

PBSH 32410 / STAT 22401 Winter 2025 J. Dignam

Exam 2

March 11 10:00-12:00

Details: 2 hrs, page of notes (two-sided)

Important Topics

- **Multiple Linear Regression - General**

- interpreting β s
- categorical predictors/indicator variables and continuous variables
- models with main effects vs. interactions - how different?

- **Multiple Linear Regression - Special Situations**

- familiarity with model violations - recognize from plots, etc

- transformations on Y -
 - * log transforms - what does this mean for β ?
 - * Box-Cox - what is being evaluated here?
- familiarity with transformation issues - why we use, etc

- **Logistic Regression**

- relationship of frequency data to the model and odds ratios
- basic interpretation of model coefficients - log odds ratio and odds ratios
- calculating a probability of event (1) for a given set of covariate values

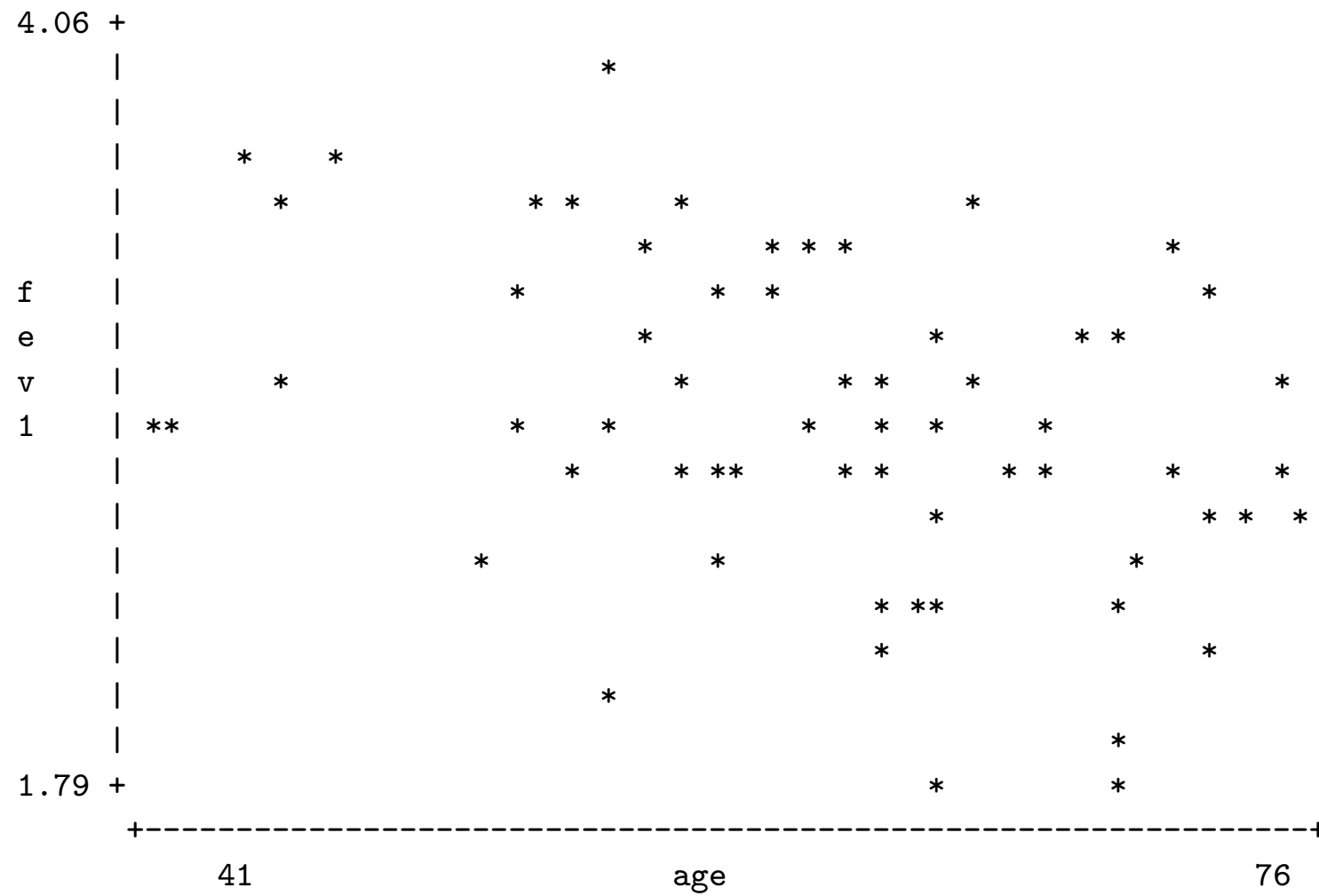
- **Poisson Regression**

- relationship of mean count and rate data to the model and incidence rate ratios
- basic interpretation of model coefficients - log of mean counts or rate, etc

Linear Regression Models

Data on FEV1 predicted by age at three geographic centers

```
. plot fev1 age
```



Linear Regression Models

```
. by center: sum age fev1
```

```
-----  
-> center = 1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
age	21	62.04762	8.558482	41	76
fev1	21	2.697619	.468614	1.79	3.47

```
-----  
-> center = 2
```

Variable	Obs	Mean	Std. Dev.	Min	Max
age	21	61.57143	9.452891	44	75
fev1	21	3.226667	.3018664	2.67	3.69

```
-----  
-> center = 3
```

Variable	Obs	Mean	Std. Dev.	Min	Max
age	24	60.04167	8.306515	42	73
fev1	24	2.93375	.4365359	2.19	4.06

Linear Regression Models

```
. reg fev1 center2 center3
```

Source		SS		df		MS		Number of obs	=	66
-----+-----										
								F(2, 63)	=	8.77
Model		2.95117175		2		1.47558588		Prob > F	=	0.0004
Residual		10.5974099		63		.168212855		R-squared	=	0.2178
-----+-----										
								Adj R-squared	=	0.1930
Total		13.5485816		65		.208439718		Root MSE	=	.41014

fev1		Coef.	Std. Err.		t	P> t		[95% Conf. Interval]		
-----+-----										
center2		.529	.1265712		4.18	0.000		.2761152		.78198
center3		.236	.122552		1.93	0.059		-.0087698		.4810317
_cons		2.697	.0894994		30.14	0.000		2.518769		2.876469

What does this model say and why does it reproduce means by center?

Linear Regression Models

```
. reg fev1 age center2 center3
```

Source	SS	df	MS	Number of obs	=	66
-----+-----				F(3, 62)	=	12.31
Model	5.05636517	3	1.68545506	Prob > F	=	0.0000
Residual	8.49221647	62	.136971233	R-squared	=	0.3732
-----+-----				Adj R-squared	=	0.3429
Total	13.5485816	65	.208439718	Root MSE	=	.3701

fev1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----						
age	-.0208577	.0053203	-3.92	0.000	-.0314928	-.0102226
center2	.5191154	.1142423	4.54	0.000	.2907483	.7474825
center3	.1942915	.1111012	1.75	0.085	-.0277966	.4163796
_cons	3.991788	.3398463	11.75	0.000	3.312445	4.671131

What is meaning of intercept here?

What is predicted FEV for 45 year old from center 2?

Linear Regression Models - with interaction effects

```
. reg fev1 age center2 center3 agebycent2 agebycent3
```

```
. . .  
. . .
```

fev1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
age	-.0117189	.0097259	-1.20	0.233	-.0311736	.0077358
center2	1.282685	.8193459	1.57	0.123	-.3562513	2.92162
center3	1.052032	.8314677	1.27	0.211	-.6111514	2.715214
agebycent2	-.0123307	.0131199	-0.94	0.351	-.0385744	.0139131
agebycent3	-.0139804	.0134875	-1.04	0.304	-.0409595	.0129987
_cons	3.424748	.6089115	5.62	0.000	2.206744	4.642753

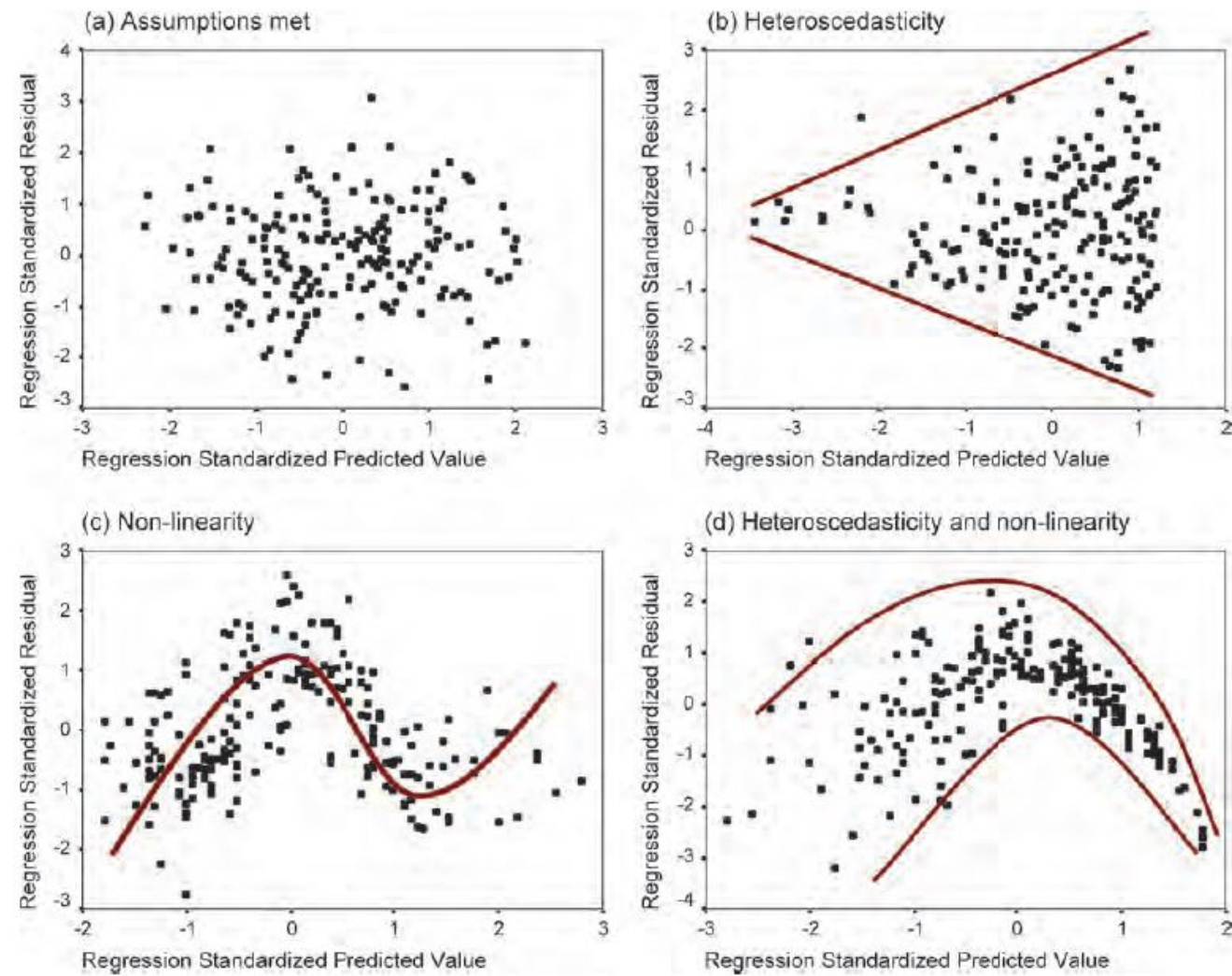
Slope in center 1: $-.01172$ per year of age

Slope in center 2: $-.01172 - .01233 = -.02405$ per year of age

Slope in center 2: $-.01172 - .01398 = -.02570$ per year of age

not statistically different here, based on tests on the interaction coefficients. What is another way to test?

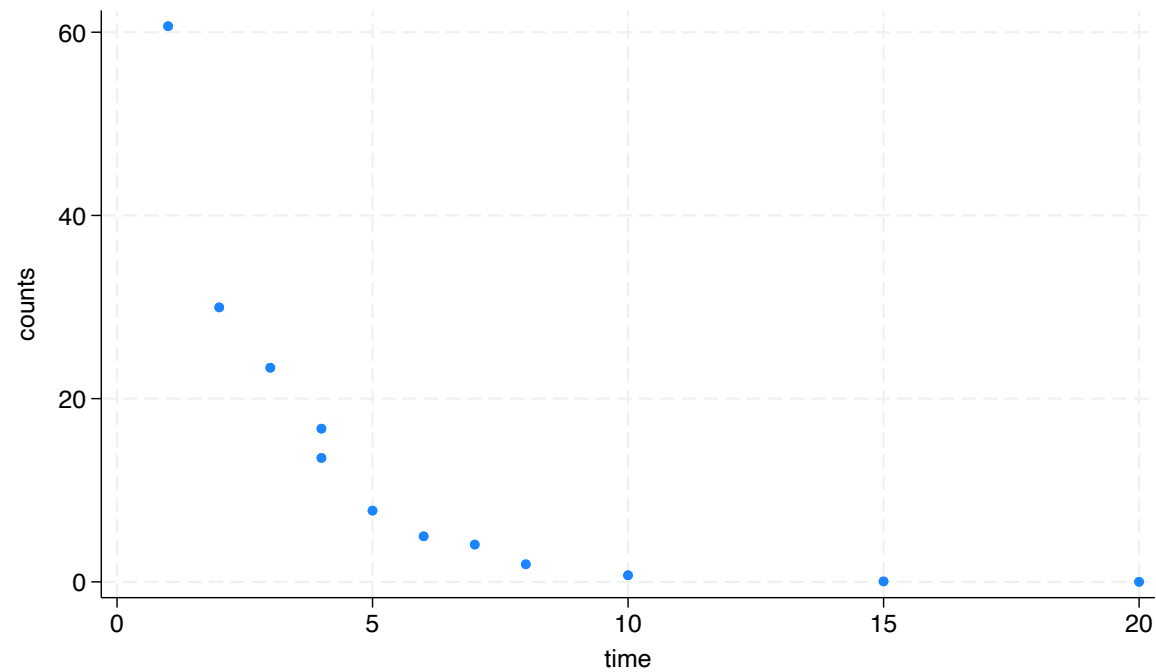
Some Diagnostic plots for OLS



(<https://tobeneo.wordpress.com/2013/12/08/multiple-regression-iii/>)

Transformations

We want to predict radioactivity counts at different times from contamination.



Is there a transformation that could help?

Transformations

```
. boxcox counts time
Fitting comparison model
. . .
Iteration 4:  Log likelihood = -39.643945
```

```
Fitting full model
```

```
Iteration 0:  Log likelihood = -47.45472
. . .
Iteration 7:  Log likelihood = -4.4707423
```

```

                                     Number of obs   =          12
                                     LR chi2(1)        =          70.35
Log likelihood = -4.4707423          Prob > chi2      =          0.000
```

```
-----
      counts | Coefficient  Std. err.      z    P>|z|    [95% conf. interval]
-----+-----
      /theta |   .0117264   .0096365    1.22   0.224   - .0071608   .0306136
-----
```

```
Estimates of scale-variant parameters
-----
```

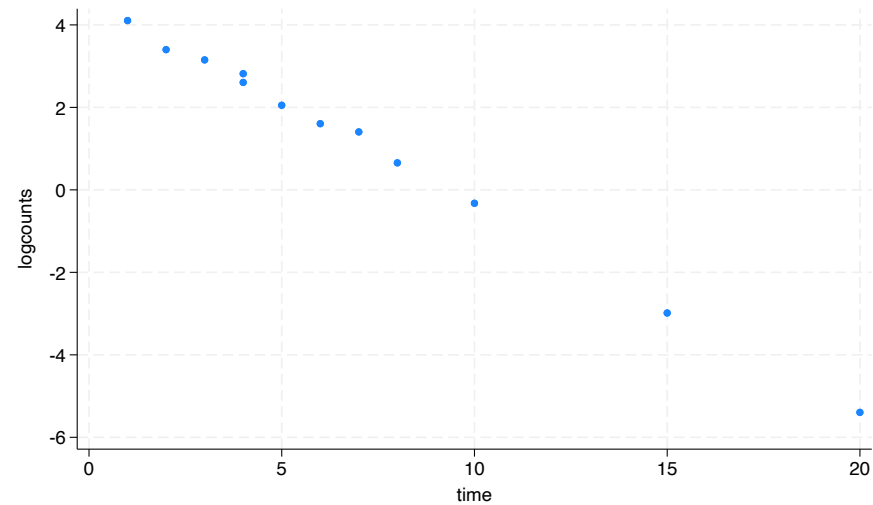
	Coefficient		
Notrans			
time	-.4975041		
_cons	4.664043		
/sigma	.1194851		
Test	Restricted	LR statistic	
H0:	log likelihood	chi2	Prob > chi2
theta = -1	-86.978782	165.02	0.000
theta = 0	-5.1925572	1.44	0.230
theta = 1	-47.45472	85.97	0.000

What is the suggested new response variable to predict w/time?

$$Y' = (Y^\theta - 1)/\theta$$

Since theta not different from zero, natural log transform is suggested. Do data look linear on log(counts) scale?

Transformations



```
. reg logcounts time
```

```
. . .
```

logcounts	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
-----+-----						
time	-.5005141	.007411	-67.54	0.000	-.5170269	-.4840013
_cons	4.636288	.0657662	70.50	0.000	4.489752	4.782825

How to interpret?

Binary Outcome Data and Regression Models

Data on possible sources of food poisoning at a gathering

```
. list, clean
```

	crabsalad	psalad	n	isick
1.	0	0	23	0
2.	0	0	0	1
3.	0	1	24	0
4.	0	1	22	1
5.	1	0	4	1
6.	1	0	31	0
7.	1	1	80	0
8.	1	1	120	1

Of those who had neither crab or potato salad, 0 out of 23 sick,

Of those who had potato salad only, 24 were not sick, 24 were sick,

etc

Binary Outcome Data and Regression Models

```
. tab isick crabsalad [fweight=n]
```

isick	crabsalad		Total
	0	1	
0	47	111	158
1	22	124	146
Total	69	235	304

Odds ratio for eating crab salad?

OR = (odds of illness in exposed) / (odds of illness in unexposed)

$$= \frac{124/111}{22/47} = 2.39$$

Binary Outcome Data and Regression Models

Running the logistic model:

```
. logit isick crabsalad [fweight=n]
```

```
Iteration 0:   log likelihood = -210.47984
```

```
. . .
```

```
Logistic regression
```

```
Number of obs      =          304
```

```
LR chi2(1)         =           9.51
```

```
Prob > chi2        =          0.0020
```

```
Log likelihood = -205.72331
```

```
Pseudo R2         =          0.0226
```

isick	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----						
crabsalad	.8698565	.2894904	3.00	0.003	.3024658	1.437247
_cons	-.7591051	.2583237	-2.94	0.003	-1.26541	-.2528

What is the odds ratio? $\exp(0.86985) = 2.39$

What is being tested? What is the inferential conclusion?

Binary Outcome Data and Regression Models

```
. logit isick crabsalad psalad [fweight=n]
```

```
. . .
```

```
Logistic regression               Number of obs   =       304
                                LR chi2(2)        =       60.45
                                Prob > chi2        =       0.0000
Log likelihood = -180.25338       Pseudo R2      =       0.1436
```

isick	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
crabsalad	.6097114	.3169859	1.92	0.054	-.0115696	1.230992
psalad	2.825864	.5361679	5.27	0.000	1.774994	3.876733
_cons	-3.007495	.5675813	-5.30	0.000	-4.119934	-1.895056

Which food item has greater risk? What is probability of being sick for those who had both?

$$\Pr(sick|both\ items) = \frac{\exp(-3.007 + 0.6097 + 2.8258)}{1 + \exp(-3.007 + 0.6097 + 2.8258)} = 0.6055$$

Binary Outcome Data and Regression Models

What is the log odds ratio comparing someone who had crab salad only to someone who had potato salad only?

Write out the difference:

$$(-3.007 + 2.826) - (-3.007 + .6097) = 2.216$$

and $\exp(2.216) = 9.17$

Note that OR for potato salad is $\exp(2.83) = 16.9$ and OR for crab salad is $\exp(.610) = 1.84$

ratio is 9.17 - OR for potato salad vs crab salad

Count Data and Regression Models

Ex: 3 different garden plantings are monitored for monarch butterfly visits. Counts are made over a fixed period:

	Gtype	count	g1	g3
1.	A	0	1	0
2.	A	3	1	0
3.	A	2	1	0
4.	A	2	1	0
5.	A	1	1	0
. . .				
9.	B	5	0	0
10.	B	9	0	0
11.	B	5	0	0
12.	B	5	0	0
13.	B	7	0	0
. . .				
17.	C	8	0	1
18.	C	14	0	1
19.	C	12	0	1
20.	C	12	0	1
21.	C	10	0	1
. . .				

Count Data and Regression Models

```
. by Gtype: sum count
```

```
-----  
-> Gtype = A
```

Variable	Obs	Mean	Std. dev.	Min	Max
count	8	1.75	1.28174	0	3

```
-----
```

```
-> Gtype = B
```

Variable	Obs	Mean	Std. dev.	Min	Max
count	8	6.5	2.329929	5	11

```
-----
```

```
-> Gtype = C
```

Variable	Obs	Mean	Std. dev.	Min	Max
count	8	11.75	3.284161	8	18

Count Data and Regression Models

```
. poisson count g1 g3
```

```
Iteration 0: Log likelihood = -50.669741
```

```
. . .
```

```
Poisson regression
```

```
Number of obs = 24
```

```
LR chi2(2) = 66.46
```

```
Prob > chi2 = 0.0000
```

```
Log likelihood = -50.619718
```

```
Pseudo R2 = 0.3963
```

count		Coefficient	Std. err.	z	P> z	[95% conf. interval]
-----+-----						
g1		-1.312186	.3010969	-4.36	0.000	-1.902325 - .7220473
g3		.5920511	.1728267	3.43	0.001	.253317 .9307852
_cons		1.871802	.138675	13.50	0.000	1.600004 2.1436

What are these numbers? Output is in $\log_e(counts)$

$\exp(1.871802) = 6.5$ - mean count in baseline (garden 2) group

$\exp(1.871802 - 1.312186) = 1.75$ - mean count in garden 1

$\exp(1.871802 + .5920511) = 11.75$ - mean count in garden 3

Rate Data and Regression Models

Here are skin cancer rates for two cities (Minneapolis (0) and Dallas (1)) and by age (in groups, midpoint of age used)

```
. list, clean
```

	cases	city	age	pyrs
1.	1	0	19.5	172675
2.	16	0	29.5	123065
3.	30	0	29.5	96216
4.	71	0	49.5	92051
5.	102	0	59.5	72159
6.	130	0	69.5	54722
7.	133	0	79.5	32185
8.	40	0	89.5	8328
9.	4	1	19.5	181343
10.	38	1	29.5	146207
11.	119	1	39.5	121374
12.	221	1	49.5	111353
13.	259	1	59.5	83004
14.	310	1	69.5	55932
15.	226	1	79.5	29007
16.	65	1	89.5	7503

Rate Data and Regression Models

Run the rate table by city:

```
. ir cases city pyrs
```

Incidence-rate comparison

	city		
	Exposed	Unexposed	Total
-----+-----+-----			
cases	1242	523	1765
pyrs	735723	651401	1387124
-----+-----+-----			
Incidence rate	.0016881	.0008029	.0012724
	Point estimate		[95% conf. interval]
	-----+-----		
Inc. rate diff.	.0008853		.0007688 .0010017
Inc. rate ratio	2.102587		1.896843 2.333224 (exact)

What is the interpretation?

Rate Data and Regression Models

Run the model with city as predictor

```
poisson cases city, exposure(pyrs)
```

```
. . .
```

```
Poisson regression
```

cases	Coefficient	Std. err.	z	P> z	[95% conf. interval]		
-----+-----							
city	.7431685	.0521268	14.26	0.000	.641002	.8453351	
_cons	-7.127299	.0437269	-163.00	0.000	-7.213002	-7.041596	
ln(pyrs)	1	(exposure)					

Interpretation: Output in (natural) log(incidence rate) for baseline and log increase/decrease for covariate increment

$\exp(-7.127299) = 0.000803$ - incidence rate in Minn.

$\exp(-7.127299 + 0.7431685) = 0.00169$ - incidence rate in Dallas.

Incidence rate ratio is $0.00169/0.00080 = 2.10$ - same as that obtained from the incidence table