Biostat III Examination 2017 Answers

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Part 1

Some of the questions provided latitude in the analytical approach (e.g. 3(b)) and some of the questions required interpretation (e.g. defining 'safe' in 5(c)). As a general comment, it was important to provide commentary on the results, where code and output were not sufficient to get full marks. Moreover, it was important to define the notation used in the equations.

Initially, we (i) set the line size, (ii) change to the data folder, (iii) read in the dataset, (iv) create categorical variables for PSA and age at study entry, and (v) save a copy of the file for use later.

```
. set linesize 80
. cd /home/marcle/repos/biostat3_2014/exam/2017
/home/marcle/repos/biostat3_2014/exam/2017
. import delimited "psa.csv", clear
(7 vars, 100,000 obs)
. egen psa_cat = cut(psa), at(0,1,2,3,10,17586) label
. egen age_cat = cut(start_age), at(50,60,70,80) label
. saveold psa, version(11) replace
(saving in Stata 12 format, which Stata 11 can read)
file psa.dta saved
```

Question 1

If we consider the lower PSA categories, then 45.4% (95% CI: 45.0, 45.8) of those aged 50-59 years at study entry have a PSA value less than 1 ng/mL; in contrast, 32.1% (95% CI: 31.6, 32.6) of those aged 60-69 years and 22.3% (95% CI: 21.7, 23.0) of those aged 70-79 years have PSA < 1 ng/mL. Based on the chi-square test, we find strong evidence for differences in the PSA categories by age categories, although the small p-value may be also an indication of the large cell sizes. Note that the confidence intervals for the proportions were not expected, but they would be useful for a description of the sample for a scientific article.

1			psa_cat			
age_cat	0-	1-	2-	3-	10-	Total
+					+	
50- l	23,233	13,613	5,750	7,051	1,526	51,173
1	45.40	26.60	11.24	13.78	2.98	100.00
+						
60- l	10,072	7,666	4,173	7,386	2,096	31,393

	32.08	24.42	13.29	23.53	6.68	100.00
70- 	3,895 22.34	3,389 19.44	2,292 13.15	5,379 30.85	2,479 14.22	17,434 100.00
Total	37,200 37.20	24,668 24.67	12,215 12.21	19,816 19.82	6,101 6.10	100,000

Pearson chi2(8) = 7.5e+03 Pr = 0.000

- . quietly capture tab psa_cat, gen(psa_cat)
- . bysort age_cat: ci proportions psa_cat1

-> age_cat = 50-

Variable	Proportion		Binomial Exact [95% Conf. Interval]
psa_cat1		.0022009	.4496882 .458335

-> age_cat = 60-

Variable	Proportion	Std. Err.	Binomial [95% Conf.	
psa_cat1		.0026346	.315673	.3260319

-> age_cat = 70-

Variable	 -	Std. Err.	Binomial Exact [95% Conf. Interval]
psa_cat1			.2172489 .2296716

For the formal test for the association, we could also use a variety of other methods, including: non-parametric tests on the PSA values; linear regression or analysis of variance for the log(PSA) values; and binomial regression for a cut-point in PSA values. Some of these results are shown below. Note that the long tail in the PSA values suggests using log(PSA) values; the assumption here is that the measurement error is also on the log-scale. For these alternative approaches, they all provide strong evidence that age at the initial PSA test is strongly associated with the PSA values. From the linear regression, we estimate that a one year increase in age will lead to 4% increase in the PSA value.

. kwallis psa, by(age_cat)
at least two populations are required
r(498);

. capture drop ln_psa

. capture drop start_age_50

. gen start_age_50 = start_age - 50

. gen ln_psa = ln(psa)

. reg ln_psa i.age_cat, base

note: 1.age_cat omitted because of collinearity

Source	SS	df	MS	Number of obs	=	31,393
				F(0, 31392)	=	0.00
Model	0	0		Prob > F	=	

```
Residual | 47741.7414 31,392 1.5208251
                                R-squared = 0.0000
Total | 47741.7414 31,392 1.5208251 Root MSE =
                                              1.2332
   ln_psa | Coef. Std. Err. t P>|t| [95% Conf. Interval]
   age_cat |
              0 (omitted)
     60- |
    _cons | .5682677 .0069602 81.65 0.000
                                    .5546254
_____
. display "Proportional change in PSA values compared with 50-59 years: " exp(.
> 3688477) " and " exp(.7930282) " for those aged 60-69 years and 70-79 years,
> respectively."
Proportional change in PSA values compared with 50-59 years: 1.4460674 and 2.210
> 0789 for those aged 60-69 years and 70-79 years, respectively.
. reg ln_psa start_age_50, base
                  df MS
                                Number of obs = 31,393
   Source |
           SS
 280.10
  ------ Adj R-squared = 0.0088
    Total | 47741.7414 31,392 1.5208251 Root MSE
______
   ln_psa | Coef. Std. Err. t P>|t| [95% Conf. Interval]
_____+___+____+
start_age_50 | .0407087 .0024324 16.74 0.000 .0359412 .0454763
    _cons | .0023887 .0345144 0.07 0.945 -.0652608 .0700382
_____
. display "Proportional change in PSA per unit change in start age: " exp(.0407
Proportional change in PSA per unit change in start age: 1.041545
. capture drop psa_ge_10
. gen psa_ge_10 = (psa>=10)
. logit psa_ge_10 i.age_cat, nolog base or
note: 1.age_cat omitted because of collinearity
                               Number of obs = 31,393
LR chi2(0) = 0.00
Logistic regression
                               Prob > chi2
Log likelihood = -7697.3549
                               Pseudo R2
                                              0.0000
______
 psa_ge_10 | Odds Ratio Std. Err. z P>|z| [95% Conf. Interval]
   age_cat |
    60- l
            1 (omitted)
    _cons | .0715432 .0016176 -116.65 0.000 .0684419 .0747849
```

Question 2

We then restrict the dataset and stset the dataset for time since study entry. We note that one individual has an age of prostate cancer diagnosis and age of death that precedes the age of study entry; that individual should be excluded from the analyses in Parts 1 and 2.

```
. use psa, clear
. keep if start_age>=50 & start_age<70 & psa<3
(35,493 observations deleted)
. stset age_dx, fail(event_dx==1) origin(start_age)
    failure event: event_dx == 1
obs. time interval: (origin, age_dx]
exit on or before: failure
   t for analysis: (time-origin)
         origin: time start_age
                         _____
    64507 total observations
       1 observation ends on or before enter()
______
    64506 observations remaining, representing
     2908 failures in single-record/single-failure data
 713493.27 total analysis time at risk and under observation
                                                            0
                                       at risk from t =
                              earliest observed entry t =
                                                            0
                                  last observed exit t = 12.65369
. list if age_dx < start_age</pre>
48357. | id | start_~e | age_dx | event_dx | age_dth | event_~h |
     | 76042 | 55 | 21.98011 | 0 | 21.98011 |
     |-----+----+
           psa | psa_cat | age_cat | _st | _d | _origin | _t | _t0 |
     | .5194139 | 0- | 50- | 0 | . | 55 | . | . |
. drop if age_dx < start_age</pre>
(1 observation deleted)
```

(a)

Using Poisson regression to model the rate of prostate cancer incidence by age and PSA categories, we can use streg, poisson or glm commands. All three approaches should give the same estimates. For men with PSA below 3 ng/mL, there was some evidence that men aged 60-69 years had slightly higher incidence rates than men aged 50-59 years (incidence rate ratio (IRR) = 1.08, 95% CI: 1.00, 1.16, p=0.06). There was much stronger evidence that the incidence rates rose with increasing PSA categories: compared with men whose initial PSA value was less than 1 ng/mL, men with values between 1 and 2 ng/mL had an IRR of 2.79 (95% CI: 2.54, 3.08; p<0.001), and men with PSA values between 2 and 3 ng/mL had 6.09 times the incidence rate (95% CI: 5.52, 6.71; p<0.001).

```
. use psa, clear
. keep if start_age>=50 & start_age<70 & psa<3
(35,493 observations deleted)
. stset age_dx, fail(event_dx==1) origin(start_age)

    failure event: event_dx == 1
obs. time interval: (origin, age_dx]
exit on or before: failure
    t for analysis: (time-origin)</pre>
```

origin: time start_age

```
64507 total observations
       1 observation ends on or before enter()
    64506 observations remaining, representing
     2908 failures in single-record/single-failure data
 713493.27 total analysis time at risk and under observation
                                at risk from t =
                             earliest observed entry t =
                                 last observed exit t = 12.65369
. streg i.age_cat i.psa_cat, dist(exp) base nolog
       failure _d: event_dx == 1
  analysis time _t: (age_dx-origin)
          origin: time start_age
Exponential regression -- log relative-hazard form
No. of failures = 64,506
Time at min
                                      Number of obs =
                                                        64,506
Time at risk = 713493.2702
                                      LR chi2(3)
Log likelihood = -12646.774
                                      Prob > chi2
                                                         0.0000
______
        _t | Haz. Ratio Std. Err. z P>|z| [95% Conf. Interval]
age_cat |
      50- | 1 (base)
      60- | 1.076608 .0413881 1.92 0.055 .9984693 1.160861
    psa_cat |
       0- | 1 (base)
1- | 2.794569 .1385949 20.72 0.000 2.535713 3.079851
2- | 6.089436 .3030691 36.30 0.000 5.523484 6.713378
     _cons | .0016795 .0000695 -154.37 0.000 .0015487 .0018214
. testparm i(1 2).psa_cat
(1) [_t]1.psa_cat = 0
(2) [_t]2.psa_cat = 0
        chi2(2) = 1329.04
       Prob > chi2 = 0.0000
. poisson _d i.age_cat i.psa_cat if _st==1, exposure(_t) nolog irr base
                                      Number of obs
Poisson regression
                                                         64,506
                                                        1447.12
                                      LR chi2(3) =
                                      Prob > chi2
                                                   = 0.0000
Log likelihood = -12646.774
                                      Pseudo R2
                                                        0.0541
______
        _d | IRR Std. Err. z P>|z| [95% Conf. Interval]
```

+						
age_cat	1					
50-		(base)				
60-	1.076608	.0413881	1 02	0.055	.9984693	1.160861
00-	1.070000	.0413001	1.92	0.000	.9904093	1.100001
	1					
psa_cat		<i>(</i> -)				
0-		(base)				
1-		.1385951	20.72		2.535716	3.079855
2-	6.089444	.3030697	36.30	0.000	5.52349	6.713386
_cons	.0016795	.0000695	-154.37	0.000	.0015487	.0018214
ln(_t)	1	(exposure)				
. capture drop	o In pt					
. gen ln_pt =	_	+==1				
(1 missing val						
			4	(:)	- f.f + (1+	\
. glm _d i.age	e_cat 1.psa_c	at 11 _st==	i, family	(poisson)	offset(In_pt) nolog elo
> rm base						
Generalized li	inear models			No. o	f obs =	64,506
${\tt Optimization}$: ML			Resid	ual df =	64,502
				Scale	parameter =	1
Deviance	= 19477.	54726		(1/df)	Deviance =	.3019681
Pearson	= 212182	.7134		(1/df) Pearson =	3.289552
				ζ=,	,	
Variance funct	-ion: V(11) =	11		[Pois	sonl	
Link function				[Log]	5011]	
LINK TUNCCION	. g(u) -	111(u)		[Fog]		
				4.7.0		2000056
	10040	77000		AIC		.3922356
Log likelihood	1 = -12646.	77363		BIC	=	-694850.7
		MIO				
_d	IRR	Std. Err.	z	P> z	[95% Conf.	<pre>Interval]</pre>
						
age_cat						
50-		(base)				
	1.076608		1 92	0.055	.9984693	1.160861
00-	1.070000	.0413001	1.32	0.000	.3304033	1.100001
psa_cat		(2)				
0-		(base)				
1-		.1385951	20.72	0.000	2.535716	3.079855
2-	6.089444	.3030696	36.30	0.000	5.52349	6.713386
_cons	.0016795	.0000695	-154.37	0.000	.0015487	.0018214
ln_pt		(offset)				
- r	<u>-</u>					

We could also have used poisson or glm without using stset. This was a common cause of errors, either due to not including person-time in the analysis (such that the analysis was for counts and not for rates), or using the wrong person-time (e.g. using the age at diagnosis as the person-time). The individual with their diagnosis preceding their initial PSA value could cause problems here and should be excluded. The output is the same as before.

```
. use psa, clear
```

[.] keep if start_age>=50 & start_age<70 & psa<3

^{(35,493} observations deleted)

[.] drop if age_dx < start_age</pre>

⁽¹ observation deleted)

- . capture drop person_time
- . gen person_time = age_dx start_age

.

. poisson event_dx i.age_cat i.psa_cat, exposure(person_time) nolog irr base

Poisson regression	Number of obs	=	64,506
	LR chi2(3)	=	1447.12
	Prob > chi2	=	0.0000
Log likelihood = -12646.774	Pseudo R2	=	0.0541

event_dx	IRR	Std. Err.	z	P> z	[95% Conf.	Interval]
age_cat 50- 60-	1 1.076608	(base) .0413881	1.92	0.055	.9984693	1.160861
psa_cat 0- 1- 2-	1 2.794573 6.089444	(base) .1385951 .3030697	20.72 36.30	0.000	2.535716 5.52349	3.079855 6.713386
_cons ln(person~e)	.0016795 1	.0000695 (exposure)	-154.37	0.000	.0015487	.0018214

.-----

> ase

Generalized linear	models	No. of obs	=	64,506
Optimization :	ML	Residual df	=	64,502
		Scale parameter	=	1
Deviance =	19477.54726	(1/df) Deviance	=	.3019681
Pearson =	212182.7134	(1/df) Pearson	=	3.289552
Variance function: Link function :		[Poisson] [Log]		
Log likelihood =	-12646 77363	AIC BIC	=	.3922356

event_dx	 	IRR	OIM Std. Err.	z	P> z	[95% Conf.	Interval]
age_cat		4	(1)				
50-	ı	1	(base)				
60-	1	1.076608	.0413881	1.92	0.055	.9984693	1.160861
	1						
psa_cat	1						
0-	1	1	(base)				
1-	1	2.794573	.1385951	20.72	0.000	2.535716	3.079855
2-	1	6.089444	.3030696	36.30	0.000	5.52349	6.713386
	1						
_cons		.0016795	.0000695	-154.37	0.000	.0015487	.0018214

ln_pt | 1 (offset)

[.] capture drop ln_pt

[.] gen ln_pt = ln(person_time)

[.] glm event_dx i.age_cat i.psa_cat, family(poisson) offset(ln_pt) nolog eform b

(b)

To assess the interactions, we fit three models. First, we fit a main effects model and store the estimates. We use quietly because the printed output is not used here. Second, we fit an interaction model to assess the size of the interactions. We then compare the first and second models for a formal test for interaction. Similarly, we use a Wald test to test for an interaction. Third, we re-parameterise the effects so that we can more easily describe the interactions. From these models, we find that there is strong evidence for an interaction, although the likelihood-ratio and Wald p-values are difficult to interpret due to the large cell sizes. There is clear evidence that the differences between PSA categories vary by age categories: for men aged 50-59 years, the incidence rate ratios for 1-2 and 2-3 ng/mL compared with 0-1 ng/mL are 3.48 (95% CI: 3.07, 3.94) and 7.79 (95% CI: 6.86, 8.83), respectively; in contrast, for men aged 60-69 years, the same IRRs were 1.89 (95% CI: 1.62, 2.21) and 4.03 (95% CI: 3.46, 4.69), respectively.

```
. use psa, clear
```

- . keep if start_age>=50 & start_age<70 & psa<3
- (35,493 observations deleted)
- . quietly stset age_dx, fail(event_dx==1) origin(start_age)
- . quietly streg i.age_cat i.psa_cat, dist(exp) base nolog
- . quietly est store base
- . streg i.age_cat##i.psa_cat, dist(exp) base nolog

Exponential regression -- log relative-hazard form

No. of subject No. of failure Time at risk	es = 2	,908		Number	of obs	=	64,506
				LR chi2	2(5)	=	1494.40
Log likelihood	l = -12623	.134			chi2		
	Haz. Ratio					Conf.	Interval]
age_cat							
O –	1	(base)					
	1.772385		7.12	0.000	1.514	4011	2.074851
psa_cat							
0-	1	(base)					
1-	3.480924	.2215444	19.60	0.000	3.07	2696	3.943388
2-	7.785864	.5020712	31.83	0.000	6.86	1469	8.834796
I							
age_cat#							
psa_cat							
60-#1-	.5435565	.0553788	-5.98	0.000	.445	1663	.6636929
60-#2-	.5175907	.0521871	-6.53	0.000	.424	7784	.6306821
I							
_cons	.0014023	.0000731	-126.03	0.000	.0012	2661	.0015531

. lrtest base

Likelihood-ratio test LR chi2(2) = 47.28 (Assumption: base nested in .) Prob > chi2 = 0.0000

[.] testparm i1.age_cat#i(1 2).psa_cat

```
( 1) [_t]1.age_cat#1.psa_cat = 0
```

(2) [_t]1.age_cat#2.psa_cat = 0

chi2(2) = 48.48Prob > chi2 = 0.0000

. streg i.age_cat i.age_cat#i.psa_cat, dist(exp) base nolog

Exponential regression -- log relative-hazard form

No. of subject No. of failure Time at risk	s = 2	,908		Number	of obs	=	64,506
				LR chi2	(5)	=	1494.40
Log likelihood	= -12623	.134		Prob >			0.0000
_							
	Haz. Ratio					Conf.	Interval]
age_cat							
•	4	(1)					
50-	1						
60-	1.772385	.1424837	7.12	0.000	1.514	1011	2.074851
age_cat#							
psa_cat							
50-#1-	3.480924	.2215444	19.60	0.000	3.072	2696	3.943388
50-#2-	7.785864	.5020712	31.83	0.000	6.861	1469	8.834796
60-#1-	1.892079	.1505279	8.02	0.000	1.618	3901	2.211354
60-#2- I	4.029891	.3123558	17.98	0.000	3.461	1918	4.691046
i							
_cons	.0014023	.0000731	-126.03	0.000	.0012	2661	.0015531

(c)

For the first interaction model above, the regression equation is:

$$\begin{split} \log(\lambda(t|psa_cat, age_cat)) &= \beta_0 + \beta_1 I(age_cat = "60 - ") + \\ &\quad \beta_2 I(psa_cat = "1 - ") + \\ &\quad \beta_3 I(psa_cat = "2 - ") + \\ &\quad \beta_4 I(psa_cat = "1 - " \& age_cat = "60 - ") + \\ &\quad \beta_5 I(psa_cat = "2 - " \& age_cat = "60 - ") \end{split}$$

where $\lambda(t|psa_cat, age_cat)$ is the prostate cancer incidence rate at time t given psa_cat and age_cat , β_k are the regression parameters for $k = 0, \dots, 5$, and I() are indicator functions.

For the second interaction model above, the regression equation is:

$$\begin{split} \log(\lambda(t|psa_cat, age_cat)) &= \beta_0 + \beta_1 I(age_cat = "60 - ") + \\ \beta_2 I(psa_cat = "1 - " \& age_cat = "50 - ") + \\ \beta_3 I(psa_cat = "2 - " \& age_cat = "50 - ") + \\ \beta_4 I(psa_cat = "1 - " \& age_cat = "60 - ") + \\ \beta_5 I(psa_cat = "2 - " \& age_cat = "60 - ") \end{split}$$

(d)

Although not asked for, we can use the regression equation in (c) to define the rate equation for a man aged 62 years with a PSA value of 1.1 ng/mL: $\exp(\hat{\beta}_0 + \hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_4)$. We can calculate the predicted rate by hand from the fitted model. We can also obtain a 95% confidence interval using the lincom command. We find that the predicted incidence rate is 4.70 per 1000 person-years (95% CI: 4.26, 5.20).

. streg i.age_cat##i.psa_cat, dist(exp) base nolog nohr

Exponential regression -- log relative-hazard form

No. of subjects		,506 ,908		Number	of obs	=	64,506
Time at risk	= 713493.	2702					
				LR chi2	2(5)	=	1494.40
Log likelihood	= -12623	.134		Prob >	chi2	=	0.0000
_t	Coef.	Std. Err.	z	P> z	[95%	Conf.	Interval]
age_cat							
50- I	0	(base)					
60- l	.572326	.080391	7.12	0.000	.414	7626	.7298894
1							
psa_cat							
0-	0	(base)					
1-	1.247298	.0636453	19.60	0.000	1.12	2555	1.37204
2-	2.05231	.064485	31.83	0.000	1.92	5922	2.178698
1							
age_cat#							
psa_cat							
60-#1-	6096216	.1018824	-5.98	0.000	8093	3074	4099358
60-#2-	6585705	.1008269	-6.53	0.000	856	1877	4609534
1							
_cons	-6.569647	.0521286	-126.03	0.000	-6.67	1817	-6.467477

[.] display exp(-6.569647+.572326+1.247298+-.6096216)

(1) [_t]1.age_cat + [_t]1.psa_cat + [_t]1.age_cat#1.psa_cat + [_t]_cons = 0

_t	-		[95% Conf.	Interval]
			.0042566	.0051952

(e)

The formula for the risk calculation is $1 - \exp(-\hat{\lambda}t)$. We can use the confidence interval for the rate $\hat{\lambda}$ with t = 10. The code is quite simple:

^{.00470258}

[.] lincom _cons+i1.age_cat+i1.psa_cat+i1.age_cat#1.psa_cat, eform

[.] display 1-exp(-10*.0047026)

^{.04593741}

```
. display 1-exp(-10*.0042566)
.04167279
. display 1-exp(-10*.0051952)
.05062556
```

Upper: .05062594

To do this in code, it is simpler to not use eform option, as lincom only returns the estimate and standard error, rather than the confidence interval. We re-run the lincom command and then use the returned values to calculate the confidence interval:

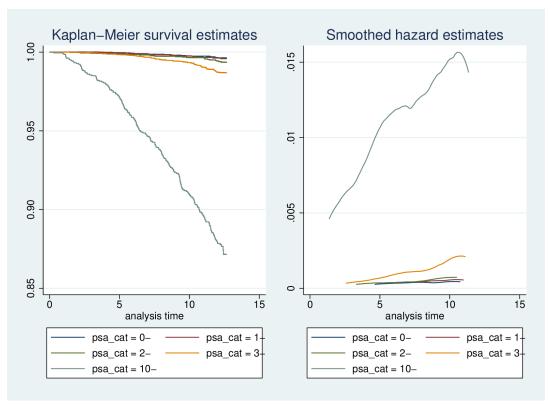
Part 2

Question 3

(a)

We can read in the dataset, keep the rows required and stset the data for time to death, modelling for prostate cancer death. In our plot of the Kaplan-Meier curves, we restrict the y-axis using the ylabel option. From the first panel of the plot, we observe that the risk of prostate cancer death within ten years is very low for PSA values less than 3 ng/mL. Moreover, the risk for men with PSA values between 3 and 10 ng/mL is also comparatively low. The prostate cancer mortality risks for men with a PSA above 10 ng/mL are substantial, with approximately 10% of men dying due to prostate cancer by ten years. For men aged 60-69 years, there are only moderate competing risks, which are censored in these Kaplan-Meier curve calculations. Following a student's suggestion, we also plot the hazards (second panel). We find evidence that the hazards are rising with time, although we are cautious in our interpretation of the smoothed hazard curves.

```
. use psa, clear
. keep if start_age>=60 & start_age<70
(68,607 observations deleted)
. stset age_dth, fail(event_dth==1) origin(start_age)
    failure event: event_dth == 1
obs. time interval: (origin, age_dth]
exit on or before: failure
   t for analysis: (time-origin)
           origin: time start_age
     31393 total observations
         0 exclusions
     31393 observations remaining, representing
       386 failures in single-record/single-failure data
343413.911 total analysis time at risk and under observation
                                                at risk from t =
                                     earliest observed entry t =
                                                                         0
                                          last observed exit t = 12.65369
. sts graph, by(psa_cat) ylabel(0.85(0.05)1) saving(q3a1, replace)
        failure _d: event_dth == 1
   analysis time _t:
                     (age_dth-origin)
            origin: time start_age
(file q3a1.gph saved)
. sts graph, by(psa_cat) hazard saving(q3a2, replace)
        failure _d: event_dth == 1
   analysis time _t: (age_dth-origin)
            origin: time start_age
(file q3a2.gph saved)
. graph combine q3a1.gph q3a2.gph
. graph export q3a.eps, replace
(file q3a.eps written in EPS format)
. * the following line is only needed on Linux
. !! convert -density 300 q3a.eps q3a.png
```



We could further complement this analysis by a description of the level for the survival curves. For men with an initial PSA value that was $10~\rm ng/mL$ or over, survival at five and ten years was 97.2% and 91.0%, respectively. For men with an initial PSA value between 3 and $10~\rm ng/mL$, ten-year survival was 99.3%.

- . use psa, clear
- . keep if start_age>=60 & start_age<70
 (68,607 observations deleted)</pre>
- . quietly stset age_dth, fail(event_dth==1) origin(start_age)
- . sts list, by(psa_cat) at (5 10)

		Beg.		Survivor	Std.		
	Time	Total	Fail	Function	Error	[95% Co	nf. Int.]
0-							
	5	9245	5	0.9995	0.0002	0.9987	0.9998
	10	7890	17	0.9975	0.0005	0.9961	0.9983
1-							
	5	7086	2	0.9997	0.0002	0.9989	0.9999
	10	6138	14	0.9976	0.0006	0.9961	0.9985
2-							
	5	3913	4	0.9990	0.0005	0.9974	0.9996
	10	3417	9	0.9966	0.0010	0.9941	0.9980
3-							
	5	6928	11	0.9985	0.0005	0.9972	0.9991
	10	6014	33	0.9933	0.0010	0.9911	0.9950
10-							
	5	1908	58	0.9715	0.0037	0.9633	0.9779
	10	1552	114	0.9097	0.0066	0.8958	0.9217

Note: Survivor function is calculated over full data and evaluated at indicated times; it is not calculated from aggregates shown at left.

An alternative approach would be to use life-tables.

- . use psa, clear
- . keep if start_age>=60 & start_age<70

(68,607 observations deleted)

- . quietly stset age_dth, fail(event_dth==1) origin(start_age)
- . ltable _t _d, by(psa_cat) interval(1(1)10)

			Beg.				Std.		
	Inte	erval	Total	Deaths	Lost	Survival	Error	[95% Con	f. Int.]
0-									
-	0		10072	0	5	1.0000	0.0000		
	1	2	10067	0	176	1.0000	0.0000		
	2	3	9891	0	173	1.0000	0.0000		
	3	4	9718	2	212	0.9998	0.0001	0.9992	0.9999
	4	5	9504	3	257	0.9995	0.0002	0.9987	0.9998
	5	6	9244	1	267	0.9994	0.0003	0.9986	0.9997
	6	7	8976	5	249	0.9988	0.0004	0.9978	0.9993
	7	8	8722	2	252	0.9986	0.0004	0.9975	0.9992
	8	9	8468	4	283	0.9981	0.0005	0.9969	0.9988
	9	10	8181	5	287	0.9975	0.0005	0.9961	0.9983
	10		7889	8	7881	0.9954	0.0009	0.9933	0.9969
1-									
	0		7666	0	3	1.0000	0.0000		
	1	2	7663	0	117	1.0000	0.0000		
	2	3	7546	0	149	1.0000	0.0000		
	3	4	7397	1	146	0.9999	0.0001	0.9990	1.0000
	4	5	7250	1	164	0.9997	0.0002	0.9989	0.9999
	5	6	7085	4	179	0.9992	0.0003	0.9981	0.9996
	6	7	6902	1	174	0.9990	0.0004	0.9979	0.9995
	7	8	6727	4	188	0.9984	0.0005	0.9971	0.9991
	8	9	6535	3	206	0.9979	0.0006	0.9965	0.9988
	9	10	6326	2	187	0.9976	0.0006	0.9961	0.9985
	10		6137	10	6127	0.9944	0.0012	0.9915	0.9963
2-									
	0		4173	0	2	1.0000	0.0000		
	1	2	4171	1	49	0.9998	0.0002	0.9983	1.0000
	2	3	4121	2	52	0.9993	0.0004	0.9977	0.9998
	3	4	4067	0	70	0.9993	0.0004	0.9977	0.9998
	4	5	3997	1	84	0.9990	0.0005	0.9974	0.9996
	5	6	3912	2	98	0.9985	0.0006	0.9967	0.9993
	6	7	3812	1	81	0.9982	0.0007	0.9963	0.9992
	7	8	3730	3	96	0.9974	0.0008	0.9952	0.9986
	8	9	3631	0	101	0.9974	0.0008	0.9952	0.9986
	9	10	3530	3	111	0.9966	0.0010	0.9941	0.9980
	10		3416	9	3407	0.9913	0.0020	0.9864	0.9945
3-									
	0		7386	0	4	1.0000	0.0000	•	
	1	2	7382	2	89	0.9997	0.0002	0.9989	0.9999
	2	3	7291	0	95	0.9997	0.0002	0.9989	0.9999
	3	4	7196	5	117	0.9990	0.0004	0.9980	0.9995
	4	5	7074	4	143	0.9985	0.0005	0.9972	0.9991
	5	6	6927	4	181	0.9979	0.0005	0.9965	0.9987
	6	7	6742	7	160	0.9968	0.0007	0.9952	0.9979
	7	8	6575	11	174	0.9951	0.0008	0.9932	0.9965

8	9	6390	5	198	0.9943	0.0009	0.9922	0.9959
9	10	6187	6	168	0.9934	0.0010	0.9911	0.9951
10	•	6013	37	5976	0.9812	0.0022	0.9763	0.9851
10-								
0	•	2096	2	2	0.9990	0.0007	0.9962	0.9998
1	2	2092	13	22	0.9928	0.0019	0.9881	0.9957
2	3	2057	15	33	0.9855	0.0026	0.9793	0.9898
3	4	2009	11	34	0.9801	0.0031	0.9730	0.9853
4	5	1964	17	40	0.9715	0.0037	0.9633	0.9779
5	6	1907	25	40	0.9586	0.0044	0.9489	0.9665
6	7	1842	23	42	0.9465	0.0051	0.9357	0.9556
7	8	1777	18	45	0.9368	0.0055	0.9251	0.9467
8	9	1714	24	53	0.9235	0.0061	0.9107	0.9345
9	10	1637	24	62	0.9097	0.0066	0.8959	0.9218
10	•	1551	55	1496	0.8474	0.0102	0.8262	0.8662

(b)

We can compare the PSA categories using a log-rank test. For describing for the form of the association, we can use the interpretation from (a). We can also interpret the pattern of observed versus expected values, or, more directly, use Cox regression. From a Cox model with pca_cat as a categorical covariate, we find strong evidence for the change in mortality risk by PSA categories. Note that the Cox regression was not required here.

. sts test psa_cat

Log-rank test for equality of survivor functions

psa_cat	Events observed	Events expected
0-	 30	122.30
1-	l 26	94.54
2-	J 22	52.44
3-	l 81	92.19
10-	227	24.53
	+	
Total	J 386	386.00

```
chi2(4) = 1809.90
Pr>chi2 = 0.0000
```

. stcox i.psa_cat, nolog

Cox regression -- no ties

No. of subjects = 31,393 Number of obs
No. of failures = 386
Time at risk = 343413.9114

31,393

			LR chi2(4)	=	799.72
Log likelihood	=	-3528.6169	Prob > chi2	=	0.0000

_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf.	<pre>Interval]</pre>
	+					
psa_cat						
1-	1.120885	.3003368	0.43	0.670	.6629561	1.895122
2-	1.709692	.4798985	1.91	0.056	.9862606	2.963768
3-	3.58108	.7653739	5.97	0.000	2.355533	5.44426
10-	37.74785	7.33327	18.69	0.000	25.79464	55.24017

(c)

We can use the sts list command to estimate the risks. The ten-year risks for those aged 60-69 years for PSA categories 0-, 1-, 2-, 3-9 and 10+ ng/mL were 0.25% (95% CI: 0.17, 0.39), 0.24% (95% CI: 0.15, 0.39), 0.34% (95% CI: 0.20, 0.59) and 0.0% (95% CI: 0.87, 0.39) and 0.87, 0.39) (95% CI: 0.87, 0.39)

. sts list, by(psa_cat) at (5 10) fail

	Time	Beg. Total	Fail	Failure Function	Std. Error	[95% Co	onf. Int.]
0-							
	5	9245	5	0.0005	0.0002	0.0002	0.0013
	10	7890	17	0.0025	0.0005	0.0017	0.0039
1-							
	5	7086	2	0.0003	0.0002	0.0001	0.0011
	10	6138	14	0.0024	0.0006	0.0015	0.0039
2-							
	5	3913	4	0.0010	0.0005	0.0004	0.0026
	10	3417	9	0.0034	0.0010	0.0020	0.0059
3-							
	5	6928	11	0.0015	0.0005	0.0009	0.0028
	10	6014	33	0.0067	0.0010	0.0050	0.0089
10-							
	5	1908	58	0.0285	0.0037	0.0221	0.0367
	10	1552	114	0.0903	0.0066	0.0783	0.1042

Note: Failure function is calculated over full data and evaluated at indicated times; it is not calculated from aggregates shown at left.

A variety of other approaches would be used here, including life-tables, direct rate calculations and Poisson regression. Given evidence for a changing hazard, it would be sensible to split for time rather than assuming a constant hazard. Splitting at five years, we can use Poisson regression and nlcom using the following code:

- . use psa, clear
- . quietly keep if start_age>=60 & start_age<70</pre>
- . quietly stset age_dth, fail(event_dth==1) origin(start_age) id(id)
- . quietly stsplit fuband, at(0(5)15)
- . streg i.fuband if psa_cat == 4, dist(exp) nolog base

failure _d: event_dth == 1

```
analysis time _t: (age_dth-origin)
origin: time start_age
id: id

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

No. of subjects No. of failures		,096 227		Number o	of obs	=	5,554	
Time at risk	= 22183.74	4759						
				LR chi2((2)	=	40.29	
Log likelihood	g likelihood = -833.14411			Prob > chi2 =			0.0000	
- ·		Std. Err.					_	
fuband								
0	1	(base)						
5 l	2.289127	.3692051	5.13	0.000	1.668	8717	3.140199	
10	2.820484	.5308447	5.51	0.000	1.950	0377	4.078765	
1								
_cons	.0057385	.0007535	-39.30	0.000	.004	4364	.0074227	
. nlcom 1-exp(-(exp(_b[_cons])*5+exp(_b[_cons]+_b[5.fuband])*5))								

t I	Coef	Std Err	7	P> 7	[95% Conf Interval]	

_nl_1: 1-exp(-(exp(_b[_cons])*5+exp(_b[_cons]+_b[5.fuband])*5))

Question 4

(a)

Fitting the Cox regression model with main effects for age and PSA, we find that age is strongly associated with prostate cancer mortality, with men aged 60-69 years having 7.38 (95% CI: 4.55, 11.97) times the prostate cancer mortality compared with those aged 50-59 years. For PSA categories, taking a reference group for those with an initial PSA of between 0 and 1 ng/mL, there was no significant difference in mortality for those with a PSA between 1 and 2 ng/mL (rate ratio (RR) = 1.12; 95% CI: 0.70, 1.80), although the number of events was small, as represented by the wider confidence intervals; for those with a PSA value between 2 and 3 ng/mL, the risk was higher (RR = 1.86, 95% CI: 1.14, 3.03).

Cox regression -- no ties

No. of subject		,506 99		Number o	of obs	=	64,506
Time at risk	= 725128.	7179					
				LR chi2	(3)	=	95.81
Log likelihood	= -1032.	7654		Prob > d	chi2	=	0.0000
_t	Haz. Ratio	Std. Err.	Z	P> z	[95% C	Conf.	Interval]
+							
age_cat							
50-	1	(base)					
60-	7.379064	1.821191	8.10	0.000	4.5490)46	11.96967
1							
psa_cat							
0-	1	(base)					
1-	1.124633	.2685629	0.49	0.623	.70427	771	1.795884
2-	1.862285	.4630303	2.50	0.012	1.1439	951	3.031692

(b)

For the given dataset, there are several time scales of interest. First, we could consider time from the PSA test, which may be related to the time to the next PSA test, and hence to diagnosis, treatment and survival. However, for the men with PSA below 3 ng/mL, the time course to next PSA test is unclear. If we model for time since test, we then assume that the shape of the baseline hazard is the same for all groups. Calculations of survival and risks are simpler when we use this as the primary time scale. Second, we could adjust for attained age as the primary time scale. This is possibly a good choice, as age is closely related to prostate cancer mortality. The form of question (a) suggests that start age is categorical, but either time scale could be appropriate. We also provide code using attained age as the primary time scale. We see that the results comparing PSA categories are similar to those using time since test as the primary time scale. Third, in another dataset, we could possibly have used calendar period as the time scale, although changes in calendar period would generally be less than age or time since PSA test.

```
. stset age_dth, fail(event_dth==1) entry(start_age)
```

```
failure event: event_dth == 1
obs. time interval: (0, age_dth]
enter on or after: time start_age
```

exit on or before: failure

64506 total observations
0 exclusions

64506 observations remaining, representing

99 failures in single-record/single-failure data

725128.718 total analysis time at risk and under observation

at risk from t = 0earliest observed entry t = 50last observed exit t = 81.6323

. stcox i.psa_cat, nolog base

failure _d: event_dth == 1
analysis time _t: age_dth
enter on or after: time start_age

Cox regression -- no ties

```
No. of subjects =
                  64,506
                                     Number of obs
                                                        64,506
No. of failures =
Time at risk
            = 725128.7179
                                     LR chi2(2)
                                                         4.58
Log likelihood =
               -946.36737
                                     Prob > chi2
                                                        0.1014
       _t | Haz. Ratio Std. Err. z P>|z|
                                             [95% Conf. Interval]
psa_cat |
      0- |
                  1 (base)
       1- |
                    .2545572
                               0.27
                                     0.788
             1.066148
                                             .6677001
                                                      1.702367
       2- |
             1.685212
                     .4187237
                               2.10
                                     0.036
                                             1.035516
                                                      2.742534
```

(c)

For the Cox model in 4 (a),

$$\lambda(t|age\ cat, psa\ cat) = \lambda_0(t) \exp(\beta_1 I(age\ cat = "60 - ") + \beta_2 I(psa\ cat = "1 - ") + \beta_3 I(psa\ cat = "2 - "))$$

This uses the same notation as in 2 (c), with the extension that $\lambda_0(t)$ is the baseline hazard function for $psa_cat = "0 - "$ and $age_cat = "50 - "$.

(d)

$$Risk(t = 10|age_cat = "60 - ", psa_cat = "1 - ") = S_0(t = 10)^{HR(age=62, PSA=1.1)} = S_0(t = 10)^{\exp(\beta_1 + \beta_2)}$$

where β_1 and β_2 are the regression parameters in 2 (c).

(e)

This answer assumes that 3 (c) was answered using the Kaplan-Meier estimator. The answer would change if another method had been used for 3 (c).

For 3 (c), survival and risks were calculated using the Kaplan-Meier estimator. For 4 (d), the risk is calculated from the Cox model, combining the hazard ratio with the Breslow estimator of baseline survival. These two approaches are closely related, where both assume a non-parametric baseline survival. The Kaplan-Meier curves are calculated separately for each stratum or group, with no modelling across strata or groups. The Cox model includes a model for the covariates, providing an opportunity to estimate risks for smaller groups under the assumption that the model holds. A Cox model stratified by both age and PSA categories would give the same as the Kaplan-Meier estimators.

(f)

As suggested by some of the students, we could first check whether there is any evidence for time-dependence using Schoenfeld residuals. These tests suggest no evidence for non-proportionality for either age or PSA categories.

- . use psa, clear
- . keep if start_age>=50 & start_age<70 & psa<3

(35,493 observations deleted)

- . quietly stset age_dth, fail(event_dth==1) origin(start_age) id(id)
- . quietly tab psa_cat, gen(psa_cat)
- . quietly stcox i.age_cat i.psa_cat, nolog
- . estat phtest, detail

Test of proportional-hazards assumption

Time: Time

	 _	rho	chi2	df	Prob>chi2
Ob.age_cat	-			1	
1.age_cat		-0.12656	1.60	1	0.2060
Ob.psa_cat		•		1	
1.psa_cat		-0.03177	0.10	1	0.7518
2.psa_cat	1	-0.03362	0.11	1	0.7364
	-+-				
global test			1.84	3	0.6060

Note that the numbers of prostate cancer deaths are not large, particularly in the first five years. Using (i) time-splitting at five years, we calculate indicators for splitting and use the indicators in the Cox model. The stsplit command takes care of the left truncation and event indicators. The hazard ratios for the time-varying effects are not individually significant and the Wald test also suggests no time-varying effects (p=0.83).

```
. use psa, clear
. keep if start_age>=50 & start_age<70 & psa<3
(35,493 observations deleted)
. stset age_dth, fail(event_dth==1) origin(start_age) id(id)
              id: id
failure event: event_dth == 1
obs. time interval: (age_dth[_n-1], age_dth]
exit on or before: failure
   t for analysis: (time-origin)
           origin: time start_age
                            _____
     64507 total observations
        1 observation ends on or before enter()
______
     64506 observations remaining, representing
     64506 subjects
        99 failures in single-failure-per-subject data
725128.718 total analysis time at risk and under observation
                                                                   0
                                           at risk from t =
                                  earliest observed entry t =
                                      last observed exit t = 12.65369
. quietly tab psa_cat, gen(psa_cat)
. stsplit timeband, at(0,5,100)
(60,769 observations (episodes) created)
. gen timeband5 = timeband==5
. stcox i.age_cat i.psa_cat c.psa_cat2#c.timeband5 c.psa_cat3#c.timeband5, nolo
        failure _d: event_dth == 1
  analysis time _t: (age_dth-origin)
            origin: time start_age
               id: id
Cox regression -- no ties
No. of subjects =
                      64,506
                                            Number of obs
                                                                 125,275
No. of failures =
Time at risk = 725128.7179
                                            LR chi2(5)
                                                                   96.19
                                                           =
```

Log likelihood	l = -1032.	5763		Prob > c	hi2	=	0.0000
t	Haz. Ratio	Std. Err.	z	P> z	[95%	Conf.	Interval]
age_cat 60-		1.821329	8.10	0.000	4.549	9374	11.97056
psa_cat							
1- 2-	.8321468 2.109579	.6077836 1 415804	-0.25 1.11			3379 1454	
	2.100010	1.110001	1.11	0.200	.000	101	7.000710
c.psa_cat2# c.timeband5		1.083939	0.44	0.662	.3084	1046	6.378932
c.psa_cat3# c.timeband5		.6251042	-0.20	0.842	.2104	1024	3.564083
. testparm c.p	osa_cat2#c.tir	meband5 c.ps	 a_cat3#c.	timeband5	 ;		
chi Prob		0.36 0.8332 dertake a simi		is using the	texp a	nd tvc	options:
analysis ti	et age_dth, fa psa_cat, gen _cat i.psa_cat ure _d: event ume _t: (age	ail(event_dt (psa_cat) t, nolog tvc t_dth == 1 _dth-origin)					5)
Cox regression	origin: time id: id id no ties	staft_age					
No. of subject No. of failure Time at risk	es =	99		Number o	of obs	=	64,506
Log likelihood							96.19 0.0000
 _t	Haz. Ratio	 Std. Err.	z	P> z	 [95%	Conf.	 Interval]
+							
main age_cat 60-	7.379604	1.821329	8.10	0.000	4.549	9374	11.97056
psa_cat							
1-	.8321468	.6077836	-0.25	0.801	. 1988	3379	3.482578
2-	2.109579	1.415804	1.11	0.266	.5661	1454	7.860746

tvc | psa_cat2 | 1.402602 1.083939 0.44 0.662 .3084046 6.378932 psa_cat3 | .8659628 .6251042 -0.20 0.842 .2104024 3.564083

Note: Variables in tvc equation interacted with _t>=5.

- . test ([tvc]psa_cat2=0) ([tvc]psa_cat3=0)
- (1) [tvc]psa_cat2 = 0
- (2) [tvc]psa_cat3 = 0

chi2(2) = 0.36Prob > chi2 = 0.8332

For a continuous time-varying effect under (ii), we can also use the texp and tvc options. Again, there was no evidence for a time-varying effect.

- . use psa, clear
- . keep if start_age>=50 & start_age<70 & psa<3

(35,493 observations deleted)

- . quietly stset age_dth, fail(event_dth==1) origin(start_age) id(id)
- . quietly tab psa_cat, gen(psa_cat)
- . stcox i.age_cat i.psa_cat, nolog tvc(psa_cat2 psa_cat3) texp(_t)

Cox regression -- no ties

No. of subject	es =	99		Number of	obs	=	64,506
Time at risk	= 725128.7	179		LR chi2(5	5)	=	96.05
Log likelihood	d = -1032.6	5439		Prob > ch	-		
_t	Haz. Ratio					Conf.	<pre>Interval]</pre>
main	+ I						
age_cat	! 						
•	7.381746	1.82195	8.10	0.000	4.550)583	11.97433
psa_cat	! 						
-	1.491879	1.166488	0.51	0.609	.3222	2445	6.906873
2-	2.631034	2.124173	1.20	0.231	.5406	374	12.80403
tvc	+ I						
	.9676291	.0839432	-0.38	0.704	.8163	3304	1.146969
-	.9604461					2889	1.145498

Note: Variables in tvc equation interacted with _t.

- . test ([tvc]psa_cat2=0) ([tvc]psa_cat3=0)
- (1) [tvc]psa_cat2 = 0
- (2) [tvc]psa_cat3 = 0

```
chi2(2) = 0.24
Prob > chi2 = 0.8862
```

Changing the time scale to attained age, we again found no evidence for a linearly time-varying effect (p=0.50).

- . use psa, clear
- . keep if start_age>=50 & start_age<70 & psa<3

(35,493 observations deleted)

- . quietly stset age_dth, fail(event_dth==1) entry(start_age) id(id)
- . quietly tab psa_cat, gen(psa_cat)
- . stcox i.psa_cat, nolog tvc(psa_cat2 psa_cat3) texp(_t-60)

failure _d: event_dth == 1

analysis time _t: age_dth

enter on or after: time start_age

id: id

Cox regression -- no ties

No. of subjects		,506 99		Number	of obs	=	64,506
Time at risk	= 725128.7	7179					
				LR chi2	(4)	=	5.95
Log likelihood	= -945.68	3365		Prob >	chi2	=	0.2033
_t	Haz. Ratio	Std. Err.	Z	P> z	[95%	${\tt Conf.}$	<pre>Interval]</pre>
+							
main							
psa_cat							
1-	1.447093	.9009586	0.59	0.553	.427	1097	4.902907
2-	3.375659	2.153459	1.91	0.057	.9668	3195	11.78614
+							
tvc							
psa_cat2	.9743253	.0468119	-0.54	0.588	.8867	7632	1.070534
psa_cat3	.9431796	.0471376	-1.17	0.242	.855	1724	1.040244

Note: Variables in tvc equation interacted with _t-60.

- . test ([tvc]psa_cat2=0) ([tvc]psa_cat3=0)
- (1) [tvc]psa_cat2 = 0
- (2) [tvc]psa_cat3 = 0

$$chi2(2) = 1.37$$

Prob > $chi2 = 0.5037$

Finally, using stpm2, we again find no evidence of a time-varying effect.

- . use psa, clear
- . keep if start_age>=50 & start_age<70 & psa<3

(35,493 observations deleted)

- . quietly stset age_dth, fail(event_dth==1) origin(start_age) id(id)
- . quietly tab psa_cat, gen(psa_cat)
- . stpm2 i.age_cat i.psa_cat, tvc(psa_cat2 psa_cat3) dftvc(2) df(3) scale(hazard
- >) nolog base

Log likelihood = -692.12018 Number of obs = 64,506

	Coef.	Std. Err.	z	P> z	[95% Conf.	Interval]
xb						
age_cat						
50- l	0	(base)				
60-	1.998929	.2468118	8.10	0.000	1.515186	2.482671
psa_cat						
0-	0	(base)				
1-	.1301003	.261253	0.50	0.618	3819463	.6421468
2-	.7558834	.2635744	2.87	0.004	.2392871	1.27248
1						
_rcs1	1.350218	.3070149	4.40	0.000	.7484803	1.951956
_rcs2	.2412636	.1689149	1.43	0.153	0898034	.5723306
_rcs3	0292311	.0230025	-1.27	0.204	0743153	.015853
_rcs_psa_c~21	0347741	.4192894	-0.08	0.934	8565663	.7870181
_rcs_psa_c~22	.0172805	.2135957	0.08	0.936	4013594	.4359204
_rcs_psa_c~31	5562371	.3425757	-1.62	0.104	-1.227673	.1151989
_rcs_psa_c~32	266076	.1840284	-1.45	0.148	626765	.094613
_cons	-8.081832	.2561783	-31.55	0.000	-8.583932	-7.579732

. testparm _rcs_psa*

```
(1) [xb]_rcs_psa_cat21 = 0
```

- $(2) [xb]_{rcs_psa_cat22} = 0$
- $(3) [xb]_{rcs_{psa_{cat}31}} = 0$
- (4) [xb]_rcs_psa_cat32 = 0

Stratified Cox regr. -- no ties

chi2(4) = 4.22Prob > chi2 = 0.3773

(g)

Fitting a stratified Cox model with strata for PSA categories, we find evidence that the prostate cancer mortality rate is considerably higher in men aged 60-69 years compared with men aged 50-50 years (HR=7.38, 95% CI: 4.55, 11.97). The un-stratified Cox model includes one baseline hazard that is shared across the groups, while the stratified Cox model includes different baseline hazards for each stratum (in this case, PSA categories). This is a useful approach to deal with non-proportionality by PSA categories. However, given the lack of evidence for non-proportionality, the age effect is similar across the two models.

Log likelihood	d = -924.8	9875	LR chi2 Prob > c		=	84.55 0.0000
_	Haz. Ratio					_
age_cat 50-	+ 1 7.381171	(base)	0.000	4.550		11.9734
			 	Strati	fied	by psa_cat

Question 5

(a)

We can define *safety* in terms of the levels of risk for prostate cancer incidence and prostate cancer death. As an additional analysis, we provide Kaplan-Meier estimators of the five- and ten-year risks for prostate cancer incidence and death by age and PSA categories (see Stata output and Table below). This is a simple, non-parametric approach that avoids modelling.

For men aged 50-59 years, the ten-year risk for prostate cancer incidence increases rapidly by PSA category, with approximately a 1% risk for PSA values below 1 ng/mL, 3% for PSA values between 1 and 2 ng/mL and 7% for PSA values between 2 and 3 ng/mL. The risks are considerably higher above 3 ng/mL because men are more likely to be referred to a urologist to undertake a biopsy to diagnose the cancer. For men in this age group with a PSA below 3 ng/mL, the ten-year risks of prostate cancer death are less than 0.1%. Interestingly, the ten-year risk of prostate cancer death among men with PSA between 3 and 10 ng/mL is only 0.3%, which is in marked contrast to the 19% ten-year risk of prostate cancer incidence. For men with a PSA value in excess of 10 ng/mL, the ten-year risk of prostate cancer death is 1 in 20.

For men aged 60-69 years at their initial PSA test, the risks are higher. The ten-year risks of prostate cancer diagnosis for men with PSA values between 0 and 1, 1 and 2, and 2 and 3 ng/mL are 2%, 4% and 9%, respectively; for the same PSA categories, the ten-year risks of prostate cancer death are 0.3, 0.2 and 0.3%, respectively.

The question arises as to the level of risk that is acceptable for choosing between 5 and 10 yearly re-testing. Is a ten-year risk of 0.3% acceptable for men in their 60s? As a working recommendation, the prostate cancer mortality risks are low, suggesting that 5 or 10 year re-testing would be 'safe'.

Note, however, that our interpretation of these data depend on the population, which has had moderately heavy testing. This issue is discussed further in the following question.

Age group (years)	$\begin{array}{c} {\rm PSA\ category} \\ {\rm (ng/mL)} \end{array}$	Ten-year risk of PC incidence (%)	Ten-year risks of PC death (%)
50-59	0-	0.8	0.0
	1-	2.8	0.0
	2-	7.4	0.0
	3-	18.7	0.3
	10-	39.0	5.0
60-69	0-	2.3	0.3
	1-	4.3	0.2
	2-	9.4	0.3
	3-	22.8	0.7
	10-	42.0	9.0

- . use psa, clear
- . quietly stset age_dx, fail(event_dx==1) origin(start_age)
- . sts list, by(age_cat psa_cat) at (5 10) fail

	Beg.		Failure	Std.		
Time		Fail	Function	Error	[95% C	onf. Int.]
50- 0-						
5	21966	67	0.0029	0.0004	0.0023	0.0037
10	19782	106	0.0080	0.0006	0.0069	0.0093
50- 1-						
5	12918	61	0.0046	0.0006	0.0036	0.0059
10	11576	282	0.0275	0.0015	0.0248	0.0305
50- 2-						
5	5394	131	0.0233	0.0020	0.0196	0.0276
10	4668	266	0.0738	0.0036	0.0671	0.0811
50- 3-						
5	6260	536	0.0773	0.0032	0.0713	0.0839
10	5108	709	0.1860	0.0048	0.1769	0.1956
50- 10-						
5	1219	245	0.1638	0.0096	0.1459	
10	818	317	0.3897	0.0129	0.3650	0.4156
60- 0-						
5	9097	159	0.0161	0.0013	0.0138	0.0188
10	7711	62	0.0234	0.0016	0.0206	0.0267
60- 1-			0.0440	0.0040		
5	7005	87	0.0118	0.0013	0.0096	0.0146
10	5886	204	0.0427	0.0025	0.0381	0.0478
60- 2-	2700	107	0 0220	0.0000	0.0006	0 0200
5 10	3782	137	0.0338	0.0028	0.0286	0.0398
60- 3-	3096	222	0.0944	0.0048	0.0855	0.1042
5	6083	895	0.1241	0.0039	0.1167	0.1320
10	4655	677	0.1241	0.0059	0.1107	0.1320
60- 10-	4000	011	0.2200	0.0001	0.2102	0.2501
5	1528	431	0.2120	0.0091	0.1949	0.2305
10	957	374	0.4204	0.0114	0.3983	0.4431
70- 0-	501	0,1	0.1201	0.0111	0.0000	0.1101
5	3289	94	0.0250	0.0026	0.0205	0.0306
10	2302	15			0.0252	0.0366
70- 1-						
5	3028	31	0.0094	0.0017	0.0067	0.0134
10	2162	30	0.0208	0.0027	0.0162	0.0267
70- 2-						
5	2025	43	0.0194	0.0029	0.0144	0.0260
10	1452	53	0.0487	0.0049	0.0399	0.0592
70- 3-						
5	4483	373	0.0720	0.0036	0.0653	0.0794
10	3047	223	0.1247	0.0048	0.1155	0.1345
70- 10-						
5	1737	386	0.1663	0.0078	0.1517	0.1822
10	933	247	0.3068	0.0105	0.2868	0.3279

Note: Failure function is calculated over full data and evaluated at indicated times; it is not calculated from aggregates shown at left.

[.] quietly stset age_dth, fail(event_dth==1) origin(start_age)

[.] sts list, by(age_cat psa_cat) at (5 10) fail

T:	ime	Beg. Total	Fail	Failure Function	Std. Error	[95% Co	nf. Int.]
50- 0-	 -						
	5	22030	0	0.0000			
	10	19939	4	0.0002	0.0001	0.0001	0.0005
50- 1-	_						
	5	12978	1	0.0001	0.0001	0.0000	0.0005
	10	11905	3	0.0003	0.0002	0.0001	0.0009
50- 2-							
	5	5523	0	0.0000			
	10	5038	4	0.0008	0.0004	0.0003	0.0020
50- 3-		0774	_	0.0007		0 0000	0 0047
	5	6774	5	0.0007	0.0003	0.0003	0.0017
50- 10	10	6251	16	0.0032	0.0007	0.0021	0.0049
50- 10	5	1443	20	0.0134	0.0030	0.0087	0.0207
	10	1285	52	0.0502	0.0058	0.0400	0.0207
60- 0-		1200	02	0.0002	0.0000	0.0100	0.0020
	5	9245	5	0.0005	0.0002	0.0002	0.0013
	10	7890	17	0.0025	0.0005	0.0017	0.0039
60- 1-							
	5	7086	2	0.0003	0.0002	0.0001	0.0011
	10	6138	14	0.0024	0.0006	0.0015	0.0039
60- 2-	_						
	5	3913	4	0.0010	0.0005	0.0004	0.0026
	10	3417	9	0.0034	0.0010	0.0020	0.0059
60- 3-				0.0045			
	5	6928	11	0.0015	0.0005	0.0009	0.0028
60- 10	10	6014	33	0.0067	0.0010	0.0050	0.0089
60- 10	0- 5	1908	58	0.0285	0.0037	0.0221	0.0367
	10	1552	114	0.0283	0.0037	0.0221	0.1042
70- 0-		1002	114	0.0000	0.0000	0.0700	0.1042
	5	3376	16	0.0045	0.0011	0.0027	0.0073
	10	2382	28	0.0140	0.0021	0.0104	0.0188
70- 1-	_						
	5	3056	7	0.0022	0.0008	0.0010	0.0045
	10	2206	15	0.0081	0.0017	0.0053	0.0122
70- 2-	-						
	5	2061	9	0.0042	0.0014	0.0022	0.0080
	10	1518	23	0.0170	0.0030	0.0120	0.0241
70- 3-		4000	2.4	2 222	0.0011	0.0040	0.000
	5	4820	34	0.0067	0.0011	0.0048	0.0094
70 47	10	3463	106	0.0324	0.0027	0.0275	0.0381
70- 10	0- 5	2071	172	0.0730	0.0054	0.0632	0.0843
	10	1316	199	0.1768	0.0034	0.0632	0.0643
		1010	133	0.1700			0.1041

Note: Failure function is calculated over full data and evaluated at indicated times; it is not calculated from aggregates shown at left.

The risks from (a) are estimated from a population with moderately intense PSA testing. The

⁽b) The simplest answer here is that less testing would lead to fewer prostate cancer diagnoses, where men with prostate cancer but without clinical symptoms would die due to other causes. Based on the European Randomised Study of Prostate Cancer, we could expect that mortality would increase by approximately 20% with no testing and prostate cancer incidence would be considerably lower.

research question relates to the counterfactual were a man to not be tested, what would be the ten-year risks? Under that counterfactual, we have under-estimated the risks of death by approximately 20%.

Various answers discussed the issue of *lead-time bias*, which is more of an issue with survival from prostate cancer incidence to death, rather than mortality rates from an cohort with no previous diagnosis of prostate cancer.

Question 6

The partial likelihood for a Cox regression model with a single covariate is

$$L = \prod_{i} \frac{\exp(\beta x_i)}{\sum_{j \in R_i} \exp(\beta x_i)}$$

where i is an index for the events, j is an index for the risk set R_i for event i, and x_i and x_j are covariates.

For a nested case-control study, the likelihood for a single covariate is

$$L = \prod_{i} \frac{\exp(\beta x_i)}{\sum_{j \in R_i^*} \exp(\beta x_i)}$$

where i is an index for the events (or cases), j is an index for a *sample* of the risk R_i^* (or controls) for event (or case) i, and x_i and x_j are the covariates.

The difference in the formulations is the risk set: the full risk set is used for Cox regression, while the nested case-control study only includes a sample of the risk set. The sampling from the risk set will decrease the precision of the estimated regression parameters.

The odds ratio from the nested case-control study will estimate a hazard ratio.