

Event history models

Silje Synnøve Lyder Hermansen

2024-04-22

Time

Political science is full of phenomena that involve time

- ▶ unemployment, cabinets (governments), war, peace, negotiations. . .
- ▶ they contain two components:
 - ▶ an event (a binary outcome)
 - ▶ a duration (a “spell”)

⇒ *glass half full/half empty situation*

Class half-full? Or empty?

- ▶ **opportunity:** duration may be a substantive measure of its own
 - ▶ e.g. ability for a cabinet to stay in office
- ▶ **constraint:** observations are censored (i.e. we don't know when the spell ends)
 - ▶ we can't truncate them (code them with max observed length): bias the slope (β)
 - ▶ we can't remove them: bias the sample

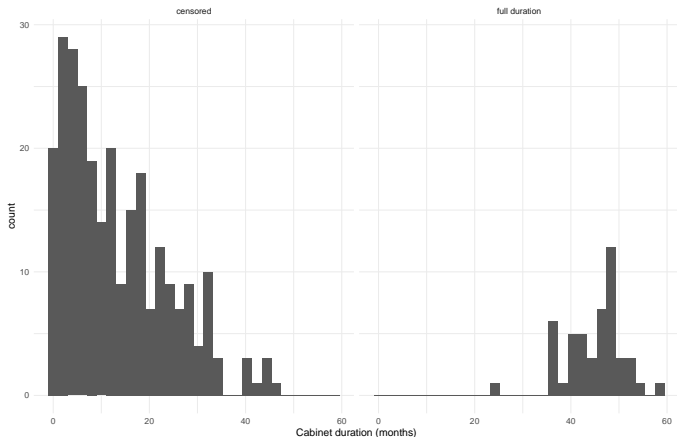
⇒ *model them as such*

Censoring: two sets of observations

Censoring means that we don't observe the entire length of some spells

The problem of censoring: cabinet duration

Duration lengths depends on whether we observed the entire period



Choices and priorities

Choices and priorities

Event history models require us to make quite a few choices

- ▶ information leveraged in the **outcome** (event/duration)
- ▶ **unit of analysis** (spell, spell + change in x, TSCS)
 - ▶ as a consequence: the nesting/correlation between repeated measures
- ▶ **functional form** (survival or hazard; parametric/estimated or semi-parametric/empirical)
- ▶ **ties** what to do when many observations experience the same event?

Data structures: unit of analysis

Data structures: unit of analysis

Event history models often end up with complicated data structures and a host of “outcome” variables

- ▶ division between continuous time models and discrete time models is blurry
- ▶ unit of analysis:
 - ▶ spell-level: as simple as it gets (duration + event/no event)
 - ▶ spell-level + time varying covariates
 - ▶ fixed time period

⇒ *Think ahead, because you will be doing data-wrangling*

Spell-level: focus on duration

We can set up a data set with one observation == one duration/spell.

- ▶ **two outcomes:**
 - ▶ **duration:** how long governments stay in power
 - ▶ **censoring:** all cabinets will end, but we don't always observe it (censor == 1).
- ▶ covariates: don't change during the spell

```
## duration censor12
## 1      7         1
## 2     27         1
## 3      6         1
## 4     49         0
## 5      7         1
## 6      3         1
```

Time-varying covariates: focus on time

If we want to include time-varying predictors, we need to make a new observation for each change in x (and not only in y)

- ▶ we “slice” up the duration for each unit
- ▶ **four dependent variables** to account for the nesting:
 - ▶ **start** and **stop** times (i.e. duration/counter) → focus of duration models
 - ▶ occurrence of **event** (i.e. censoring) → focus of BTSCS (e.g. logits)
 - ▶ id for each **spell** that is now “sliced up”

Time-series cross-section/panel

Same as panel data

- ▶ **a fixed period for all units** i.e. all units are observed at fixed time intervals (day, week year. . .)
- ▶ **event(s)** are reported

Outcome leveraged

Outcome leveraged

We have potentially two outcomes

```
## duration censor12
## 1      7         1
## 2     27         1
## 3      6         1
## 4     49         0
## 5      7         1
## 6      3         1
```

Focus on :

- ▶ **event** and control for duration: BTSCS approach
- ▶ **duration** (spell) punctuated by events: duration models
 - ▶ survival
 - ▶ failure

Event: Binary Time-Series-Cross-Section (BTSCS)

Event: Binary Time-Series-Cross-Section (BTSCS)

With panel data where the event is indicated, we may simply...

- ▶ regress the **binary event** on predictors of choice (logit, probit, log-log)
- ▶ control for the duration:
 - ▶ fixed effects for each duration (problem if we have low ratio event/no event)
 - ▶ “splines” (moving averages; hard to know what goes on)
 - ▶ cubic term
 - ▶ linear (!)

⇒ *ignore/treat as noise the censoring and the time between events*

Both: Duration models

Different focus in outcomes

Duration models draw information from both duration and event:

- ▶ explicit assumption that duration is partially unobserved.
- ▶ censored observations contribute with information about duration, but not event

Functional forms (duration)

Functional forms (duration)

Duration models assume a baseline probability that an event will occur that vary over time

▶ **accelerated failure time (AFTs)**

▶ survival function

▶ $S(t) = 1 - F(t) = Pr(T > t)$

▶ probability that observation has lasted until now

▶ **proportional hazard**

▶ hazard function

▶ $h(t) = \frac{f(t)}{S(t)} = \frac{f(t)}{1-F(t)}$

▶ probability that the observation will experience the event, given that it has lasted until now

⇒ *Same regression coefficients, but reverted (+/-)*

Proportional hazards

Proportional hazards

The outcome is hazard rates $h_i(t)$

- ▶ the proportion of observations that experience event in a given period
- ▶ among those that entered the period without having experienced the event

Hazards are proportional to the β

$$h_i(t) = h_o(t) \exp(x_i^T \beta)$$

- ▶ $h_o(t)$ **baseline hazard varies over time:**
 - ▶ constant
 - ▶ increasing/decreasing
 - ▶ empirically determined
- ▶ $\exp(x_i^T \beta)$ **single set of slope coefficients**
 - ▶ proportional to (i.e. multiplicative) the baseline hazard
 - ▶ $\exp(\beta)$ reports the marginal change
 - ▶ positive β : increase in hazard/probability of event in period (decrease in duration)
 - ▶ negative β : decrease in hazard/probability of event in period (increase in duration)

⇒ *Assumption that coefficients are constant across time*

Two types of models

There are two estimation strategies/models

▶ **parametric models**

- ▶ duration is continuous
- ▶ parameters determine the shape of the baseline hazard
- ▶ e.g. Weibull, exponential . . .

▶ **semi-parametric model**

- ▶ duration is ordinal
- ▶ Cox proportional hazard

Cox proportional hazard models

Cox proportional hazard models

- ▶ order data according to event date
 - ▶ main asset: agnostic about functional form
- ▶ “partial likelihood”:
 - ▶ within first date (period):
 - ▶ compare events to no-events
 - ▶ remove observations with events from data
 - ▶ within second date (period):
 - ▶ rinse and repeat
 - ▶ main weakness: **ties**
 - ▶ observations with the same event time
 - ▶ options for ordering/simulation (Efron, Breslow, exact)

Two assumptions to test in duration models

- ▶ proportional hazard: are coefficients the same over time
 - ▶ parametric and semi-parametric models
- ▶ functional form (parametric models)
- ▶ ties (Cox proportional hazard)

Dependencies between observations

Dependencies between observations

Observations are often not independent from each other in these models

- ▶ **risk set** a duration for a natural unit is sliced up
- ▶ **repeated events**
- ▶ **Time dependency** (i.e. dates)
- ▶ **different populations** split-population data

Hierarchical data structures

Different vocabularies, same thing

- ▶ strata / fixed-effects (+ clustering of errors)
- ▶ frailty / random effects
- ▶ split population / zero-inflated models

Split population model

We model two outcomes in two equations

- ▶ **the “at-risk” group** the probability of an event occurring at any given time for those who have **not** yet experienced the event
- ▶ **the “affected” group** the probability of an event occurring at any given time for those who have **already** experienced the event.