Event history analysis

An introduction

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PART II

Estimation using STATA

Estimation using STATA

- The aim of this workshop is to illustrate how to use Stata to estimate multivariate continuous & discrete time survival time models.
- These include the parametric models (e.g., Weibull hazard and piecewise constant exponential hazard functions).
- Stata provides an extensive suite of estimators. Parametric regression survival-time models are estimated by maximum likelihood

Estimation using STATA

We will take a few steps

1. Prepare the data for survival analysis
2. Understand the 'survival dynamics' of the phenomenon under investigation (Kaplan-Meier estimates)
3. Estimate the phenomenon with a continuous/discrete time model and time-invariant explanatory variables
4. Include time-varying explanatory variables

Continuous time models in STATA

Preparing survival continuous time data for analysis

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  - Data do not need to be weighted
  - **Survival time** and **censoring variables** already exist (we have already derived them from start and end dates)
  - **No time-varying covariates**, for the moment.
- Here I assume that there is a Stata format **data set ready to use**.

Data structure of continuous time models (an example)

```
. use cancer,clear
(Patient Survival in Drug Trial)
. de
Contains data from cancer.dta
  obs:            48                          Patient Survival in Drug Trial
 vars:             4                          16 Nov 1998 11:49
 size:           576 (100.0% of memory free)
-------------------------------------------------------------------------------
   1. studytim  int    %8.0g                  Months to death or end of exp.
   2. died      int    %8.0g                  1 if patient died
   3. drug      int    %8.0g                  Drug type (1=placebo)
   4. age       int    %8.0g                  Patient's age at start of exp.
-------------------------------------------------------------------------------
```

- `studytim` is the survival time
- `died` is the censoring indicator;
- `drug` and `age` are potential explanatory variables.

Data structure of continuous time models (an example)

studytime	died	drug	age	_st	_d	_t	_t0
11	Yes	Placebo	55	1	1	11	0
12	Yes	Placebo	49	1	1	12	0
12	Yes	Placebo	62	1	1	12	0
15	Yes	Placebo	51	1	1	15	0
17	Yes	Placebo	49	1	1	17	0
22	Yes	Placebo	57	1	1	22	0
23	Yes	Placebo	52	1	1	23	0
6	Yes	Other	67	1	1	6	0
6	No	Other	65	1	0	6	0
7	Yes	Other	58	1	1	7	0
9	No	Other	56	1	0	9	0
10	No	Other	49	1	0	10	0
11	No	Other	61	1	0	11	0

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15	Yes	Placebo	51	1	1	15	0
17	Yes	Placebo	49	1	1	17	0
22	Yes	Placebo	57	1	1	22	0
23	Yes	Placebo	52	1	1	23	0
6	Yes	Other	67	1	1	6	0
6	No	Other	65	1	0	6	0
7	Yes	Other	58	1	1	7	0
9	No	Other	56	1	0	9	0
10	No	Other	49	1	0	10	0
11	No	Other	61	1	0	11	0

- One row in the data set for each 'subject' (e.g. person or firm).
- Columns in the data set (variables) contain at least two types of information for each subject:
    1. the length of time in the state (the survival time = the length of time the subject was exposed to the risk of experiencing a 'failure');
    2. censoring status (a variable typically equal to 1 if the person experienced a 'failure', and equal to 0 otherwise).
    3. At least one (time-invariant, for now) variable used as regressor in estimation of multivariate hazard models.

Data structure of continuous time models (an example)

`stset` is the only command required to organise the data.

`stset timevar , failure(censvar)`

- `stset timevar` identifies the phenomenon at issue (`studytime`)
- `failure(censvar)` specifies the failure event (`died`)– there is a failure whenever the variable is not equal to zero and not missing

```
. stset studytim , failure(died)

     failure event:  died != 0 & died < .
obs. time interval:  (0, studytim]
 exit on or before:  failure

------------------------------------------------------------------------------
       48  total obs.
        0  exclusions
------------------------------------------------------------------------------
       48  obs. remaining, representing
       31  failures in single record/single failure data
      744  total analysis time at risk, at risk from t =         0
                             earliest observed entry t =         0
                                  last observed exit t =        39
```

Data structure of continuous time models (an example)

`stset` creates a set of new variables in the data

```
. de _*

              storage  display     value
variable name   type   format      label      variable label
-------------------------------------------------------------------------------
_st             byte   %8.0g
_d              byte   %8.0g
_t              byte   %10.0g
_t0             byte   %10.0g

. su _*

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
         _st |        48           1           0          1          1
          _d |        48    .6458333    .4833211          0          1
          _t |        48        15.5    10.25629          1         39
         _t0 |        48           0           0          0          0
```

- *_st* is a 0/1 variable, equal to 1 for observations whose data has been `stset`;
- *_d* variable is the binary censoring indicator (`died` in this case);
- *_t* is the duration variable (`studytim` in this case);
- *_t0* records the date of entry to the study for each case, i.e. when they were first observed at risk of the event (i.e. $t = 0$);

Data structure of continuous time models (an example)

`stsum` shows how the data are currently set

```
. stsum

         failure _d:  died
   analysis time _t:  studytim

         |               incidence       no. of    |------ Survival time -----|
         | time at risk     rate        subjects        25%        50%        75%
---------+---------------------------------------------------------------------
   total |          744   .0416667           48           8         17         33
```

- There are 31 failures (deaths in this case);
- The incidence rate, $0.04167 = 31/744$;
- The median survival time since the start of the study is 17 months

Estimation using `streg`

The basic syntax is

`streg [varlist], dist(distname) nohr time tr nolog`

- specifies the survival model to be estimated;
- is one of the following: exponential, weibull, gompertz, lognormal, loglogistic or gamma

Estimation of a Weibull model using `streg`

```
. streg drug age, dist(weibull) nolog nohr

        failure _d:  died
  analysis time _t:  studytim


Weibull regression -- log relative-hazard form

No. of subjects =           48                  Number of obs    =        48
No. of failures =           31
Time at risk    =          744
                                                LR chi2(2)       =     35.39
Log likelihood  =   -42.931335                  Prob > chi2      =    0.0000

------------------------------------------------------------------------------
          _t |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        drug |  -2.196936   .4087791    -5.374   0.000    -2.998129   -1.395744
         age |   .1202027   .0371599     3.235   0.001     .0473707    .1930348
       _cons |  -10.58396   2.326271    -4.550   0.000    -15.14337   -6.024553
-------------+----------------------------------------------------------------
       /ln_p |   .5204297   .1389037     3.747   0.000     .2481834     .792676
------------------------------------------------------------------------------
           p |   1.682751   .2337403                       1.281695    2.209301
         1/p |   .5942651   .0825456                        .452632    .7802168
------------------------------------------------------------------------------
```

The `nohr` option means that **coefficient estimates** are shown.

Estimation of a Weibull model using `streg`

```
. streg, hr

Weibull regression -- log relative-hazard form

No. of subjects =           48                Number of obs    =        48
No. of failures =           31
Time at risk    =          744
                                              LR chi2(2)       =     35.39
Log likelihood  =   -42.931335                Prob > chi2      =    0.0000

------------------------------------------------------------------------------
          _t | Haz. Ratio   Std. Err.       z     P>|z|      [95% Conf. Interval]
-------------+----------------------------------------------------------------
        drug |   .1111431    .045433    -5.374   0.000      .0498803    .2476487
         age |   1.127725   .0419062     3.235   0.001      1.048511    1.212925
-------------+----------------------------------------------------------------
       /ln_p |   .5204297   .1389037     3.747   0.000      .2481834     .792676
------------------------------------------------------------------------------
           p |   1.682751   .2337403                         1.281695    2.209301
         1/p |   .5942651   .0825456                          .452632    .7802168
------------------------------------------------------------------------------
```

The `hr` option means that hazard *ratios* are shown.

Interpretation of coefficient & hazard ratio of `drug`

$$\beta_{drug} \simeq -2.2$$

The **coefficient estimates** indicate that those receiving the drug (`drug` $= 1$) have lower [*coeff.* < 0] hazard rates *ceteris paribus* (i.e. lower conditional death rates and hence longer survival times).

$$exp(\beta_{drug}) \simeq 0.11$$

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The **hazard ratio** compares the hazard rates of two categories (in this case): those who receive the drug and those who do not

$$\Downarrow$$

The hazard *rate* for those who received the drug is only 11% of the hazard rate for those who received the placebo.

Interpretation of coefficient & hazard ratio of age

$$\beta_{(age)} \simeq 0.12$$

The **coefficient estimates** indicate that older people (age increasing) have higher $[coeff. > 0]$ hazard rates *ceteris paribus* (i.e. higher conditional death rates and hence shorter survival times).

$$exp(\beta_{(age)}) \simeq 1.13$$

The **hazard ratio** "compares" the hazard rates of people with age (say) X to those with age $X + 1$

$$\Downarrow$$

The hazard *rate* of a one year rise in age ($\Delta X = 1$) is associated with a 13% higher hazard rate.

Generalizing the interpretation of βs & hazard ratios

A dummy (or categorical) variable (ex. `drug`)

β (coeff. estimate) and hazard *ratio* contrast the hazard rate of group **G** to that of the baseline group **B**

If $\beta > 0$ or hazard ratio > 1 $\rightarrow$hazard (**G**) $>$ hazard (**B**)

If $\beta < 0$ or hazard ratio < 1 $\rightarrow$hazard (**G**) $<$ hazard (**B**)

A continuous variable (ex. `age`)

β (coeff. estimate) and hazard *ratio* capture the elasticity of the hazard with respect to a **one unit** change in the explanatory variable X

If $\beta > 0$ or hazard ratio $> 1 \Rightarrow \Delta X = 1 \rightarrow \uparrow$ *hazard*

If $\beta < 0$ or hazard ratio $< 1 \Rightarrow \Delta X = 1 \rightarrow \downarrow$ *hazard*

More on the interpretation of βs & hazard ratios of a continuous variable

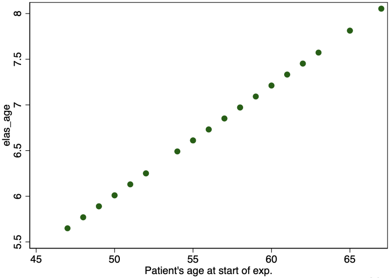
The elasticity of the hazard rate with respect to a one unit change ($\Delta X_k = 1$) in the k^{th} explanatory variable is given by $\beta_k X_{ik}$

For age, it is $0.12 * age_i$.

Let age_i vary and calculate the elasticity of the hazard *wrt* age:

```
ge elas_age = _b[age]*age
```

Let's plot 'elasticity of age' (y-axis) vs. 'age' (x-axis)



More on the interpretation of βs & hazard ratios of a continuous variable

More generally, hazard rate ratios at each survival time are related to absolute differences in characteristics (exploiting the properties of exponential functions):

$$h(t, X_1)/h(t, X_2) = exp[\beta X_1]/exp[\beta X_2] \equiv exp[\beta(X_1 - X_2)]$$

Example 1. A 10-year difference in age, other things equal, is associated with a hazard rate ratio of some 3.3:

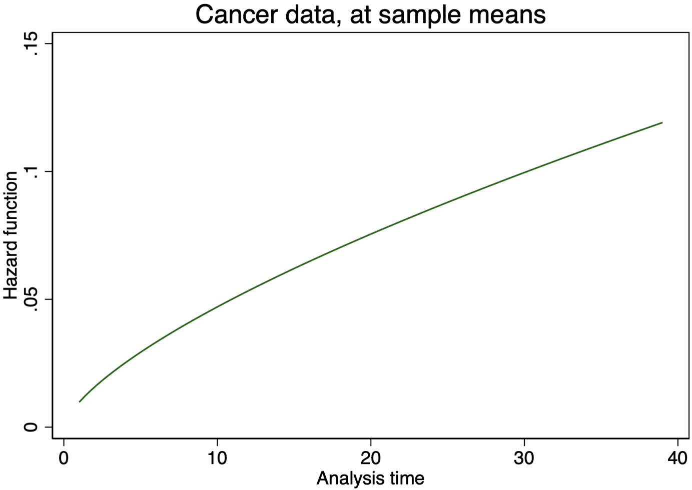
$$\frac{h(t; age = y + 10, drug = x)}{h(t; age = y, drug = x)} = exp(\beta_{age} * 10) \approx 3.3$$

Example 2. Some one aged y+10 and who is receiving the drug has a hazard ratio that is 37% of some one aged y who gets the placebo:

$$\frac{h(t; age = y + 10, drug = 1)}{h(t; age = y, drug = 0)} = exp(\beta_{age} * 10 + \beta_{drug} * 1) \approx 0.37$$

Estimated hazard function

```
stcurv, hazard title("Cancer data, at sample means")
```



Estimated hazard function

Recall the general formula

$$h(t; \mathbf{X}) = h_0(t) \exp(\beta \mathbf{X})$$

In this case we calculate the function $h_0(t)$ keeping the covariates at their means:

$$h(t; \overline{age}, \overline{drug}) = h_0(t) \exp(\beta \overline{\mathbf{X}})$$

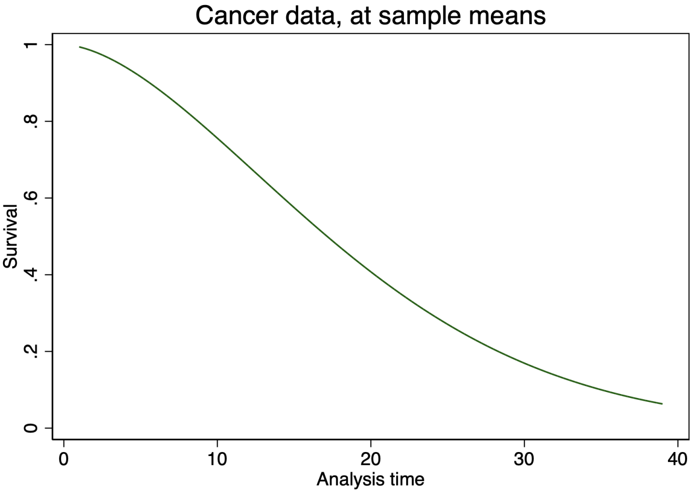
The *baseline* hazard function is a function of time, and is identical for all the individuals (or firms, etc...), regardless of their characteristics.

The curve is monotonically increasing.

The risk of death increases over time (time since treatment began).

Estimated survival function

```
stcurv, survival title("Cancer data, at sample
means")
```



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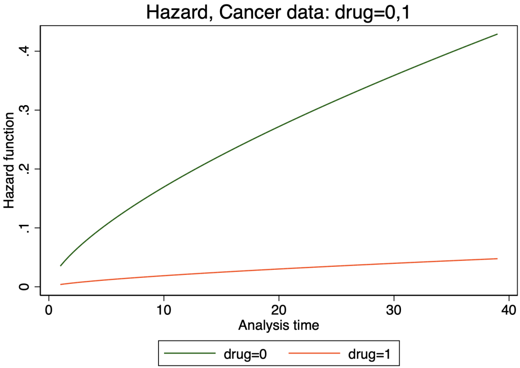

- Patients with the placebo `(drug = 0)`: $h_0(t)\exp(\beta_{age}\overline{age})$
- Patients with the treatment `(drug = 1)`: $h_0(t)\exp(\beta_{age}\overline{age} + \beta_{drug})$

Estimated survival function

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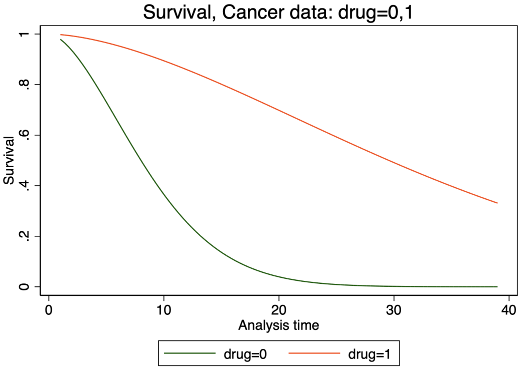
```



- Patients with the placebo `(drug = 0)`: $S(t, \overline{age}, drug = 0)$
- Patients with the treatment `(drug = 1)`: $S(t, \overline{age}, drug = 1)$

Additional commands

```
predict xb, xb
```

- Generates a new variable equal to the estimate βX_i for each person i
- Calculates the shape parameter (α, in the case of Weibul) that is stored in the '**e**stimation class' $e(aux_p)$
- Provides the parameters to estimate, for instance, mean and median survival time for groups of people
  - Mean survival time for the 50 years old with a placebo
  - Median survival time for the 35 years old with a treatment
- More details in the lecture notes

Discrete time models in STATA

Preparing survival discrete time data for analysis and estimation

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Preparing survival discrete time data for analysis and estimation

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- All one has to do is **re-organise the data set**, define some new variables (to specify the baseline hazard function in particular), and then **apply logit or cloglog regression**.
  - For each unit of analysis (e.g., person), there are as many data rows as there are time intervals at risk of the event occurring for each unit of analysis.
  - "1 row - 1 person" (continuous models) $\Rightarrow$ "Each person contributes T_i rows" (discrete models), where T_i is the number of time periods (e.g. months) i was at risk of the event.
  - A unique identifier variable for each subject is needed, plus a spell month (or semester, or year) identifier variable for each subject.

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- All one has to do is **re-organise the data set**, define some new variables (to specify the baseline hazard function in particular), and then **apply logit or cloglog regression**.
- The binary dependent variable also needs to be created.
  - If subject *i*'s survival time is **censored**, the binary dependent variable is equal to 0 for all of *i*'s spell months;
  - If subject *i*'s survival time is **not censored**, the binary dependent variable is equal to 0 for all but the last of *i*'s spell months (month 1,..., T_{i-1}) and equal to 1 for the last month (month T_i).
- Full tutorial on the lecture notes.

Preparing survival discrete time data for analysis and estimation. An example.

Data Editor (Browse) — cancer.dta

id[1] 1

	id	j	studytime	died	dead	drug	age	_st	_d	_t	_t0
13	6	2	4	Yes	0	placebo	67	1	1	4	0
14	6	3	4	Yes	0	placebo	67	1	1	4	0
15	6	4	4	Yes	1	placebo	67	1	1	4	0
16	7	1	5	Yes	0	placebo	63	1	1	5	0
17	7	2	5	Yes	0	placebo	63	1	1	5	0
18	7	3	5	Yes	0	placebo	63	1	1	5	0
19	7	4	5	Yes	0	placebo	63	1	1	5	0
20	7	5	5	Yes	1	placebo	63	1	1	5	0
21	8	1	5	Yes	0	placebo	58	1	1	5	0
22	8	2	5	Yes	0	placebo	58	1	1	5	0
23	8	3	5	Yes	0	placebo	58	1	1	5	0
24	8	4	5	Yes	0	placebo	58	1	1	5	0
25	8	5	5	Yes	1	placebo	58	1	1	5	0
26	9	1	8	Yes	0	placebo	56	1	1	8	0
27	9	2	8	Yes	0	placebo	56	1	1	8	0
28	9	3	8	Yes	0	placebo	56	1	1	8	0
29	9	4	8	Yes	0	placebo	56	1	1	8	0
30	9	5	8	Yes	0	placebo	56	1	1	8	0
31	9	6	8	Yes	0	placebo	56	1	1	8	0
32	9	7	8	Yes	0	placebo	56	1	1	8	0
33	9	8	8	Yes	1	placebo	56	1	1	8	0
34	10	1	8	No	0	placebo	58	1	0	8	0
35	10	2	8	No	0	placebo	58	1	0	8	0

id: the unit of analysis (persons)

Preparing survival discrete time data for analysis and estimation. An example.

Data Editor (Browse) — cancer.dta

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18	7	3	5	Yes	0	placebo	63	1	1	5	0
19	7	4	5	Yes	0	placebo	63	1	1	5	0
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21	8	1	5	Yes	0	placebo	58	1	1	5	0
22	8	2	5	Yes	0	placebo	58	1	1	5	0
23	8	3	5	Yes	0	placebo	58	1	1	5	0
24	8	4	5	Yes	0	placebo	58	1	1	5	0
25	8	5	5	Yes	1	placebo	58	1	1	5	0
26	9	1	8	Yes	0	placebo	56	1	1	8	0
27	9	2	8	Yes	0	placebo	56	1	1	8	0
28	9	3	8	Yes	0	placebo	56	1	1	8	0
29	9	4	8	Yes	0	placebo	56	1	1	8	0
30	9	5	8	Yes	0	placebo	56	1	1	8	0
31	9	6	8	Yes	0	placebo	56	1	1	8	0
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35	10	2	8	No	0	placebo	58	1	0	8	0

id: the unit of analysis (persons)

j: time unit (months)

Preparing survival discrete time data for analysis and estimation. An example.

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17	7	2	5	Yes	0	placebo	63	1	1	5	0
18	7	3	5	Yes	0	placebo	63	1	1	5	0
19	7	4	5	Yes	0	placebo	63	1	1	5	0
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21	8	1	5	Yes	0	placebo	58	1	1	5	0
22	8	2	5	Yes	0	placebo	58	1	1	5	0
23	8	3	5	Yes	0	placebo	58	1	1	5	0
24	8	4	5	Yes	0	placebo	58	1	1	5	0
25	8	5	5	Yes	1	placebo	58	1	1	5	0
26	9	1	8	Yes	0	placebo	56	1	1	8	0
27	9	2	8	Yes	0	placebo	56	1	1	8	0
28	9	3	8	Yes	0	placebo	56	1	1	8	0
29	9	4	8	Yes	0	placebo	56	1	1	8	0
30	9	5	8	Yes	0	placebo	56	1	1	8	0
31	9	6	8	Yes	0	placebo	56	1	1	8	0
32	9	7	8	Yes	0	placebo	56	1	1	8	0
33	9	8	8	Yes	1	placebo	56	1	1	8	0
34	10	1	8	No	0	placebo	58	1	0	8	0
35	10	2	8	No	0	placebo	58	1	0	8	0

id: the unit of analysis (persons)

j: time unit (months)

studytime: time elapsed (in months)

Preparing survival discrete time data for analysis and estimation. An example.

Data Editor (Browse) — cancer.dta

id[1] 1

Edit mode Save

	id	j	studytime	died	dead	drug	age	_st	_d	_t	_t0
13	6	2	4	Yes	0	placebo	67	1	1	4	0
14	6	3	4	Yes	0	placebo	67	1	1	4	0
15	6	4	4	Yes	1	placebo	67	1	1	4	0
16	7	1	5	Yes	0	placebo	63	1	1	5	0
17	7	2	5	Yes	0	placebo	63	1	1	5	0
18	7	3	5	Yes	0	placebo	63	1	1	5	0
19	7	4	5	Yes	0	placebo	63	1	1	5	0
20	7	5	5	Yes	1	placebo	63	1	1	5	0
21	8	1	5	Yes	0	placebo	58	1	1	5	0
22	8	2	5	Yes	0	placebo	58	1	1	5	0
23	8	3	5	Yes	0	placebo	58	1	1	5	0
24	8	4	5	Yes	0	placebo	58	1	1	5	0
25	8	5	5	Yes	1	placebo	58	1	1	5	0
26	9	1	8	Yes	0	placebo	56	1	1	8	0
27	9	2	8	Yes	0	placebo	56	1	1	8	0
28	9	3	8	Yes	0	placebo	56	1	1	8	0
29	9	4	8	Yes	0	placebo	56	1	1	8	0
30	9	5	8	Yes	0	placebo	56	1	1	8	0
31	9	6	8	Yes	0	placebo	56	1	1	8	0
32	9	7	8	Yes	0	placebo	56	1	1	8	0
33	9	8	8	Yes	1	placebo	56	1	1	8	0
34	10	1	8	No	0	placebo	58	1	0	8	0
35	10	2	8	No	0	placebo	58	1	0	8	0

id: the unit of analysis (persons)

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Preparing survival discrete time data for analysis and estimation. An example.

Data Editor (Browse) — cancer.dta

	id	j	studytime	died	dead	drug	age	_st	_d	_t	_t0
13	6	2	4	Yes	0	placebo	67	1	1	4	0
14	6	3	4	Yes	0	placebo	67	1	1	4	0
15	6	4	4	Yes	1	placebo	67	1	1	4	0
16	7	1	5	Yes	0	placebo	63	1	1	5	0
17	7	2	5	Yes	0	placebo	63	1	1	5	0
18	7	3	5	Yes	0	placebo	63	1	1	5	0
19	7	4	5	Yes	0	placebo	63	1	1	5	0
20	7	5	5	Yes	1	placebo	63	1	1	5	0
21	8	1	5	Yes	0	placebo	58	1	1	5	0
22	8	2	5	Yes	0	placebo	58	1	1	5	0
23	8	3	5	Yes	0	placebo	58	1	1	5	0
24	8	4	5	Yes	0	placebo	58	1	1	5	0
25	8	5	5	Yes	1	placebo	58	1	1	5	0
26	9	1	8	Yes	0	placebo	56	1	1	8	0
27	9	2	8	Yes	0	placebo	56	1	1	8	0
28	9	3	8	Yes	0	placebo	56	1	1	8	0
29	9	4	8	Yes	0	placebo	56	1	1	8	0
30	9	5	8	Yes	0	placebo	56	1	1	8	0
31	9	6	8	Yes	0	placebo	56	1	1	8	0
32	9	7	8	Yes	0	placebo	56	1	1	8	0
33	9	8	8	Yes	1	placebo	56	1	1	8	0
34	10	1	8	No	0	placebo	58	1	0	8	0
35	10	2	8	No	0	placebo	58	1	0	8	0

id: the unit of analysis (persons)

j: time unit (months)

studytime: time elapsed (in months)

died: final outcome (dead or alive)

dead: period *j*-specific outcome

Preparing survival discrete time data for analysis and estimation. An example.

Data Editor (Browse) — cancer.dta

Edit mode Save

id[1] 1

	id	j	studytime	died	dead	drug	age	_st	_d	_t	_t0
13	6	2	4	Yes	0	placebo	67	1	1	4	0
14	6	3	4	Yes	0	placebo	67	1	1	4	0
15	6	4	4	Yes	1	placebo	67	1	1	4	0
16	7	1	5	Yes	0	placebo	63	1	1	5	0
17	7	2	5	Yes	0	placebo	63	1	1	5	0
18	7	3	5	Yes	0	placebo	63	1	1	5	0
19	7	4	5	Yes	0	placebo	63	1	1	5	0
20	7	5	5	Yes	1	placebo	63	1	1	5	0
21	8	1	5	Yes	0	placebo	58	1	1	5	0
22	8	2	5	Yes	0	placebo	58	1	1	5	0
23	8	3	5	Yes	0	placebo	58	1	1	5	0
24	8	4	5	Yes	0	placebo	58	1	1	5	0
25	8	5	5	Yes	1	placebo	58	1	1	5	0
26	9	1	8	Yes	0	placebo	56	1	1	8	0
27	9	2	8	Yes	0	placebo	56	1	1	8	0
28	9	3	8	Yes	0	placebo	56	1	1	8	0
29	9	4	8	Yes	0	placebo	56	1	1	8	0
30	9	5	8	Yes	0	placebo	56	1	1	8	0
31	9	6	8	Yes	0	placebo	56	1	1	8	0
32	9	7	8	Yes	0	placebo	56	1	1	8	0
33	9	8	8	Yes	1	placebo	56	1	1	8	0
34	10	1	8	No	0	placebo	58	1	0	8	0
35	10	2	8	No	0	placebo	58	1	0	8	0

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studytime: time elapsed (in months)

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dead: period *j*-specific outcome

drug: subject to treatment (or not)

Preparing survival discrete time data for analysis and estimation. An example.

Data Editor (Browse) — cancer.dta

Edit mode Save

id[1] 1

	id	j	studytime	died	dead	drug	age	_st	_d	_t	_t0
13	6	2	4	Yes	0	placebo	67	1	1	4	0
14	6	3	4	Yes	0	placebo	67	1	1	4	0
15	6	4	4	Yes	1	placebo	67	1	1	4	0
16	7	1	5	Yes	0	placebo	63	1	1	5	0
17	7	2	5	Yes	0	placebo	63	1	1	5	0
18	7	3	5	Yes	0	placebo	63	1	1	5	0
19	7	4	5	Yes	0	placebo	63	1	1	5	0
20	7	5	5	Yes	1	placebo	63	1	1	5	0
21	8	1	5	Yes	0	placebo	58	1	1	5	0
22	8	2	5	Yes	0	placebo	58	1	1	5	0
23	8	3	5	Yes	0	placebo	58	1	1	5	0
24	8	4	5	Yes	0	placebo	58	1	1	5	0
25	8	5	5	Yes	1	placebo	58	1	1	5	0
26	9	1	8	Yes	0	placebo	56	1	1	8	0
27	9	2	8	Yes	0	placebo	56	1	1	8	0
28	9	3	8	Yes	0	placebo	56	1	1	8	0
29	9	4	8	Yes	0	placebo	56	1	1	8	0
30	9	5	8	Yes	0	placebo	56	1	1	8	0
31	9	6	8	Yes	0	placebo	56	1	1	8	0
32	9	7	8	Yes	0	placebo	56	1	1	8	0
33	9	8	8	Yes	1	placebo	56	1	1	8	0
34	10	1	8	No	0	placebo	58	1	0	8	0
35	10	2	8	No	0	placebo	58	1	0	8	0

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died: final outcome (dead or alive)
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drug: subject to treatment (or not)
age: age when observations start

Preparing survival discrete time data for analysis and estimation. An example.

Data Editor (Browse) — cancer.dta

Edit mode Save

id[1] 1

	id	j	studytime	died	dead	drug	age	_st	_d	_t	_t0
13	6	2	4	Yes	0	placebo	67	1	1	4	0
14	6	3	4	Yes	0	placebo	67	1	1	4	0
15	6	4	4	Yes	1	placebo	67	1	1	4	0
16	7	1	5	Yes	0	placebo	63	1	1	5	0
17	7	2	5	Yes	0	placebo	63	1	1	5	0
18	7	3	5	Yes	0	placebo	63	1	1	5	0
19	7	4	5	Yes	0	placebo	63	1	1	5	0
20	7	5	5	Yes	1	placebo	63	1	1	5	0
21	8	1	5	Yes	0	placebo	58	1	1	5	0
22	8	2	5	Yes	0	placebo	58	1	1	5	0
23	8	3	5	Yes	0	placebo	58	1	1	5	0
24	8	4	5	Yes	0	placebo	58	1	1	5	0
25	8	5	5	Yes	1	placebo	58	1	1	5	0
26	9	1	8	Yes	0	placebo	56	1	1	8	0
27	9	2	8	Yes	0	placebo	56	1	1	8	0
28	9	3	8	Yes	0	placebo	56	1	1	8	0
29	9	4	8	Yes	0	placebo	56	1	1	8	0
30	9	5	8	Yes	0	placebo	56	1	1	8	0
31	9	6	8	Yes	0	placebo	56	1	1	8	0
32	9	7	8	Yes	0	placebo	56	1	1	8	0
33	9	8	8	Yes	1	placebo	56	1	1	8	0
34	10	1	8	No	0	placebo	58	1	0	8	0
35	10	2	8	No	0	placebo	58	1	0	8	0

id: the unit of analysis (persons)

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studytime: time elapsed (in months)

died: final outcome (dead or alive)

dead: period j-specific outcome

drug: subject to treatment (or not)

age: age when observations start

$\_st$, $\_d$, $\_t$, $\_t0$: see continuous case

Preparing survival discrete time data for analysis and estimation. An example.

Data Editor (Browse) — cancer.dta Edit mode Save

id[1] 1

	id	j	studytime	died	dead	drug	age	_st	_d	_t	_t0
13	6	2	4	Yes	0	placebo	67	1	1	4	0
14	6	3	4	Yes	0	placebo	67	1	1	4	0
15	6	4	4	Yes	1	placebo	67	1	1	4	0
16	7	1	5	Yes	0	placebo	63	1	1	5	0
17	7	2	5	Yes	0	placebo	63	1	1	5	0
18	7	3	5	Yes	0	placebo	63	1	1	5	0
19	7	4	5	Yes	0	placebo	63	1	1	5	0
20	7	5	5	Yes	1	placebo	63	1	1	5	0
21	8	1	5	Yes	0	placebo	58	1	1	5	0
22	8	2	5	Yes	0	placebo	58	1	1	5	0
23	8	3	5	Yes	0	placebo	58	1	1	5	0
24	8	4	5	Yes	0	placebo	58	1	1	5	0
25	8	5	5	Yes	1	placebo	58	1	1	5	0
26	9	1	8	Yes	0	placebo	56	1	1	8	0
27	9	2	8	Yes	0	placebo	56	1	1	8	0
28	9	3	8	Yes	0	placebo	56	1	1	8	0
29	9	4	8	Yes	0	placebo	56	1	1	8	0
30	9	5	8	Yes	0	placebo	56	1	1	8	0
31	9	6	8	Yes	0	placebo	56	1	1	8	0
32	9	7	8	Yes	0	placebo	56	1	1	8	0
33	9	8	8	Yes	1	placebo	56	1	1	8	0
34	10	1	8	No	0	placebo	58	1	0	8	0
35	10	2	8	No	0	placebo	58	1	0	8	0

id: the unit of analysis (persons)

j: time unit (months)

studytime: time elapsed (in months)

died: final outcome (dead or alive)

dead: period *j*-specific outcome

drug: subject to treatment (or not)

age: age when observations start

_st, *_d*, *_t*, *_t0*: see continuous case

Choose the functional form for the baseline hazard function

- We define new time-varying covariates which are functions of survival time t per person.
- Different alternatives are possible
  - log(time)
  - polynomial in time (e.g., $\alpha t + \gamma t^2 + \delta t^3 ...$)
  - piece-wise constant
  - fully non-parametric (e.g., $\gamma_1 * j_1 + \gamma_2 * j_2 + \gamma_3 * j_3 + ... + \gamma_k * j_k$, where j_k are duration-interval-specific dummy variables). *Caveat*: check whether events occur at each value of j_k.

Choose the functional form for the baseline hazard function

	id	j	studytime	lnj	j2	j3	dur1	dur2	dur3	dur4	dur5	dur6	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10
1	1	1	1	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
2	2	1	1	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
3	3	1	2	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
4	3	2	2	.6931472	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
5	4	1	3	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
6	4	2	3	.6931472	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
7	4	3	3	1.098612	9	27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
8	5	1	4	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
9	5	2	4	.6931472	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
10	5	3	4	1.098612	9	27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
11	5	4	4	1.386294	16	64	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
12	6	1	4	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
13	6	2	4	.6931472	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
14	6	3	4	1.098612	9	27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
15	6	4	4	1.386294	16	64	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
16	7	1	5	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
17	7	2	5	.6931472	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
18	7	3	5	1.098612	9	27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
19	7	4	5	1.386294	16	64	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
20	7	5	5	1.609438	25	125	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
21	8	1	5	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
22	8	2	5	.6931472	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
23	8	3	5	1.098612	9	27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
24	8	4	5	1.386294	16	64	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
25	8	5	5	1.609438	25	125	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
26	9	1	8	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
27	9	2	8	.6931472	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
28	9	3	8	1.098612	9	27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
29	9	4	8	1.386294	16	64	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
30	9	5	8	1.609438	25	125	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
31	9	6	8	1.791759	36	216	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
32	9	7	8	1.94591	49	343	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0
33	9	8	8	2.079442	64	512	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0
34	10	1	8	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
35	10	2	8	.6931472	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
36	10	3	8	1.098612	9	27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
37	10	4	8	1.386294	16	64	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
38	10	5	8	1.609438	25	125	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
39	10	6	8	1.791759	36	216	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
40	10	7	8	1.94591	49	343	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0
41	10	8	8	2.079442	64	512	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0

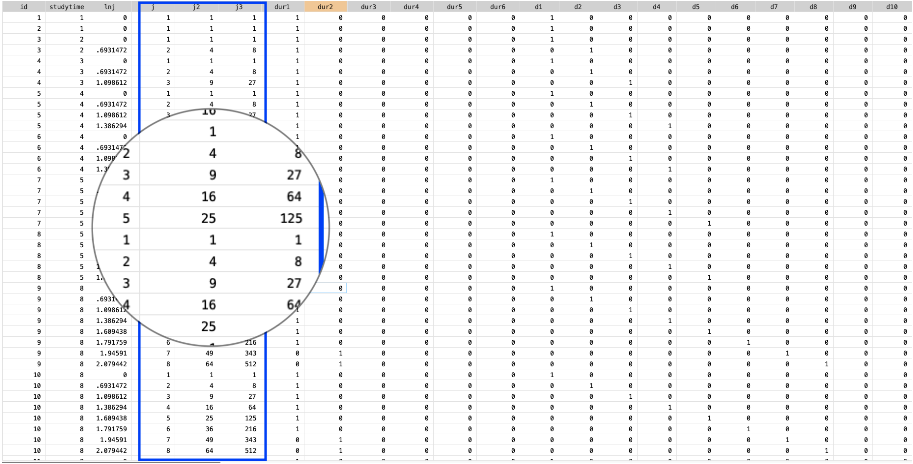
Choose the functional form for the baseline hazard function

id	studytime	j	lnj	j2	j3	dur1	dur2	dur3	dur4	dur5	dur6	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10
1	1	1	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
2	1	1	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
3	2	1	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
3	2	2	.6931472	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
4	3	1	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
4	3	2	.6931472	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
4	3	3	1.098612	9	27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
5	4	1	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
5	4	2	.6931472	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
5	4	3	1.098612	9	27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
5	4	4	1.386294	16	64	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
6	4	1	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
6	4	2	.6931472	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
6	4	3	1.098612	9	27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
6	4	4	1.386294	16	64	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
7	5	1	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
7	5	[illegible]	[illegible]	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
7	5	[illegible]	[illegible]	9	27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
7	5	[illegible]	[illegible]	16	64	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
7	[illegible]	[illegible]	[illegible]	[illegible]	125	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
8	[illegible]	[illegible]	[illegible]	[illegible]	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
8	[illegible]	[illegible]	[illegible]	[illegible]	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
8	[illegible]	[illegible]	[illegible]	[illegible]	27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
8	[illegible]	[illegible]	[illegible]	[illegible]	64	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
8	[illegible]	[illegible]	[illegible]	[illegible]	125	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
9	[illegible]	[illegible]	[illegible]	[illegible]	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
9	8	[illegible]	[illegible]	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
9	8	[illegible]	[illegible]	9	27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
9	8	[illegible]	[illegible]	16	64	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
9	8	5	[illegible]	25	125	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
9	8	6	1.791759	36	216	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
9	8	7	1.94591	49	343	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0
9	8	8	2.079442	64	512	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0
10	8	1	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
10	8	2	.6931472	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
10	8	3	1.098612	9	27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
10	8	4	1.386294	16	64	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
10	8	5	1.609438	25	125	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
10	8	6	1.791759	36	216	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
10	8	7	1.94591	49	343	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0
10	8	8	2.079442	64	512	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0

j	lnj
1	0
2	.6931472
3	1.098612
4	1.386294
5	1.609438

log(time)

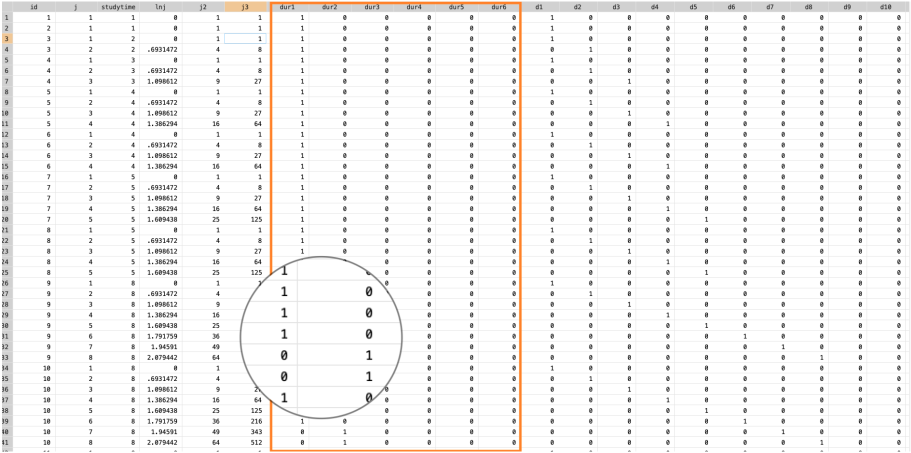
Choose the functional form for the baseline hazard function



id	studytime	lnj	j	j2	j3	dur1	dur2	dur3	dur4	dur5	dur6	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10
1	1	0	1	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
2	1	0	1	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
3	2	0	1	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
3	2	.6931472	2	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
4	3	0	1	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
4	3	.6931472	2	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
4	3	1.098612	3	9	27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
5	4	0	1	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
5	4	.6931472	2	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
5	4	1.098612	3	[illegible]	27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
5	4	1.386294	[illegible]	[illegible]	[illegible]	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
6	4	0	[illegible]	[illegible]	[illegible]	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
6	4	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
6	4	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
6	4	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
7	5	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
7	5	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
7	5	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
7	5	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
7	5	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
8	5	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
8	5	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
8	5	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
8	5	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
8	5	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
9	8	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
9	8	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
9	8	1.098612	[illegible]	[illegible]	[illegible]	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
9	8	1.386294	[illegible]	[illegible]	[illegible]	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
9	8	1.609438	[illegible]	[illegible]	[illegible]	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
9	8	1.791759	6	[illegible]	216	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
9	8	1.94591	7	49	343	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0
9	8	2.079442	8	64	512	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0
10	8	0	1	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
10	8	.6931472	2	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
10	8	1.098612	3	9	27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
10	8	1.386294	4	16	64	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
10	8	1.609438	5	25	125	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
10	8	1.791759	6	36	216	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
10	8	1.94591	7	49	343	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0
10	8	2.079442	8	64	512	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0

Polynomial in time (e.g., $\alpha t + \gamma t^2 + \delta t^3 ...$)

Choose the functional form for the baseline hazard function



	id	j	studytime	lnj	j2	j3	dur1	dur2	dur3	dur4	dur5	dur6	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10
1	1	1	1	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
2	2	1	1	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
3	3	1	2	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
4	3	2	2	.6931472	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
5	4	1	3	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
6	4	2	3	.6931472	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
7	4	3	3	1.098612	9	27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
8	5	1	4	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
9	5	2	4	.6931472	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
10	5	3	4	1.098612	9	27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
11	5	4	4	1.386294	16	64	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
12	6	1	4	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
13	6	2	4	.6931472	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
14	6	3	4	1.098612	9	27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
15	6	4	4	1.386294	16	64	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
16	7	1	5	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
17	7	2	5	.6931472	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
18	7	3	5	1.098612	9	27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
19	7	4	5	1.386294	16	64	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
20	7	5	5	1.609438	25	125	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
21	8	1	5	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
22	8	2	5	.6931472	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
23	8	3	5	1.098612	9	27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
24	8	4	5	1.386294	16	64	[illegible]	[illegible]	0	0	0	0	0	0	0	1	0	0	0	0	0	0
25	8	5	5	1.609438	25	125	[illegible]	[illegible]	0	0	0	0	0	0	0	0	1	0	0	0	0	0
26	9	1	8	0	1	1	[illegible]	[illegible]	0	0	0	0	1	0	0	0	0	0	0	0	0	0
27	9	2	8	.6931472	4	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	1	0	0	0	0	0	0	0	0
28	9	3	8	1.098612	9	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	0	1	0	0	0	0	0	0	0
29	9	4	8	1.386294	16	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	0	0	1	0	0	0	0	0	0
30	9	5	8	1.609438	25	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	0	0	0	1	0	0	0	0	0
31	9	6	8	1.791759	36	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	0	0	0	0	1	0	0	0	0
32	9	7	8	1.94591	49	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	0	0	0	0	0	1	0	0	0
33	9	8	8	2.079442	64	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	0	0	0	0	0	0	1	0	0
34	10	1	8	0	1	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	1	0	0	0	0	0	0	0	0	0
35	10	2	8	.6931472	4	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	1	0	0	0	0	0	0	0	0
36	10	3	8	1.098612	9	[illegible]	[illegible]	[illegible]	0	0	0	0	0	0	1	0	0	0	0	0	0	0
37	10	4	8	1.386294	16	64	[illegible]	[illegible]	0	0	0	0	0	0	0	1	0	0	0	0	0	0
38	10	5	8	1.609438	25	125	[illegible]	[illegible]	0	0	0	0	0	0	0	0	1	0	0	0	0	0
39	10	6	8	1.791759	36	216	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
40	10	7	8	1.94591	49	343	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0
41	10	8	8	2.079442	64	512	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0

Piece-wise constant

Choose the functional form for the baseline hazard function

	id	j	studytime	lnj	j2	j3	dur1	dur2	dur3	dur4	dur5	dur6	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10
1	1	1	1	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
2	2	1	1	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
3	3	1	2	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
4	3	2	2	.6931472	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
5	4	1	3	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
6	4	2	3	.6931472	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
7	4	3	3	1.098612	9	27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
8	5	1	4	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
9	5	2	4	.6931472	4	8	1	0	0	0	0	0	0	1	0	[illegible]	[illegible]	0	0	0	0	0
10	5	3	4	1.098612	9	27	1	0	0	0	0	0	0	0	[illegible]	[illegible]	[illegible]	0	0	0	0	0
11	5	4	4	1.386294	16	64	1	0	0	0	0	0	0	0	[illegible]	[illegible]	[illegible]	0	0	0	0	0
12	6	1	4	0	1	1	1	0	0	0	0	0	1	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0
13	6	2	4	.6931472	4	8	1	0	0	0	0	0	0	[illegible]	[illegible]	0	[illegible]	[illegible]	0	0	0	0
14	6	3	4	1.098612	9	27	1	0	0	0	0	0	0	[illegible]	1	0	0	[illegible]	0	0	0	0
15	6	4	4	1.386294	16	64	1	0	0	0	0	0	0	[illegible]	0	1	0	[illegible]	0	0	0	0
16	7	1	5	0	1	1	1	0	0	0	0	0	1	[illegible]	0	0	0	[illegible]	0	0	0	0
17	7	2	5	.6931472	4	8	1	0	0	0	0	0	0	[illegible]	0	0	0	[illegible]	0	0	0	0
18	7	3	5	1.098612	9	27	1	0	0	0	0	0	0	[illegible]	1	0	0	[illegible]	0	0	0	0
19	7	4	5	1.386294	16	64	1	0	0	0	0	0	0	[illegible]	0	1	0	[illegible]	0	0	0	0
20	7	5	5	1.609438	25	125	1	0	0	0	0	0	0	[illegible]	0	0	1	[illegible]	0	0	0	0
21	8	1	5	0	1	1	1	0	0	0	0	0	1	[illegible]	0	0	0	[illegible]	0	0	0	0
22	8	2	5	.6931472	4	8	1	0	0	0	0	0	0	[illegible]	0	0	0	[illegible]	0	0	0	0
23	8	3	5	1.098612	9	27	1	0	0	0	0	0	0	[illegible]	1	0	0	[illegible]	0	0	0	0
24	8	4	5	1.386294	16	64	1	0	0	0	0	0	0	[illegible]	0	1	0	[illegible]	0	0	0	0
25	8	5	5	1.609438	25	125	1	0	0	0	0	0	0	[illegible]	[illegible]	0	[illegible]	[illegible]	0	0	0	0
26	9	1	8	0	1	1	1	0	0	0	0	0	1	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0
27	9	2	8	.6931472	4	8	1	0	0	0	0	0	0	1	[illegible]	[illegible]	[illegible]	0	0	0	0	0
28	9	3	8	1.098612	9	27	1	0	0	0	0	0	0	0	[illegible]	[illegible]	[illegible]	0	0	0	0	0
29	9	4	8	1.386294	16	64	1	0	0	0	0	0	0	0	0	[illegible]	0	0	0	0	0	0
30	9	5	8	1.609438	25	125	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
31	9	6	8	1.791759	36	216	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
32	9	7	8	1.94591	49	343	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0
33	9	8	8	2.079442	64	512	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0
34	10	1	8	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
35	10	2	8	.6931472	4	8	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
36	10	3	8	1.098612	9	27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
37	10	4	8	1.386294	16	64	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
38	10	5	8	1.609438	25	125	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
39	10	6	8	1.791759	36	216	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
40	10	7	8	1.94591	49	343	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0
41	10	8	8	2.079442	64	512	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0

Fully non-parametric (e.g., $\gamma_1 * j_1 + \gamma_2 * j_2 + \gamma_3 * j_3 + ... + \gamma_k * j_k$)

Estimation of a discrete-time model

Logistic model

```
logit depvar varlist, [or noconstant]
```

`'depvar'` is the (new) event variable – `dead` in the illustration – and `'varlist'` refers to the explanatory variables (covariates) together with the variables used to summarise the baseline hazard function.

The `'noconstat'` option means estimate a model without a constant term – we mainly use this for estimating models with a fully non-parametric baseline hazard.

Estimation of a discrete-time model

Logistic model

Odds ratios of hazard rates refer to ratios of form $\frac{h_1/(1-h_1)}{h_0/(1-h_0)}$ from a one-unit change in an explanatory variable from zero to one ($\Delta X = 1$ as $X = 0 \rightarrow X = 1$).

I personally find these difficult to interpret.

On the other hand, as $h \rightarrow 0$, the odds ratio tends to the hazard ratio $\frac{h1}{h0}$, which does have a ready interpretation.

Estimation of a discrete-time logistic (or logit) model

```
logit dead drug age lnj, nolog

Logistic regression                             Number of obs =    744
                                                LR chi2(3)    =  35.41
                                                Prob > chi2   = 0.0000
Log likelihood = -111.16102                     Pseudo R2     = 0.1374
```

dead	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
drug	-2.297714	.4388526	-5.24	0.000	-3.157849	-1.437579
age	.1253644	.0391588	3.20	0.001	.0486145	.2021143
lnj	.6781536	.2582365	2.63	0.009	.1720194	1.184288
_cons	-10.25004	2.383314	-4.30	0.000	-14.92125	-5.578826

- Drug recipients ($\texttt{drug} = 1$) have lower hazard rates ($\beta_{drug} < 0$ if $\texttt{drug} = 0 \rightarrow \texttt{drug} = 1$
- Hazard rate increases with age ($\beta_{age} > 0$ if $age \uparrow$)
- Baseline hazard rises with elapsed survival time ($\texttt{lnj} > 0$)

Comparison of discrete and continuous-time models

Discrete time (logistic): `logit dead drug age lnj, nolog`

```
Logistic regression                                     Number of obs =    744
                                                        LR chi2(3)    =  35.41
                                                        Prob > chi2   = 0.0000
Log likelihood = -111.16102                             Pseudo R2     = 0.1374
```

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_cons	-10.25004	2.383314	-4.30	0.000	-14.92125	-5.578826

Continuous time (Weibull): `streg drug age, dist(weibull) nolog nohr`

```
Weibull regression -- log relative-hazard form

No. of subjects =           48                     Number of obs   =        48
No. of failures =           31
Time at risk    =          744
                                                   LR chi2(2)      =     35.39
Log likelihood  =   -42.931335                     Prob > chi2     =    0.0000
```

_t	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
drug	-2.196936	.4087791	-5.374	0.000	-2.998129	-1.395744
age	.1202027	.0371599	3.235	0.001	.0473707	.1930348
_cons	-10.58396	2.326271	-4.550	0.000	-15.14337	-6.024553
/ln_p	.5204297	.1389037	3.747	0.000	.2481834	.792676
p	1.682751	.2337403			1.281695	2.209301
1/p	.5942651	.0825456			.452632	.7802168

Comparison of discrete and continuous-time models

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```
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                                                        LR chi2(3)    =  35.41
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```
No. of subjects =          48                  Number of obs   =         48
No. of failures =          31
Time at risk    =         744
                                               LR chi2(2)      =      35.39
Log likelihood  =   -42.931335                 Prob > chi2     =     0.0000
```

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Comparison of discrete and continuous-time models

Discrete time (logistic): `logit dead drug age lnj, nolog`

```
Logistic regression                                     Number of obs =    744
                                                        LR chi2(3)    =  35.41
                                                        Prob > chi2   = 0.0000
Log likelihood = -111.16102                             Pseudo R2     = 0.1374
```

dead	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
drug	$\boxed{-2.297714}$	.4388526	-5.24	0.000	-3.157849	-1.437579
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lnj	.6781536	.2582365	2.63	0.009	.1720194	1.184288
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Continuous time (Weibull): `streg drug age, dist(weibull) nolog nohr`

```
No. of subjects =           48                     Number of obs    =        48
No. of failures =           31
Time at risk    =          744
                                                   LR chi2(2)       =     35.39
Log likelihood  =   -42.931335                     Prob > chi2      =    0.0000
```

_t	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
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p	1.682751	.2337403			1.281695	2.209301
1/p	.5942651	.0825456			.452632	.7802168

Comparison of discrete and continuous-time models

Discrete time models

Pros

- Time-varying covariates $X(t)$
- More flexible baseline hazard function

Continuous time models

Pros

- Cost-effective dataset construction
- Time-invariant covariates X
- Long time span with frequent events

Estimation of a discrete-time logit model

`logistic dead drug age ln`

dead	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
drug	.1004883	.0440996	-5.24	0.000	.0425171	.2375022
age	1.133561	.044389	3.20	0.001	1.049816	1.223988
lnj	1.970237	.5087869	2.63	0.009	1.187701	3.268358
_cons	.0000354	.0000843	-4.30	0.000	3.31e-07	.003777

`logit dead drug age lnj, or`

dead	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
drug	.1004883	.0440996	-5.24	0.000	.0425171	.2375022
age	1.133561	.044389	3.20	0.001	1.049816	1.223988
lnj	1.970237	.5087869	2.63	0.009	1.187701	3.268358
_cons	.0000354	.0000843	-4.30	0.000	3.31e-07	.003777

Logit and logistic models are equivalent.

`logistic` → OR

`logit` → coefficients (log odds)

`logit [...], 'or'` → OR

Estimation of a discrete-time logit model

Cubic polynomial: `logit dead drug age j j2 j3, nolog`

dead	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
drug	-2.39327	.4626735	-5.17	0.000	-3.300093	-1.486447
age	.123828	.039411	3.14	0.002	.0465838	.2010721
j	.0881094	.1809724	0.49	0.626	-.26659	.4428087
j2	.0009124	.0127206	0.07	0.943	-.0240196	.0258444
j3	-.0000481	.0002508	-0.19	0.848	-.0005397	.0004436
_cons	-9.678605	2.441734	-3.96	0.000	-14.46431	-4.892895

Piece-wise constant baseline: `logit dead drug age dur1-dur6, nocons nolog`

dead	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
drug	-2.280694	.4565036	-5.00	0.000	-3.175425	-1.385963
age	.1190845	.0389076	3.06	0.002	.042827	.195342
dur1	-9.098389	2.265066	-4.02	0.000	-13.53784	-4.658941
dur2	-8.434023	2.178112	-3.87	0.000	-12.70304	-4.165002
dur3	-8.438919	2.182175	-3.87	0.000	-12.7159	-4.161936
dur4	-7.596855	2.169892	-3.50	0.000	-11.84977	-3.343945
dur5	-7.445229	2.273184	-3.28	0.001	-11.90059	-2.98987
dur6	-7.499636	2.382459	-3.15	0.002	-12.16917	-2.830103

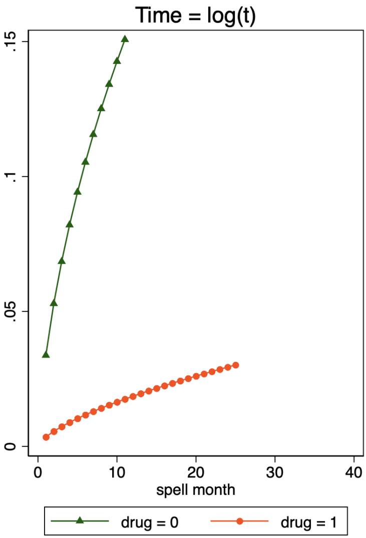
Estimation of a discrete-time logit model

Fully non-parametric baseline: `logit dead drug age d1-d39, nolog`

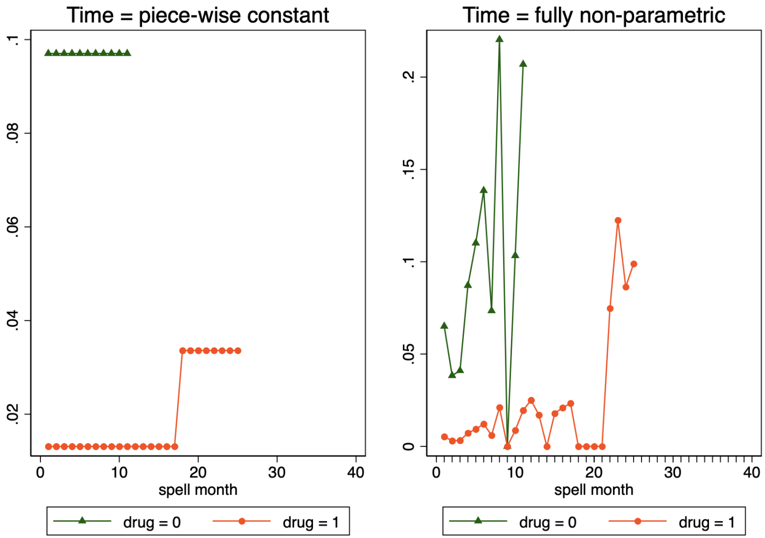
```
note: d38 != 0 predicts failure perfectly;
      d38 omitted and 1 obs not used.

note: d39 != 0 predicts failure perfectly;
      d39 omitted and 1 obs not used.


Logistic regression                                     Number of obs =    573
                                                        Wald chi2(23) = 159.53
Log likelihood = -96.988418                             Prob > chi2   = 0.0000
```

dead	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
drug	-2.572486	.5104139	-5.04	0.000	-3.572879	-1.572093
age	.130051	.0406452	3.20	0.001	.0503879	.209714
d1	-9.817929	2.507439	-3.92	0.000	-14.73242	-4.903439
d2	-10.37478	2.586792	-4.01	0.000	-15.4448	-5.304765
d3	-10.30505	2.584837	-3.99	0.000	-15.37124	-5.238863
d4	-9.501784	2.473035	-3.84	0.000	-14.34884	-4.654724
d5	-9.242106	2.418842	-3.82	0.000	-13.98295	-4.501263
d6	-8.980254	2.376713	-3.78	0.000	-13.63853	-4.321983
d7	-9.687424	2.476246	-3.91	0.000	-14.54078	-4.834071
d8	-8.416641	2.31529	-3.64	0.000	-12.95453	-3.878756
d9	0	(omitted)				
d10	-9.313809	2.482374	-3.75	0.000	-14.17917	-4.448445
d11	-8.496452	2.365123	-3.59	0.000	-13.13201	-3.860896
d12	-8.242216	2.375201	-3.47	0.001	-12.89752	-3.586907
d13	-8.635718	2.447953	-3.53	0.000	-13.43362	-3.837819
d14	0	(omitted)				
d15	-8.588234	2.440998	-3.52	0.000	-13.3725	-3.803967
d16	-8.425413	2.464191	-3.42	0.001	-13.25514	-3.595688
d17	-8.312966	2.4293	-3.42	0.001	-13.07431	-3.551625

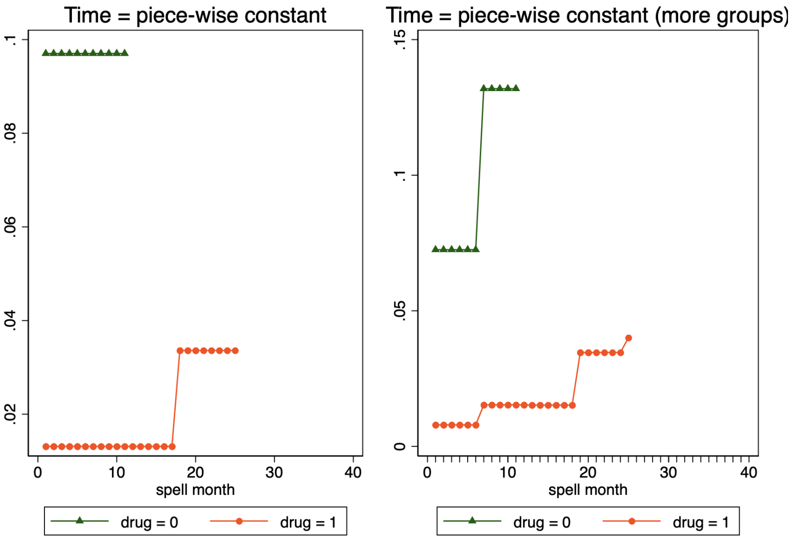
Graphical representation of a discrete-time logit hazard



Graphical representation of a discrete-time logit hazard



Graphical representation of a discrete-time logit hazard



Comparison of baseline hazard functions

Parametric functions (logarithmic, quadratic, cubic, etc.)

Pros

- Smooth hazard
- Few observations (units of analysis or transitions)

Partially or fully parametric functions (piecewise, time-dummy, etc.)

Pros

- Baseline of your choice
- Easy interpretation
- Many observations (units of analysis or transitions)

More on discrete-time models

- Parametric models
  - Complementary log-log regression
  - GLM
- Within and out-of-sample prediction
- Survival functions
- Implementation on software STATA

Full display of these topics on the Lecture notes and do-files.