

Cox Model With Time Varying Covariates

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24 Nov 2023

Introduction

The Cox Proportional Hazards Model is an important model in *event history and survival analysis*. One important aspect of the Cox Model is its ability to include *time varying covariates*, covariates whose value changes over time.

The example below draws heavily from—but is slightly adapted from—the Stata `help stcox` file.

Get Data

```
. use https://www.stata-press.com/data/r17/drugtr2, clear // simulated drug data
```

Per the Stata documentation:

“Consider a dataset consisting of 45 observations on recovery time from walking pneumonia. Recovery time (in days) is recorded in the variable `time`, and there are measurements on the covariates `age`, `drug1`, and `drug2`, where `drug1` and `drug2` interact a choice of treatment with initial dosage level. The study was terminated after 30 days, so those who had not recovered by that time were censored (`cured = 0`).”

stset The Data

```
. stset time, failure(cured) // set up data for survival analysis
Survival-time data settings
      Failure event: cured!=0 & cured<.
Observed time interval: (0, time]
Exit on or before: failure
```

45	total observations
0	exclusions

45	observations remaining, representing	
36	failures in single-record/single-failure data	
677.9	total analysis time at risk and under observation	
	At risk from t =	0
	Earliest observed entry t =	0
	Last observed exit t =	30

Model 1: Drugs Are *Time Invariant* Covariates

```
. stcox age drug1 drug2 // Cox model
      Failure _d: cured
      Analysis time _t: time
Iteration 0:  Log likelihood = -116.54385
Iteration 1:  Log likelihood = -102.77311
```

```

Iteration 2: Log likelihood = -101.92794
Iteration 3: Log likelihood = -101.92504
Iteration 4: Log likelihood = -101.92504
Refining estimates:
Iteration 0: Log likelihood = -101.92504
Cox regression with Breslow method for ties
No. of subjects =    45                Number of obs =    45
No. of failures =    36
Time at risk    = 677.9
Log likelihood = -101.92504            LR chi2(3)    = 29.24
                                        Prob > chi2    = 0.0000

```

_t	Haz. ratio	Std. err.	z	P> z	[95% conf. interval]	
age	.8759449	.0253259	-4.58	0.000	.8276873	.9270162
drug1	1.008482	.0043249	1.97	0.049	1.000041	1.016994
drug2	1.00189	.0047971	0.39	0.693	.9925323	1.011337

```
. est store M1 // store estimates
```

Model 2: Drugs Are *Time Varying Covariates*

```

. stcox age, tvc(drug1 drug2) // Cox model
      Failure _d: cured
      Analysis time _t: time
Iteration 0: Log likelihood = -116.54385
Iteration 1: Log likelihood = -104.50191
Iteration 2: Log likelihood = -103.87961
Iteration 3: Log likelihood = -103.87525
Iteration 4: Log likelihood = -103.87525
Refining estimates:
Iteration 0: Log likelihood = -103.87525
Cox regression with Breslow method for ties
No. of subjects =    45                Number of obs =    45
No. of failures =    36
Time at risk    = 677.9
Log likelihood = -103.87525            LR chi2(3)    = 25.34
                                        Prob > chi2    = 0.0000

```

_t	Haz. ratio	Std. err.	z	P> z	[95% conf. interval]	
main						
age	.8786593	.0250789	-4.53	0.000	.8308552	.9292139
tvc						
drug1	1.000272	.000335	0.81	0.416	.9996161	1.000929
drug2	.9998618	.000364	-0.38	0.704	.9991486	1.000576

Note: Variables in tv equation interacted with _t.

```
. est store M2 // store estimates
```

Model 3: Drugs Are *Time Varying Covariates (Manually Specified)*

```

. generate id=_n // multiple record data needs an id
. streset, id(id) // `streset` the data
-> stset time, id(id) failure(cured)
Survival-time data settings
      ID variable: id
      Failure event: cured!=0 & cured<.
      Observed time interval: (time[_n-1], time]
      Exit on or before: failure

```

```

45 total observations
0 exclusions

45 observations remaining, representing
45 subjects
36 failures in single-failure-per-subject data
677.9 total analysis time at risk and under observation
      At risk from t = 0
      Earliest observed entry t = 0
      Last observed exit t = 30

. stsplot, at(failures) // split data at each recovery time
(31 failure times)
(812 observations (episodes) created)

. generate drug1emt = drug1 * _t // manual interaction of drug1 and time

. generate drug2emt = drug2 * _t // manual interaction of drug2 and time

. stcox age drug1emt drug2emt // Cox model
      Failure _d: cured
      Analysis time _t: time
      ID variable: id
Iteration 0: Log likelihood = -116.54385
Iteration 1: Log likelihood = -104.50191
Iteration 2: Log likelihood = -103.87961
Iteration 3: Log likelihood = -103.87525
Iteration 4: Log likelihood = -103.87525
Refining estimates:
Iteration 0: Log likelihood = -103.87525
Cox regression with Breslow method for ties
No. of subjects = 45      Number of obs = 857
No. of failures = 36
Time at risk = 677.9
Log likelihood = -103.87525      LR chi2(3) = 25.34
      Prob > chi2 = 0.0000

      _t      Haz. ratio      Std. err.      z      P>|z|      [95% conf. interval]
-----+-----+-----+-----+-----+-----
      age      .8786593      .0250789      -4.53      0.000      .8308552      .9292139
      drug1emt      1.000272      .000335      0.81      0.416      .9996161      1.000929
      drug2emt      .9998618      .000364      -0.38      0.704      .9991486      1.000576

. est store M3 // store estimates

```

Nice Table of Estimates to Compare Models

```
. est table M1 M2 M3, star equations(1)
```

Variable	M1	M2	M3
#1			
age	-.13245204***	-.12935802***	-.12935802***
drug1	.00844606*		
drug2	.00188866		
drug1emt			.0002724
drug2emt			-.00013819
tvc			
drug1		.0002724	
drug2		-.00013819	

Legend: * p<0.05; ** p<0.01; *** p<0.001