Longitudinal Data Analysis for Social Science Researchers

Thinking About Event Histories

www.longitudinal.stir.ac.uk

DURATIONS

In simple form –

"Time to an EVENT"

Survival Data – Time to an event

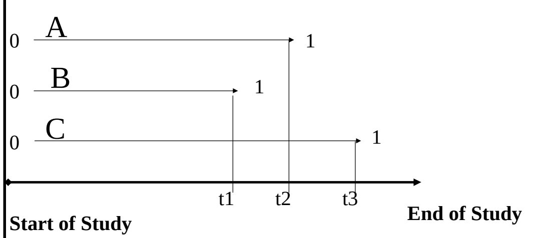
In the medical area…

- Time from diagnosis to death
- Duration from treatment to full health
- Time to return of pain after taking a pain killer

Survival Data – Time to an event

Social Sciences…

- Duration of unemployment
- Duration of housing tenure
- Duration of marriage
- Time to conception



These durations are a continuous Y so why can't we use standard regression techniques?

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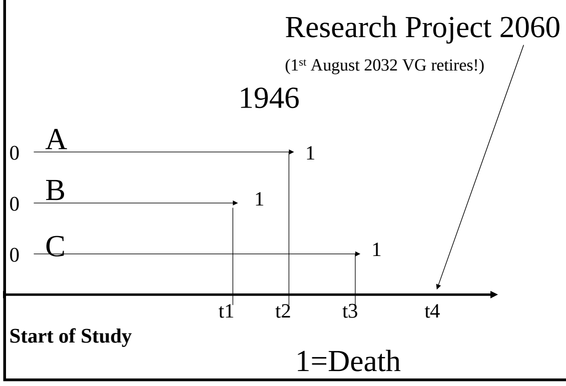
Two examples of when we can

1946 Birth Cohort Study



Breast Feeding Study –

Data Collection Strategy

1. Retrospective questioning of mothers

2. Data collected by Midwives

3. Health Visitor and G.P. Record

Breast Feeding Study –

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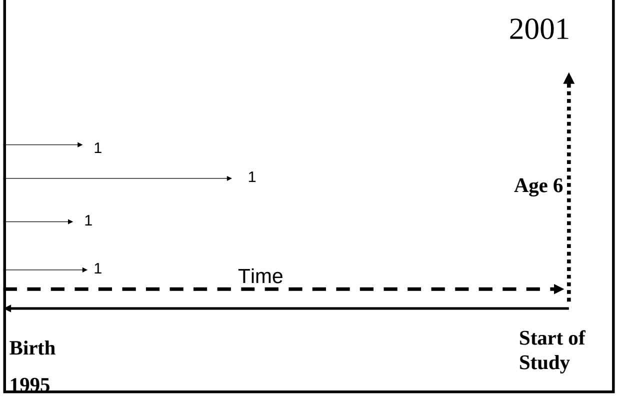


These durations are a continuous Y so why can't we use standard regression techniques?

We can. It might be better to model the log of Y however. These models are sometimes known as 'accelerated life models'.

These durations are a continuous Y so why can't we use standard regression techniques?

Here we have censored observations. An old guideline used to be that if less than 10% of observations were censored then a standard regression approach was okay. However, you'd have trouble getting this past a good referee and there is now no excuse given that techniques are widely understood and suitable software is available.

Accelerated Life Model

$$\text{Log}_e\, t_i = \beta_0 + \beta_1 x_{1i} + e_i$$

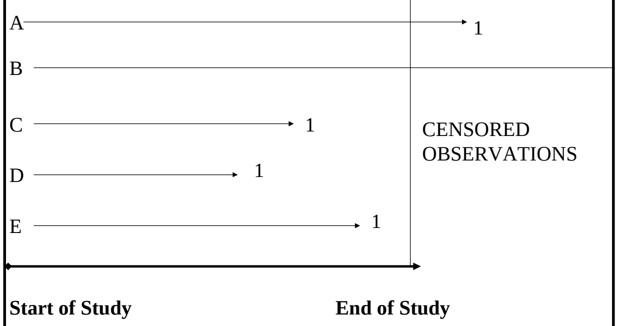
error term

Beware this is log *t*

explanatory variable

constant

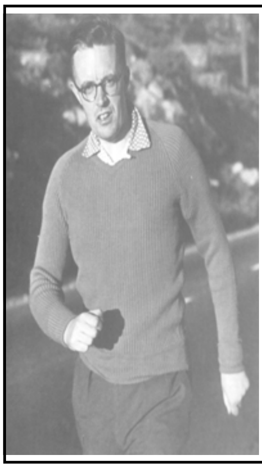
CENSORING



Cox Regression (proportional hazard model)

is a method for modelling time-to-event data in the presence of censored cases

- Explanatory variables in your model (continuous and categorical)
- Estimated coefficients for each of the covariates
- Handles the censored cases correctly



Cox, D.R. (1972) ‘Regression models and life tables’ *JRSS,B,* 34 pp.187-220.

Event History with Cox Model

- No longer modelling the duration
- Modelling the Hazard
- **Hazard**: measure of the probability that an event occurs at time *t* conditional on it not having occurred before *t*
- A more technical account follows later on!

An Example

- Duration of first job after leaving education
- Data from the BHPS
- 15,401 individual records
- 11,061 (72%) failures i.e. job spell ended
- 4,340 (28%) censored – no information on exact end of first job (e.g. still in job)
- Time in months
- Mean 78; s.d.102; min 1; max 793 *(66 years)*

My interests…

- Gender
  - males 7,992 (52%)
  - females 7,409 (48%)
- School system
  - Compulsory school age 14 2,244 (15%)
  - Compulsory school age 15 5,034 (33%)
  - Compulsory school age 16 8,123 (53%)

What is the data structure?

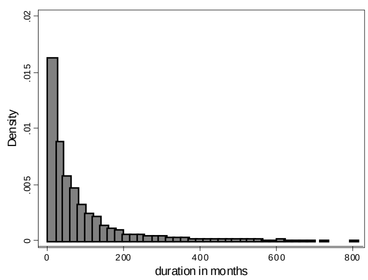
pid	start time	end time	duration	gender	cohort	censored

The row is a person

The tricky part is often calculating the duration

Remember we need an indicator for censored cases

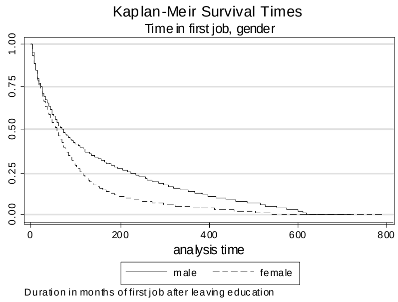
Histogram of duration



Descriptive Analysis Durations Months

	Mean	Median
• Gender		
– males	89	44
– females	66	39
• School system		
– Compulsory school age 14	146	77
– Compulsory school age 15	106	71
– Compulsory school age 16	42	25

Kaplan-Meir Survival Plot



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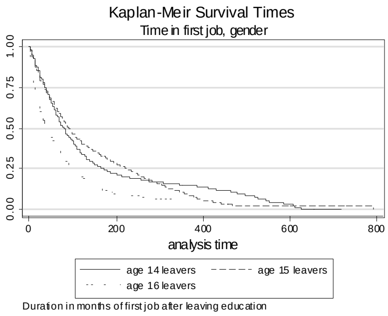

A Cox's Regression – (Hazard Model)

- This is in the *st* suite in STATA
- You must tell STATA what is the duration variable and what is the censor variable

stset duration, failure(status)

A Cox's Regression – (Hazard Model)

- Think of this as being similar to a logit model.
- One way of fixing this conceptually is that there is a binary response but we are interested in the time to this outcome.

STATA Output

```
Cox regression -- Breslow method for ties

No. of subjects =       15401                  Number of obs   =     15401
No. of failures =       11061
Time at risk    =     1203448
                                               LR chi2(3)      =   1232.10
Log likelihood  =  -95143.889                  Prob > chi2     =    0.0000

------------------------------------------------------------------------------
          _t | Haz. Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         fem |   1.435757   .0278343    18.66   0.000     1.382226    1.491361
     cohort1 |   1.047218   .0296894     1.63   0.104     .9906154    1.107056
     cohort2 |   1.937524   .0545469    23.49   0.000      1.83351    2.047439
------------------------------------------------------------------------------
```

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stcox, nohr

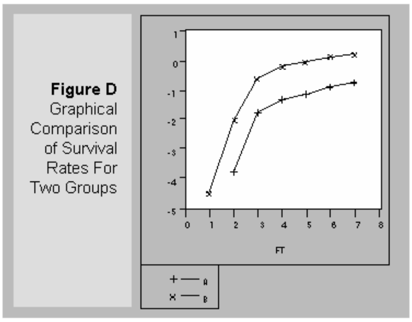
These are the Coefficients rather than Haz Ratios
(i.e. anti ln (.36)=1.44)

_t	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
fem	.3616921	.0193865	18.66	0.000	.3236952	.3996889
cohort1	.0461375	.0283507	1.63	0.104	-.0094289	.1017039
cohort2	.6614111	.0281529	23.49	0.000	.6062324	.7165897

Checking and Testing the Proportional Hazard Assumption

- Key assumption is that the hazard ratio is proportional over time.
- More on this in Prof Wright’s talk.
- See also (see ST (manual) p.142 - 147 for a discussion).
- A simple visualisation might help.

Checking and Testing the Proportional Hazard Assumption



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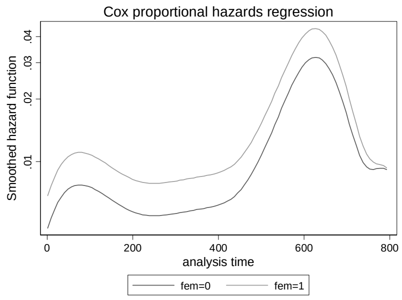

Checking and Testing the Proportional Hazard Assumption
A simple example with one X var

Time: Rank(t)

	rho	chi2	df	Prob>chi2
fem	**0.11224**	**142.09**	**1**	**0.0000**
global test		**142.09**	**1**	**0.0000**

Ho: Fem=0 is proportional to Fem=1

Reject this null hypothesis.

See [ST] pg. 142 and more in Professor Wright's talk!

Treatment of tied durations

- If time could be measured on a true continuous scale then no observations would be tied.
- In reality because of the resolution (or scale) that we measure time on there may be tied observations.
- The basic problem is this affects the size of the risk set - we don't know who left first.
- There are various methods for handling this the default is Breslow; this is okay if there are not too many ties (see ST (manual) p.118 for a discussion of options).

Event history data permutations

- **Single state single episode**
  - e.g. duration in first post-school job till end
  - analogous to a logit framework
- **Single episode competing risks**
  - e.g. duration in job until
  - promotion / retire / unemp
  - Analogous to a multinomial logit framework

Event history analysis software

SPSS – very limited analysis options
STATA – wide range of pre-prepared methods
SAS – as STATA
S-Plus/R – vast capacity but non-introductory
TDA – simple but powerful freeware
MLwiN; IEM; {others} – small packages targeted at specific analysis situations

[**GLIM / SABRE** – some unique options]

Discrete Time

“We believe that discrete-time methods are simply more appropriate for much of the event-history data that are currently collected because, for logistical and financial reasons, observations are often made in discrete time” (Willet and Singer 1995).

Discrete Time

- In a discrete time model the dependent variable is a binary indicator
- Therefore it can be fitted in standard software

Discrete Time

We observe this woman until she experiences the event (marriage)

pid	start age	end age
001	16	21

She need a row for each year –
Sometimes this is called person-period format

Data Structure

Pid	Y	Age
001	0	16
001	0	17
001	0	18
001	0	19
001	0	20
001	1	21

Discrete Time

Discrete time approaches are often appropriate when analysing social data collected at ‘discrete’ intervals

Being able to fit standard regression models is an obvious attraction

Another event history data permutation

Another more complex situation is analysing

- **Multi-state multi-episode**
  - e.g. adult working life histories

Paul will show an example of the state-space in his talk

Social Science Event Histories:

- *Comment: Potentially powerful techniques – however in practice they are often trickier to operationalise with 'real' social science data. Neat examples are often used in textbooks!*
- *In particular:*
  - *Many research applications have concentrated on quite simplistic state spaces (e.g. working V not in work)*
  - *Incorporating many explanatory factors can be difficult – time constant V time-varying; and duration data V panel data.*

Social Science Event Histories:

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Social Science Event Histories:

- *Is an event history analysis really what we need?*
- *Are we really interested in the 'time' to an event?*
- *Often a panel modelling approach may be more appropriate given our substantive interest*