

Illustration 6

Aim: Explaining unemployment duration, measured in number of two weeks intervals (*spell*), as a function of potential determinants such as:

- ui (UI) = 1 if filed UI claim
- $reprate$ (RR) = eligible replacement rate
- $disrate$ (DR) = eligible disregard rate
- $tenure$ (TENURE) = years tenure in lost job
- $logwage$ (LOGWAGE) = log weekly earnings in lost job (1985\$)

The duration is complete when the individual is re-employed at a full-time job, that is, when $CENSOR1 = 1$

Details: Cameron and Trivedi (2005), ch. 17.11

Illustration 6 – Question 1

```
. sum spell censor1 censor2 censor3 censor4 ui reprice disrate tenure logwage
```

Variable	Obs	Mean	Std. Dev.	Min	Max
spell	3343	6.247981	5.611271	1	28
censor1	3343	.3209692	.4669188	0	1
censor2	3343	.1014059	.3019106	0	1
censor3	3343	.1717021	.3771777	0	1
censor4	3343	.3754113	.4843014	0	1
ui	3343	.5527969	.4972791	0	1
reprice	3343	.4544717	.1137918	.066	2.059
disrate	3343	.1094376	.0735274	.002	1.02
tenure	3343	4.114867	5.862322	0	40
logwage	3343	5.692994	.5356591	2.70805	7.600402

- Non-negative outcome
- 32.01% of the observations present complete durations, which means that they are not censored on the right (censored observations present *censor1=0*)

Illustration 6 – Question 2

```
.stset spell, fail(censor1=1)
```

```
      failure event:  censor1 == 1  
obs. time interval:  (0, spell]  
exit on or before:  failure
```

```
-----  
3343  total observations  
      0  exclusions  
-----
```

```
3343  observations remaining, representing  
1073  failures in single-record/single-failure data  
20887 total analysis time at risk and under observation  
                                     at risk from t =          0  
                                     earliest observed entry t =      0  
                                     last observed exit t =        28
```

Illustration 6 – Question 2

```
. sts list
```

```
      failure _d:  censor1 == 1
analysis time _t:  spell
```

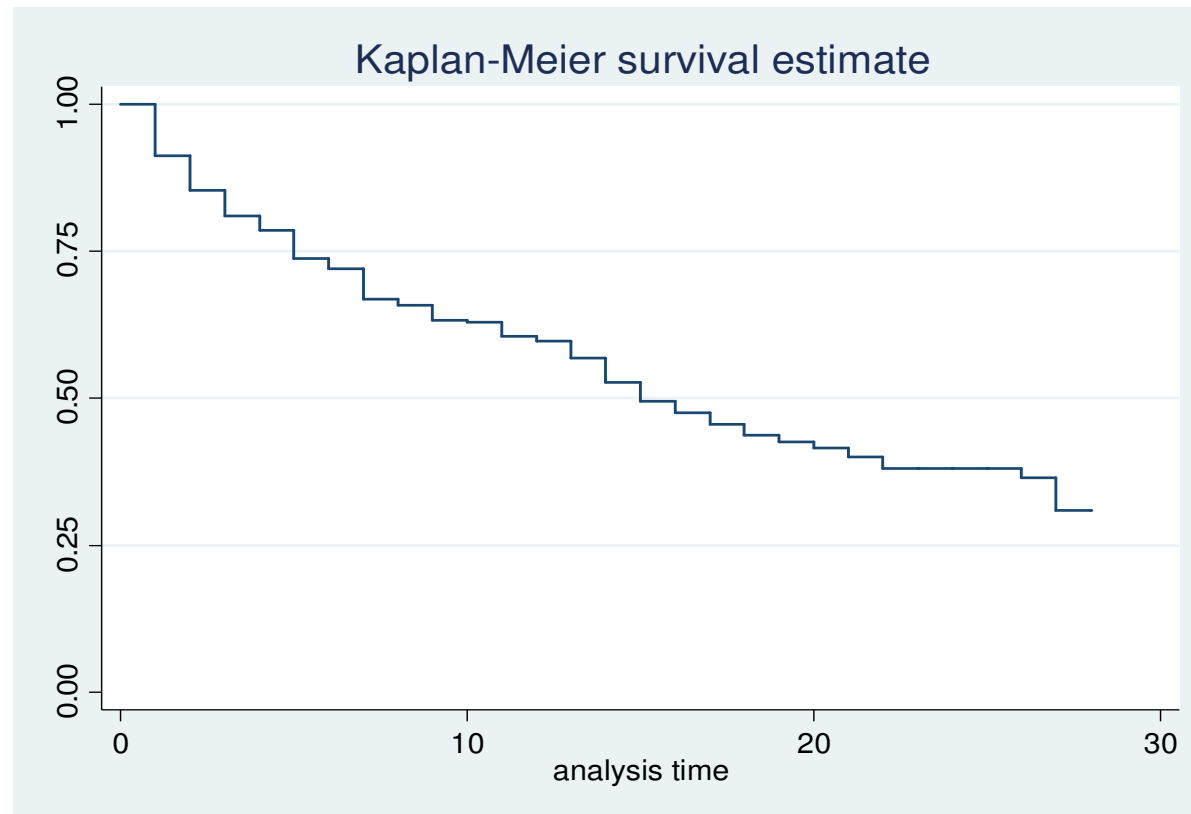
Time	Beg. Total	Fail	Net Lost	Survivor Function	Std. Error	[95% Conf. Int.]	
1	3343	294	246	0.9121	0.0049	0.9019	0.9212
2	2803	178	304	0.8541	0.0062	0.8415	0.8659
3	2321	119	305	0.8103	0.0071	0.7960	0.8238
4	1897	56	165	0.7864	0.0076	0.7712	0.8008
5	1676	104	233	0.7376	0.0085	0.7206	0.7538
6	1339	32	111	0.7200	0.0088	0.7023	0.7369
7	1196	85	178	0.6688	0.0098	0.6492	0.6876
8	933	15	70	0.6581	0.0100	0.6380	0.6773
9	848	33	98	0.6325	0.0106	0.6113	0.6528
10	717	3	55	0.6298	0.0106	0.6086	0.6503
11	659	26	77	0.6050	0.0113	0.5825	0.6267

(...)

- $(1-0.9121)*100\%=8.8\%$ of the individuals exit unemployment within the two first weeks and $(1-0.8541)*100\%= 14.6\%$ exit unemployment within one month

Illustration 6 – Question 2

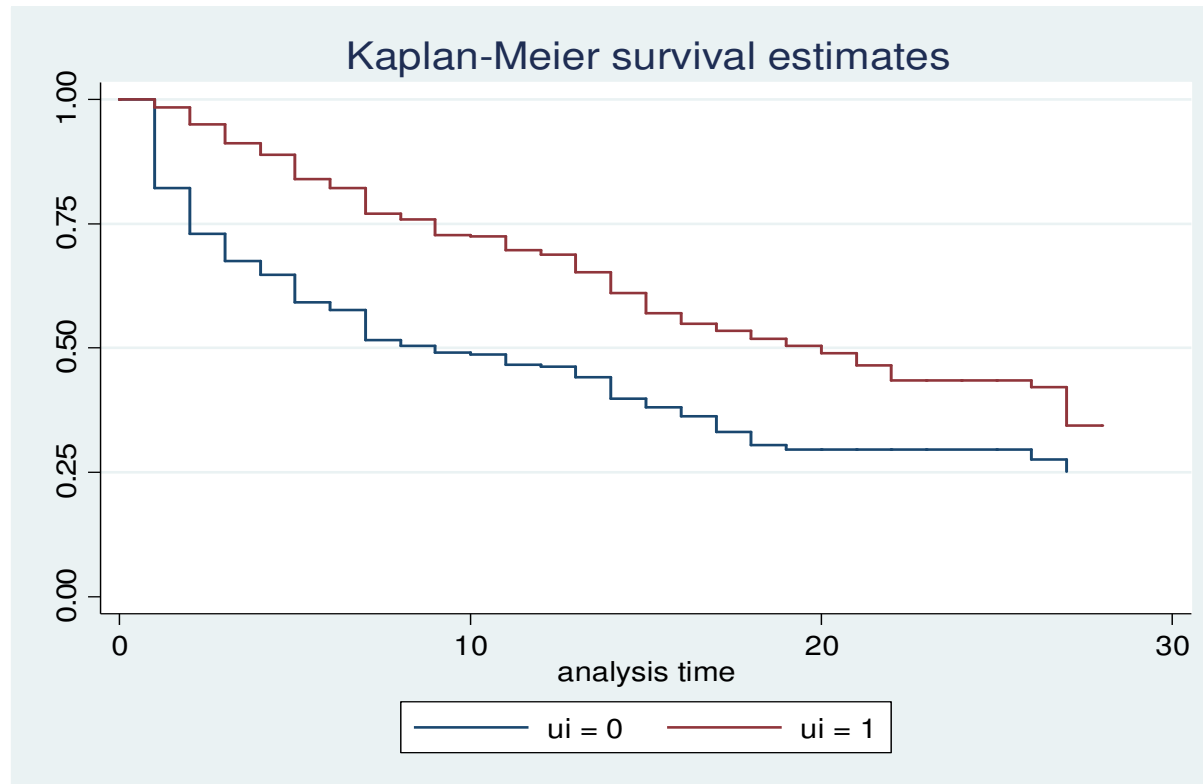
. sts graph



- Survival decreases more rapidly at first and then slowly

Illustration 6 – Question 2

```
. sts graph, by(ui)
```



- Those claiming unemployment insurance ($ui=1$) are more likely to remain unemployed

Illustration 6 – Question 3

```
. gen RR = rebrate  
. gen DR = disrate  
. gen UI = ui  
. gen RRUI = RR*UI  
. gen DRUI = DR*UI  
. gen LOGWAGE = logwage
```

```
. global xlist RR DR UI RRUI DRUI LOGWAGE tenure slack abolpos explode stateur  
houshead married female child ychild nonwhite age schlt12 schgt12 smsa bluecoll  
mining constr transp trade fire services pubadmin year85 year87 year89 midatl  
encen wncen southatl escen wscen mountain pacific
```

Illustration 6 – Question 3

```
. streg $xlist, nohr robust dist(exponential)
```

```
    failure _d:  censor1 == 1
```

```
    analysis time _t:  spell
```

```
(...)
```

```
Exponential regression -- log relative-hazard form
```

```
No. of subjects      =          3343
```

```
Number of obs       =          3343
```

```
No. of failures      =          1073
```

```
Time at risk         =          20887
```

```
Wald chi2(40)       =          565.24
```

```
Log pseudolikelihood =    -2700.6903
```

```
Prob > chi2         =          0.0000
```

		Robust				
	_t	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
-----+-----						
RR		.4720235	.6005534	0.79	0.432	-.7050396 1.649087
DR		-.5756396	.7624489	-0.75	0.450	-2.070012 .9187327
UI		-1.424561	.2493917	-5.71	0.000	-1.91336 -.9357622
RRUI		.9655904	.6118408	1.58	0.115	-.2335956 2.164776
DRUI		-.1990635	1.019118	-0.20	0.845	-2.196498 1.798371
LOGWAGE		.3508005	.115598	3.03	0.002	.1242327 .5773684
...						
_cons		-4.079107	.8767097	-4.65	0.000	-5.797426 -2.360788

```
estimates store bexponential
```

Illustration 6 – Question 3

```
. streg $xlist, nohr robust dist(weibull)
```

Weibull regression -- log relative-hazard form

No. of subjects = 3343 Number of obs = 3343

...

Wald chi2(40) = 501.65

Log pseudolikelihood = -2687.5995 Prob > chi2 = 0.0000

		Robust				
_t		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
-----+-----						
RR		.4481156	.6381895	0.70	0.483	-.8027127 1.698944
DR		-.4269187	.8086983	-0.53	0.598	-2.011938 1.158101
UI		-1.496066	.2639679	-5.67	0.000	-2.013434 -.9786984
RRUI		1.015226	.6455611	1.57	0.116	-.2500501 2.280503
DRUI		-.2988417	1.065384	-0.28	0.779	-2.386956 1.789272
LOGWAGE		.3655253	.12212	2.99	0.003	.1261745 .6048761
(...)						
_cons		-4.357886	.9196792	-4.74	0.000	-6.160424 -2.555347
-----+-----						
/ln_p		.1215314	.0194374	6.25	0.000	.0834348 .1596281
-----+-----						
p		1.129225	.0219492			1.087014 1.173075
1/p		.8855632	.0172131			.8524608 .9199511

```
. estimates store bweibull
```

Illustration 6 – Question 3

$$(\dots)$$

No. of subjects	=	3343	Number of obs	=	3343
No. of failures	=	1073			
Time at risk	=	20887			

$$(\dots)$$

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Illustration 6 – Question 3

```
. estimates table bexponential bweibull bgompertz, b star(0.1 0.05 0.01)
```

Variable	bexponential	bweibull	bgompertz
RR	.47202347	.4481156	.47240504
DR	-.57563962	-.42691874	-.56278942
UI	-1.4245611***	-1.496066***	-1.4283547***
RRUI	.96559044	1.0152264	.96894134
DRUI	-.19906351	-.29884166	-.21124952
LOGWAGE	.35080054***	.36552527***	.35247218***
(...)			
_cons	-4.0791071***	-4.3578855***	-4.0973303***
ln_p _cons		.12153144***	
gamma _cons			.00265803

legend: * p<.1; ** p<.05; *** p<.01

- Weibull is preferred to exponential ($\alpha = \exp(0.122) = 1.129$): the probability of the spell terminating increases for longer spells
- In all the models only UI and LOGWAGE are significant, with little variation across the three models:
 - For those claiming insurance the hazard rate changes $[\exp(-1.496) - 1] * 100\% = -77,6\%$

Illustration 6 – Question 4

```
. stcox $xlist, nohr robust
```

```
(...)
```

```
Cox regression -- Breslow method for ties
```

```
No. of subjects      =          3343          Number of obs   =          3343
No. of failures      =          1073
Time at risk        =          20887
```

```
Log pseudolikelihood = -7717.2334          Wald chi2(40)   =          540.98
                                          Prob > chi2     =          0.0000
```

```
-----+-----
```

			Robust				
		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
RR		.5222796	.5711698	0.91	0.361	-.5971926	1.641752
DR		-.752507	.72175	-1.04	0.297	-2.167111	.6620971
UI		-1.317719	.2372893	-5.55	0.000	-1.782798	-.8526409
RRUI		.8822462	.582115	1.52	0.130	-.2586783	2.023171
DRUI		-.0951357	.977774	-0.10	0.922	-2.011538	1.821266
LOGWAGE		.3352639	.1106483	3.03	0.002	.1183972	.5521306

```
(...)
```

```
. estimates store bcox
```

Illustration 6 – Question 4

```
. estimates table bcox, b star(0.1 0.05 0.01) keep(RR DR UI RRUI DRUI LOGWAGE)
```

```
-----  
Variable |      bcox  
-----+-----  
      RR |   .52227964  
      DR |  -.75250697  
      UI | -1.3177194***  
     RRUI |   .88224619  
     DRUI |  -.09513573  
    LOGWAGE |   .33526391***  
-----
```

```
legend: * p<.1; ** p<.05; *** p<.01
```

- The conclusions do not change

Illustration 6 – Question 5

The Figures are produced using the code in CT

```
. streg $xlist, nohr robust dist(exponential)
. predict resid, csnell
. stset resid, fail(censor1)
. sts generate survivor=s
. generate cumhaz = -ln(survivor)
. sort resid

. graph twoway (scatter cumhaz resid, c(J) msymbol(i) msize(small) clstyle(p1)) (scatter
resid resid, c(1) msymbol(i) msize(small) clstyle(p2)), scale (1.2) plotregion(style(none))
title("Exponential Model Residuals") xtitle("Generalized (Cox-Snell) Residual",
size(medlarge)) xscale(titlegap(*5)) ytitle("Cumulative Hazard", size(medlarge))
yscale(titlegap(*5)) legend(pos(6) ring(0) col(1)) legend(size(small)) legend( label(1
"Cumulative Hazard") label(2 "45 degree line"))

. graph export exp.wmf, replace

. drop resid survivor cumhaz
```

Illustration 6 – Question 5

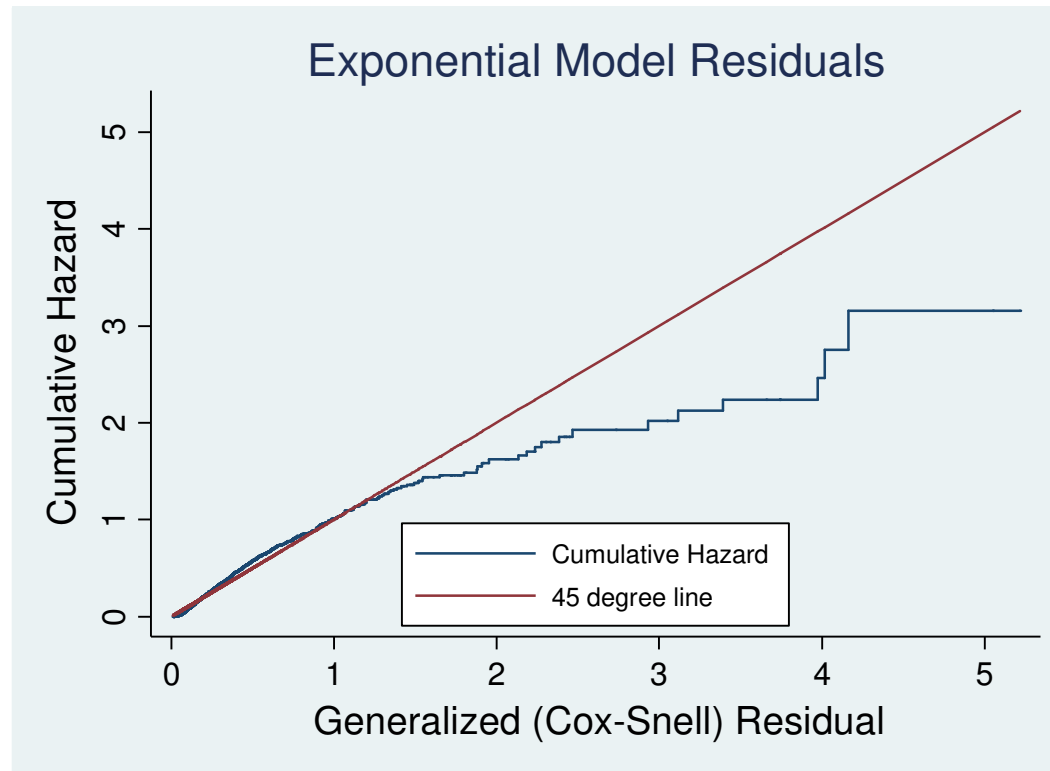


Illustration 6 – Question 5

```
stset spell, fail(censor1=1)
streg $xlist, nolog nohr dist(weibull) robust
estimates store bweib
```

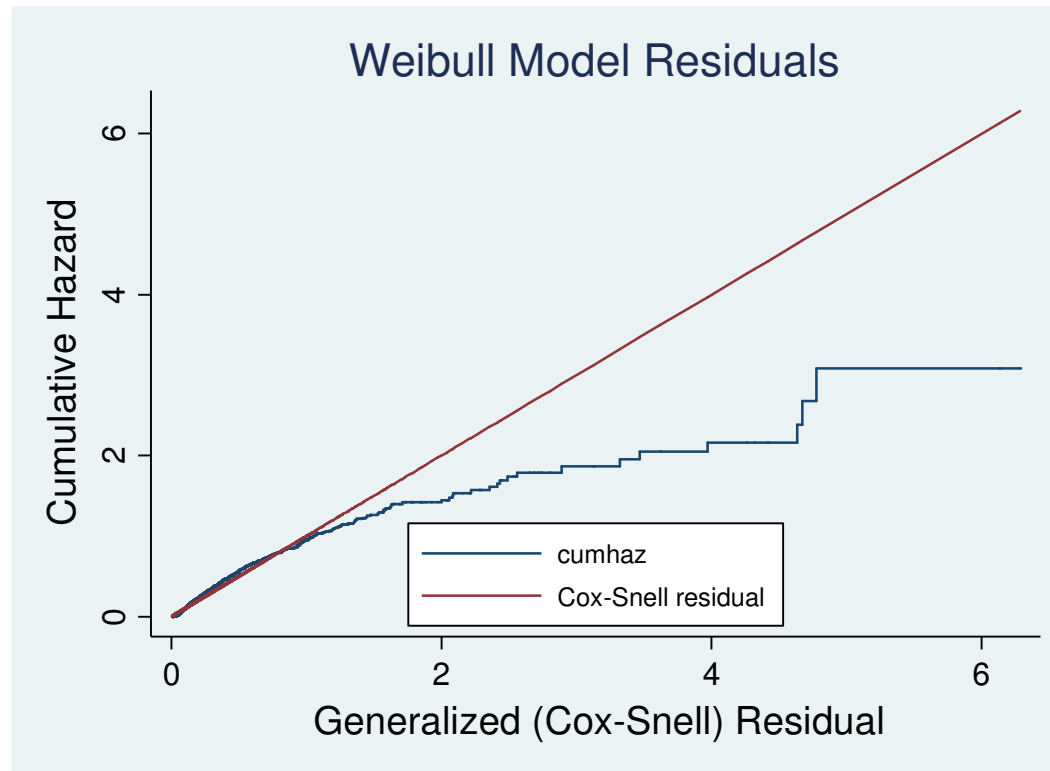
```
predict resid, csnell
stset resid, fail(censor1)
sts generate survivor=s
generate cumhaz = -ln(survivor)
sort resid
```

```
graph twoway (scatter cumhaz resid, c(J) msymbol(i) msize(small) clstyle(p1))
(scatter resid resid, c(1) msymbol(i) msize(small) clstyle(p2)), scale(1.2)
plotregion(style(none)) title("Weibull Model Residuals") xtitle("Generalized
(Cox-Snell) Residual", size(medlarge)) xscale(titlegap(*5)) ytitle("Cumulative
Hazard", size(medlarge)) yscale(titlegap(*5)) legend(pos(6) ring(0) col(1))
legend(size(small))
legend( label(1 "Cumulative Hazard") label(2 "45 degree line"))
```

```
graph export Weibull16.wmf, replace
```

```
drop resid survivor cumhaz
```

Illustration 6 – Question 5



- In both the exponential and the Weibull case the residuals are not close to the reference line

Illustration 6 – Question 6

```
stset spell, fail(censor1)
streg $xlist, nolog nohr dist(exponential) frailty(gamma) robust
estimates store bexpgamma

predict resid, csnell
stset resid, fail(censor1)
sts generate survivor=s
generate cumhaz = -ln(survivor)
sort resid

graph twoway (scatter cumhaz resid, c(J) msymbol(i) msize(small) clstyle(p1))
              (scatter resid resid, c(1) msymbol(i) msize(small) clstyle(p2)), scale (1.2)
plotregion(style(none)) title("Exponential-Gamma Model Residuals")
xtitle("Generalized (Cox-Snell) Residual", size(medlarge)) xscale(titlegap(*5))
ytitle("Cumulative Hazard", size(medlarge)) yscale(titlegap(*5)) legend(pos(6)
ring(0) col(1)) legend(size(small)) legend( label(1 "Cumulative Hazard")
label(2 "45 degree line"))

graph export exp_gamma.wmf, replace

drop resid survivor cumhaz
```

Illustration 6 – Question 6

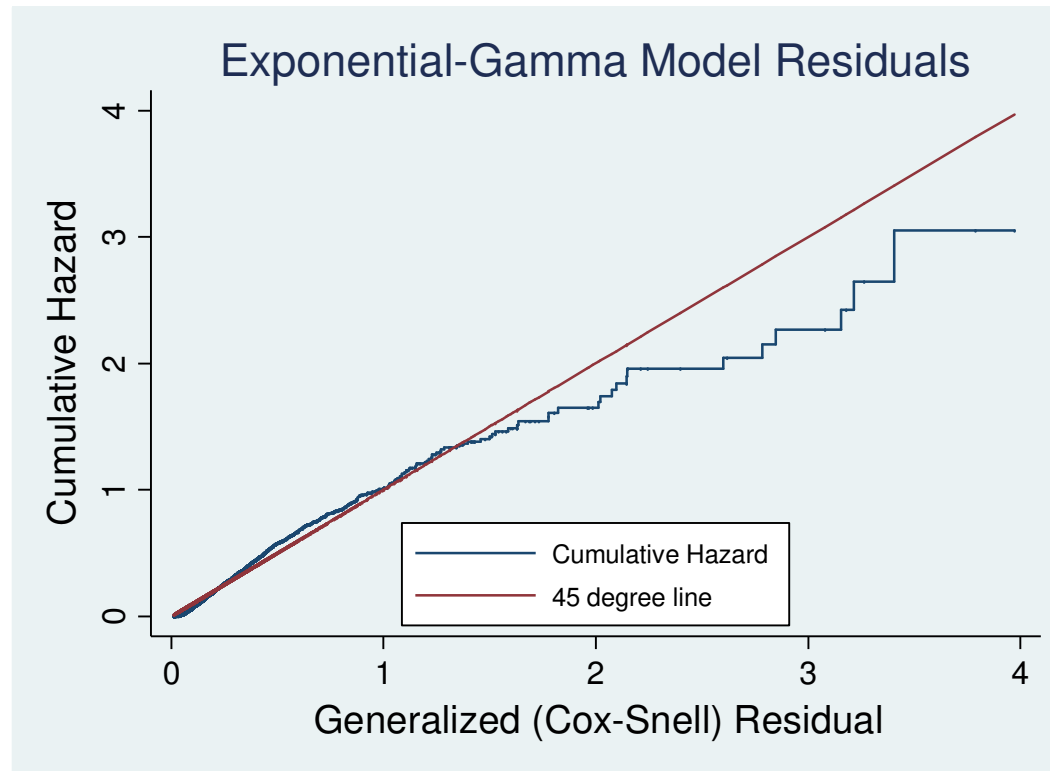


Illustration 6 – Question 6

```
stset spell, fail(censor1=1)
streg $xlist, nolog nohr dist(weibull) frailty(invgauss) robust
estimates store bweibIG

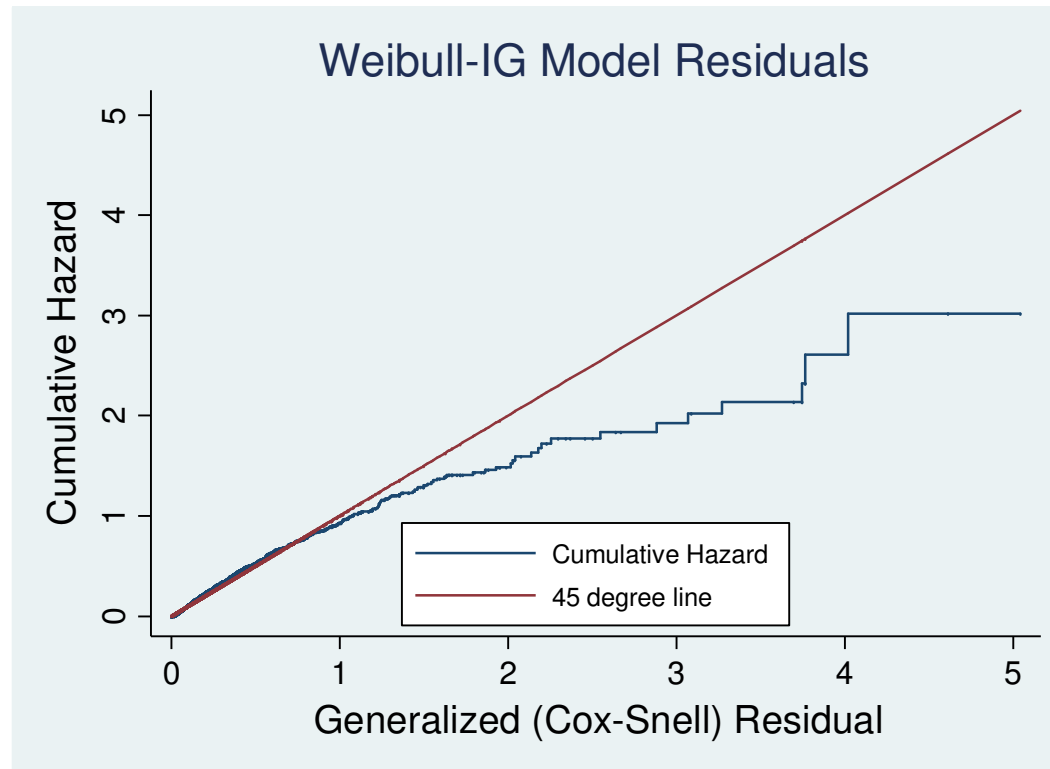
predict resid, csnell
stset resid, fail(censor1)
sts generate survivor=s
generate cumhaz = -ln(survivor)
sort resid

graph twoway (scatter cumhaz resid, c(J) msymbol(i) msize(small) clstyle(p1))
(scatter resid resid, c(1) msymbol(i) msize(small) clstyle(p2)), scale (1.2)
plotregion(style(none)) title("Weibull-IG Model Residuals") xtitle("Generalized
(Cox-Snell) Residual", size(medlarge)) xscale(titlegap(*5)) ytitle("Cumulative
Hazard", size(medlarge)) yscale(titlegap(*5)) legend(pos(6) ring(0) col(1))
legend(size(small)) legend( label(1 "Cumulative Hazard") label(2 "45 degree
line"))

graph export Weibull16_IG.wmf, replace

drop resid survivor cumhaz
```

Illustration 6 – Question 6



- Improvements relative to baseline cases where heterogeneity is overlooked are not relevant. Mispecification is apparent. In fact, the original paper using these data uses a more flexible hazard function

Illustration 6 – Question 6

```
. estimates table bexpgamma bweibIG, b star(0.1 0.05 0.01)
```

Variable	bexpgamma	bweibIG
RR	.50058284	.73562769
DR	-.88244688	-1.0725662
UI	-1.5845375***	-2.574752***
RRUI	1.0911676*	1.7335706*
DRUI	.05740483	-.060621
LOGWAGE	.37928053***	.57565599***
...		
ln_the _cons	-1.4629948***	1.8526958***
ln_p _cons		.56116668***

legend: * p<.1; ** p<.05; *** p<.01

Note that p corresponds to α , which is obtained from $\ln(p)$ as $\exp(0.561)=1.753$, σ^2 is theta and thus $\sigma^2 = \exp(1.853) = 6.379$. The duration dependence was underestimated when heterogeneity is ignored.

Illustration 7 – Question 1

```
. drop if ltotexp==.  
(109 observations deleted)
```

```
. summarize ltotexp suppins totchr age female white
```

Variable	Obs	Mean	Std. Dev.	Min	Max
ltotexp	2,955	8.059866	1.367592	1.098612	11.74094
suppins	2,955	.5915398	.4916322	0	1
totchr	2,955	1.808799	1.294613	0	7
age	2,955	74.24535	6.375975	65	90
female	2,955	.5840948	.4929608	0	1
white	2,955	.9736041	.1603368	0	1

Illustration 7 – Question 1

```
. summarize ltotexp, d  
      ln(totexp) if totexp > 0
```

	Percentiles	Smallest		
1%	4.394449	1.098612		
5%	5.703783	1.791759		
10%	6.364751	2.197225	Obs	2,955
25%	7.267525	2.639057	Sum of Wgt.	2,955
50%	8.111928		Mean	8.059866
		Largest	Std. Dev.	1.367592
75%	8.922258	11.56003		
90%	9.772752	11.59225	Variance	1.870308
95%	10.23785	11.72489	Skewness	-.3857887
99%	11.05072	11.74094	Kurtosis	3.842263

Illustration 7 – Question 1

```
. quantile ltotexp
```

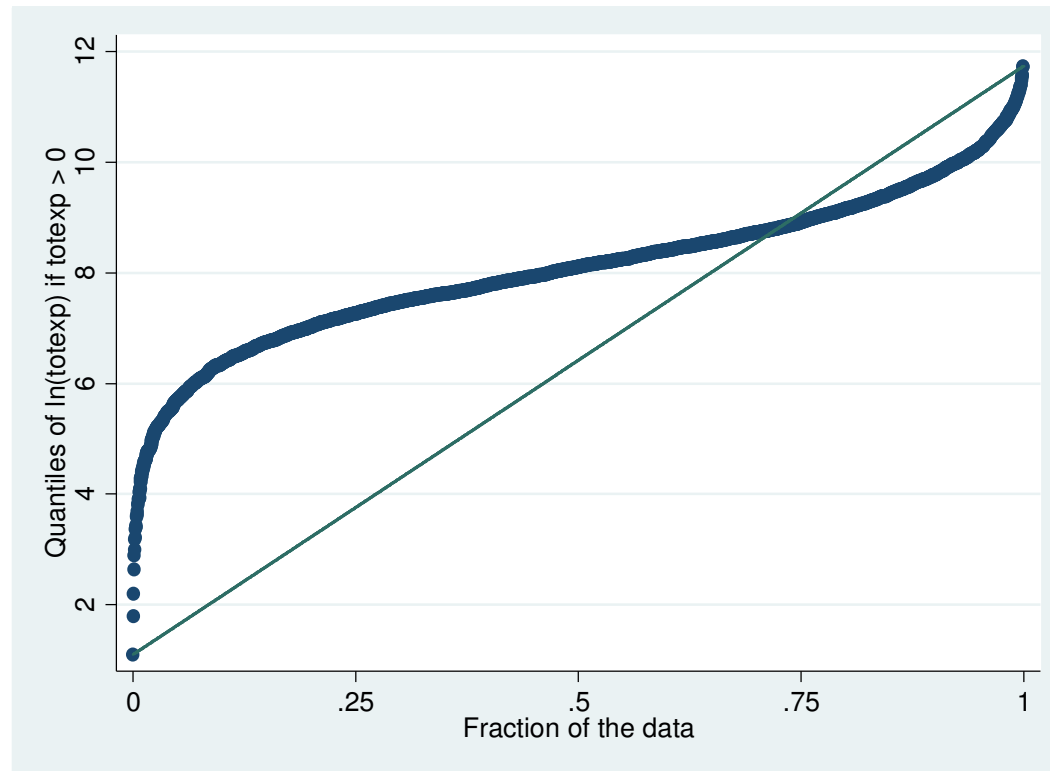


Illustration 7 – Question 2

```
. greg ltotexp suppins totchr age female white, nolog
```

Median regression
Raw sum of deviations 1555.48 (about 8.111928)
Min sum of deviations 1398.492

Number of obs = 2,955
Pseudo R2 = 0.1009

ltotexp	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
suppins	.2769771	.0535936	5.17	0.000	.1718924	.3820617
totchr	.3942664	.0202472	19.47	0.000	.3545663	.4339664
age	.0148666	.0041479	3.58	0.000	.0067335	.0229996
female	-.0880967	.0532006	-1.66	0.098	-.1924109	.0162175
white	.4987457	.1630984	3.06	0.002	.1789474	.818544
_cons	5.648891	.341166	16.56	0.000	4.979943	6.317838

Illustration 7 – Question 2

```
. mat b = e(b)
. qui predict double xb
. qui gen double expxb = exp(xb)
. su expxb, mean
. mat b = r(mean) * b
. mat li b, ti("Marginal effects ($) on total medical expenditures")
```

```
b[1,6]:  Marginal effects ($) on total medical expenditures
           suppins      totchr      age      female      white      _cons
y1      1037.755    1477.2049    55.700813   -330.07346    1868.6593    21164.8
```

- Interpretation of some effects on the conditional median of expenditures
 - An additional chronic medical condition increases the conditional median of expenditures on 1477,20\$
 - A individual with private insurante presents a conditional median of expenditures 1037,755\$ higher than na individual that does not possess insurance

Illustration 7 – Question 3

```
. quietly regress ltotexp suppins totchr age female white
. estimates store OLS

. quietly qreg ltotexp suppins totchr age female white, quantile(.25)
. estimates store Q25

. quietly qreg ltotexp suppins totchr age female white, quantile(.50)
. estimates store Q50

. quietly qreg ltotexp suppins totchr age female white, quantile(.75)
. estimates store Q75

. set seed 10101
. quietly bsqreg ltotexp suppins totchr age female white, quantile(.50) reps(400)
. estimates store bsQ50
```

Illustration 7 – Question 3

```
. estimates table OLS Q25 Q50 Q75 bsQ50, b(%7.3f) star(0.1 0.05 0.01)
```

Variable	OLS	Q25	Q50	Q75	bsQ50
suppins	0.257***	0.386***	0.277***	0.149**	0.277***
totchr	0.445***	0.459***	0.394***	0.374***	0.394***
age	0.013***	0.016***	0.015***	0.018***	0.015***
female	-0.077*	-0.016	-0.088*	-0.122**	-0.088*
white	0.318**	0.338*	0.499***	0.193	0.499**
_cons	5.898***	4.748***	5.649***	6.600***	5.649***

legend: * p<.1; ** p<.05; *** p<.01

- Individual significance is similar for *suppins*, *totchr* and *age*, but differs for *female* and *white*
- Robust individual significance for LAD is equivalent to standard case
- OLS and QR coefficients differ, even when comparing OLS with LAD (both measures of central location)
- Specially for *suppins*, impact differs across quantiles: impact is higher in low quantiles

Illustration 7 – Question 4

```
. quietly regress ltotexp suppins totchr age female white  
  
. estat hettest suppins totchr age female white, iid
```

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Ho: Constant variance

Variables: suppins totchr age female white

chi2(5) = 71.38

Prob > chi2 = 0.0000

- Homoskedasticity is rejected. The previous interpretation of partial effects would need adjustments.
- Check this result with the Machado and Santos Silva command `qreg2` (needs to be previously installed)...

Illustration 7 – Question 5

```
. set seed 10101
. sqreg ltotexp suppins totchr age female white, quantile(0.25,.50,0.75)
reps(400)
(...)
```

Simultaneous quantile regression

	Number of obs =	2,955
bootstrap(400) SEs	.25 Pseudo R2 =	0.1292
	.50 Pseudo R2 =	0.1009
	.75 Pseudo R2 =	0.0873

		Bootstrap				
	ltotexp	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
-----+-----						
q25						
	suppins	.3856797	.0642742	6.00	0.000	.2596529 .5117065
	totchr	.459022	.0234579	19.57	0.000	.4130265 .5050175
	age	.0155106	.0043944	3.53	0.000	.0068941 .0241271
	female	-.0160694	.0581328	-0.28	0.782	-.1300543 .0979155
	white	.3375936	.1110348	3.04	0.002	.11988 .5553072
	_cons	4.747962	.3485751	13.62	0.000	4.064487 5.431438
-----+-----						

(cont.)

Illustration 7 – Question 5

(cont.)

-----+-----							
q50							
suppins		.2769771	.0579685	4.78	0.000	.1633144	.3906398
totchr		.3942664	.0195859	20.13	0.000	.355863	.4326698
age		.0148666	.0044102	3.37	0.001	.0062192	.0235139
female		-.0880967	.0554863	-1.59	0.112	-.1968926	.0206992
white		.4987457	.2199888	2.27	0.023	.0673984	.9300929
_cons		5.648891	.3966791	14.24	0.000	4.871095	6.426687
-----+-----							
q75							
suppins		.1488548	.0649951	2.29	0.022	.0214143	.2762952
totchr		.3735364	.0228424	16.35	0.000	.3287478	.418325
age		.0182506	.0049533	3.68	0.000	.0085383	.027963
female		-.1219365	.0562735	-2.17	0.030	-.2322759	-.0115971
white		.1931923	.2045296	0.94	0.345	-.2078428	.5942275
_cons		6.599972	.4247018	15.54	0.000	5.76723	7.432714

Illustration 7 – Question 5

```
. test [q25=q50=q75]:suppins
```

```
( 1)  [q25]suppins - [q50]suppins = 0
```

```
( 2)  [q25]suppins - [q75]suppins = 0
```

```
F( 2, 2949) = 5.28  
Prob > F = 0.0051
```

```
. test [q25=q50=q75]: totchr
```

```
( 1)  [q25]totchr - [q50]totchr = 0
```

```
( 2)  [q25]totchr - [q75]totchr = 0
```

```
F( 2, 2949) = 6.39  
Prob > F = 0.0017
```

- Equality of coefficients is rejected in both cases, at a significance level of 5%

Illustration 7 – Question 6

```
. ssc install grqreg
checking grqreg consistency and verifying not already installed...
installing into c:\ado\plus\...
installation complete.
```

```
. qreg ltotexp suppins totchr age female white, q(.50) nolog
Median regression                               Number of obs =      2,955
Raw sum of deviations  1555.48 (about 8.111928)
Min sum of deviations  1398.492                Pseudo R2      =      0.1009
```

ltotexp	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
suppins	.2769771	.0535936	5.17	0.000	.1718924	.3820617
totchr	.3942664	.0202472	19.47	0.000	.3545663	.4339664
age	.0148666	.0041479	3.58	0.000	.0067335	.0229996
female	-.0880967	.0532006	-1.66	0.098	-.1924109	.0162175
white	.4987457	.1630984	3.06	0.002	.1789474	.818544
_cons	5.648891	.341166	16.56	0.000	4.979943	6.317838

```
. grqreg, cons ci ols olscl reps(40)
```

Illustration 7 – Question 6

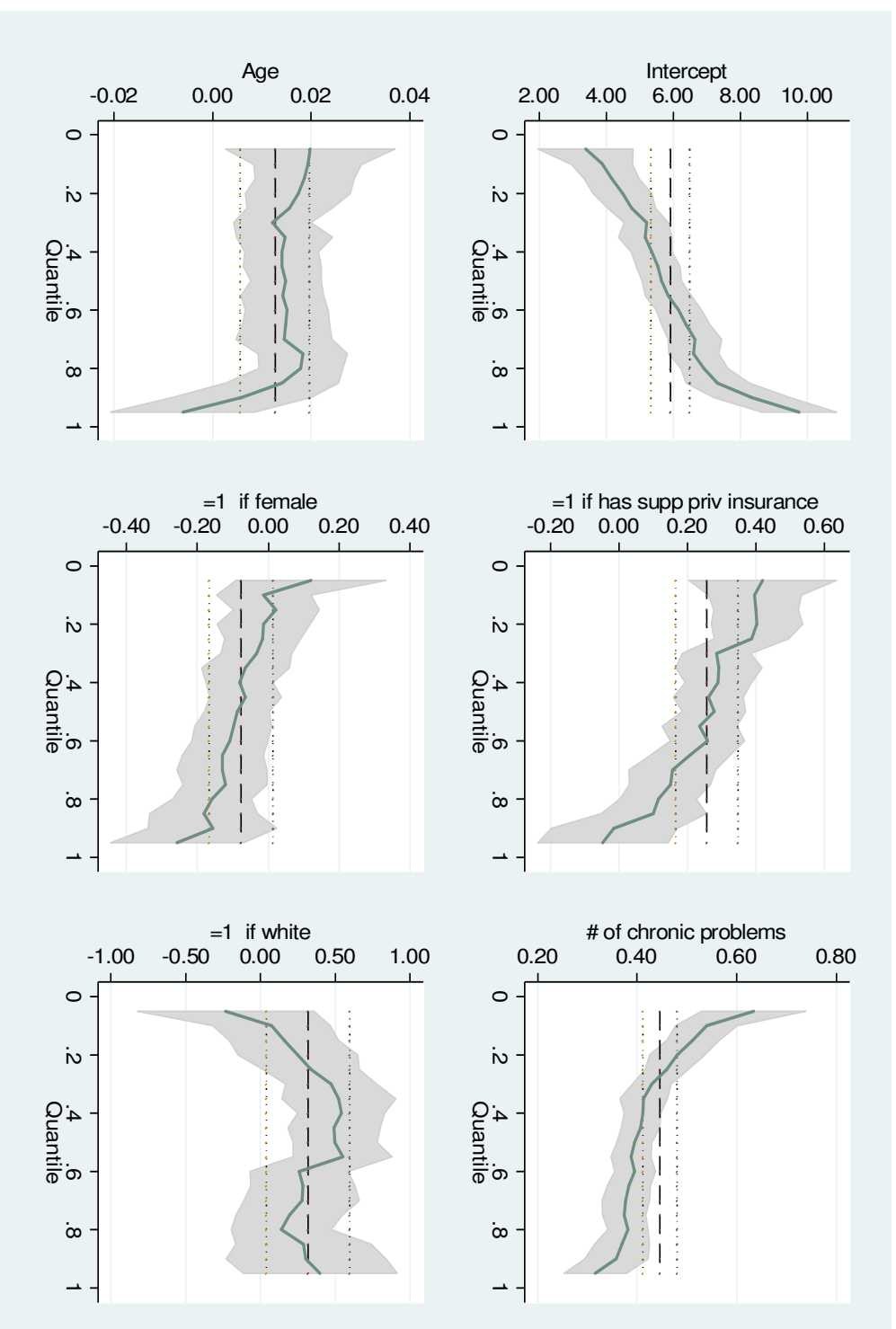


Illustration 8 – Question 1

```
. sum docvis private totchr age female white
```

Variable	Obs	Mean	Std. Dev.	Min	Max
-----+-----					
docvis	3677	6.822682	7.394937	0	144
private	3677	.4966005	.5000564	0	1
totchr	3677	1.843351	1.350026	0	8
age	3677	74.24476	6.376638	65	90
female	3677	.6010335	.4897525	0	1
-----+-----					
white	3677	.9709002	.1681092	0	1

Illustration 8 – Question 1

```
. sum docvis, d
```

docvis					

Percentiles		Smallest			
1%	0	0			
5%	0	0			
10%	0	0	Obs		3677
25%	2	0	Sum of Wgt.		3677
50%	5		Mean		6.822682
		Largest	Std. Dev.		7.394937
75%	9	59			
90%	15	73	Variance		54.68509
95%	20	106	Skewness		4.174335
99%	33	144	Kurtosis		49.67923

```
. set seed 10101  
. generate docvisu= docvis+runiform()  
. quantile docvis  
. quantile docvisu
```

Illustration 8 – Question 2

```
. quantile docvis
```

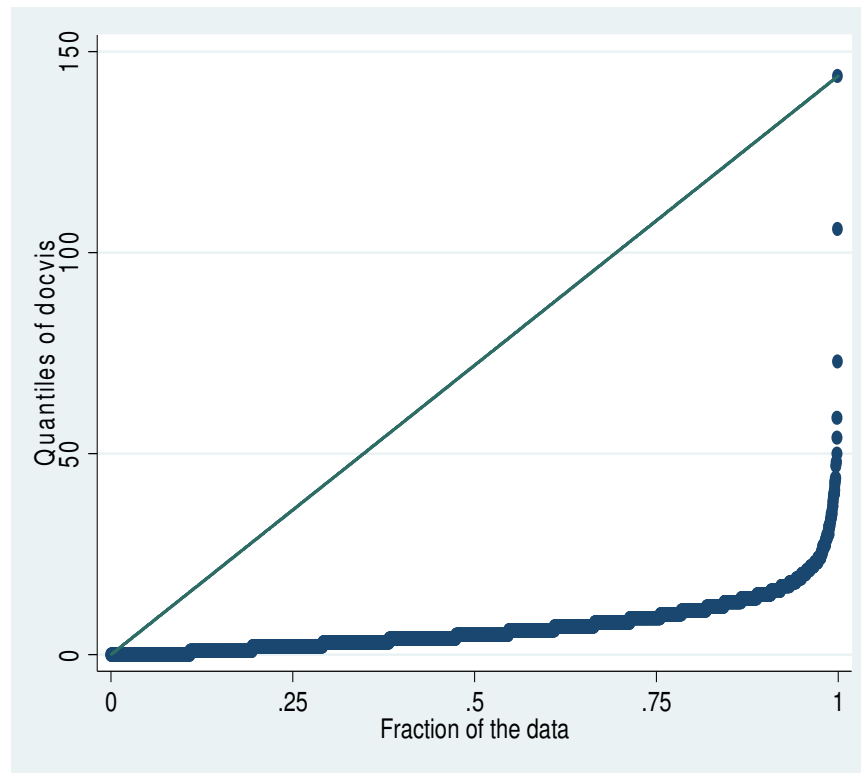


Illustration 8 – Question 2

```
. set seed 10101  
. generate docvisu= docvis+runiform()  
. quantile docvis  
. quantile docvisu
```

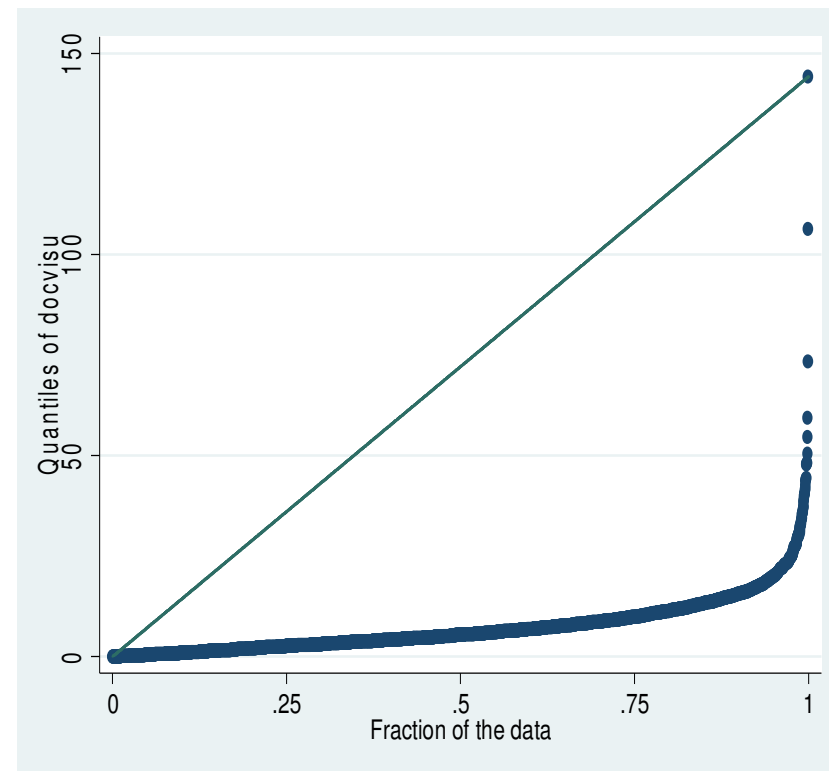
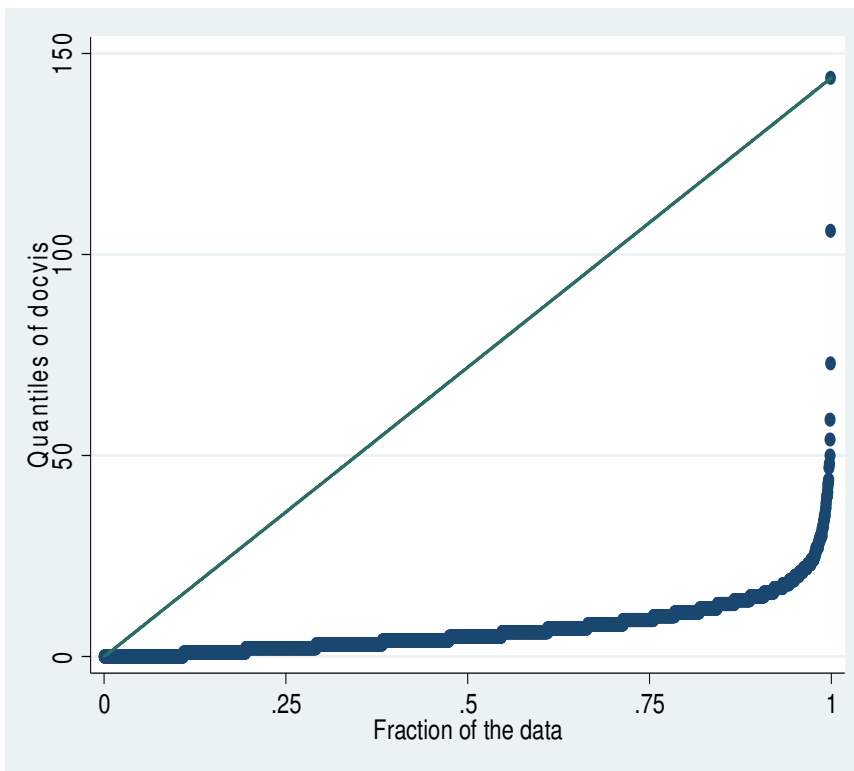


Illustration 8 – Question 3

```
. nbreg docvis private totchr age female white, vce(robust)
```

```
Negative binomial regression
```

```
Number of obs    =    3677
```

```
Dispersion      = mean      Wald chi2(5)      =      642.51
```

```
Log pseudolikelihood = -10634.246      Prob > chi2      =      0.0000
```

		Robust					
docvis		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
private		.1721237	.0344177	5.00	0.000	.1046663	.2395811
totchr		.3002597	.0123475	24.32	0.000	.2760591	.3244604
age		.005416	.0028296	1.91	0.056	-.0001299	.010962
female		-.022273	.0345702	-0.64	0.519	-.0900292	.0454833
white		.0811637	.0981205	0.83	0.408	-.111149	.2734764
_cons		.7305526	.2290788	3.19	0.001	.2815665	1.179539
/lnalpha		-.4123734	.0387841			-.4883889	-.3363579
alpha		.662077	.0256781			.6136142	.7143674

- Only two significant variables, with the expected signs

Illustration 8 – Question 3

```
. mfx
```

Marginal effects after nbreg

```
y = Predicted number of events (predict)  
= 6.2779353
```

variable	dy/dx	Std. Err.	z	P> z	[	95% C.I.	]	X
private*	1.082549	.21481	5.04	0.000	.661523	1.50358		.4966
totchr	1.885011	.0771	24.45	0.000	1.7339	2.03613		1.84335
age	.0340016	.01767	1.92	0.054	-.000622	.068626		74.2448
female*	-.1401461	.21798	-0.64	0.520	-.567381	.287089		.601033
white*	.4905679	.57117	0.86	0.390	-.62891	1.61005		.9709

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Illustration 8 – Question 4

```
. ssc install qcount
checking qcount consistency and verifying not already installed...
installing into c:\ado\stbplus\...
installation complete.
```

```
. qcount docvis private totchr age female white, q(.50) rep(500)
```

Count Data Quantile Regression

(Quantile 0.50)

Number of obs = 3677

No. jittered samples = 500

docvis	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
private	.2026718	.040978	4.95	0.000	.1223564	.2829872
totchr	.3465017	.0181826	19.06	0.000	.3108645	.382139
age	.0084275	.0033868	2.49	0.013	.0017896	.0150655
female	.0025244	.0413117	0.06	0.951	-.078445	.0834937
white	.1200437	.0980561	1.22	0.221	-.0721427	.3122302
_cons	.0338473	.2525817	0.13	0.893	-.4612037	.5288983

- An additional significant variable: age

Illustration 8 – Question 4

```
. qcount_mfx
```

Marginal effects after qcount

$$y = Qz(0.50|X)$$

$$= 5.05847 (0.0975)$$

	ME	Std. Err.	z	P> z	[95% C.I]		X
private	.92609303	.18593848	4.98	0.0000	0.5617	1.2905	0.50
totchr	1.5795176	.07860898	20.1	0.0000	1.4254	1.7336	1.84
age	.03841669	.01533359	2.51	0.0122	0.0084	0.0685	74.24
female	.01150429	.18823153	.0611	0.9513	-0.3574	0.3804	0.60
white	.51745093	.4008875	1.29	0.1968	-0.2683	1.3032	0.97

	ME	[95% C. Set]		X
private	0	0	1	0.50
totchr	1	1	1	1.84
age	0	0	0	74.24
female	0	-1	0	0.60
white	0	-1	1	0.97

- Over Qz, similar to those of BN. In the original scale, only *totchr* imposes variation on the count

Illustration 8 – Question 5

```
. quietly qcount docvis private totchr age female white, q(.25) rep(500)
. qcount_mfx
```

Marginal effects after qcount

```
y = Qz(0.25|X)
= 2.47577 (0.0666)
```

	ME	Std. Err.	z	P> z	[95% C.I]	X
private	.76479684	.1149431	6.65	0.0000	0.5395 0.9901	0.50
totchr	1.0358285	.03800236	27.3	0.0000	0.9613 1.1103	1.84
age	.02386525	.00758687	3.15	0.0017	0.0090 0.0387	74.24
female	.15941462	.12641299	1.26	0.2073	-0.0884 0.4072	0.60
white	-.14911412	.21579416	-.691	0.4896	-0.5721 0.2738	0.97

	ME	[95% C. Set]	X
private	1	1 1	0.50
totchr	1	1 1	1.84
age	0	0 0	74.24
female	0	0 0	0.60
white	0	-1 0	0.97

Illustration 8 – Question 5

```
. quietly qcount docvis private totchr age female white, q(.75) rep(500)
. qcount_mfx
```

Marginal effects after qcount

```
y = Qz(0.75|X)
= 9.06561 (0.1600)
```

	ME	Std. Err.	z	P> z	[95% C.I]	X
private	1.2253771	.33163708	3.69	0.0002	0.5754 1.8754	0.50
totchr	2.3236381	.13395758	17.3	0.0000	2.0611 2.5862	1.84
age	.0264796	.02548337	1.04	0.2988	-0.0235 0.0764	74.24
female	-.00437375	.32837804	-.0133	0.9894	-0.6480 0.6392	0.60
white	1.1880344	.81541512	1.46	0.1451	-0.4102 2.7862	0.97

	ME	[95% C. Set]	X
private	1	0 1	0.50
totchr	2	2 2	1.84
age	0	0 0	74.24
female	0	-1 0	0.60
white	1	-1 2	0.97

Illustration 8 – Question 5

- Note that standard errors decrease as we go from $q=0.25$ to $q=0.75$, reflecting the fact that precision is higher where more observations concentrate. Typically, standard errors are expected to be smaller at the central location (LAD), but in this case we have lots of zeros and small counts
- Comparing the AME over the quantiles for the most significant covariates: *private* and *totchar*:

	q=0.25	q=0.50	q=0.75
<i>private</i>	1	0	1
<i>totchar</i>	1	1	2

- Different impact at different locations