# **STATA® Features**

Interval-censored Cox model

- Genuine semiparametric modeling
- Left-censoring, right-censoring, interval-censoring
- Current-status and general interval-censored data
- Single- or multiple-record data **New**
- Stratified estimation
- Time-varying covariates **New**
- Two estimators for baseline hazard
- Robust and cluster—robust standard errors **New**
- Graphs of survivor, cumulative hazard, and hazard functions
- Residual diagnostics
- Graphical checks of proportional-hazards assumption
- Graphical checks of goodness of fit **New**
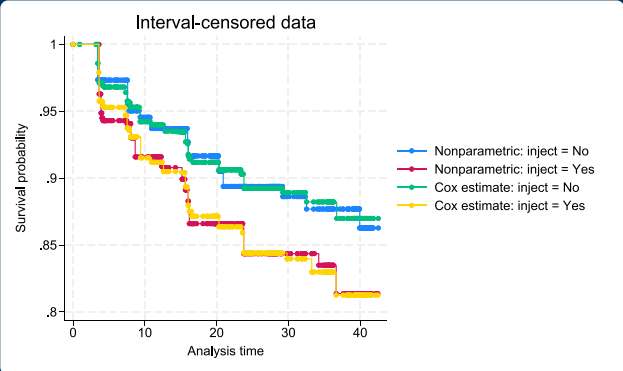
Do you know the exact failure times or event times?

You can fit the Cox proportional hazards model in Stata even if you don't.

Fit the model

The Cox proportional hazards model is widely used with right-censored event-time data because it does not require parameterization of the baseline hazard function and, under the proportional-hazards assumption, the hazard ratios are constant over time.

If we know the exact failure times, we can fit a Cox proportional hazards model using the **stcox** command. For instance, we can type

```
. stcox age_mean i.inject
```

to study the effect of mean age and injection status on failure times.

It is just as easy to fit a Cox proportional hazards model with interval-censored data, where we know only that the failure occurred sometime between two time points. With a single-record-per-subject data, we specify the variables containing the upper and lower endpoints for the failure time in **stintcox**'s **interval()** option.

```
. stintcox age_mean i.inject, interval(ltime rtime)
```

Graph the results

Use **stcurve** to plot the survivor, hazard, or cumulative hazard function.

```
. stcurve, survival at(inject = (0 1))
```


Interval-censored Cox regression
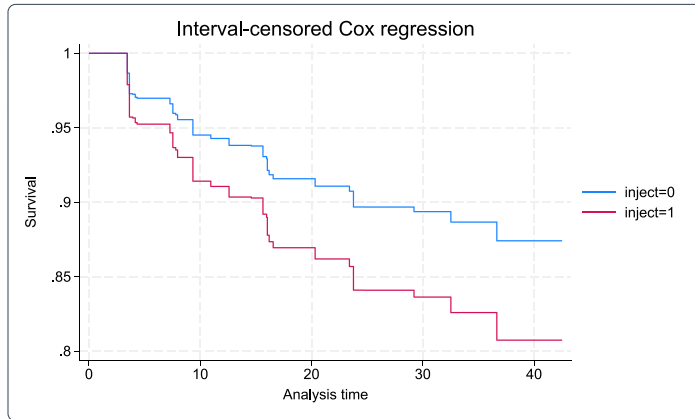
Check the proportional-hazards assumption

We can assess the proportional-hazards assumption graphically using the **stintphplot** command.

```
. stintphplot, interval(ltime rtime) by(inject)
  adjustfor(age_mean)
```
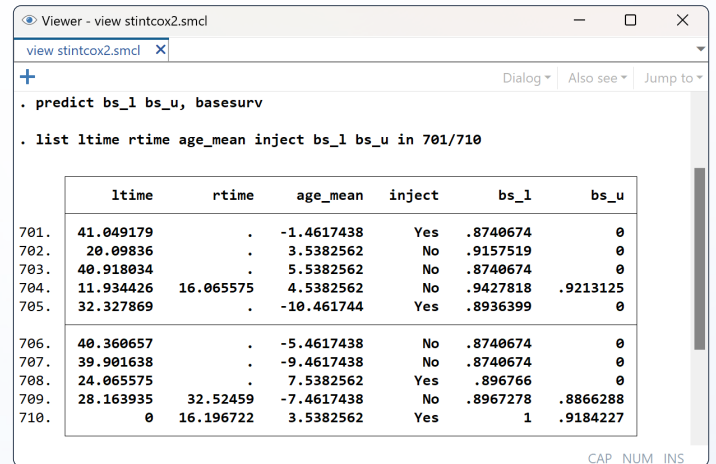

Cox estimates for interval-censored data
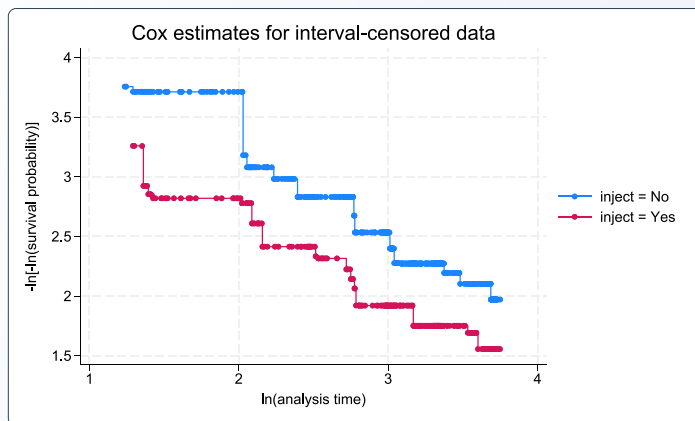
Or we can test this assumption when fitting the model. Specify the **tvc()** option to interact covariates with time, and test for coefficients of time-interacted covariates equal to zero.

```
. stintcox age_mean i.inject, interval(ltime rtime)
  tvc(age_mean i.inject)
```

Predict baseline survivor function

For each individual, we can predict the baseline survivor functions corresponding to the lower and upper endpoints of our interval.


```
. predict bs_l bs_u, basesurv

. list ltime rtime age_mean inject bs_l bs_u in 701/710
```

	ltime	rtime	age_mean	inject	bs_l	bs_u
701.	41.049179	.	-1.4617438	Yes	.8740674	0
702.	20.09836	.	3.5382562	No	.9157519	0
703.	40.918034	.	5.5382562	No	.8740674	0
704.	11.934426	16.065575	4.5382562	No	.9427818	.9213125
705.	32.327869	.	-10.461744	Yes	.8936399	0
706.	40.360657	.	-5.4617438	No	.8740674	0
707.	39.901638	.	-9.4617438	No	.8740674	0
708.	24.065575	.	7.5382562	Yes	.896766	0
709.	28.163935	32.52459	-7.4617438	No	.8967278	.8866288
710.	0	16.196722	3.5382562	Yes	1	.9184227

Type or point and click