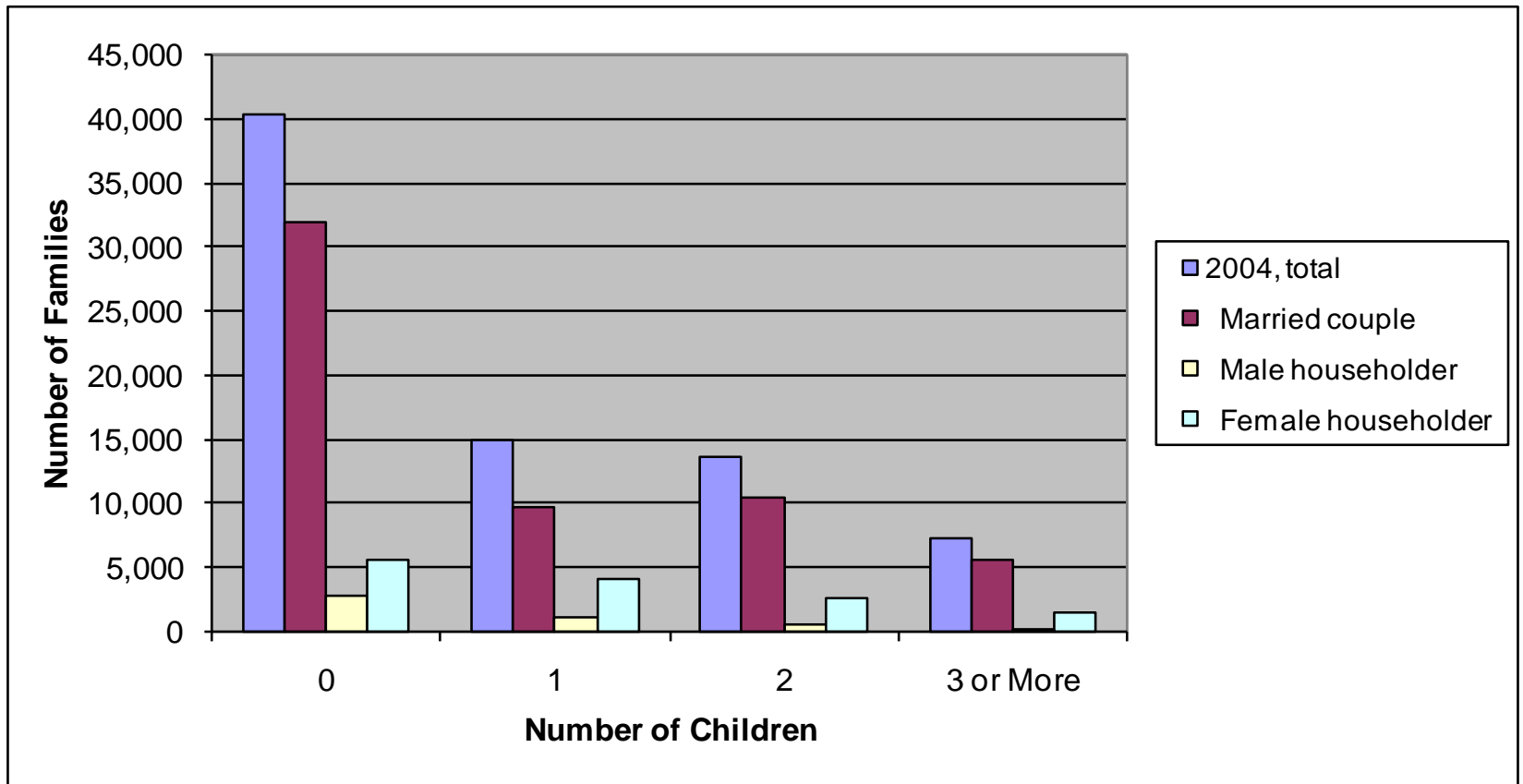


# Poisson and Related Models

Categorical and Limited  
Dependent Variables

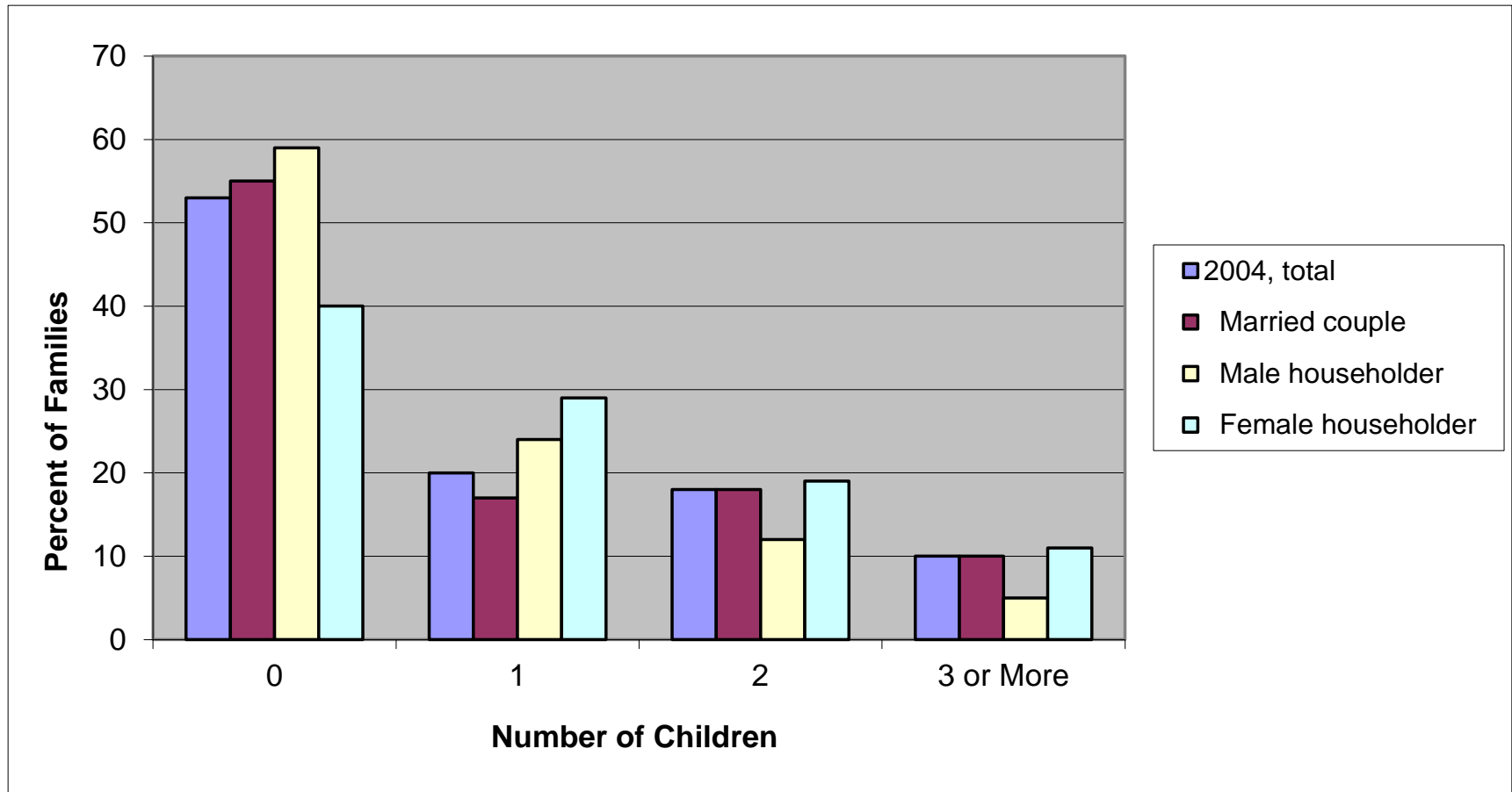
Paul A. Jargowsky

# Number of Families by Number of Children, by Family Type, 2004



Source: 2006 U.S. Statistical Abstract, Table 62

# The Probability of Each Outcome Varies by Family Type



# Mean number of Children per Family: the Rate of Child Production Varies by Family Type

## Families (1,000) by Number of Children, 2004

	Total	Number of Children:				<u>Mean Number Of Children*</u>
		0	1	2	3+	
Total	76,217	40,273	14,964	13,696	7,283	0.89
Married couple	57,719	31,926	9,763	10,481	5,548	0.87
Male Headed	4,716	2,786	1,146	550	235	0.65
Female Headed	13,781	5,560	4,055	2,665	1,501	1.06

\*assuming an average of 3.5 for families in "3+" category.

$$\mu = \sum_{i=1}^n \Pr(c = i)(i) = \Pr(0)(0) + \Pr(1)(1) + \Pr(2)(2) + \Pr(3+)(3.5)$$

# OLS on Counts?

- Not a continuous DV
- Not really censored or truncated or ordinal, which assume some continuous disturbance term
- Coefficients from OLS on counts are inefficient, inconsistent, and biased
- Need a different approach

# Poisson Distribution for Counts

When an event occurs and reoccurs *randomly* and *independently*, the total number of occurrences of an event ( $Y$ ) over *a fixed period of time* will have a Poisson Distribution, given by:

$$\Pr(Y = k) = \frac{e^{-\mu} \mu^k}{k!}, \quad k = 0, 1, 2, \dots$$

Note: this is a  
*discrete*  
probability  
distribution.

$$\mu = E[Y_i]$$

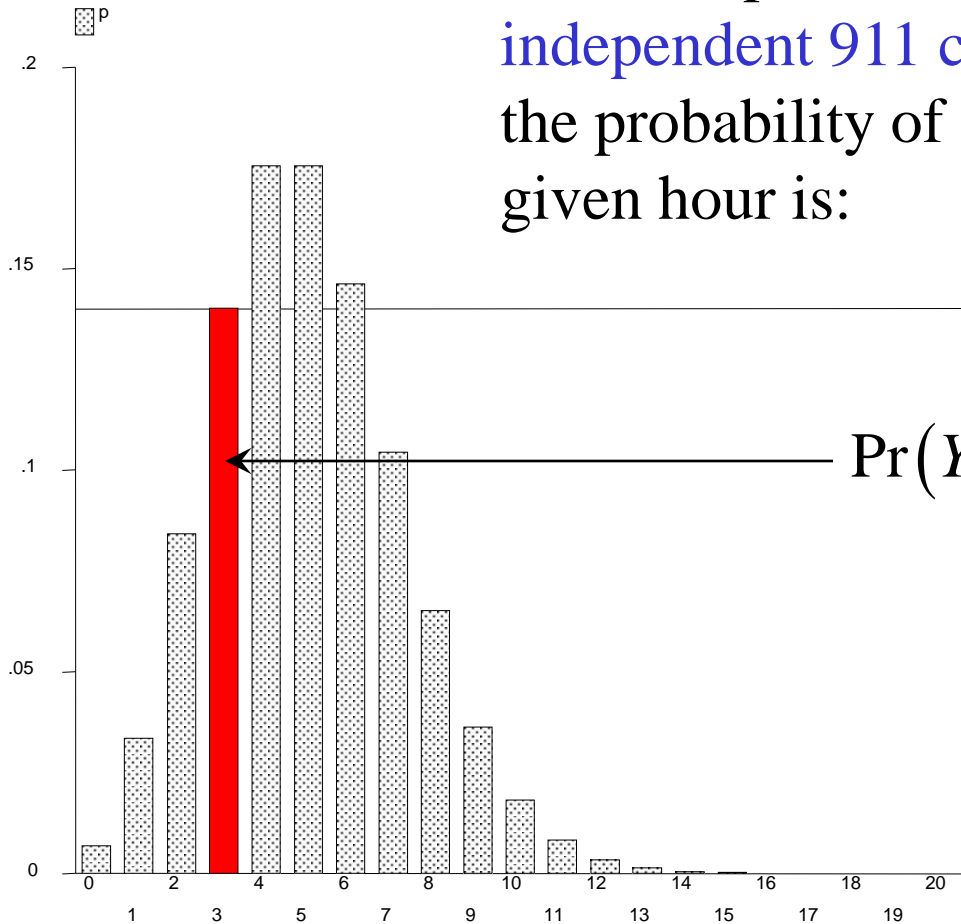
The expected arrival  
rate, or “incidence rate”

$$\sigma^2 = E[(Y - \mu)^2] = \mu$$

Equidispersion, i.e.  
mean = variance

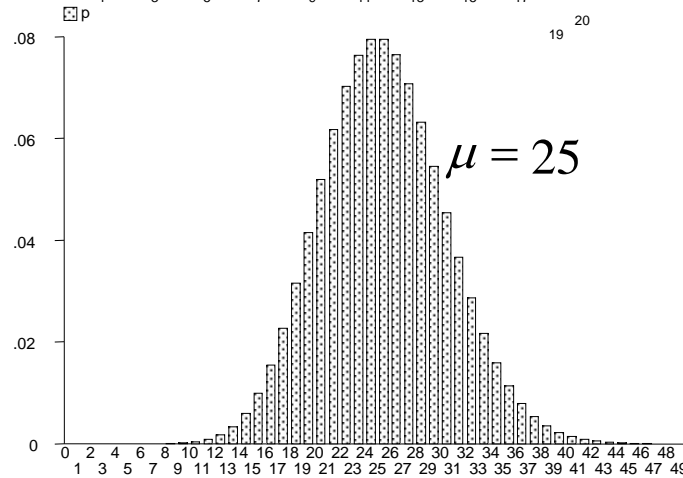
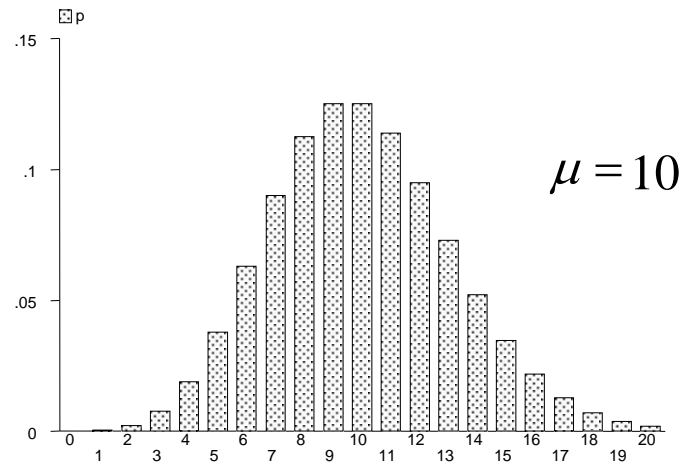
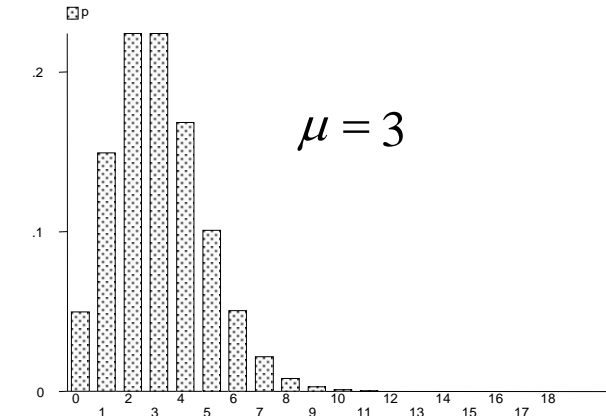
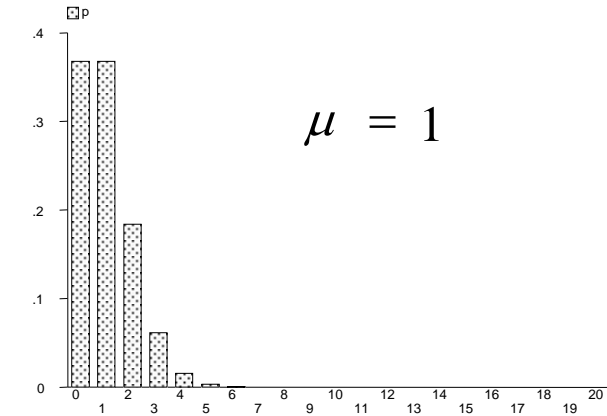
# Poisson PDF Application

For example, if the mean number of independent 911 calls per hour is 5, the probability of getting 3 calls in a given hour is:



$$\begin{aligned}\Pr(Y = 3) &= \frac{e^{-5} 5^3}{3!} \\ &= \frac{(0.00674)(125)}{6} \\ &= 0.14\end{aligned}$$

# Poisson Distributions with Different Means



The Poisson converges to normal. If the mean is more than 10, OLS works fine.

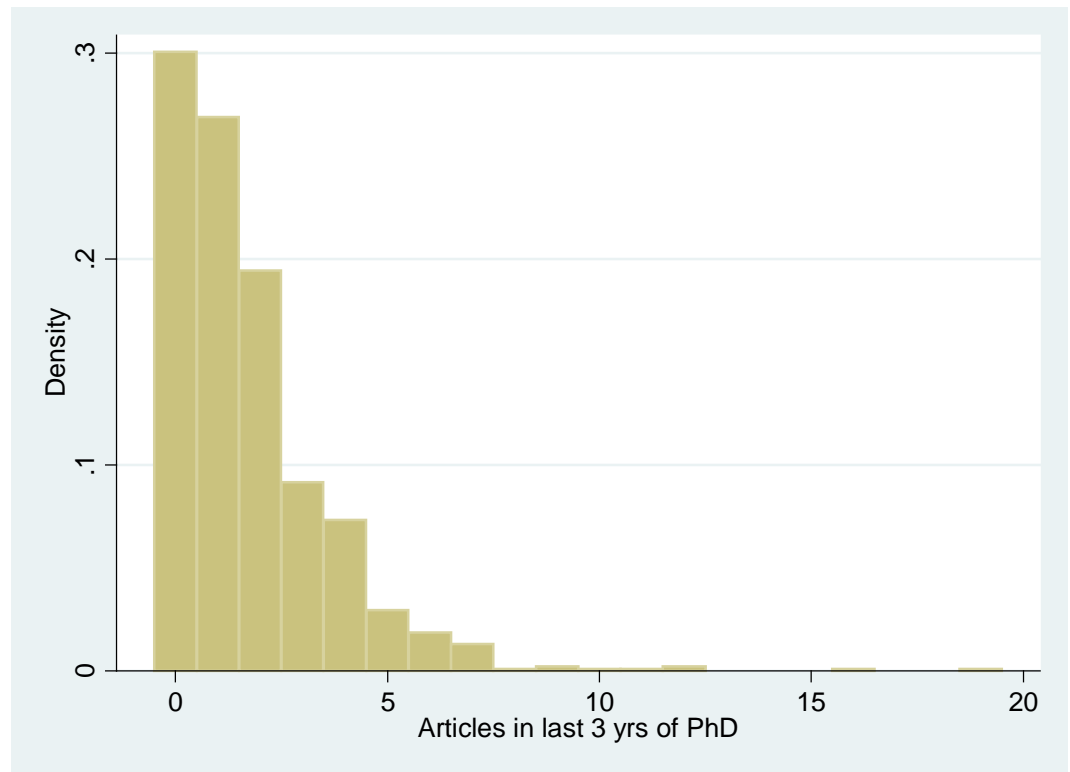


# Count of Articles Published (couart2.dta)

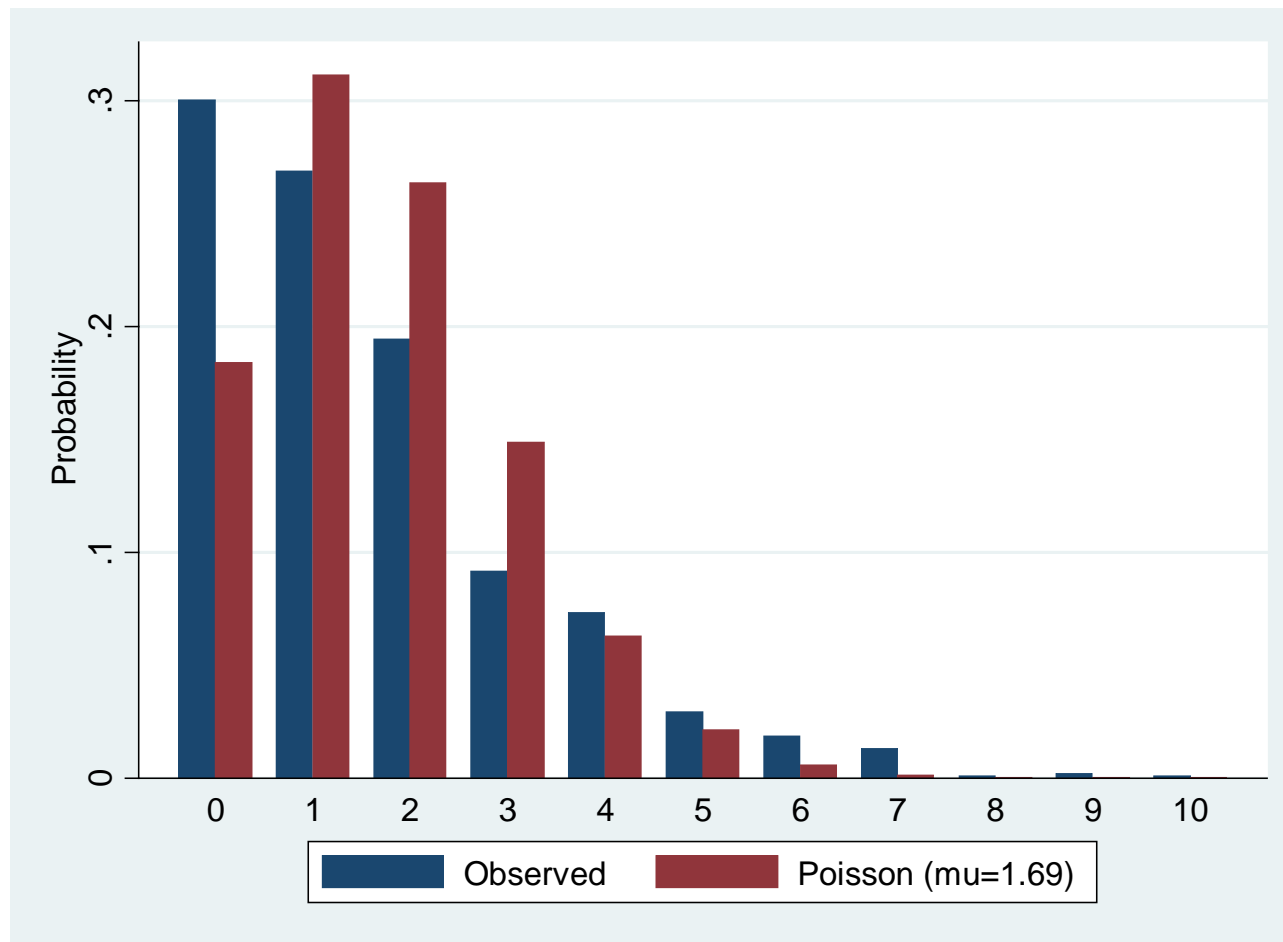
```
. tab art
```

Articles in last 3 yrs of PhD		
	Freq.	Percent
0	275	30.05
1	246	26.89
2	178	19.45
3	84	9.18
4	67	7.32
5	27	2.95
6	17	1.86
7	12	1.31
8	1	0.11
9	2	0.22
10	1	0.11
11	1	0.11
12	2	0.22
16	1	0.11
19	1	0.11
Total	915	100.00

```
. histogram art, discrete
```



# Is it Poisson?



Not exactly. There are both more zeros and more people with 4+ articles than Poisson would predict, i.e. greater variance in articles.

# Overdispersion

Variable	Obs	Mean	Std. Dev.	Min	Max
art	915	1.692896	1.926069	0	19
ment	915	8.767212	9.483915	0	76.99998

$$Y_i = \{0, 1, 2, 3, \dots, 19\} \quad \mu = 1.69 \quad \sigma = 1.93 \quad \sigma^2 = 3.73 \quad \sigma^2 > \mu$$

Overdispersion: the variance exceeds the mean. Perhaps the underlying mean is not the same for each person, and varies as a function of the person's characteristics, e.g. mentor publications.

Why overdispersion? Perhaps not all observations have the same incidence rate. It depends on the independent variables ( $\mathbf{X}$ ). If control for relevant  $\mathbf{X}$ , maybe they have the same *conditional* mean. How do  $\mathbf{X}$ s affect the mean?

# Some Publish More than Others

$\mu_i = \mathbf{x}_i \boldsymbol{\beta}$  is biased, inconsistent, and inefficient.

$\mu_i = f(\mathbf{x}_i)$  Needs to be positive. Linear does not work.

$\mu_i = e^{\beta_1 + \beta_2 X_{2i} + \dots + \beta_k X_{ki}} = e^{\mathbf{x}_i \boldsymbol{\beta}}$  works.  $0 < e^{\mathbf{x}_i \boldsymbol{\beta}} < \infty$

$$\Pr(Y_i | \mathbf{x}_i) = \frac{e^{-\mu_i} \mu_i^{Y_i}}{Y_i!}, \quad \text{where } \mu_i = e^{\mathbf{x}_i \boldsymbol{\beta}} \text{ and}$$

$$\mathbf{x}_i \boldsymbol{\beta} = \beta_1 + \beta_2 X_{2i} + \dots + \beta_k X_{ki}$$

Note that  $\mu_i = e^{\mathbf{x}_i \boldsymbol{\beta}}$  implies  $\ln(\mu_i) = \mathbf{x}_i \boldsymbol{\beta}$ , except  $\ln(0)$  is undefined.

# Poisson Likelihood Function

Poisson Regression:  $\mu_i = E(Y_i | \mathbf{x}_i) = e^{\mathbf{x}_i \boldsymbol{\beta}}$

$$\mathcal{L} = \prod_{i=1}^n \Pr(Y_i | \mathbf{x}_i) = \prod_{i=1}^n \left[ \frac{e^{-\mu_i} \mu_i^{Y_i}}{Y_i!} \right] = \prod_{i=1}^n \left[ \frac{e^{-(e^{\mathbf{x}_i \boldsymbol{\beta}})} (e^{\mathbf{x}_i \boldsymbol{\beta}})^{Y_i}}{Y_i!} \right]$$

Maximize  $\ln(\mathbf{L})$  with respect to  $\hat{\boldsymbol{\beta}}$ .

Assuming distribution has equidispersion *after controlling for observed heterogeneity* (i.e. the Poisson model fits the conditional distribution), the MLE coefficient estimates are consistent and asymptotically efficient (general properties of ML estimators).

# Poisson (null model)

```
. poisson art
```

```
Iteration 0:    log likelihood = -1742.5735
```

```
Iteration 1:    log likelihood = -1742.5735
```

```
Poisson regression
```

```
Number of obs    =          915
```

```
LR chi2(0)       =           0.00
```

```
Prob > chi2      =            .
```

```
Pseudo R2       =          0.0000
```

```
Log likelihood = -1742.5735
```

art	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
_cons	.5264408	.0254082	20.72	0.000	.4766416	.57624

$$\hat{\mu} = e^{\hat{\beta}} = e^{0.526} = 1.69$$

# Poisson Regression

```
. poisson art fem mar kid5 phd ment
```

```
Iteration 0:    log likelihood = -1651.4574
Iteration 1:    log likelihood = -1651.0567
Iteration 2:    log likelihood = -1651.0563
Iteration 3:    log likelihood = -1651.0563
```

```
Poisson regression              Number of obs   =           915
                                LR chi2(5)       =          183.03
                                Prob > chi2       =           0.0000
Log likelihood = -1651.0563      Pseudo R2      =           0.0525
```

art	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
fem	-.2245942	.0546138	-4.11	0.000	-.3316352	-.1175532
mar	.1552434	.0613747	2.53	0.011	.0349512	.2755356
kid5	-.1848827	.0401272	-4.61	0.000	-.2635305	-.1062349
phd	.0128226	.0263972	0.49	0.627	-.038915	.0645601
ment	.0255427	.0020061	12.73	0.000	.0216109	.0294746
_cons	.3046168	.1029822	2.96	0.003	.1027755	.5064581

# Predicted Values

Unmarried male with no kids, mentor = 9, PhD = 3

$$\mathbf{x}_i \hat{\boldsymbol{\beta}} = 0.305 + 0 + 0 + 0 + 0.0129(3) + 0.0255(9) = 0.573$$

The incidence rate (predicted mean):  $\mu_i = e^{\mathbf{x}_i \boldsymbol{\beta}} = e^{0.573} = 1.77$

Probabilities:  $\Pr(0) = \frac{(e^{-1.77})(1.77^0)}{0!} = \frac{(0.170)(1)}{1} = 0.17$

$$\Pr(1) = \frac{(e^{-1.77})(1.77^1)}{1!} = \frac{(0.170)(1.77)}{1} = 0.30$$

$$\Pr(2) = \frac{(e^{-1.77})(1.77^2)}{2!} = \frac{(0.170)(3.13)}{2} = 0.27$$

$\Pr(3) = 0.16$ ,  $\Pr(4) = 0.07$ , and so on....



# Prvalue

```
. prvalue, x(fem=0 kid5=0 mar=0 ment=9 phd=3)
```

poisson: Predictions for art

Confidence intervals by delta method

		95% Conf. Interval	
Rate:	1.7735	[ 1.5802,	1.9669]
$\Pr(y=0 x):$	0.1697	[ 0.1369,	0.2025]
$\Pr(y=1 x):$	0.3010	[ 0.2756,	0.3264]
$\Pr(y=2 x):$	0.2669	[ 0.2603,	0.2735]
$\Pr(y=3 x):$	0.1578	[ 0.1367,	0.1789]
$\Pr(y=4 x):$	0.0700	[ 0.0530,	0.0870]
$\Pr(y=5 x):$	0.0248	[ 0.0161,	0.0335]
$\Pr(y=6 x):$	0.0073	[ 0.0040,	0.0107]
$\Pr(y=7 x):$	0.0019	[ 0.0008,	0.0029]
$\Pr(y=8 x):$	0.0004	[ 0.0001,	0.0007]
$\Pr(y=9 x):$	0.0001	[ 0.0000,	0.0001]

	fem	mar	kid5	phd	ment
x=	0	0	0	3	9

# Marginal Effect on Mean

For the person described above, the marginal effect of an additional publication by the mentor is

$$\frac{\partial \hat{\mu}_i}{\partial x_k} = \frac{\partial e^{\mathbf{x}_i \hat{\beta}}}{\partial x_k} = e^{\mathbf{x}_i \hat{\beta}} \hat{\beta}_k = \mu_i \hat{\beta}_k$$

$$\frac{\partial \hat{\mu}_i}{\partial \text{ment}_i} = (1.77)(0.0255) = 0.0451$$

```
. prchange, x(fem=0 kid5=0 mar=0 ment=9 phd=3)
```

```
poisson: Changes in Rate for art
      min->max      0->1      -+1/2      -+sd/2      MargEfct
fem      -0.3568      -0.3568      -0.3992      -0.1987      -0.3983
mar       0.2978       0.2978       0.2756       0.1303       0.2753
kid5     -0.7550     -0.2994     -0.3284     -0.2510     -0.3279
phd       0.0876       0.0220       0.0227       0.0224       0.0227
ment      8.6639       0.0365       0.0453       0.4307       0.0453
```

```
exp(xb):      1.7735
           fem      mar      kid5      phd      ment
x=           0        0        0        3        9
sd(x)= .498679 .473186 .76488 .984249 9.48392
```

# Incidence Rate Ratio (IRR) , aka Factor Change in the Mean

What is the change in the mean (the expected number of publications, or whatever) if  $X_2$  is increased by 1 unit?

$$X'_2 = X_2 + 1$$

$$\mu = e^{\beta_1 + \beta_2 X_{2i} + \dots + \beta_k X_{ki}}$$

$$\mu' = e^{\beta_1 + \beta_2 (X_{2i} + 1) + \dots + \beta_k X_{ki}}$$

$$= e^{\beta_1 + \beta_2 X_{2i} + \beta_2 + \dots + \beta_k X_{ki}}$$

The IRR is *constant*:

$$\frac{\mu'}{\mu} = \frac{e^{\beta_1 + \beta_2 X_{2i} + \beta_2 + \dots + \beta_k X_{ki}}}{e^{\beta_1 + \beta_2 X_{2i} + \dots + \beta_k X_{ki}}} = e^{\beta_2}$$

Generally:

$e^{\beta_j}$  when  $X_j$  changes by 1 unit, or

$e^{\delta\beta_j}$  when  $X_j$  changes by  $\delta$

# Factor Change: Example

How does having a young child affect articles published during last 3 years of Ph.D? For one child:

$$\hat{\beta}_{kid5} = -0.185 \quad \frac{\mu'}{\mu} = e^{-0.185} = 0.83$$

The mean number of articles declines 17 percent. Note: does not depend on what the original mean was or the values of the other Xs (like odds ratio in logit). (Also, long way works.)

For **two** children:  $\frac{\mu''}{\mu} = e^{(2)(-0.185)} = 0.69$

Could use a standard deviation change in X, if appropriate.

# Exposure Time May Vary

- $\mu$  is a rate (arrivals per hour, articles per career), etc.
- Observations with longer time period should have greater counts even if the same mean.
- E.g. if rate is 5 per hour, then expected count is 10 over two hours, 15 over three hours, etc.
- If data consist of observations observed for different periods, this “exposure time” must be taken into account.

$$E[y_i | \mathbf{x}_i, t_i] = \mu_i t_i$$

# Incorporating Exposure Time

$$\mu_i = e^{\mathbf{x}_i\boldsymbol{\beta}}$$

$$\mu_i t_i = e^{\mathbf{x}_i\boldsymbol{\beta}} t_i$$

$$= e^{\mathbf{x}_i\boldsymbol{\beta}} e^{\ln t_i}$$

$$= e^{(\beta_1 + \beta_2 X_{2i} + \dots + \beta_K X_{Ki} + \ln t_i)}$$

Exposure time can be included in log form with the coefficient constrained to 1.

*poisson* options:

*exposure*(varname\_e)

include  $\ln(\text{varname}_e)$  in model with coefficient constrained to 1

*offset*(varname\_o)

include  $\text{varname}_o$  in model with coefficient constrained to 1

# Poisson vs. Reg: Ment

**. poisson art ment**

Poisson regression

Number of obs = 915  
 LR chi2(1) = 147.86  
 Prob > chi2 = 0.0000  
 Pseudo R2 = 0.0424

Log likelihood = -1668.6432

<b>art</b>	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
<b>ment</b>	<b>.0260498</b>	<b>.0019175</b>	<b>13.59</b>	0.000	.0222917	.029808
_cons	.2599057	.0343609	7.56	0.000	.1925596	.3272518

**. reg art ment**

Source	SS	df	MS	Number of obs	=	915
Model	317.204914	1	317.204914	F( 1, 913)	=	94.23
Residual	3073.49891	913	3.3663734	Prob > F	=	0.0000
Total	3390.70383	914	3.7097416	R-squared	=	0.0936
				Adj R-squared	=	0.0926
				Root MSE	=	1.8348

<b>art</b>	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
<b>ment</b>	<b>.0621168</b>	<b>.0063991</b>	<b>9.71</b>	0.000	.0495581	.0746755
_cons	1.148305	.0826231	13.90	0.000	.9861515	1.310458

# Approximate Log Model

variable name	storage type	display format	value label	variable label
art	byte	%8.0g		Articles in last 3 yrs of PhD
lnart	float	%9.0g		Log of art + .5

**. reg lnart ment**

Source	SS	df	MS	Number of obs =	915
Model	57.1044744	1	57.1044744	F( 1, 913) =	84.96
Residual	613.632624	913	.672105832	Prob > F =	0.0000
Total	670.737099	914	.733848029	R-squared =	0.0851
				Adj R-squared =	0.0841
				Root MSE =	.81982

lnart	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
ment	<b>.0263557</b>	<b>.0028593</b>	<b>9.22</b>	0.000	.0207441 .0319672
_cons	.2088502	.0369181	5.66	0.000	.136396 .2813044

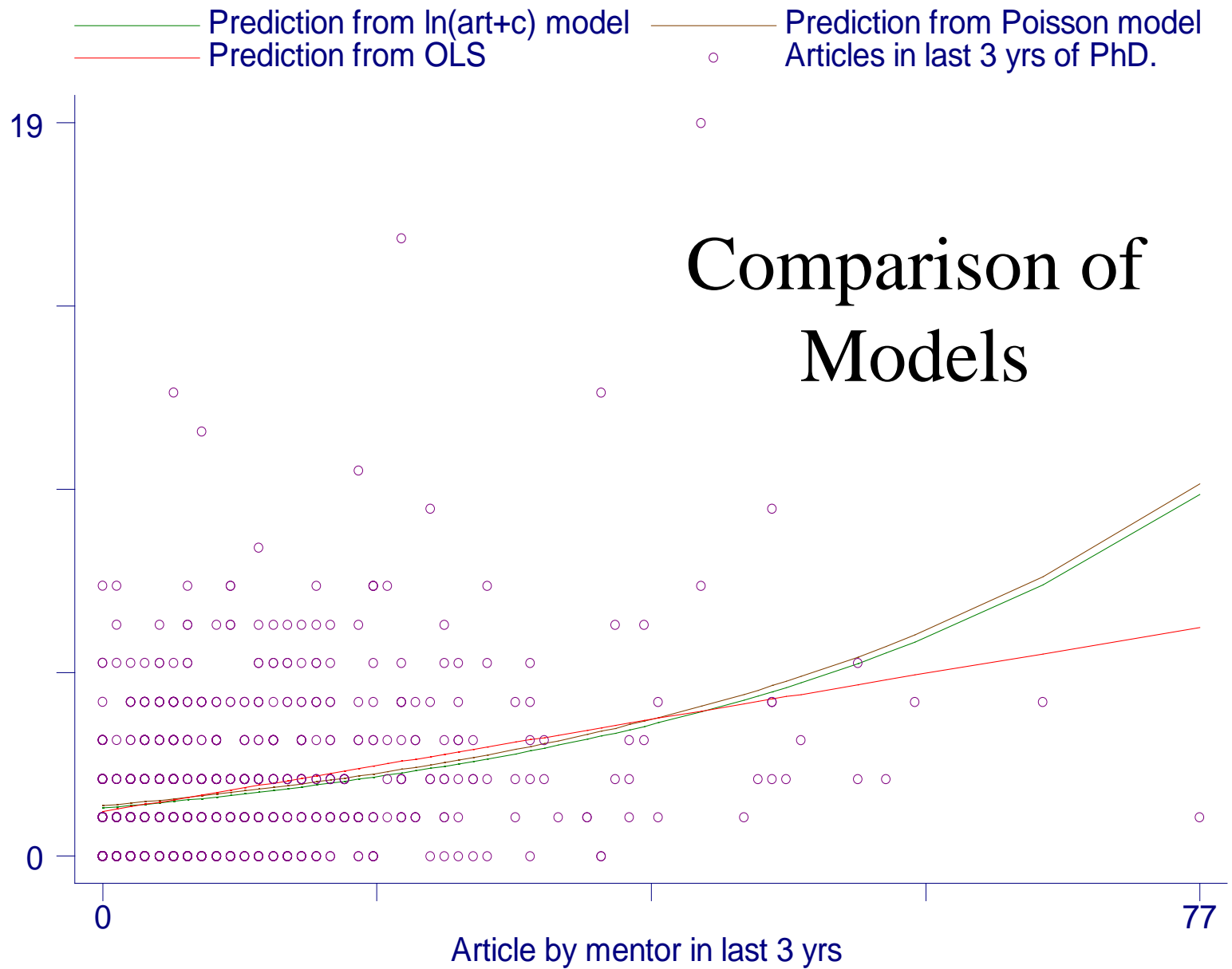
**. predict lnarthat**

(option xb assumed; fitted values)

**. gen arthat=exp(lnarthat)**



Articles in last 3 yrs of PhD.



# Poisson vs. Reg: Kid5

```
. poisson art kid5
```

Poisson regression

Number of obs = 915

LR chi2(1) = 4.20

Prob > chi2 = 0.0405

Pseudo R2 = 0.0012

Log likelihood = -1740.4757

-----		art	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----								
	kid5		-.0697818	.034501	-2.02	0.043	-.1374026	-.002161
	_cons		.5596001	.0298806	18.73	0.000	.5010353	.6181649

```
. reg art kid5
```

-----		art	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----								
	kid5		-.113856	.0832528	-1.37	0.172	-.277245	.0495331
	_cons		1.749264	.0758244	23.07	0.000	1.600454	1.898075

```
. reg lnart kid5
```

-----		lnart	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----								
	kid5		-.0583203	.0370156	-1.58	0.115	-.1309659	.0143252
	_cons		.4687894	.0337128	13.91	0.000	.4026258	.5349531

# Observed vs. Unobserved Heterogeneity

$$\textit{Poisson} : \mu_i = E(Y_i | \mathbf{X}_i) = e^{\mathbf{X}_i \boldsymbol{\beta}} \quad \text{Var}(Y_i | \mathbf{X}_i) = \mu_i$$

Assumes all observations with the same Xs have the same mean. This is not realistic (e.g. left out variables). Also assumes independence: publishing one article does not change the mean (contagion effect). Also unrealistic.

$$\textit{Negative Binomial} : \mu_i = e^{(\mathbf{X}_i \boldsymbol{\beta} + \varepsilon_i)} \quad \text{Var}(Y_i | \mathbf{x}_i) = ??$$

Allows for *unobserved* heterogeneity, and also allows for non-independence (contagion). Read results the same as Poisson.

# Incorporating Overdispersion

$$\mu_i^{NB} = e^{\mathbf{x}_i \boldsymbol{\beta} + \varepsilon_i} = e^{\mathbf{x}_i \boldsymbol{\beta}} e^{\varepsilon_i} = \mu_i \delta_i$$

Need an identifying assumption. If we assume  $E(\delta_i)=1$  (corresponding to  $E(\varepsilon_i)=0$  as in OLS, then:

$$E[\mu_i^{NB}] = E[\mu_i \delta_i] = \mu_i (1) = \mu_i$$

The NB has the same expected mean as the Poisson, but the standard errors in Poisson are biased downward, leading to incorrectly large z scores.

If we also assume  $\delta_i$  has a gamma distribution with a constant variance, then  $Y_i | \mathbf{X}_i$  has a negative binomial distribution.

$$Var(Y_i | X) = \mu_i + \alpha \mu_i^2$$

Alpha is an overdispersion parameter (from either unobserved heterogeneity or “contagion”).

# Negative Binomial Regression

```
nbreg art fem mar kid5 phd ment
```

Negative binomial regression

Number of obs = 915

LR chi2(5) = 97.96

Dispersion = mean

Prob > chi2 = 0.0000

Log likelihood = -1560.9583

Pseudo R2 = 0.0304

-----							
art	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]		
-----+-----							
fem	-.2164184	.0726724	-2.98	0.003	-.3588537	-.0739832	
mar	.1504895	.0821063	1.83	0.067	-.0104359	.3114148	
kid5	-.1764152	.0530598	-3.32	0.001	-.2804105	-.07242	
phd	.0152712	.0360396	0.42	0.672	-.0553652	.0859075	
ment	.0290823	.0034701	8.38	0.000	.0222811	.0358836	
_cons	.256144	.1385604	1.85	0.065	-.0154294	.5277174	
-----+-----							
/lnalpha	-.8173044	.1199372			-1.052377	-.5822318	
-----+-----							
alpha	.4416205	.0529667			.3491069	.5586502	
-----							

Likelihood-ratio test of alpha=0: chibar2(01) = 180.20 Prob>=chibar2 = 0.000

# Zero Inflated Models

Often more zeros than expected. If we assume that a *separate process generates at least some of the zeros*, we get the ZIP or ZINB model:

$$\Pr(Y_i = 0 | \mathbf{x}_i) = \Psi_i + (1 - \Psi_i)(\text{poisson part})$$

$$\Pr(Y_i > 0 | \mathbf{x}_i) = (1 - \Psi_i)(\text{poisson part})$$

$$\text{e.g. } \Psi_i = \Phi(\mathbf{z}_i \gamma)$$

$$\begin{aligned} E(Y_i | \mathbf{x}_i, \mathbf{z}_i) &= [0 \times \Psi_i] + [\mu_i \times (1 - \Psi_i)] \\ &= \mu_i - \mu_i \Psi_i \end{aligned}$$

```
zip depvar [indepvars] [if] [in] [weight],  
        inflate(varlist[, offset(varname)]|_cons) [options]
```

```
zinb depvar [indepvars] [if] [in] [weight],  
        inflate(varlist[, offset(varname)]|_cons) [options]
```

You need to specify the equation that generates the extra zeros.

# ZIP Analysis

```
. zip art fem mar kid5 phd ment, inflate(fem mar kid5 phd ment)
```

Zero-inflated Poisson regression

Number of obs = 915

Nonzero obs = 640

Zero obs = 275

Inflation model = logit

LR chi2(5) = 78.56

Log likelihood = -1604.773

Prob > chi2 = 0.0000

		art	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
art								
	fem		-.2091446	.0634047	-3.30	0.001	-.3334155	-.0848737
	mar		.103751	.0711111	1.46	0.145	-.035624	.243126
	kid5		-.1433196	.0474293	-3.02	0.003	-.2362793	-.0503599
	phd		-.0061662	.0310086	-0.20	0.842	-.066942	.0546096
	ment		.0180977	.0022948	7.89	0.000	.0135999	.0225955
	_cons		.640839	.1213072	5.28	0.000	.4030814	.8785967
inflate								
	fem		.1097465	.2800813	0.39	0.695	-.4392028	.6586958
	mar		-.3540107	.3176103	-1.11	0.265	-.9765155	.2684941
	kid5		.2171001	.196481	1.10	0.269	-.1679956	.6021958
	phd		.0012702	.1452639	0.01	0.993	-.2834418	.2859821
	ment		-.134111	.0452461	-2.96	0.003	-.2227918	-.0454302
	_cons		-.5770618	.5093853	-1.13	0.257	-1.575439	.421315

# Zero Truncated Poisson

- Another possibility is *zero truncated* model.
- In general, the goal of modifications is to adjust for lack of fit by a standard Poisson.
- In this case, maybe you only have data on published authors, so that the minimum in the data is 1.

```
ztp depvar [indepvars] [if] [in] [weight] [, options]
```

```
ztnb depvar [indepvars] [if] [in] [weight] [, options]
```



# Comparison of Poisson, Poisson on Zero Truncated Data, and Zero Truncated Poisson

	<b>poisson</b>	<b>wrong</b>	<b>ztp</b>
fem	-0.225*** (-4.11)	-0.162** (-2.98)	-0.229*** (-3.51)
mar	0.155* (2.53)	0.0682 (1.11)	0.0965 (1.32)
kid5	-0.185*** (-4.61)	-0.0990* (-2.47)	-0.142** (-2.93)
phd	0.0128 (0.49)	-0.0131 (-0.49)	-0.0127 (-0.41)
ment	0.0255*** (12.73)	0.0150*** (7.08)	0.0187*** (8.22)
_cons	0.305** (2.96)	0.827*** (8.04)	0.671*** (5.48)
N	<b>915</b>	<b>640</b>	<b>640</b>

# ZTNB Example

```
. drop if art==0
```

```
(275 observations deleted)
```

```
. ztnb art fem mar kid5 phd ment
```

```
Zero-truncated negative binomial regression      Number of obs      =          640
                                                LR chi2(5)          =          44.58
Dispersion      = mean                        Prob > chi2          =          0.0000
Log likelihood = -1027.3185                    Pseudo R2           =          0.0212
```

art	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
fem	-.2446712	.0972181	-2.52	0.012	-.4352153	-.0541272
mar	.1034172	.1094297	0.95	0.345	-.1110611	.3178955
kid5	-.1532593	.0722291	-2.12	0.034	-.2948257	-.011693
phd	-.0029336	.0480673	-0.06	0.951	-.0971437	.0912766
ment	.0237382	.0042868	5.54	0.000	.0153362	.0321402
_cons	.355125	.1968307	1.80	0.071	-.0306562	.7409062
/lnalpha	-.6034753	.2249915			-1.044451	-.1625001
alpha	.5469076	.1230496			.3518851	.850016

```
Likelihood-ratio test of alpha=0:  chibar2(01) = 105.43 Prob>=chibar2 = 0.000
```