## stata

# **Survival analysis**

From Kaplan–Meier estimates of the survivor function to the Cox proportional hazards model, from competing-risks regression to multilevel survival models, Stata has everything you need to analyze your survival- or event-time data.



#### Survival-time data

- Single failure or multiple failures; right-, left-, and interval-censoring; left-truncation; gaps
- Multiple events New
- Support for complex survey designs

#### Life tables

- Tables and graphs with Cls
- Tests for equality of survivor functions
- Tests for trend

#### Graph survivor, cumulative hazard, and other functions <sup>Updated</sup>

#### Cox proportional hazards model

- Stratified estimation
- Time-varying covariates
- Shared frailty models
- Harrell's C, Somer's D, Gönen and Heller's K
- Tests for proportional hazards
- Goodness-of-fit plots <sup>Updated</sup>

#### Parametric survival models

- Weibull, exponential, Gompertz, lognormal, loglogistic, and generalized gamma
- Stratified models
- Individual or shared frailty
- Predictions of mean or median time to failure, survival probabilities, and hazards
- Goodness-of-fit plots <sup>Updated</sup>
- Bayesian estimation
- Finite mixture models

#### Competing risks model

- Fine and Gray proportional subhazards model
- Graph cumulative subhazard and cumulative incidence

#### Multilevel survival models

- Weibull, exponential, lognormal, loglogistic, and gamma
- Marginal predictions and marginal means

#### Structural equation models

- Weibull, exponential, lognormal, loglogistic, and gamma models
- Survival outcomes with other outcomes
- Path models, growth curve models, and more

#### Additive models of relative risk

 Cox, parametric survival, interval-censored Cox, and interval-censored parametric survival models

#### Power analysis

Log-rank test of survival curves, Cox models, exponential regression

#### Sample-size analysis for group sequential designs (GSDs)

Log-rank test of survival curves

#### Causal inference (treatment-effects estimation)

- Regression adjustment, inverse-probability weighting (IPW), and doubly robust methods
- Average treatment effects (ATEs) and ATEs on the treated (ATETs)

#### Lasso and elastic net for Cox model

- Select predictors via cross-validation, adaptive lasso, or BIC
- Penalized and postselection predictions
- Graph survivor and other functions

We begin by specifying that we have survival data using stset. Here studytime records the time of failure or censoring, and the variable died indicates whether the subject died or was censored.



We are now ready to graph the survivor function for each level

#### Kaplan-Meier survival estimates 1.00 0.75 Control 0.50 5 mg 10 mg 0.25 0.00 30 10 20 40 Analysis time

#### or to fit a Cox proportional hazards model,

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and test for violations of the proportional-hazards assumption.

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We can fit a Weibull model,

. streg age i.dose, distribution(weibull)

and plot the estimated survivor function for each dosage level,



or compute the marginal predictions of mean survival time for each dosage.

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And that's just the beginning.

### of our treatment, sts graph, by(dose)

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