Competing-risks regression

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- Competing risks are events that occur instead of the failure event of interest, and we cannot treat these as censored
- When you have competing events, you want to focus on *cause-specific* hazards rather than standard hazards
- When you have competing events, you want to focus on the *cumulative incidence function* (CIF) rather than the survival function
- Cox regression is fine for cause-specific hazards, but for CIFs you need to go through a lot of work
- Competing-risks regression by the method of Fine and Gray (1999) is a useful alternative
- Implemented in the stcrreg command, new to Stata 11

- A competing-risk event is an event that impedes what a researcher actually "wants" to see
- For example, if a researcher is interested in recurrence of breast cancer, cancer occurring in another location would be a competing event
- In general you cannot treat competing events as censored because
 - 1. The competing events might be dependent, and you usually can't test this
 - 2. You are unwilling to apply your results to a counter-factual world where the competing event doesn't exist



- What confuses the matter is that, often, it is okay to think of competing events as censorings. But this is merely a computational device
- That is, the software will often let you treat competing events as censored, but your interpretation of the results should never do so
- Even more confusing is that some software, such as that for Kaplan-Meier curves, is not appropriate if you treat competing events as censored



- Consider data on 423 women treated for breast cancer
- 175 women were given an experimental new drug, and the other 248 women the standard therapy
- Time in months until disease progression occurred either at an old tumor site (local relapse) or at a new site (distant relapse) was recorded; local relapse is the event of interest
- If no event occurred after within 60 months, observations were censored
- Age and race also recorded



. use bc_compete, clear
(Breast cancer with competing risks)
. describe
Contains data from bc_compete.dta
 obs: 423 Breast cancer with competing risks
vars: 5 13 Jul 2010 04:27
size: 11,844 (99.9% of memory free)

variable name	0	display format	value label	variable label
age drug race time status	float float float	%9.0g %9.0g %9.0g %9.0g %9.0g	race	Age at start of the trial 1 treatment; 0 control 1 white; 2 black; 3 other time in months 0 censored; 1 local relapse; 2 distant relapse

Sorted by:



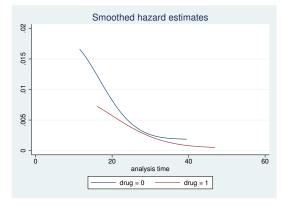
- A cause-specific hazard is the instantaneous risk of failure from a specific cause given that failure (from any cause) has yet to happen
- In our example, we have two cause-specific hazards: one for local relapse and one for distant relapse
- You can estimate, graph, and test a cause-specific hazard with "standard" survival software, if you treat the other event as censored
- You need only to modify your interpretation, specifically, you need to consider both hazards jointly and not attempt to disentangle them



Cause-specific hazard for local relapse

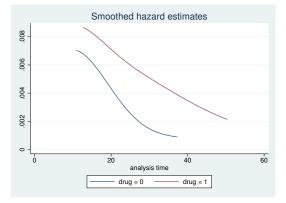
```
. stset time, failure(status = 1)
  (output omitted)
```

. sts graph, hazard by(drug) kernel(gauss)



Cause-specific hazard for distant relapse

- . stset time, failure(status = 2)
 (output omitted)
- . sts graph, hazard by(drug) kernel(gauss)



Because we believe in proportionality of cause-specific hazards we can use stcox to test for differences

. quietly stset time, failure(status = 1)								
. stcox drug								
Cox regression Breslow method for ties								
No. of subjects = 423				Number	of obs	=	423	
No. of failure	es =	135						
Time at risk	= 15	5018						
				LR ch	12(1)	=	3.85	
Log likelihood = -785.18921				Prob >	> chi2	=	0.0496	
_t	Haz. Ratio	Std. Err.	z	P> z	[95% Co	onf.	Interval]	
drug	.7030953	.1283705	-1.93	0.054	.491589	95	1.005601	



Cox regressions for the effect of drug

. quietly stset time, failure(status = 2)							
. stcox drug							
Cox regression Breslow method for ties							
No. of subjects = 423				Number	r of obs	=	423
No. of failure	s =	78					
Time at risk	= 15	018					
					i2(1)		
Log likelihood = -443.31893				Prob >	> chi2	=	0.0094
I							
_t	Haz. Ratio	Std. Err.	z	P> z	[95% Con	f.	Interval]
drug	1.804488	.4120596	2.58	0.010	1.1534		2.823112

Interpretation: Drug treatment somewhat decreases risk of local relapse while at the same time increasing the risk of distant relapse

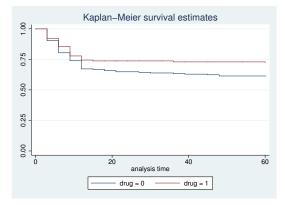


- Despite the ominous name, a CIF is just the probability that you observe a specific type of event before a given time
- In our analysis, we have two CIFs; one for local relapse and one for distant relapse
- For example, the CIF for local relapse at 5 months is just the probability of a local relapse before 5 months
- CIFs begin at zero at time zero and increase to an upper limit equal to the eventual probability that the event will take place, but this is not equal to one because of competing events
- Mathematically, the CIF for local relapse is a function of *both* cause-specific hazards



Kaplan-Meier curves are not appropriate for competing risks

- . quietly stset time, failure(status = 1)
- . sts graph, survival by(drug)



- The previous Kaplan-Meier curve attempts to answer the question "What is the probability of no local relapse before (say) 5 months?"
- In a competing-risks setting, a Kaplan-Meier curve is inadequate for three reasons
- First, it fails to acknowledge that local relapse may never occur. In reality, the probability of local relapse after time zero is not equal to 1
- Second, the Kaplan-Meier calculation does not take into account dependence between competing events



- Third, with competing risks it is better to reverse the temporal ordering of the question
- It makes better sense to ask "What is the probability of local relapse within 5 months?" than to ask "What is the probability that nothing happens for the first five months, but when something does happen I want it to be a local and not a distant relapse?"
- In summary, using Kaplan-Meier demands too much of your data; it requires independent risks and a world where the competing event doesn't occur
- As such, you should use the cumulative incidence function (CIF) instead



Cumulative incidence functions

-Nonparametric estimation

You can estimate CIFs nonparametrically using stcompet, by Coviello and Boggess (2004) and available from the SSC

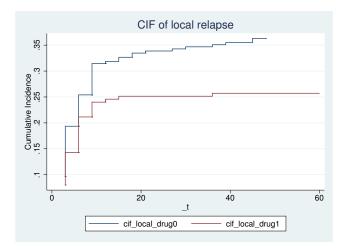
```
. quietly stset time, failure(status = 1)
. stcompet cif = ci, compet1(2) by(drug)
. gen cif_local_drug0 = cif if status == 1 & drug == 0
(333 missing values generated)
. gen cif_local_drug1 = cif if status == 1 & drug == 1
(378 missing values generated)
```

. twoway line cif_local_* _t, connect(step step) sort
> ytitle(Cumulative Incidence) title(CIF of local relapse)



Cumulative incidence functions

-Nonparametric estimation





- Nonparametric estimation is flexible, but it cannot adjust for external covariates such as age and race
- Previously we applied Cox regression on drug to both cause-specific hazards
- These we could then extend to adjust for age and race, at the cost of the proportionality assumption
- We could then use the resulting cause-specific hazards to derive estimates of the CIFs

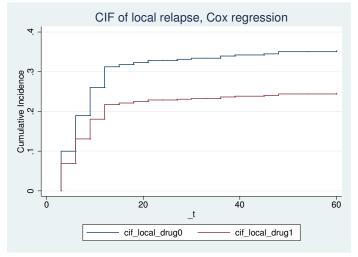


- To calculate a CIF from Cox regression, we need to
 - 1. Predict the baseline hazard contributions from both Cox regressions on drug, that for local relapse and that for distant relapse
 - Transform the baseline hazard contributions (which assume drug == 0) to those for drug == 1 where appropriate
 - 3. Use the hazard contributions to calculate a product limit estimator of event-free survival for both levels of drug
 - Calculate the estimated CIF manually for both drug == 0 and drug == 1; see page 209 of [ST] for details
 - 5. Plot the results
- The point: Assessing covariate effects on the CIF using Cox regression is a lot of work



The Cox regression approach

Comparative CIF curves from Cox regression





The Fine and Gray approach (stcrreg)
Modeling the subhazard

- An easier way to do CIF covariate analysis is with competing risks regression, according to the model of Fine and Gray (1999)
- They posit a model for the hazard of the subdistribution for the failure event of interest, known as the *subhazard*
- Unlike cause-specific hazards, there is a one-to-one correspondence between subhazards and CIFs for respective event types; that is the CIF for local relapse is a function of only the subhazard for local relapse
- Covariates affect the subhazard proportionally, similar to Cox regression
- You do this in Stata 11 using stcrreg. stcurve after stcrreg will plot comparative CIFs for you



— The Fine and Gray approach (stcrreg)

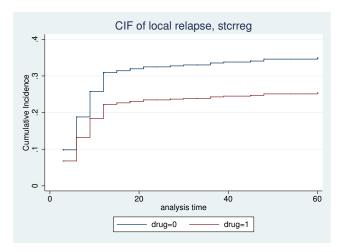
Using stcrreg

. quietly stset time, failure(status = 1)							
. stcrreg drug, compete(status = 2)							
Competing-risk	No. of	obs	=	423			
				No. of	subjects	s =	423
Failure event : status == 1				No. fa	iled	=	135
Competing event: status == 2				No. co	mpeting	=	78
	No. ce	nsored	=	210			
	Wald c	hi2(1)	=	4.68			
Log pseudolikelihood = -794.95545				Prob >	chi2	=	0.0305
		Robust					
_t	SHR	Std. Err.	z	P> z	[95% Co	onf.	Interval]
drug	.6810812	.1209317	-2.16	0.031	.480906	68	.9645769



Competing-risks regression The Fine and Gray approach (stcrreg) Stcurve after stcrreg

. stcurve, cif at1(drug=0) at2(drug=1) title("CIF of local relapse, stcrreg")



- Competing risks are events that prevent an event of interest from occurring
- If you have competing risks, you want to look at cause-specific hazards instead of standard hazards
- If you have competing risks, you want to look at CIFs instead of survival functions
- CIF analysis with Cox regression is possible, but difficult
- stcrreg followed by stcurve is the easier way to go
- Keep in mind, however, that easier does not mean correct. There are model assumptions to be made for either of the two approaches



Coviello, V. and M. Boggess. 2004. Cumulative incidence estimation in the presence of competing risks. *The Stata Journal.* **4**: 103–112.

Fine, J. and R. Gray. 1999. A proportional hazards model for the subdistribution of a competing risk. *Journal of the American Statistical Association.* **94**: 496–509.

