ECON 546: Spring 2010 Solution to Assignment 3 Q.1. (a) By independence - $L = c^{n} TT x_{i}^{-(c+1)}$ log Lu = n log(c) - (c+1) = log(xi) log LR = nlog(2) - (2+1) Elog(2i) $= n \log(1) - 3 \sum \log(x_i)$ (2)gL/2c) = N/c - Elog(xi) =0 => 2 = (n / E log(xi)] (d'log L/dc') = - M/c2 < 0 (Everynhere) So, LRT = 2 [log Lu - log LR] = $2 \int \left[n \log(\tilde{c}) - (\tilde{c} + i) \mathcal{E}[\log(\pi i)] \right]$ - [n log(2) - 3 2 log(2)]] = 2 { $n\log\left[\frac{n}{z}\right] - (n + Z\log(x)) - n\log(x)$ + 3 2 log(xi) }

2 = 2 { $n \left[log \left(\frac{1}{z_{Ni}} \right) - 1 - log (2) \right] + 2 Z log (x_i) }$ = 2 { n [log (2011) - 10693148] + 2 Elog(xi)} (b) I = - E [22/03 L/202] = 1/22 IA = limit [+I] = Ver $I^* = (\sqrt{\tilde{c}})$ [So that plin $(\pi I^*) = IA$] + Wald = $n(\tilde{c}-2)^2/\tilde{c}^2$ $= \Lambda \left[1 - \frac{2}{2}\right]^{2} = \Lambda \left[1 - \frac{2}{2}\right] \frac{2}{3} \left[\frac{1}{3}\right]^{2}$ (e) $LM = (D\log Lu)^2 I^*(\tilde{c}_0)^{-1}$ where Eo = 2. So, LM =4 (2 - Zlag(a;)) 2/n = W! n = 200; $11\chi_i = 1.2204032 \times 10^{39}$ (d) 50, Zlog(xi) = lig TI xi = 90 Then, LRT = 2.14388 Wald = 2.0 LM = 2.0 Each statistic do Xin. 5% critical value is 3.84, so in each case DO NOT REJECT Ho.

QUESTION 2 (a)

'INITIALIZE VARIOUS VALUES

'----scalar nrep=5000

'CC DENOTES THE TRUE VALUE OF THE PARAMETER, "C" 'IN THE NEXT LINE OF CODE WE IMPOSE THE NULL HYPOTHESIS TO BE TRUE, SO IN THIS CASE THE "POWERS" OF THE TESTS THAT ARE CALCULATED BELOW ARE ACTUALLY THE TRUE SIGNIFICANCE LEVELS FOR THIS SAMPLE SIZE

scalar crit=@qchisq(0.95,1) smpl 1 10

'START THE MONTE CARLO LOOP 'NOTE: THE PARETO RANDOM NUMBER GENERATOR IN EVIEWS APPEARS TO WORK FINE FOR SOME CHOICES OF "C", BUT NOT FOR OTHERS - IF C=2, FOR EXAMPLE, THERE IS A TENDENCY TO PRODUCE LARGE OUTLIERS, WHICH THEN MESS UP ALL OF THE CALCULATIONS AND RESULTS. 'SO, GENERATE THE PARETO RANDOM VALUES USING THE RESULT THE (1/U)^(1/C), WHERE U IS UNIFORM ON (0,1), WILL BE PARETO.

'_____ for !i=1 to nrep $y=(1/@runif(0,1))^{(1/cc)}$ scalar sumly=@sum(log(y)) scalar mle=n/sumlv scalar Irt=2*(n*(log(mle)-1.693148)+2*sumly)scalar wald=n*(mle-2)^2/(mle^2) scalar $Im=(4/n)^*((n/2)-sumly)^2$ if(Im>crit) then sumIm=sumIm+1 endif if(Irt>crit) then sumIrt=sumIrt+1 endif if(wald>crit) then sumw=sumw+1 endif

next

'END OF MONTE CARLO LOOP scalar power_Irt=sumIrt/nrep scalar power_w=sumw/nrep scalar power_Im=sumIm/nrep

(b)	Sizes when n=1	0 n=50	n=200	n=500
LRT	0.0484	0.0500	0.0518	0.0518
LM	0.0420	0.0468	0.0516	0.0498
Wald	0.0420	0.0468	0.0516	0.0498

The LRT has the least size distortion for small sample sizes. When n > 50 the other two tests have slightly less size distortion. NOTE THAT IN FACT THE WALD AND LM TEST STATISTICS ARE IDENTICAL FOR THIS PARTICULAR PROBLEM!

- (c) Some illustrative "powers" are given below. The asymptotic critical values have been used so these powers are not "size-adjusted". We can still see the following, though:
 - (i) True size of LRT exceeds those of LM and Wald when n = 10 (see above), and yet when c < 2, the "raw" (unadjusted) powers of LM and Wald exceed LRT. So LM and Wald definitely have greater power than LRT in this situation.
 - (ii) Conversely, when c > 2, the "raw" (unadjusted) powers of LM and Wald are less than that of the LRT. So in this case we can't say which test has the greater (sizeadjusted) power, strictly speaking. However, given the very slight size distortions and the big raw power differences, the LRT is probably the superior test in this case.

с	LRT	Wald	LM
1.6	0.1094	0.1662	0.1662
1.4	0.2198	0.2988	0.2988
1.0	0.6194	0.7046	0.7046
0.6	0.9614	0.9732	0.9732
0.4	0.9968	0.9982	0.9982
2.4	0.0880	0.0258	0.0258
2.8	0.1682	0.0418	0.0418
3.2	0.2870	0.0896	0.0896
3.6	0.4132	0.1524	0.1524
4.0	0.5422	0.2316	0.2316
4.8	0.7636	0.4274	0.4274
6.0	0.9338	0.7058	0.7058
8.0	0.9940	0.9396	0.9396

"Powers" when n=10 (not size-adjusted):

(d) Clearly, we need to "size-adjust" the tests. For each test separately, find the actual critical value (by trial and error) that ensures that the rejection rate is exactly 5% when n=10 and c=2. Then use *these* critical values with different values of c to get the appropriate rejection rates (powers) of the tests.

QUESTION 3



Clearly the variance exceeds the mean – there is over-dispersion – perhaps the Poisson model is not the best choice. Let's see.

(b) The following is a reasonable model – you may have found a better one:

View Proc Object Print Name Freeze Estimate Forecast Stats Resids

Dependent Variable: FLIGHTS Method: ML/QML - Poisson Count (Quadratic hill climbing) Date: 03/18/08 Time: 09:20 Sample: 1 311 Included observations: 310 Convergence achieved after 8 iterations QML (Huber/White) standard errors & covariance

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C SELECTED*MASTER MASTER DECEASED MILITARY CSMH EVA	0.616915 -0.018627 36.70969 -0.757208 0.258431 0.449001 0.021593	0.083739 0.004881 9.672076 0.150722 0.095619 0.139126 0.002556	7.367157 -3.816373 3.795430 -5.023886 2.702729 3.227290 8.449300	0.0000 0.0001 0.0001 0.0000 0.0069 0.0012 0.0000
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood Restr. log likelihood LR statistic (6 df) Probability(LR stat)	0.201108 0.185289 1.468018 652.9882 -531.7639 -573.5634 83.59901 6.66E-16	Mean deper S.D. depen Akaike info Schwarz cr Hannan-Qu Avg. log like LR index (F	ndent var dent var criterion iterion inn criter. elihood ?seudo-R2)	2.045161 1.626408 3.475896 3.560270 3.509625 -1.715367 0.072877

(c) Military background is significant and has a positive marginal effect. Date of birth (BORN) and gender are not significant. Academic achievement is significant if the astronaut has a Masters degree rather than a Bachelors of Doctorate. The Masters effect impacts on both the intercept and also on the marginal effect of the year of selection – the latter is significant only if the astronaut has a Masters, and not otherwise.

(**d**)

View Proc Object Print Name Freeze Estimate Forecast Stats Resids

Dependent Variable: FLIGHTS Method: ML/QML - Poisson Count (Quadratic hill climbing) Date: 03/18/08 Time: 09:15 Sample: 1 311 Included observations: 311 Convergence achieved after 8 iterations QML (Huber/White) standard errors & covariance

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C SELECTED	20.31522 -0.009884	6.407385 0.003235	3.170594 -3.055659	0.0015 0.0022
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood Restr. log likelihood LR statistic (1 df) Probability(LR stat)	0.016077 0.012893 1.613283 804.2286 -569.8638 -574.8707 10.01385 0.001554	Mean deper S.D. depend Akaike info Schwarz cri Hannan-Qui Avg. log like LR index (P	ident var dent var criterion terion nn criter. lihood seudo-R2)	2.045016 1.623785 3.677581 3.701631 3.687194 -1.832360 0.008710



Model does not fit very well - does not explain the variation in the data.

View Proc Object Print 1	Name Freeze E	Estimate Foreca	st Stats Resid	s		
Dependent Variable: FLIGHTS Method: ML/QML - Poisson Count (Quadratic hill climbing) Date: 03/18/08 Time: 09:18 Sample: 1 311 Included observations: 310 Convergence achieved after 8 iterations QML (Huber/White) standard errors & covariance						
Variable	Coefficient	Std. Error	z-Statistic	Prob.		
C SELECTED CSMH MOONC DECEASED EVA	25.49079 -0.012520 0.484414 -0.288915 -0.729454 0.020268	6.726606 0.003393 0.143501 0.134803 0.150855 0.002507	3.789548 -3.690369 3.375695 -2.143234 -4.835459 8.084374	0.0002 0.0002 0.0007 0.0321 0.0000 0.0000		
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood Restr. log likelihood LR statistic (5 df)	0.182686 0.169244 1.482403 668.0459 -537.0700 -573.5634 72.98684	Mean dependent var2.045S.D. dependent var1.626Akaike info criterion3.503Schwarz criterion3.575Hannan-Quinn criter.3.532Avg. log likelihood-1.732LR index (Pseudo-R2)0.063		2.045161 1.626408 3.503677 3.575998 3.532588 -1.732484 0.063626		



This is much better. Note that by the SC values, this model is not as good as the one in part (b) above.

(e) Estimate the corresponding Negative Binomial model and apply Wald test:

Wald Test: Equation: EQ01

Test Statistic	Value	df	Probability				
F-statistic Chi-square	0.550059 0.550059	(1, 303) 1	0.4589 0.4583				
Null Hypothesis Summary:							
Normalized Restri	Value	Std. Err.					
EXP(C(7))		0.033778	0.045544				

Delta method computed using analytic derivatives.

View Proc Object Print Name Freeze Estimate Forecast Stats Resids

Dependent Variable: FLIGHTS Method: ML - Negative Binomial Count (Quadratic hill climbing) Date: 06/18/04 Time: 15:49 Sample: 1 311 Included observations: 310 Excluded observations: 1 Convergence achieved after 9 iterations QML (Huber/White) standard errors & covariance

	Coefficient	Std. Error	z-Statistic	Prob.	
C CSMH MOONC SELECTED DECEASED EVA	26.28630 0.484820 -0.297669 -0.012921 -0.733482 0.020284	7.167289 0.144979 0.136000 0.003615 0.151823 0.002579	3.667538 3.344080 -2.188733 -3.573835 -4.831170 7.864618	0.0002 0.0008 0.0286 0.0004 0.0000 0.0000	
Mixture Parameter					
SHAPE:C(7)	-3.387936	1.348327	-2.512696	0.0120	
R-squared Adjusted R-squared S.E. of regression Sum squared resid	0.181493 0.165285 1.485931 669.0208	Mean deper S.D. depen Akaike info Schwarz cri	ndent var dent var criterion terion	2.045161 1.626408 3.508366 3.592741	

Cannot reject the null that the restriction holds- the test supports the Poisson model.

(f) From the Poisson model –

Forecast	<u>×</u>
Forecast equation EQ01	
Series to forecast © Expected dependent variab © In	dex - where E(Dep) = exp(Index)
Series names Forecast name: flightsf S.E. (optional): GARCH(optional):	Method Static forecast (no dynamics in equation) Structural (ignore ARMA) Coef uncertainty in S.E. calc
Forecast sample	Output Forecast graph Forecast evaluation
Insert actuals for out-of-sample obse	rvations Cancel

Generate Series by Equation						
Enter equation						
z=((flights-flightsf)^2-flights)/(flightsf*@sqrt(2))						
Sample						
1 311						
OK Cancel						

Equation Estimation	×
Specification Options	
Equation specification Dependent variable followed by list of regressors including ARMA and PDL terms, OR an explicit equation like Y=c(1)+c(2) [*] X.	4
zd	A
Estimation settings	
Method: LS - Least Squares (NLS and ARMA)	•
Sample: 1 311	*
OK	Cancel

View Proc Object Print Name Freeze Estimate Forecast Stats Resids

Dependent Variable: Z Method: Least Squares Date: 03/18/08 Time: 09:29 Sample: 1 311 Included observations: 310

Variable	Coefficient	Std. Error	t-Statistic	Prob.
С	0.081785	0.050531	1.618530	0.1066
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood	0.000000 0.000000 0.889682 244.5843 -403.1340	Mean depen S.D. depend Akaike info Schwarz crit Durbin-Wats	dent var lent var criterion terion son stat	0.081785 0.889682 2.607316 2.619370 1.860553

Equation: UNTITLED Workfile: ASTRONAUTS::Astronauts\

View Proc Object Print Name Freeze Estimate Forecast Stats Resids

Dependent Variable: Z Method: Least Squares Date: 03/18/08 Time: 09:30 Sample: 1 311 Included observations: 310

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FLIGHTSF	0.016451	0.023336	0.704929	0.4814
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood	-0.006859 -0.006859 0.892728 246.2618 -404.1935	Mean depen S.D. depend Akaike info Schwarz crit Durbin-Wats	ident var lent var criterion terion son stat	0.081785 0.889682 2.614152 2.626205 1.853656

In each case, we cannot reject the null that the coefficient is zero (at the 10% level) – this again supports the Poisson model.

View Proc Object Print Name Freeze Estimate Forecast Stats Resids

Dependent Variable: FLIGHTS Method: ML/QML - Poisson Count (Quadratic hill climbing) Date: 03/18/08 Time: 09:27 Sample: 1 311 Included observations: 310 Convergence achieved after 8 iterations QML (Huber/White) standard errors & covariance

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C CSMH MOONC SELECTED DECEASED EVA	25.49079 0.484414 -0.288915 -0.012520 -0.729454 0.020268	6.726606 0.143501 0.134803 0.003393 0.150855 0.002507	3.789548 3.375695 -2.143234 -3.690369 -4.835459 8.084374	0.0002 0.0007 0.0321 0.0002 0.0000 0.0000
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood Restr. log likelihood LR statistic (5 df) Probability(LR stat)	0.182686 0.169244 1.482403 668.0459 -537.0700 -573.5634 72.98684 2.44E-14	Mean deper S.D. depend Akaike info Schwarz cri Hannan-Qui Avg. log like LR index (P	ident var Jent var criterion terion nn criter. lihood seudo-R2)	2.045161 1.626408 3.503677 3.575998 3.532588 -1.732484 0.063626

(i) The hours of extra-vehicular activity is a continuous variable. The marginal effect is calculated as series marg_eff_eva=flightsf*c(6)

Series: MARG_EFF_EVA Workhile: ASTRU					
View Proc Object Properties Print Name Freeze					
	MARG_EF				
Mean	0.041451				
Median	0.038533				
Maximum	0.132455				
Minimum	0.015735				
Std. Dev.	0.014890				
Skewness	1.925981				
Kurtosis	10.61127				

A representative m.e. would be 0.04. So, 10 extra hours of EVA implies 4 extra expected flights, other things being equal.

(ii) The medal effect is via a dummy variable – obtain the prediction of conditional mean with this dummy set to unity and then to zero, and take the difference to get the marginal effect. I'll set the other regressors to their sample medians. (There are other options here.)

 $\begin{array}{l} scalar marg_eff_csmh=@exp(c(1)+c(2)*1+c(3)*@median(moonc)+c(4)*@median(selected) \\ +c(5)*@median(deceased)+c(6)*@median(eva))-\\ @exp(c(1)+c(2)*0+c(3)*@median(moonc)+c(4)*@median(selected)+\\ c(5)*@median(deceased)+c(6)*@median(eva)) \end{array}$

The marginal effect is 1.180856. So, being awarded the medal increases the expected number of flights by 1,2, other things being equal.