral F	100 Estimation
🔲 Negative Binomial	🔲 Gamma (3-parameter)	Noncentral t	C Estimate N
🔽 Poisson	🔲 Generalized Gamma	Normal	C Specify N
🔲 🗆 Zero-Inflated Neg. Binomial	🔲 Generalized Logistic	Pareto	
🔽 Zero-Inflated Poisson	Half Normal (2-parameter)	Pareto (2-parameter)	Negative Binomial Trials
🗖 Beta	🔲 Inverse Gaussian	🔲 Rayleigh (2-parameter)	<ul> <li>Estimate k</li> <li>Specify k</li> </ul>
🔲 Beta (4-parameter)	🔲 Johnson	🔲 Smallest Extreme Value	
🔲 Birnbaum-Saunders	Laplace	🔲 Student's t	
🗖 Cauchy	🔲 Largest Extreme Value	🔲 Triangular	Extended Threshold Parameters
🗖 Chi-Square	🔲 Logistic	🔲 Uniform	© Estimate
🗖 Erlang	Loglogistic	🔲 Weibull	C Specify lower/upper 0.0 1.0
Exponential	Loglogistic (3-parameter)	🔲 Weibull (3-parameter)	

# **Tables and Graphs**

Tables and Graphs		×
TABLES Analysis Summary	GRAPHS Density Trace	ОК
Tests for Normality	Symmetry Plot	Cancel
Goodness-of-Fit Tests	Frequency Histogram	All
Tail Areas	Quantile Plot	Store
Critical Values	Quantile-Quantile Plot	Help
Normal Tolerance Limits	Distribution Functions 1	
Distribution-Free Limits	Distribution Functions 2	
Comparison of Alternative Distributions		

## **Fitted Distributions**

Histogram for Defects



### **Analysis Summary**

**Distribution Fitting (Uncensored Data) - Defects** 

Data variable: Defects

3600 values ranging from 0.0 to 6.0

#### Fitted Distributions

Poisson	Zero-Inflated Poisson
mean = 0.410833	conditional mean = 0.976894
	P(structural zero) = 0.57945

#### **Goodness-of-Fit Tests**

#### Goodness-of-Fit Tests for Defects

Chi-Square Test

	Poisson	Zero-Inflated Poisson
Chi-Square	496.55	3.16622
D.f.	3	3
P-Value	0.0	0.366697

# Zero-Inflated Count Regression Fits a regression model where the dependent variable has excess zeroes

C:\Data\webinar\zip\bioChemists.sgd								
	articles	gender	status	kids	department	mentor		
4	number published in last 3 years		marital status	aged 5 or younger	prestige of PhD department	articles published in last 3 years		
	Numeric	Character	Character	Numeric	Fixed	Numeric		
1	0	Male	Married	0	2.52	7		
2	0	Female	Single	0	2.05	6		
3	0	Female	Single	0	3.75	6		
4	0	Male	Married	1	1.18	3		
5	0	Female	Single	0	3.75	26		
6	0	Female	Married	2	3.59	2		
7	0	Female	Single	0	3.19	3		
8	0	Male	Married	2	2.96	4		
9	0	Male	Single	0	4.62	6		
10	0	Female	Married	0	1.25	0		
11	0	Male	Single	0	2.96	14		
12	0	Female	Single	0	0.75	13		
13	0	Female	Married	1	3.69	3		
14	0	Female	Married	0	3.40	4		
15	0	Female	Married	0	1.79	0		
	bioChemists B C							

#### **Two Models for Zero-Inflated Regression**

#### 1. Zero-inflated model

- Count component: Poisson or negative binomial distribution to describe the distribution of counts (Y=0,1,2,...)
- Zero component: binomial distribution to describe the probability of excess zeroes

#### 2. Hurdle model

- Count component: zero-truncated Poisson, negative binomial or geometric distribution to describe the distribution of positive counts (Y=1,2,3,...)
- Zero component: binomial or censored Poisson, negative binomial or geometric distribution to describe the probability of all zeroes

## **ZIP** Regression

- For the count component, a log-linear function links the conditional Poisson mean  $\lambda$  to the independent variables  $\log(\lambda_i) = \beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + ... + \beta_k X_{k,i}$
- For the excess zeroes, a logit function links the binomial probability parameter α to the independent variables

$$\alpha_{i} = \frac{1}{1 + \exp(\beta_{0} + \beta_{1}X_{1,i} + \beta_{2}X_{2,i} + \dots + \beta_{k}X_{k,i})}$$

# Data Input Dialog Box

Zero In	flated Count Regression ×	
articles gender status kids department mentor	Dependent Variable:          Image: Status         Image: Status	
	Quantitative Factors:	
	(Weights:)	
Sort column names	Delete Transform Help	

# **Model Specification**

		component	
jender Itatus lids lepartment nentor	gender status kids department mentor		
Include quadratic effects	Include 2-factor interactions     Cancel	Include nested effects	

# Analysis Summary

Model	Count distribution
Zero inflated	Poisson
O Hurdle	C Negative binomial
	C Geometric
Link function	
Eogit	_ Zero distribution
C Probit	Binomial
C Complementary log-log	C Poisson
🔿 Cauchit	C Negative binomial
C Log	C Geometric
Optimization	
• BFGS	Maximum iterations:
O Nelder-Mead	10000
C Congugate gradient	Estimate starting values using EM
Diagnostics	
<ul> <li>Compare to null model</li> </ul>	Compare to model without zero inflation

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# **Tables and Graphs**

Tables and Graphs		×
TABLES Analysis Summary	GRAPHS Probability Distribution	ОК
Probability Distribution	Means Plot	Cancel
✓ Predictions	Count Component	All
Unusual Residuals	Zero Component	Store
R Script and Messages	Observed versus Predicted	Help
	Residual Plots	



# **Analysis Summary**

##	Count model						
##		Estimate	Std. Error	z value	$\Pr( z )$		
##	(Intercept)	0.535427	0.112484	4.760	1.94e-06	***	
##	genderMale	0.209144	0.063405	3.299	0.000972	***	
##	statusSingle	-0.103752	0.071111	-1.459	0.144563		
##	kids	-0.143320	0.047429	-3.022	0.002513	**	
##	department	-0.006160	0.031009	-0.199	0.842543		
##	mentor	0.018098	0.002294	7.888	3.08e-15	***	
##							
##	Zero-inflati	on model co	pefficients	(binomia	al with lo	git	link):
##		Estimate	Std. Error	z value	$\Pr( z )$		
##	(Intercept)	-0.821111	0.480292	-1.710	0.08734		
##	genderMale	-0.109743	0.280082	-0.392	0.69519		
##	statusSingle	0.354033	0.317610	1.115	0.26499		
##	kids	0.217099	0.196481	1.105	0.26919		
##	department	0.001182	0.145270	0.008	0.99351		
##	mentor	-0.134103	0.045243	-2.964	0.00304	**	
##							
##	Signif. code	s: 0 '***'	0.001 '**	0.01 '*	•' 0.05 '.	.' O.	1 ' '

1

## **Model Comparisons**

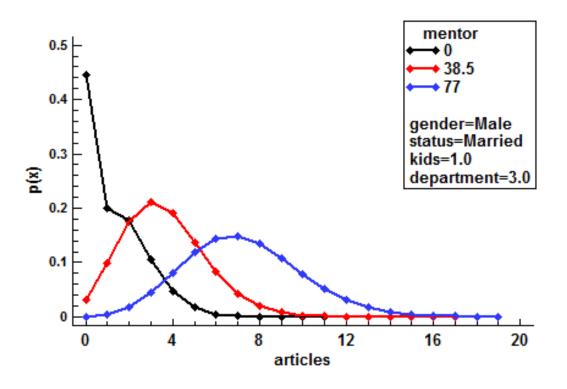
```
# Comparison to model with only a constant
mnull <- update(model, . \sim 1)
pchisq(2 * (logLik(model) - logLik(mnull)), df = 10, lower.tail = FALSE)
## 'log Lik.' 5.351991e-27 (df=12)
# Comparison to model without zero inflation
p1<-glm(articles~gender+status+kids+department+mentor,family="poisson",data=d)
vuong(p1,model)
## Vuong Non-Nested Hypothesis Test-Statistic:
## (test-statistic is asymptotically distributed N(0,1) under the
## null that the models are indistinguishible)
##
##
                Vuong z-statistic H A p-value
## Raw
                        -4.180476 model2 > model1 1.4545e-05
                       -3.638531 model2 > model1 0.0001371
## AIC-corrected
                       -2.332734 model2 > model1 0.0098310
## BIC-corrected
```

# Simplifying the Model

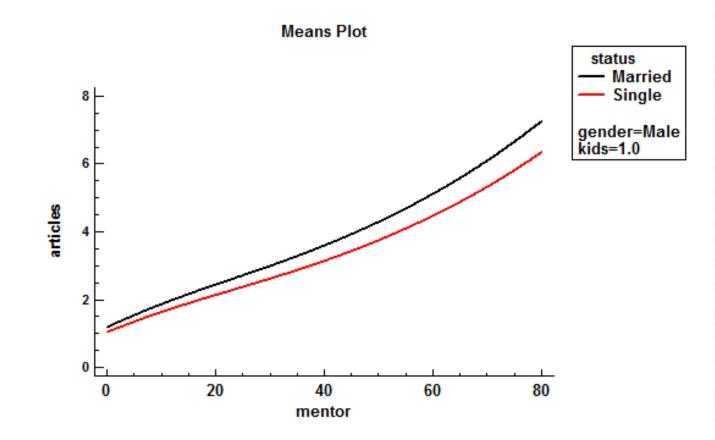
```
## Count model coefficients (poisson with log link):
##
                Estimate Std. Error z value Pr(|z|)
## (Intercept) 0.52604 0.06139 8.569 < 2e-16 ***
## genderMale 0.21826 0.05878 3.713 0.000205 ***
## statusSingle -0.13483 0.06587 -2.047 0.040670 *
## kids -0.16277 0.04337 -3.753 0.000175 ***
## mentor 0.01819 0.00221 8.227 < 2e-16 ***
##
## Zero-inflation model coefficients (binomial with logit link):
##
               Estimate Std. Error z value Pr(|z|)
## (Intercept) -0.68569 0.20548 -3.337 0.000847 ***
## mentor
            -0.13007 0.04023 -3.233 0.001224 **
## ---
                   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Signif. codes:
```

# **Probability Distribution**

#### **Probability Distribution**



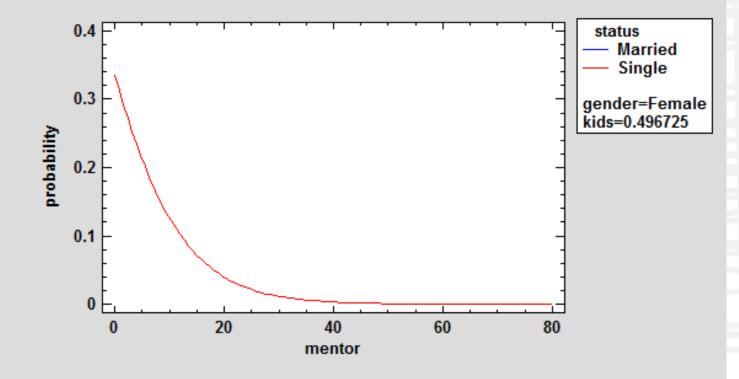
# Means Plot



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# Zero Component

Zero Component



#### Predictions

Predictions for articles

	Row	Observed Value	Fitted Value	Residual	Pearson Residual	Count Component	Zero Component
-	916		1.10732			1.36291	0.187532

- Conditional mean:  $\hat{\lambda} = 1.36291$
- Prob. of excess zero:  $\hat{\alpha} = 0.187532$
- Unconditional mean:  $\hat{Y} = (1 \hat{\alpha})\hat{\lambda} = 1.10732$

#### References

• Long, J. Scott. 1990. The origins of sex differences in science. Social Forces. 68(3):1297-1316.

• R Package "MASS" (2016) <u>https://cran.r-</u> project.org/web/packages/MASS/MASS.pdf

• R Package "PSCL" (2017) <u>https://cran.r-</u> project.org/web/packages/pscl/pscl.pdf

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