```
  ___  ____  ____  ____  ____(R)
 /__    /   ____/   /   ____/
___/   /   /___/   /   /___/
  Statistics/Data Analysis
```

User: iman
Project: iman

1 . sum gender age LDL_chol HOMA2_IR BMI sysBloodPr diastBloodPressure

Variable	Obs	Mean	Std. Dev.	Min	Max
gender	150	.54	.5000671	0	1
age	150	40.20667	4.928069	27	53
LDL_chol	150	94.80755	15.40653	59.88626	133.1309
HOMA2_IR	150	2.278219	.709836	.4866602	4.361196
BMI	150	28.28346	2.990533	20.30083	35.16374
sysBloodPr	150	149.7291	10.43408	123.4009	175.7543
diastBlood~e	150	94.25166	11.38758	69.99635	124.0379

2 .
3 . corr age LDL_chol HOMA2_IR BMI sysBloodPr diastBloodPressure
(obs=150)

	age	LDL_chol	HOMA2_IR	BMI	sysBlo~r	diastB~e
age	1.0000					
LDL_chol	0.9919	1.0000				
HOMA2_IR	0.9941	0.9947	1.0000			
BMI	0.9938	0.9948	0.9960	1.0000		
sysBloodPr	0.9958	0.9953	0.9958	0.9962	1.0000	
diastBlood~e	0.9915	0.9951	0.9962	0.9945	0.9949	1.0000

4 .
5 . tab λ01Δt1

λ01Δt1	Freq.	Percent	Cum.
0	63	42.00	42.00
1	58	38.67	80.67
2	25	16.67	97.33
3	4	2.67	100.00
Total	150	100.00	

6 .
7 . tab λ12Δt1

λ12Δt1	Freq.	Percent	Cum.
0	96	64.00	64.00
1	43	28.67	92.67
2	9	6.00	98.67
3	2	1.33	100.00
Total	150	100.00	

8 .
9 . tab λ23Δt1

λ23Δt1	Freq.	Percent	Cum.
0	121	80.67	80.67
1	23	15.33	96.00
2	4	2.67	98.67
3	2	1.33	100.00
Total	150	100.00	

10 .
11 . tab λ34Δt1

λ34Δt1	Freq.	Percent	Cum.
0	**128**	**85.33**	**85.33**
1	**22**	**14.67**	**100.00**
Total	**150**	**100.00**	

12 .
13 . tab µ10Δt1

µ10Δt1	Freq.	Percent	Cum.
0	**121**	**80.67**	**80.67**
1	**24**	**16.00**	**96.67**
2	**3**	**2.00**	**98.67**
3	**2**	**1.33**	**100.00**
Total	**150**	**100.00**	

14 .
15 . tab µ21Δt1

µ21Δt1	Freq.	Percent	Cum.
0	**127**	**84.67**	**84.67**
1	**17**	**11.33**	**96.00**
2	**5**	**3.33**	**99.33**
3	**1**	**0.67**	**100.00**
Total	**150**	**100.00**	

16 .
17 . tab µ32Δt1

µ32Δt1	Freq.	Percent	Cum.
0	**130**	**86.67**	**86.67**
1	**17**	**11.33**	**98.00**
2	**3**	**2.00**	**100.00**
Total	**150**	**100.00**	

18 .
19 . tab µ20Δt1

µ20Δt1	Freq.	Percent	Cum.
0	**138**	**92.00**	**92.00**
1	**11**	**7.33**	**99.33**
2	**1**	**0.67**	**100.00**
Total	**150**	**100.00**	

20 .
21 . tab µ31Δt1

µ31Δt1	Freq.	Percent	Cum.
0	**139**	**92.67**	**92.67**
1	**9**	**6.00**	**98.67**
2	**2**	**1.33**	**100.00**
Total	**150**	**100.00**	

22 .
23 . tab ageCtegory

ageCtegory	Freq.	Percent	Cum.
1	**22**	**14.67**	**14.67**
2	**109**	**72.67**	**87.33**
3	**19**	**12.67**	**100.00**
Total	**150**	**100.00**	

24 .
25 . tab MBIcategory

MBIcategory	Freq.	Percent	Cum.
1	**22**	**14.67**	**14.67**
2	**83**	**55.33**	**70.00**
3	**45**	**30.00**	**100.00**
Total	**150**	**100.00**	

26 .
27 . tab LDLcholCategory

LDLcholCategory	Freq.	Percent	Cum.
1	**5**	**3.33**	**3.33**
2	**93**	**62.00**	**65.33**
3	**52**	**34.67**	**100.00**
Total	**150**	**100.00**	

28 .
29 . tab HOMA2_IRcategory

HOMA2_IRcategory	Freq.	Percent	Cum.
1	**10**	**6.67**	**6.67**
2	**93**	**62.00**	**68.67**
3	**47**	**31.33**	**100.00**
Total	**150**	**100.00**	

```
.
. tab  systPrCategory
```

systPrCategory	Freq.	Percent	Cum.
1	4	2.67	2.67
2	123	82.00	84.67
3	23	15.33	100.00
Total	150	100.00	

```
.
. tab  diastPrCategory
```

diastPrCategory	Freq.	Percent	Cum.
1	33	22.00	22.00
2	69	46.00	68.00
3	48	32.00	100.00
Total	150	100.00	

```
.
. mkspline HOMAsp = HOMA2_IR, cubic displayknots
```

	knot1	knot2	knot3	knot4	knot5
HOMA2_IR	1.0879	1.802248	2.263381	2.752956	3.480719

```
.
. mkspline LDLsp = LDL_chol, cubic displayknots
```

	knot1	knot2	knot3	knot4	knot5
LDL_chol	71.22266	83.70328	94.62621	104.4809	124.1413

```
.
. mkspline sysPS = sysBloodPr, cubic displayknots
```

	knot1	knot2	knot3	knot4	knot5
sysBloodPr	133.0965	143.8759	149.4107	155.5788	168.0359

```
.
. mkspline DiasPS = diastBloodPressure, cubic displayknots
```

	knot1	knot2	knot3	knot4	knot5
diastBlood~e	74.44541	87.43943	94.06548	101.1098	114.4986

```
.
. lowess λ01Δt1 gender, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin)
>  lpattern(solid) connect(direct))
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```
 .
 . lowess λ01Δt1 age, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin) lin
 > attern(solid) connect(direct))

 .
 . lowess λ01Δt1 LDL_chol, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin
 > k) lpattern(solid) connect(direct))

 .
 . lowess λ01Δt1 BMI, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin) lin
 > attern(solid) connect(direct))

 .
 . lowess λ01Δt1 HOMA2_IR, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin
 > k) lpattern(solid) connect(direct))

 .
 . lowess λ01Δt1 sysBloodPr, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medth
 > ick) lpattern(solid) connect(direct))

 .
 . lowess λ01Δt1 diastBloodPressure, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwid
 > width(thick) lpattern(solid) connect(direct))

 .
 . lowess λ12Δt1 gender, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin)
 >  lpattern(solid) connect(direct))

 .
 . lowess λ12Δt1 age, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin) lin
 > attern(solid) connect(direct))

 .
 . lowess λ12Δt1 LDL_chol, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin
 > k) lpattern(solid) connect(direct))

 .
 . lowess λ12Δt1 BMI, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin) lin
 > attern(solid) connect(direct))

 .
 . lowess λ12Δt1 HOMA2_IR, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin
 > k) lpattern(solid) connect(direct))

 .
 . lowess λ12Δt1 sysBloodPr, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medth
 > ick) lpattern(solid) connect(direct))

 .
 . lowess λ12Δt1 diastBloodPressure, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwid
 > width(thick) lpattern(solid) connect(direct))

 .
 . lowess λ23Δt1 gender, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin)
 >  lpattern(solid) connect(direct))
```

```
.
. lowess λ23Δt1 age, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin) lin
> attern(solid) connect(direct))

.
. lowess λ23Δt1 LDL_chol, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin
> k) lpattern(solid) connect(direct))

.
. lowess λ23Δt1 BMI, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin) lin
> attern(solid) connect(direct))

.
. lowess λ23Δt1 HOMA2_IR, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin
> k) lpattern(solid) connect(direct))

.
. lowess λ23Δt1 sysBloodPr, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medth
> ick) lpattern(solid) connect(direct))

.
. lowess λ23Δt1 diastBloodPressure, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwid
> width(thick) lpattern(solid) connect(direct))

.
. lowess λ34Δt1 gender, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin)
>  lpattern(solid) connect(direct))

.
. lowess λ34Δt1 age, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin) lin
> attern(solid) connect(direct))

.
. lowess λ34Δt1 LDL_chol, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin
> k) lpattern(solid) connect(direct))

.
. lowess λ34Δt1 BMI, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin) lin
> attern(solid) connect(direct))

.
. lowess λ34Δt1 HOMA2_IR, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin
> k) lpattern(solid) connect(direct))

.
. lowess λ34Δt1 sysBloodPr, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medth
> ick) lpattern(solid) connect(direct))

.
. lowess λ34Δt1 diastBloodPressure, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwid
> width(thick) lpattern(solid) connect(direct))

.
. lowess µ10Δt1 gender, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin)
>  lpattern(solid) connect(direct))
```

```
100 .
101 . lowess µ10Δt1 age , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin) li
    > pattern(solid) connect(direct))

102 .
103 . lowess µ10Δt1 LDL_chol , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthi
    > ck) lpattern(solid) connect(direct))

104 .
105 . lowess µ10Δt1 HOMA2_IR , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthi
    > ck) lpattern(solid) connect(direct))

106 .
107 . lowess µ10Δt1 BMI , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin) li
    > pattern(solid) connect(direct))

108 .
109 . lowess µ10Δt1 sysBloodPr , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medt
    > hick) lpattern(solid) connect(direct))

110 .
111 . lowess µ10Δt1 diastBloodPressure , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwi
    > lwidth(thick) lpattern(solid) connect(direct))

112 .
113 . lowess µ21Δt1 gender, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin)
    >  lpattern(solid) connect(direct))

114 .
115 . lowess µ21Δt1 age , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin) li
    > pattern(solid) connect(direct))

116 .
117 . lowess µ21Δt1 LDL_chol , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthi
    > ck) lpattern(solid) connect(direct))

118 .
119 . lowess µ21Δt1 HOMA2_IR , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthi
    > ck) lpattern(solid) connect(direct))

120 .
121 . lowess µ21Δt1 BMI , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin) li
    > pattern(solid) connect(direct))

122 .
123 . lowess µ21Δt1 sysBloodPr , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medt
    > hick) lpattern(solid) connect(direct))

124 .
125 . lowess µ21Δt1 diastBloodPressure , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwi
    > lwidth(thick) lpattern(solid) connect(direct))

126 .
127 . lowess µ32Δt1 gender, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin)
    >  lpattern(solid) connect(direct))
```

```
.
. lowess µ32Δt1 age , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin) li
> pattern(solid) connect(direct))

.
. lowess µ32Δt1 LDL_chol , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthi
> ck) lpattern(solid) connect(direct))

.
. lowess µ32Δt1 HOMA2_IR , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthi
> ck) lpattern(solid) connect(direct))

.
. lowess µ32Δt1 BMI , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin) li
> pattern(solid) connect(direct))

.
. lowess µ32Δt1 sysBloodPr , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medt
> hick) lpattern(solid) connect(direct))

.
. lowess µ32Δt1 diastBloodPressure , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwi
> lwidth(thick) lpattern(solid) connect(direct))

.
. lowess µ20Δt1 gender, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin)
>  lpattern(solid) connect(direct))

.
. lowess µ20Δt1 age , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin) li
> pattern(solid) connect(direct))

.
. lowess µ20Δt1 LDL_chol , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthi
> ck) lpattern(solid) connect(direct))

.
. lowess µ20Δt1 HOMA2_IR , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthi
> ck) lpattern(solid) connect(direct))

.
. lowess µ20Δt1 BMI , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin) li
> pattern(solid) connect(direct))

.
. lowess µ20Δt1 sysBloodPr , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medt
> hick) lpattern(solid) connect(direct))

.
. lowess µ20Δt1 diastBloodPressure , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwi
> lwidth(thick) lpattern(solid) connect(direct))

.
. lowess µ31Δt1 gender, bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin)
>  lpattern(solid) connect(direct))
```

```
156 .
157 . lowess µ31∆t1 age , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin) li
    > pattern(solid) connect(direct))

158 .
159 . lowess µ31∆t1 LDL_chol , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthi
    > ck) lpattern(solid) connect(direct))

160 .
161 . lowess µ31∆t1 HOMA2_IR , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthi
    > ck) lpattern(solid) connect(direct))

162 .
163 . lowess µ31∆t1 BMI , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medthin) li
    > pattern(solid) connect(direct))

164 .
165 . lowess µ31∆t1 sysBloodPr , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwidth(medt
    > hick) lpattern(solid) connect(direct))

166 .
167 . lowess µ31∆t1 diastBloodPressure , bwidth(0.4) recast(connected) mcolor(red) msize(medlarge) lwi
    > lwidth(thick) lpattern(solid) connect(direct))

168 .
169 . poisson λ01∆t1 LDLsp2 HOMAsp1 sysPS2 c.LDLsp2#c.HOMAsp1 c.LDLsp2#c.sysPS2 c.sysPS2#c.HOMAsp1, vc
    > ) sformat(%8.3f)

Iteration 0:   log pseudolikelihood = -112.93301
Iteration 1:   log pseudolikelihood = -110.47099
Iteration 2:   log pseudolikelihood = -110.43006
Iteration 3:   log pseudolikelihood = -110.43004
Iteration 4:   log pseudolikelihood = -110.43004

Poisson regression                              Number of obs     =        150
                                                Wald chi2(6)      =     535.34
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -110.43004               Pseudo R2         =     0.3552
```

λ01∆t1	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
LDLsp2	0.523	0.243	2.149	0.032	0.046	1.000
HOMAsp1	4.096	0.328	12.470	0.000	3.452	4.740
sysPS2	-0.628	0.347	-1.809	0.070	-1.308	0.052
c.LDLsp2#c.HOMAsp1	-0.179	0.070	-2.540	0.011	-0.317	-0.041
c.LDLsp2#c.sysPS2	0.003	0.000	8.144	0.000	0.002	0.003
c.sysPS2#c.HOMAsp1	0.151	0.098	1.547	0.122	-0.040	0.342
_cons	-9.510	0.725	-13.122	0.000	-10.930	-8.089

```
170 .
171 . poisson λ01Δt1 LDLsp2 HOMAsp1 sysPS2 c.LDLsp2#c.HOMAsp1 c.LDLsp2#c.sysPS2 c.sysPS2#c.HOMAsp1, vc
    > 5.3f) sformat(%8.3f)

    Iteration 0:   log pseudolikelihood = -112.93301
    Iteration 1:   log pseudolikelihood = -110.47099
    Iteration 2:   log pseudolikelihood = -110.43006
    Iteration 3:   log pseudolikelihood = -110.43004
    Iteration 4:   log pseudolikelihood = -110.43004

    Poisson regression                                Number of obs     =        150
                                                      Wald chi2(6)      =     535.34
                                                      Prob > chi2       =     0.0000
    Log pseudolikelihood = -110.43004                 Pseudo R2         =     0.3552
```

λ01Δt1	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
LDLsp2	1.687	0.411	2.149	0.032	1.047	2.718
HOMAsp1	60.097	19.739	12.470	0.000	31.569	114.403
sysPS2	0.534	0.185	-1.809	0.070	0.270	1.054
c.LDLsp2#c.HOMAsp1	0.836	0.059	-2.540	0.011	0.728	0.960
c.LDLsp2#c.sysPS2	1.003	0.000	8.144	0.000	1.002	1.003
c.sysPS2#c.HOMAsp1	1.163	0.113	1.547	0.122	0.960	1.408
_cons	0.000	0.000	-13.122	0.000	0.000	0.000

```
172 .
173 . estat gof

             Deviance goodness-of-fit =  27.55006
             Prob > chi2(143)         =    1.0000

             Pearson goodness-of-fit  =  24.45824
             Prob > chi2(143)         =    1.0000

174 .
175 . estat ic

    Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	150	-171.2729	-110.43	7	234.8601	255.9345

Note: N=Obs used in calculating BIC; see **[R] BIC note**.

```
176 .
177 . predict est01,xb
```

```
178 .
179 . gen est01count=exp(est01)

180 .
181 . gen est01countround=round( est01count )

182 .
183 . tab est01countround
```

est01countround	Freq.	Percent	Cum.
0	75	50.00	50.00
1	34	22.67	72.67
2	37	24.67	97.33
3	4	2.67	100.00
Total	150	100.00	

```
184 .
185 . poisson λ12Δt1 LDLsp2 HOMAsp1 sysPS2   c.LDLsp2#c.HOMAsp1   c.sysPS2#c.HOMAsp1, vce(robust) cfor
    > f)

    Iteration 0:   log pseudolikelihood = -110.19868
    Iteration 1:   log pseudolikelihood = -76.739509
    Iteration 2:   log pseudolikelihood = -68.155535
    Iteration 3:   log pseudolikelihood =  -67.88722
    Iteration 4:   log pseudolikelihood = -67.886656
    Iteration 5:   log pseudolikelihood = -67.886656

    Poisson regression                              Number of obs     =        150
                                                    Wald chi2(5)      =     284.30
                                                    Prob > chi2       =     0.0000
    Log pseudolikelihood = -67.886656               Pseudo R2         =     0.4811
```

λ12Δt1	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
LDLsp2	0.311	0.396	0.785	0.432	-0.465	1.086
HOMAsp1	5.486	0.571	9.599	0.000	4.366	6.606
sysPS2	-0.314	0.545	-0.577	0.564	-1.383	0.754
c.LDLsp2#c.HOMAsp1	-0.105	0.116	-0.902	0.367	-0.332	0.123
c.sysPS2#c.HOMAsp1	0.079	0.158	0.502	0.616	-0.231	0.389
_cons	-14.884	1.363	-10.923	0.000	-17.555	-12.213

```
186 .
187 . poisson λ12Δt1 LDLsp2 HOMAsp1 sysPS2   c.LDLsp2#c.HOMAsp1   c.sysPS2#c.HOMAsp1, vce(robust) irr
    > %8.3f)

    Iteration 0:   log pseudolikelihood = -110.19868
    Iteration 1:   log pseudolikelihood = -76.739509
    Iteration 2:   log pseudolikelihood = -68.155535
    Iteration 3:   log pseudolikelihood =  -67.88722
    Iteration 4:   log pseudolikelihood = -67.886656
    Iteration 5:   log pseudolikelihood = -67.886656

    Poisson regression                              Number of obs     =        150
                                                    Wald chi2(5)      =     284.30
                                                    Prob > chi2       =     0.0000
    Log pseudolikelihood = -67.886656               Pseudo R2         =     0.4811
```

λ12Δt1	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
LDLsp2	**1.364**	**0.540**	**0.785**	**0.432**	**0.628**	**2.962**
HOMAsp1	**241.179**	**137.821**	**9.599**	**0.000**	**78.690**	**739.192**
sysPS2	**0.730**	**0.398**	**-0.577**	**0.564**	**0.251**	**2.126**
c.LDLsp2#c.HOMAsp1	**0.901**	**0.105**	**-0.902**	**0.367**	**0.717**	**1.131**
c.sysPS2#c.HOMAsp1	**1.083**	**0.171**	**0.502**	**0.616**	**0.794**	**1.476**
_cons	**0.000**	**0.000**	**-10.923**	**0.000**	**0.000**	**0.000**

188 .
189 . estat gof

Deviance goodness-of-fit = **20.26627**
Prob > chi2(**144**) = **1.0000**

Pearson goodness-of-fit = **18.12217**
Prob > chi2(**144**) = **1.0000**

190 .
191 . estat ic

Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	**150**	**-130.82**	**-67.88666**	**6**	**147.7733**	**165.8371**

Note: N=Obs used in calculating BIC; see **[R] BIC note**.

192 .
193 . predict est12,xb

194 .
195 . gen est12count=exp(est12)

196 .
197 . gen est12countround=round(est12count)

198 .
199 . tab est12countround

est12countround	Freq.	Percent	Cum.
0	**102**	**68.00**	**68.00**
1	**35**	**23.33**	**91.33**
2	**11**	**7.33**	**98.67**
3	**1**	**0.67**	**99.33**
4	**1**	**0.67**	**100.00**
Total	**150**	**100.00**	

```
200 .
201 . poisson λ23Δt1 LDLsp2 HOMAsp1 sysPS2   c.LDLsp2#c.HOMAsp1    c.LDLsp2#c.sysPS2   c.sysPS2#c.HOMA
    > t(%5.3f) sformat(%8.3f)

    Iteration 0:   log pseudolikelihood = -160.12839
    Iteration 1:   log pseudolikelihood = -107.21927  (backed up)
    Iteration 2:   log pseudolikelihood = -81.300112
    Iteration 3:   log pseudolikelihood = -39.228241
    Iteration 4:   log pseudolikelihood =  -37.90122
    Iteration 5:   log pseudolikelihood = -37.865806
    Iteration 6:   log pseudolikelihood =  -37.86568
    Iteration 7:   log pseudolikelihood =  -37.86568

    Poisson regression                                Number of obs     =        150
                                                      Wald chi2(6)      =     191.48
                                                      Prob > chi2       =     0.0000
    Log pseudolikelihood =  -37.86568                 Pseudo R2         =     0.6020
```

λ23Δt1	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
LDLsp2	-1.480	0.685	-2.159	0.031	-2.823	-0.137
HOMAsp1	6.174	3.093	1.996	0.046	0.112	12.237
sysPS2	2.497	0.967	2.583	0.010	0.602	4.391
c.LDLsp2#c.HOMAsp1	0.390	0.192	2.032	0.042	0.014	0.766
c.LDLsp2#c.sysPS2	-0.001	0.002	-0.403	0.687	-0.005	0.004
c.sysPS2#c.HOMAsp1	-0.655	0.274	-2.392	0.017	-1.191	-0.118
_cons	-20.866	7.293	-2.861	0.004	-35.160	-6.572

```
202 .
203 . poisson λ23Δt1 LDLsp2 HOMAsp1 sysPS2   c.LDLsp2#c.HOMAsp1    c.LDLsp2#c.sysPS2   c.sysPS2#c.HOMA
    > ormat(%5.3f) sformat(%8.3f)

    Iteration 0:   log pseudolikelihood = -160.12839
    Iteration 1:   log pseudolikelihood = -107.21927  (backed up)
    Iteration 2:   log pseudolikelihood = -81.300112
    Iteration 3:   log pseudolikelihood = -39.228241
    Iteration 4:   log pseudolikelihood =  -37.90122
    Iteration 5:   log pseudolikelihood = -37.865806
    Iteration 6:   log pseudolikelihood =  -37.86568
    Iteration 7:   log pseudolikelihood =  -37.86568

    Poisson regression                                Number of obs     =        150
                                                      Wald chi2(6)      =     191.48
                                                      Prob > chi2       =     0.0000
    Log pseudolikelihood =  -37.86568                 Pseudo R2         =     0.6020
```

λ23Δt1	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
LDLsp2	0.228	0.156	-2.159	0.031	0.059	0.872
HOMAsp1	480.318	1485.815	1.996	0.046	1.118	2.06e+05
sysPS2	12.143	11.738	2.583	0.010	1.826	80.754
c.LDLsp2#c.HOMAsp1	1.477	0.283	2.032	0.042	1.014	2.151
c.LDLsp2#c.sysPS2	0.999	0.002	-0.403	0.687	0.995	1.004
c.sysPS2#c.HOMAsp1	0.520	0.142	-2.392	0.017	0.304	0.889

```
          _cons |      0.000      0.000   -2.861   0.004        0.000       0.001
-------------------------------------------------------------------------------------

204 .
205 . estat gof

         Deviance goodness-of-fit =  13.29285
         Prob > chi2(143)         =    1.0000

         Pearson goodness-of-fit  =  12.42161
         Prob > chi2(143)         =    1.0000

206 .
207 . estat ic

Akaike's information criterion and Bayesian information criterion

-----------------------------------------------------------------------------
       Model |          Obs  ll(null)  ll(model)      df         AIC        BIC
-------------+---------------------------------------------------------------
           . |          150 -95.14565  -37.86568       7    89.73136   110.8058
-----------------------------------------------------------------------------
               Note: N=Obs used in calculating BIC; see [R] BIC note.

208 .
209 . predict est23,xb

210 .
211 . gen est23count=exp(est23)

212 .
213 . gen est23countround=round( est23count )

214 .
215 . tab est23countround

est23countr |
      ound |      Freq.     Percent        Cum.
------------+-----------------------------------
          0 |        125       83.33       83.33
          1 |         18       12.00       95.33
          2 |          4        2.67       98.00
          3 |          3        2.00      100.00
------------+-----------------------------------
      Total |        150      100.00

216 .
217 . poisson λ34Δt1 LDLsp2 HOMAsp1 sysPS2   c.LDLsp2#c.HOMAsp1, vce(robust) cformat(%9.3f) pformat(%5

Iteration 0:   log pseudolikelihood = -51.459148
Iteration 1:   log pseudolikelihood = -33.399587
Iteration 2:   log pseudolikelihood = -28.375528
Iteration 3:   log pseudolikelihood = -27.031648
Iteration 4:   log pseudolikelihood = -26.968757
Iteration 5:   log pseudolikelihood = -26.968505
Iteration 6:   log pseudolikelihood = -26.968505

Poisson regression                              Number of obs     =        150
                                                Wald chi2(4)      =     122.33
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -26.968505               Pseudo R2         =     0.5801
```

λ34Δt1	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
LDLsp2	**0.452**	**0.055**	**8.278**	**0.000**	**0.345**	**0.559**
HOMAsp1	**10.866**	**1.402**	**7.753**	**0.000**	**8.119**	**13.613**
sysPS2	**0.073**	**0.050**	**1.472**	**0.141**	**-0.024**	**0.171**
c.LDLsp2#c.HOMAsp1	**-0.166**	**0.018**	**-9.320**	**0.000**	**-0.201**	**-0.131**
_cons	**-34.034**	**3.865**	**-8.806**	**0.000**	**-41.608**	**-26.459**

```
218 .
219 . poisson λ34Δt1 LDLsp2 HOMAsp1 sysPS2   c.LDLsp2#c.HOMAsp1, vce(robust) irr cformat(%9.3f) pforma

    Iteration 0:   log pseudolikelihood = -51.459148
    Iteration 1:   log pseudolikelihood = -33.399587
    Iteration 2:   log pseudolikelihood = -28.375528
    Iteration 3:   log pseudolikelihood = -27.031648
    Iteration 4:   log pseudolikelihood = -26.968757
    Iteration 5:   log pseudolikelihood = -26.968505
    Iteration 6:   log pseudolikelihood = -26.968505

    Poisson regression                              Number of obs     =        150
                                                    Wald chi2(4)      =     122.33
                                                    Prob > chi2       =     0.0000
    Log pseudolikelihood = -26.968505               Pseudo R2         =     0.5801
```

λ34Δt1	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
LDLsp2	**1.571**	**0.086**	**8.278**	**0.000**	**1.412**	**1.748**
HOMAsp1	**52375.984**	**73411.343**	**7.753**	**0.000**	**3357.911**	**8.17e+05**
sysPS2	**1.076**	**0.054**	**1.472**	**0.141**	**0.976**	**1.187**
c.LDLsp2#c.HOMAsp1	**0.847**	**0.015**	**-9.320**	**0.000**	**0.818**	**0.877**
_cons	**0.000**	**0.000**	**-8.806**	**0.000**	**0.000**	**0.000**

```
220 .
221 . estat gof

         Deviance goodness-of-fit =   9.93701
         Prob > chi2(145)         =    1.0000

         Pearson goodness-of-fit  =  8.963525
         Prob > chi2(145)         =    1.0000

222 .
223 . estat ic

    Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	**150**	**-64.23104**	**-26.9685**	**5**	**63.93701**	**78.99019**

Note: N=Obs used in calculating BIC; see **[R] BIC note**.

```
224 .
225 . predict est34,xb

226 .
227 . gen est34count=exp(est34)

228 .
229 . gen est34countround=round( est34count )

230 .
231 . tab est34countround

 est34countr
       ound |      Freq.     Percent        Cum.
------------+-----------------------------------
          0 |        133       88.67       88.67
          1 |         14        9.33       98.00
          2 |          3        2.00      100.00
------------+-----------------------------------
      Total |        150      100.00

232 .
233 . poisson µ10Δt1 LDLsp2 HOMAsp2  sysPS2   c.LDLsp2#c.HOMAsp2    c.LDLsp2#c.sysPS2 c.sysPS2#c.HOMAs
    > (%5.3f) sformat(%8.3f)

    Iteration 0:   log pseudolikelihood = -156.14216
    Iteration 1:   log pseudolikelihood = -98.267306
    Iteration 2:   log pseudolikelihood = -63.346557
    Iteration 3:   log pseudolikelihood = -39.002967
    Iteration 4:   log pseudolikelihood = -38.151225
    Iteration 5:   log pseudolikelihood =  -38.14473
    Iteration 6:   log pseudolikelihood = -38.144729

    Poisson regression                              Number of obs     =        150
                                                    Wald chi2(6)      =     331.08
                                                    Prob > chi2       =     0.0000
    Log pseudolikelihood = -38.144729               Pseudo R2         =     0.5900

    ------------------------------------------------------------------------------------
                       |               Robust
                µ10Δt1 |      Coef.   Std. Err.       z    P>|z|     [95% Conf. Interval]
    -------------------+----------------------------------------------------------------
                LDLsp2 |     -0.454      0.244   -1.862   0.063      -0.932       0.024
               HOMAsp2 |     -4.489      2.962   -1.515   0.130     -10.294       1.316
                sysPS2 |      1.340      0.312    4.301   0.000       0.729       1.951
                       |
    c.LDLsp2#c.HOMAsp2 |      0.290      0.096    3.029   0.002       0.102       0.478
                       |
     c.LDLsp2#c.sysPS2 |     -0.010      0.004   -2.789   0.005      -0.017      -0.003
                       |
    c.sysPS2#c.HOMAsp2 |     -0.286      0.145   -1.974   0.048      -0.571      -0.002
                       |
                 _cons |     -5.916      0.508  -11.651   0.000      -6.912      -4.921
    ------------------------------------------------------------------------------------
```

```
234 .
235 . poisson µ10Δt1 LDLsp2 HOMAsp2  sysPS2   c.LDLsp2#c.HOMAsp2    c.LDLsp2#c.sysPS2 c.sysPS2#c.HOMAs
    > rmat(%5.3f) sformat(%8.3f)

    Iteration 0:   log pseudolikelihood = -156.14216
    Iteration 1:   log pseudolikelihood = -98.267306
    Iteration 2:   log pseudolikelihood = -63.346557
    Iteration 3:   log pseudolikelihood = -39.002967
    Iteration 4:   log pseudolikelihood = -38.151225
    Iteration 5:   log pseudolikelihood =  -38.14473
    Iteration 6:   log pseudolikelihood = -38.144729

    Poisson regression                              Number of obs     =        150
                                                    Wald chi2(6)      =     331.08
                                                    Prob > chi2       =     0.0000
    Log pseudolikelihood = -38.144729               Pseudo R2         =     0.5900
```

µ10Δt1	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
LDLsp2	0.635	0.155	-1.862	0.063	0.394	1.024
HOMAsp2	0.011	0.033	-1.515	0.130	0.000	3.730
sysPS2	3.820	1.190	4.301	0.000	2.074	7.034
c.LDLsp2#c.HOMAsp2	1.337	0.128	3.029	0.002	1.108	1.612
c.LDLsp2#c.sysPS2	0.990	0.004	-2.789	0.005	0.983	0.997
c.sysPS2#c.HOMAsp2	0.751	0.109	-1.974	0.048	0.565	0.998
_cons	0.003	0.001	-11.651	0.000	0.001	0.007

```
236 .
237 . estat gof

             Deviance goodness-of-fit =  14.46465
             Prob > chi2(143)         =    1.0000

             Pearson goodness-of-fit  =  13.54881
             Prob > chi2(143)         =    1.0000

238 .
239 . estat ic

    Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	150	-93.03915	-38.14473	7	90.28946	111.3639

Note: N=Obs used in calculating BIC; see **[R] BIC note**.

```
240 .
241 . predict est10,xb

242 .
243 . gen est10count=exp(est10)

244 .
245 . gen est10countround=round( est10count )

246 .
247 . tab est10countround
```

est10countround	Freq.	Percent	Cum.
0	126	84.00	84.00
1	15	10.00	94.00
2	7	4.67	98.67
3	1	0.67	99.33
4	1	0.67	100.00
Total	150	100.00	

```
248 .
249 . poisson µ21Δt1 LDLsp2 HOMAsp2  sysPS2   c.LDLsp2#c.HOMAsp2    c.LDLsp2#c.sysPS2 c.sysPS2#c.HOMAs
    > (%5.3f) sformat(%8.3f)

    Iteration 0:   log pseudolikelihood = -189.11152
    Iteration 1:   log pseudolikelihood = -135.76136  (backed up)
    Iteration 2:   log pseudolikelihood = -72.824996
    Iteration 3:   log pseudolikelihood = -46.875924
    Iteration 4:   log pseudolikelihood = -33.535715
    Iteration 5:   log pseudolikelihood =  -30.03631
    Iteration 6:   log pseudolikelihood = -29.958911
    Iteration 7:   log pseudolikelihood = -29.958555
    Iteration 8:   log pseudolikelihood = -29.958555

    Poisson regression                              Number of obs     =        150
                                                    Wald chi2(6)      =     304.94
                                                    Prob > chi2       =     0.0000
    Log pseudolikelihood = -29.958555               Pseudo R2         =     0.6414
```

µ21Δt1	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
LDLsp2	-0.128	0.189	-0.675	0.499	-0.499	0.243
HOMAsp2	-3.288	2.812	-1.169	0.242	-8.800	2.224
sysPS2	0.913	0.201	4.546	0.000	0.519	1.307
c.LDLsp2#c.HOMAsp2	0.152	0.066	2.288	0.022	0.022	0.282
c.LDLsp2#c.sysPS2	-0.010	0.003	-2.950	0.003	-0.017	-0.003
c.sysPS2#c.HOMAsp2	-0.114	0.114	-1.001	0.317	-0.338	0.109
_cons	-7.666	0.617	-12.426	0.000	-8.875	-6.457

```
250 .
251 . poisson µ21Δt1 LDLsp2 HOMAsp2  sysPS2   c.LDLsp2#c.HOMAsp2    c.LDLsp2#c.sysPS2 c.sysPS2#c.HOMAs
    > rmat(%5.3f) sformat(%8.3f)

    Iteration 0:   log pseudolikelihood = -189.11152
    Iteration 1:   log pseudolikelihood = -135.76136  (backed up)
    Iteration 2:   log pseudolikelihood = -72.824996
    Iteration 3:   log pseudolikelihood = -46.875924
    Iteration 4:   log pseudolikelihood = -33.535715
    Iteration 5:   log pseudolikelihood =  -30.03631
    Iteration 6:   log pseudolikelihood = -29.958911
    Iteration 7:   log pseudolikelihood = -29.958555
    Iteration 8:   log pseudolikelihood = -29.958555

    Poisson regression                              Number of obs     =        150
                                                    Wald chi2(6)      =     304.94
                                                    Prob > chi2       =     0.0000
    Log pseudolikelihood = -29.958555               Pseudo R2         =     0.6414
```

µ21Δt1	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
LDLsp2	0.880	0.167	-0.675	0.499	0.607	1.275
HOMAsp2	0.037	0.105	-1.169	0.242	0.000	9.244
sysPS2	2.492	0.501	4.546	0.000	1.681	3.694
c.LDLsp2#c.HOMAsp2	1.164	0.077	2.288	0.022	1.022	1.326
c.LDLsp2#c.sysPS2	0.990	0.003	-2.950	0.003	0.983	0.997
c.sysPS2#c.HOMAsp2	0.892	0.102	-1.001	0.317	0.713	1.116
_cons	0.000	0.000	-12.426	0.000	0.000	0.002

```
252 .
253 . estat gof

             Deviance goodness-of-fit =  9.856737
             Prob > chi2(143)         =    1.0000

             Pearson goodness-of-fit  =  8.967082
             Prob > chi2(143)         =    1.0000

254 .
255 . estat ic

    Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	150	-83.54063	-29.95856	7	73.91711	94.99156

Note: N=Obs used in calculating BIC; see **[R] BIC note**.

```
. 
. predict est21,xb

. 
. gen est21count=exp(est21)

. 
. gen est21countround=round( est21count )

. 
. tab est21countround

est21countr |
      ound  |      Freq.     Percent        Cum.
------------+-----------------------------------
          0 |        132       88.00       88.00
          1 |         12        8.00       96.00
          2 |          4        2.67       98.67
          3 |          2        1.33      100.00
------------+-----------------------------------
      Total |        150      100.00

. 
. poisson µ32Δt1 LDLsp2 HOMAsp2  sysPS2   c.LDLsp2#c.HOMAsp2    c.LDLsp2#c.sysPS2 c.sysPS2#c.HOMAs
> (%5.3f) sformat(%8.3f)

Iteration 0:   log pseudolikelihood = -92.482782  
Iteration 1:   log pseudolikelihood = -68.161589  (backed up)
Iteration 2:   log pseudolikelihood = -40.839603  
Iteration 3:   log pseudolikelihood = -26.643171  
Iteration 4:   log pseudolikelihood = -26.370176  
Iteration 5:   log pseudolikelihood =   -26.3679  
Iteration 6:   log pseudolikelihood =   -26.3679  

Poisson regression                              Number of obs     =        150
                                                Wald chi2(6)      =     175.47
                                                Prob > chi2       =     0.0000
Log pseudolikelihood =   -26.3679               Pseudo R2         =     0.6134

------------------------------------------------------------------------------------
                   |               Robust
            µ32Δt1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
            LDLsp2 |      0.302      0.211    1.427   0.154      -0.113        0.716
           HOMAsp2 |     -5.214      3.196   -1.631   0.103     -11.478        1.050
            sysPS2 |      0.422      0.288    1.467   0.142      -0.142        0.987
                   |
c.LDLsp2#c.HOMAsp2 |      0.002      0.102    0.019   0.984      -0.198        0.202
                   |
 c.LDLsp2#c.sysPS2 |     -0.012      0.004   -2.749   0.006      -0.020       -0.003
                   |
c.sysPS2#c.HOMAsp2 |      0.132      0.149    0.888   0.375      -0.160        0.425
                   |
             _cons |     -7.363      0.761   -9.671   0.000      -8.855       -5.871
------------------------------------------------------------------------------------
```

```
266 .
267 . poisson µ32Δt1 LDLsp2 HOMAsp2  sysPS2   c.LDLsp2#c.HOMAsp2    c.LDLsp2#c.sysPS2 c.sysPS2#c.HOMAs
    > rmat(%5.3f) sformat(%8.3f)

    Iteration 0:   log pseudolikelihood = -92.482782
    Iteration 1:   log pseudolikelihood = -68.161589  (backed up)
    Iteration 2:   log pseudolikelihood = -40.839603
    Iteration 3:   log pseudolikelihood = -26.643171
    Iteration 4:   log pseudolikelihood = -26.370176
    Iteration 5:   log pseudolikelihood =   -26.3679
    Iteration 6:   log pseudolikelihood =   -26.3679

    Poisson regression                                Number of obs     =        150
                                                      Wald chi2(6)      =     175.47
                                                      Prob > chi2       =     0.0000
    Log pseudolikelihood =   -26.3679                 Pseudo R2         =     0.6134
```

µ32Δt1	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
LDLsp2	1.352	0.286	1.427	0.154	0.893	2.047
HOMAsp2	0.005	0.017	-1.631	0.103	0.000	2.859
sysPS2	1.526	0.439	1.467	0.142	0.868	2.683
c.LDLsp2#c.HOMAsp2	1.002	0.102	0.019	0.984	0.821	1.223
c.LDLsp2#c.sysPS2	0.988	0.004	-2.749	0.006	0.980	0.997
c.sysPS2#c.HOMAsp2	1.142	0.170	0.888	0.375	0.852	1.529
_cons	0.001	0.000	-9.671	0.000	0.000	0.003

```
268 .
269 . estat gof

             Deviance goodness-of-fit =  10.89468
             Prob > chi2(143)         =    1.0000

             Pearson goodness-of-fit  =  9.765011
             Prob > chi2(143)         =    1.0000

270 .
271 . estat ic

    Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	150	-68.20769	-26.3679	7	66.7358	87.81025

Note: N=Obs used in calculating BIC; see **[R] BIC note**.

```
272 .
273 . predict est32,xb

274 .
275 . gen est32count=exp(est32)

276 .
277 . gen est32countround=round( est32count )

278 .
279 . tab est32countround
```

est32countround	Freq.	Percent	Cum.
0	135	90.00	90.00
1	12	8.00	98.00
2	2	1.33	99.33
3	1	0.67	100.00
Total	150	100.00	

```
280 .
281 . poisson µ20Δt1 LDLsp2 HOMAsp2  sysPS2   DiasPS2, vce(robust) cformat(%9.3f) pformat(%5.3f) sform

Iteration 0:   log pseudolikelihood = -58.363157
Iteration 1:   log pseudolikelihood = -39.187617  (backed up)
Iteration 2:   log pseudolikelihood = -32.366721
Iteration 3:   log pseudolikelihood = -16.111028
Iteration 4:   log pseudolikelihood =  -15.65286
Iteration 5:   log pseudolikelihood = -15.630393
Iteration 6:   log pseudolikelihood = -15.630329
Iteration 7:   log pseudolikelihood = -15.630329

Poisson regression                              Number of obs     =        150
                                                Wald chi2(4)      =     263.12
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -15.630329               Pseudo R2         =     0.6564
```

µ20Δt1	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
LDLsp2	0.076	0.079	0.965	0.335	-0.079	0.231
HOMAsp2	-2.713	0.709	-3.829	0.000	-4.102	-1.324
sysPS2	-0.123	0.047	-2.593	0.010	-0.216	-0.030
DiasPS2	0.358	0.110	3.266	0.001	0.143	0.573
_cons	-7.034	0.501	-14.052	0.000	-8.015	-6.053

```
282 .
283 . poisson µ20Δt1 LDLsp2 HOMAsp2  sysPS2   DiasPS2, vce(robust) irr cformat(%9.3f) pformat(%5.3f) s

Iteration 0:   log pseudolikelihood = -58.363157
Iteration 1:   log pseudolikelihood = -39.187617  (backed up)
Iteration 2:   log pseudolikelihood = -32.366721
Iteration 3:   log pseudolikelihood = -16.111028
Iteration 4:   log pseudolikelihood =  -15.65286
Iteration 5:   log pseudolikelihood = -15.630393
Iteration 6:   log pseudolikelihood = -15.630329
Iteration 7:   log pseudolikelihood = -15.630329

Poisson regression                              Number of obs     =        150
                                                Wald chi2(4)      =     263.12
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -15.630329               Pseudo R2         =     0.6564
```

µ20Δt1	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
LDLsp2	**1.079**	**0.085**	**0.965**	**0.335**	**0.924**	**1.260**
HOMAsp2	**0.066**	**0.047**	**-3.829**	**0.000**	**0.017**	**0.266**
sysPS2	**0.884**	**0.042**	**-2.593**	**0.010**	**0.806**	**0.970**
DiasPS2	**1.430**	**0.157**	**3.266**	**0.001**	**1.154**	**1.773**
_cons	**0.001**	**0.000**	**-14.052**	**0.000**	**0.000**	**0.002**

```
284 .
285 . estat gof

         Deviance goodness-of-fit =  6.646953
         Prob > chi2(145)         =    1.0000

         Pearson goodness-of-fit  =  7.358672
         Prob > chi2(145)         =    1.0000

286 .
287 . estat ic
```

Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	**150**	**-45.48706**	**-15.63033**	**5**	**41.26066**	**56.31384**

Note: N=Obs used in calculating BIC; see **[R] BIC note**.

```
288 .
289 . predict est20,xb

290 .
291 . gen est20count=exp(est20)

292 .
293 . gen est20countround=round( est20count )

294 .
295 . tab est20countround
```

est20countround	Freq.	Percent	Cum.
0	**140**	**93.33**	**93.33**
1	**8**	**5.33**	**98.67**
2	**2**	**1.33**	**100.00**
Total	**150**	**100.00**	

```
296 .
297 . poisson µ31Δt1 LDLsp2 HOMAsp2  sysPS2   DiasPS2, vce(robust) cformat(%9.3f) pformat(%5.3f) sform

Iteration 0:   log pseudolikelihood = -42.819959
Iteration 1:   log pseudolikelihood = -31.034271
Iteration 2:   log pseudolikelihood = -17.167014
Iteration 3:   log pseudolikelihood = -14.391228
Iteration 4:   log pseudolikelihood =  -14.18184
Iteration 5:   log pseudolikelihood = -14.181524
Iteration 6:   log pseudolikelihood = -14.181524
```

```
Poisson regression                              Number of obs     =        150
                                                Wald chi2(4)      =     202.29
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -14.181524               Pseudo R2         =     0.6929
```

µ31Δt1	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
LDLsp2	0.145	0.070	2.079	0.038	0.008	0.282
HOMAsp2	-2.476	0.660	-3.754	0.000	-3.769	-1.183
sysPS2	-0.129	0.045	-2.899	0.004	-0.216	-0.042
DiasPS2	0.276	0.093	2.962	0.003	0.093	0.459
_cons	-7.584	0.688	-11.017	0.000	-8.934	-6.235

```
298 .
299 . poisson µ31Δt1 LDLsp2 HOMAsp2  sysPS2   DiasPS2, vce(robust) irr cformat(%9.3f) pformat(%5.3f) s

Iteration 0:   log pseudolikelihood = -42.819959
Iteration 1:   log pseudolikelihood = -31.034271
Iteration 2:   log pseudolikelihood = -17.167014
Iteration 3:   log pseudolikelihood = -14.391228
Iteration 4:   log pseudolikelihood =  -14.18184
Iteration 5:   log pseudolikelihood = -14.181524
Iteration 6:   log pseudolikelihood = -14.181524

Poisson regression                              Number of obs     =        150
                                                Wald chi2(4)      =     202.29
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -14.181524               Pseudo R2         =     0.6929
```

µ31Δt1	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
LDLsp2	1.156	0.081	2.079	0.038	1.008	1.326
HOMAsp2	0.084	0.055	-3.754	0.000	0.023	0.306
sysPS2	0.879	0.039	-2.899	0.004	0.805	0.959
DiasPS2	1.318	0.123	2.962	0.003	1.098	1.582
_cons	0.001	0.000	-11.017	0.000	0.000	0.002

```
300 .
301 . estat gof

         Deviance goodness-of-fit =  5.135637
         Prob > chi2(145)         =    1.0000

         Pearson goodness-of-fit  =  6.094638
         Prob > chi2(145)         =    1.0000

302 .
303 . estat ic

Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	150	-46.18021	-14.18152	5	38.36305	53.41622

Note: N=Obs used in calculating BIC; see **[R] BIC note**.

```
304 .
305 . predict est31,xb

306 .
307 . gen est31count=exp(est31)

308 .
309 . gen est31countround=round( est31count )

310 .
311 . tab est31countround
```

est31countround	Freq.	Percent	Cum.
0	140	93.33	93.33
1	7	4.67	98.00
2	3	2.00	100.00
Total	150	100.00	

```
312 .
313 . sum λ01Δt1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
λ01Δt1	150	.8	.8109982	0	3

```
314 .
315 . sum est01count
```

Variable	Obs	Mean	Std. Dev.	Min	Max
est01count	150	.8	.7876333	.000544	3.353649

```
316 .
317 . sum λ12Δt1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
λ12Δt1	150	.4466667	.6709371	0	3

```
318 .
319 . sum est12count
```

Variable	Obs	Mean	Std. Dev.	Min	Max
est12count	150	.4466667	.671353	4.96e-06	3.897766

```
320 .
321 . sum λ23Δt1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
λ23Δt1	150	.2466667	.5668311	0	3

```
322 .
323 . sum est23count
```

Variable	Obs	Mean	Std. Dev.	Min	Max
est23count	**150**	**.2466667**	**.564407**	**1.75e-08**	**3.0675**

```
324 .
325 . sum λ34Δt1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
λ34Δt1	**150**	**.1466667**	**.3549585**	**0**	**1**

```
326 .
327 . sum est34count
```

Variable	Obs	Mean	Std. Dev.	Min	Max
est34count	**150**	**.1466667**	**.3556577**	**3.28e-13**	**1.770857**

```
328 .
329 . sum  μ10Δt1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
μ10Δt1	**150**	**.24**	**.5517513**	**0**	**3**

```
330 .
331 . sum est10count
```

Variable	Obs	Mean	Std. Dev.	Min	Max
est10count	**150**	**.24**	**.5604656**	**.0026678**	**3.512814**

```
332 .
333 . sum  μ21Δt1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
μ21Δt1	**150**	**.2**	**.5181278**	**0**	**3**

```
334 .
335 . sum est21count
```

Variable	Obs	Mean	Std. Dev.	Min	Max
est21count	**150**	**.2**	**.5325411**	**.0004666**	**3.39939**

```
336 .
337 . sum  μ32Δt1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
μ32Δt1	**150**	**.1533333**	**.4134755**	**0**	**2**

338 .
339 . sum est32count

Variable	Obs	Mean	Std. Dev.	Min	Max
est32count	**150**	**.1533333**	**.4162083**	**.0006232**	**2.973803**

340 .
341 . sum µ20Δt1

Variable	Obs	Mean	Std. Dev.	Min	Max
µ20Δt1	**150**	**.0866667**	**.3051387**	**0**	**2**

342 .
343 . sum est20count

Variable	Obs	Mean	Std. Dev.	Min	Max
est20count	**150**	**.0866667**	**.3183499**	**.0008776**	**2.292223**

344 .
345 . sum µ31Δt1

Variable	Obs	Mean	Std. Dev.	Min	Max
µ31Δt1	**150**	**.0866667**	**.3263931**	**0**	**2**

346 .
347 . sum est31count

Variable	Obs	Mean	Std. Dev.	Min	Max
est31count	**150**	**.0866667**	**.3357546**	**.0005069**	**2.191298**

348 .
349 . histogram λ01Δt1, discrete frequency
(start=**0**, width=**1**)

350 .
351 . histogram λ12Δt1 , discrete frequency
(start=**0**, width=**1**)

352 .
353 . histogram λ23Δt1 , discrete frequency
(start=**0**, width=**1**)

354 .
355 . histogram λ34Δt1 , discrete frequency
(start=**0**, width=**1**)

356 .
357 . histogram µ10Δt1 , discrete frequency
(start=**0**, width=**1**)

```
358 .
359 . histogram μ21Δt1 , discrete frequency
    (start=0, width=1)

360 .
361 . histogram μ32Δt1 , discrete frequency
    (start=0, width=1)

362 .
363 . histogram μ20Δt1 , discrete frequency
    (start=0, width=1)

364 .
365 . histogram μ31Δt1 , discrete frequency
    (start=0, width=1)

366 .
367 . sum λ01Δt1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
λ01Δt1	**150**	**.8**	**.8109982**	**0**	**3**

```
368 .
369 . di r(sd)^2/r(mean)
    .82214765

370 .
371 . sum λ12Δt1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
λ12Δt1	**150**	**.4466667**	**.6709371**	**0**	**3**

```
372 .
373 . di r(sd)^2/r(mean)
    1.0078133

374 .
375 . sum λ23Δt1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
λ23Δt1	**150**	**.2466667**	**.5668311**	**0**	**3**

```
376 .
377 . di r(sd)^2/r(mean)
    1.3025576

378 .
379 . sum λ34Δt1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
λ34Δt1	**150**	**.1466667**	**.3549585**	**0**	**1**

```
380 .
381 . di r(sd)^2/r(mean)
    .8590604

382 .
383 . sum µ10Δt1

        Variable │        Obs        Mean    Std. Dev.       Min        Max
    ─────────────┼─────────────────────────────────────────────────────────
          µ10Δt1 │        150         .24    .5517513          0          3

384 .
385 . di r(sd)^2/r(mean)
    1.2684564

386 .
387 . sum µ21Δt1

        Variable │        Obs        Mean    Std. Dev.       Min        Max
    ─────────────┼─────────────────────────────────────────────────────────
          µ21Δt1 │        150          .2    .5181278          0          3

388 .
389 . di r(sd)^2/r(mean)
    1.3422819

390 .
391 . sum µ32Δt1

        Variable │        Obs        Mean    Std. Dev.       Min        Max
    ─────────────┼─────────────────────────────────────────────────────────
          µ32Δt1 │        150    .1533333    .4134755          0          2

392 .
393 . di r(sd)^2/r(mean)
    1.1149694

394 .
395 . sum µ20Δt1

        Variable │        Obs        Mean    Std. Dev.       Min        Max
    ─────────────┼─────────────────────────────────────────────────────────
          µ20Δt1 │        150    .0866667    .3051387          0          2

396 .
397 . di r(sd)^2/r(mean)
    1.0743418

398 .
399 . sum µ31Δt1

        Variable │        Obs        Mean    Std. Dev.       Min        Max
    ─────────────┼─────────────────────────────────────────────────────────
          µ31Δt1 │        150    .0866667    .3263931          0          2
```

```
400 .
401 . di r(sd)^2/r(mean)
    1.2292204

402 .
403 . corr HOMAsp1 HOMAsp2 LDLsp2 sysPS2 DiasPS2
    (obs=150)

                 |  HOMAsp1  HOMAsp2   LDLsp2   sysPS2  DiasPS2
    -------------+---------------------------------------------
         HOMAsp1 |   1.0000
         HOMAsp2 |   0.8869   1.0000
          LDLsp2 |   0.8572   0.9893   1.0000
          sysPS2 |   0.8674   0.9908   0.9959   1.0000
         DiasPS2 |   0.8854   0.9950   0.9944   0.9929   1.0000


404 .
405 . poisson λ01Δt1, vce(robust) cformat(%9.3f) pformat(%5.3f) sformat(%8.3f)

    Iteration 0:   log pseudolikelihood = -171.27294
    Iteration 1:   log pseudolikelihood = -171.27294

    Poisson regression                              Number of obs     =        150
                                                    Wald chi2(0)      =          .
                                                    Prob > chi2       =          .
    Log pseudolikelihood = -171.27294               Pseudo R2         =     0.0000

    ------------------------------------------------------------------------------
                 |               Robust
          λ01Δt1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
    -------------+----------------------------------------------------------------
           _cons |     -0.223      0.083   -2.696   0.007       -0.385      -0.061
    ------------------------------------------------------------------------------

406 .
407 . estat gof

             Deviance goodness-of-fit =  149.2359
             Prob > chi2(149)         =    0.4792

             Pearson goodness-of-fit  =     122.5
             Prob > chi2(149)         =    0.9449

408 .
409 . estat ic

    Akaike's information criterion and Bayesian information criterion

    -----------------------------------------------------------------------------
           Model |        Obs  ll(null)  ll(model)      df         AIC        BIC
    -------------+---------------------------------------------------------------
               . |        150 -171.2729  -171.2729       1    344.5459   347.5565
    -----------------------------------------------------------------------------
                   Note: N=Obs used in calculating BIC; see [R] BIC note.
```

410 .
411 . poisson λ12Δt1, vce(robust) cformat(%9.3f) pformat(%5.3f) sformat(%8.3f)

Iteration 0: log pseudolikelihood = **-130.82**
Iteration 1: log pseudolikelihood = **-130.82**

Poisson regression		Number of obs =	**150**
		Wald chi2(0) =	.
		Prob > chi2 =	.
Log pseudolikelihood =	**-130.82**	Pseudo R2 =	**-0.0000**

λ12Δt1	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
_cons	**-0.806**	**0.123**	**-6.571**	**0.000**	**-1.046**	**-0.566**

412 .
413 . estat gof

Deviance goodness-of-fit = **146.133**
Prob > chi2(**149**) = **0.5511**

Pearson goodness-of-fit = **150.1642**
Prob > chi2(**149**) = **0.4578**

414 .
415 . estat ic

Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	**150**	**-130.82**	**-130.82**	**1**	**263.64**	**266.6506**

Note: N=Obs used in calculating BIC; see **[R] BIC note**.

416 .
417 . poisson λ23Δt1, vce(robust) cformat(%9.3f) pformat(%5.3f) sformat(%8.3f)

Iteration 0: log pseudolikelihood = **-95.145651**
Iteration 1: log pseudolikelihood = **-95.145651**

Poisson regression		Number of obs =	**150**
		Wald chi2(0) =	.
		Prob > chi2 =	.
Log pseudolikelihood =	**-95.145651**	Pseudo R2 =	**0.0000**

λ23Δt1	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
_cons	**-1.400**	**0.188**	**-7.460**	**0.000**	**-1.767**	**-1.032**

```
418 .
419 . estat gof

         Deviance goodness-of-fit =  127.8528
         Prob > chi2(149)         =    0.8942

         Pearson goodness-of-fit  =  194.0811
         Prob > chi2(149)         =    0.0077

420 .
421 . estat ic

    Akaike's information criterion and Bayesian information criterion

    -----------------------------------------------------------------------------
           Model |          Obs  ll(null)  ll(model)      df         AIC        BIC
    -------------+---------------------------------------------------------------
               . |          150 -95.14565  -95.14565       1    192.2913   195.3019
    -----------------------------------------------------------------------------
                   Note: N=Obs used in calculating BIC; see [R] BIC note.

422 .
423 . poisson λ34Δt1, vce(robust) cformat(%9.3f) pformat(%5.3f) sformat(%8.3f)

    Iteration 0:   log pseudolikelihood = -64.231042
    Iteration 1:   log pseudolikelihood = -64.231042

    Poisson regression                              Number of obs     =        150
                                                    Wald chi2(0)      =          .
                                                    Prob > chi2       =          .
    Log pseudolikelihood = -64.231042               Pseudo R2         =     0.0000

    ------------------------------------------------------------------------------
                 |               Robust
          λ34Δt1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
    -------------+----------------------------------------------------------------
           _cons |     -1.920      0.198   -9.714   0.000       -2.307      -1.532
    ------------------------------------------------------------------------------

424 .
425 . estat gof

         Deviance goodness-of-fit =  84.46208
         Prob > chi2(149)         =    1.0000

         Pearson goodness-of-fit  =       128
         Prob > chi2(149)         =    0.8925

426 .
427 . estat ic

    Akaike's information criterion and Bayesian information criterion

    -----------------------------------------------------------------------------
           Model |          Obs  ll(null)  ll(model)      df         AIC        BIC
    -------------+---------------------------------------------------------------
               . |          150 -64.23104  -64.23104       1    130.4621   133.4727
    -----------------------------------------------------------------------------
                   Note: N=Obs used in calculating BIC; see [R] BIC note.
```

```
428 .
429 . poisson µ10Δt1 , vce(robust) cformat(%9.3f) pformat(%5.3f) sformat(%8.3f)

    Iteration 0:   log pseudolikelihood = -93.039149
    Iteration 1:   log pseudolikelihood = -93.039149

    Poisson regression                              Number of obs     =        150
                                                    Wald chi2(0)      =          .
                                                    Prob > chi2       =          .
    Log pseudolikelihood = -93.039149               Pseudo R2         =     0.0000

    ------------------------------------------------------------------------------
                 |               Robust
          µ10Δt1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
    -------------+----------------------------------------------------------------
           _cons |     -1.427       0.188   -7.603   0.000       -1.795     -1.059
    ------------------------------------------------------------------------------

430 .
431 . estat gof

             Deviance goodness-of-fit =  124.2535
             Prob > chi2(149)         =    0.9309

             Pearson goodness-of-fit  =       189
             Prob > chi2(149)         =    0.0148

432 .
433 . estat ic

    Akaike's information criterion and Bayesian information criterion

    -----------------------------------------------------------------------------
           Model |          Obs  ll(null)  ll(model)      df         AIC        BIC
    -------------+---------------------------------------------------------------
               . |          150 -93.03915  -93.03915       1    188.0783   191.0889
    -----------------------------------------------------------------------------
                   Note: N=Obs used in calculating BIC; see [R] BIC note.

434 .
435 . poisson µ21Δt1 , vce(robust) cformat(%9.3f) pformat(%5.3f) sformat(%8.3f)

    Iteration 0:   log pseudolikelihood = -83.540633
    Iteration 1:   log pseudolikelihood = -83.540633

    Poisson regression                              Number of obs     =        150
                                                    Wald chi2(0)      =          .
                                                    Prob > chi2       =          .
    Log pseudolikelihood = -83.540633               Pseudo R2         =     0.0000

    ------------------------------------------------------------------------------
                 |               Robust
          µ21Δt1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
    -------------+----------------------------------------------------------------
           _cons |     -1.609       0.212   -7.609   0.000       -2.024     -1.195
    ------------------------------------------------------------------------------
```

```
436 .
437 . estat gof

         Deviance goodness-of-fit =  117.0209
         Prob > chi2(149)         =    0.9753

         Pearson goodness-of-fit  =       200
         Prob > chi2(149)         =    0.0034

438 .
439 . estat ic

Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	150	-83.54063	-83.54063	1	169.0813	172.0919

Note: N=Obs used in calculating BIC; see **[R] BIC note**.

```
440 .
441 . poisson µ32Δt1 , vce(robust) cformat(%9.3f) pformat(%5.3f) sformat(%8.3f)

Iteration 0:   log pseudolikelihood = -68.207686
Iteration 1:   log pseudolikelihood = -68.207686  (backed up)

Poisson regression                              Number of obs     =        150
                                                Wald chi2(0)      =          .
                                                Prob > chi2       =          .
Log pseudolikelihood = -68.207686               Pseudo R2         =     0.0000
```

µ32Δt1	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
_cons	-1.875	0.220	-8.517	0.000	-2.307	-1.444

```
442 .
443 . estat gof

         Deviance goodness-of-fit =  94.57426
         Prob > chi2(149)         =    0.9998

         Pearson goodness-of-fit  =  166.1304
         Prob > chi2(149)         =    0.1599

444 .
445 . estat ic

Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	150	-68.20769	-68.20769	1	138.4154	141.426

Note: N=Obs used in calculating BIC; see **[R] BIC note**.

```
446 .
447 . poisson µ20Δt1 , vce(robust) cformat(%9.3f) pformat(%5.3f) sformat(%8.3f)

    Iteration 0:   log pseudolikelihood = -45.487064
    Iteration 1:   log pseudolikelihood = -45.487064

    Poisson regression                              Number of obs     =        150
                                                    Wald chi2(0)      =          .
                                                    Prob > chi2       =          .
    Log pseudolikelihood = -45.487064               Pseudo R2         =     0.0000

    ------------------------------------------------------------------------------
                 |               Robust
          µ20Δt1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
    -------------+----------------------------------------------------------------
           _cons |     -2.446       0.287   -8.507   0.000       -3.009      -1.882
    ------------------------------------------------------------------------------

448 .
449 . estat gof

             Deviance goodness-of-fit =  66.36042
             Prob > chi2(149)         =    1.0000

             Pearson goodness-of-fit  =  160.0769
             Prob > chi2(149)         =    0.2531

450 .
451 . estat ic

    Akaike's information criterion and Bayesian information criterion

    -----------------------------------------------------------------------------
           Model |          Obs  ll(null)  ll(model)      df         AIC        BIC
    -------------+---------------------------------------------------------------
               . |          150 -45.48706  -45.48706       1    92.97413   95.98476
    -----------------------------------------------------------------------------
                   Note: N=Obs used in calculating BIC; see [R] BIC note.

452 .
453 . poisson µ31Δt1 , vce(robust) cformat(%9.3f) pformat(%5.3f) sformat(%8.3f)

    Iteration 0:   log pseudolikelihood = -46.180212
    Iteration 1:   log pseudolikelihood = -46.180212

    Poisson regression                              Number of obs     =        150
                                                    Wald chi2(0)      =          .
                                                    Prob > chi2       =          .
    Log pseudolikelihood = -46.180212               Pseudo R2         =     0.0000

    ------------------------------------------------------------------------------
                 |               Robust
          µ31Δt1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
    -------------+----------------------------------------------------------------
           _cons |     -2.446       0.307   -7.953   0.000       -3.048      -1.843
    ------------------------------------------------------------------------------
```

```
454 .
455 . estat gof

          Deviance goodness-of-fit =  69.13301
          Prob > chi2(149)         =    1.0000

          Pearson goodness-of-fit  =  183.1538
          Prob > chi2(149)         =    0.0299

456 .
457 . estat ic

    Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	150	-46.18021	-46.18021	1	94.36042	97.37106

Note: N=Obs used in calculating BIC; see **[R] BIC note**.

458 .