

## XIII Italian Stata Users Group Meeting

# Time scales in Survival analysis: a review of definitions, methods and applications

Francesca Ghilotti, Sc.M  
Rino Bellocco, Sc.D

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# Swedish National March Cohort

## Setting:



43,880  
questionnaires  
were returned

1997

Linked to several  
Swedish registers

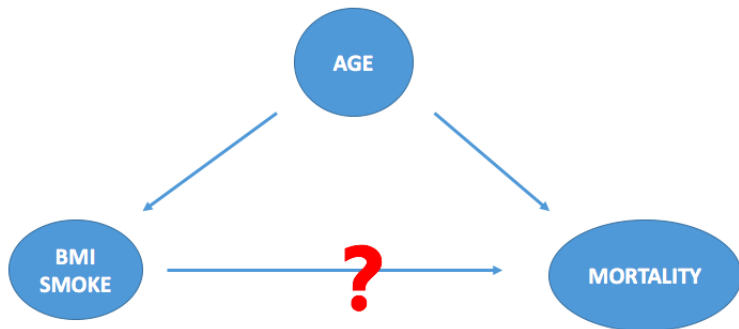
2010

2016

Waiting for the  
new linkage

# Aim

Study the relationship between BMI, smoke and overall Mortality



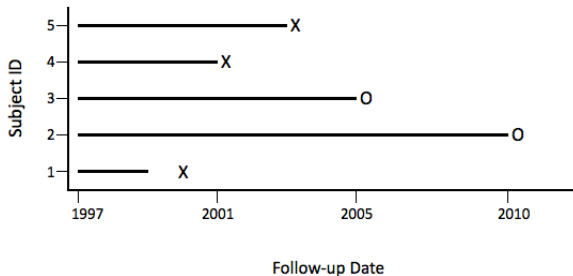
# How to declare survival data

```
stset time_of_failure, failure(failure_var)
```

Some key concepts:

- **Time origin** defines time 0, when we start recording time
- **Entry time** defines when a subject starts being at risk
- **Exit time** defines when a subject stops being at risk
- **Analysis time** difference between exit and entry times
- **Failure indicator** defines if a subject has the event or is censored

# Follow-up as time-scale



# Follow-up as time-scale: stset

```
. stset endt_death, f(out_death) orig(beginf) scale(365.25)
```

```
failure event: out_death != 0 & out_death < .  
obs. time interval: (origin, endt_death]  
exit on or before: failure  
t for analysis: (time-origin)/365.25  
origin: time beginf
```

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```
41647 total observations  
0 exclusions
```

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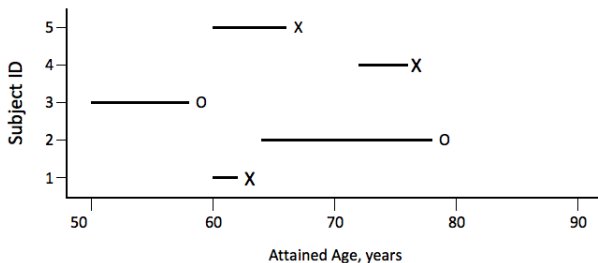
```
41647 observations remaining, representing  
4296 failures in single-record/single-failure data  
525471.316 total analysis time at risk and under observation  
at risk from t = 0  
earliest observed entry t = 0  
last observed exit t = 13.24846
```

# Follow-up as time-scale: Likelihood

ID	t	$a_0$	a
1	2	60	62
2	13+	64	77
3	8+	50	58
4	4	72	76
5	6	60	66

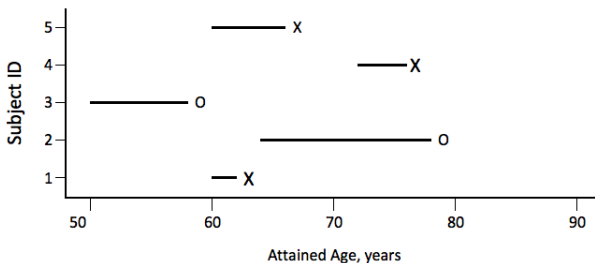
$$L(\beta) = \prod_{i=1}^n L_i = \left( \frac{\lambda_1(2)}{\lambda_1(2) + \lambda_2(2) + \lambda_3(2) + \lambda_4(2) + \lambda_5(2)} \right) \times \\ \times \left( \frac{\lambda_4(4)}{\lambda_2(4) + \lambda_3(4) + \lambda_4(4) + \lambda_5(4)} \right) \times \left( \frac{\lambda_5(6)}{\lambda_2(6) + \lambda_3(6) + \lambda_5(6)} \right)$$

# Age as time-scale





# Age as time-scale



We have to deal with delayed entries and left truncation

# Age as time-scale: stset

```
. stset endt_death, f(out_death) orig(birthd) entry(beginf) scale(365.25)
```

```
      failure event:  out_death != 0 & out_death < .  
obs. time interval:  (origin, endt_death]  
enter on or after:   time beginf  
exit on or before:   failure  
t for analysis:      (time-origin)/365.25  
      origin:        time birthd
```

---

```
41647 total observations  
0     exclusions
```

---

```
41647 observations remaining, representing  
4296 failures in single-record/single-failure data  
525471.316 total analysis time at risk and under observation  
              at risk from t = 0  
              earliest observed entry t = 18.00137  
              last observed exit t = 107.5099
```

# Age as time-scale: Likelihood

ID	t	$a_0$	a
1	2	60	62
2	13+	64	77
3	8+	50	58
4	4	72	76
5	6	60	66

$$L(\beta) = \prod_{i=1}^n L_i = \left( \frac{\lambda_1(62)}{\lambda_1(62) + \lambda_5(62)} \right) \times \left( \frac{\lambda_2(66)}{\lambda_2(66) + \lambda_5(66)} \right) \times \left( \frac{\lambda_4(76)}{\lambda_2(76) + \lambda_4(76)} \right)$$

# The hazard function

The hazard function is the instantaneous rate at which the event occurs:

$$\lambda_T(t) = \lim_{\Delta \rightarrow 0} \frac{1}{\Delta} P(T \in [t, t + \Delta) | T \geq t)$$

# Choice of the Time-Scale

Follow-up as Time-Scale:  $\lambda_T(t|a_0, z)$

Age as Time-Scale:  $\lambda_A(a|a_0, z)$

**Which time scale should be used and how do we make such a decision in general?**

# Clinical trial:

- Subjects start to be followed for the outcome after random allocation
- Reasonable to assume subjects start to be at risk upon study entry
- Time-on-Study typically used as the time-scale

# Observational study:

- Subjects already at risk prior to study entry
- Unknown time or age when first at risk
- Example: Subjects with diabetes enter study, but unknown date or age when first diagnosed (prior to study entry)
- Attained age typically used as the time-scale

# Characteristics of the two time-scales

## Follow-up as Time-Scale

- 1 Closed cohort
- 2 Risk-set decreases over time
- 3 Censoring occurs at the end of follow-up
- 4 Assumptions about the relationship between age and the outcome are needed
- 5 Preferable if time-on-study is a stronger determinant of the outcome than age at the event

## Age as Time-Scale

- 1 Open cohort
- 2 Risk-sets are not nested
- 3 Censored observations are spread across the entire range of age
- 4 Adjustment for age is handled nonparametrically
- 5 Preferable if age is a much stronger determinant of the outcome than time-on-study



# Follow-up as Time-Scale

**Model 0:**  $\lambda(t, Z) = \lambda_0(t) \cdot e^{\beta z}$

Unadjusted for  $a_0$

**Model 1:**  $\lambda(t, Z, a_0) = \lambda_0(t) \cdot e^{\beta z + \gamma_1 a_0}$

Adjusted for  $a_0$  as a linear covariate

**Model 2:**  $\lambda(t, Z, a_0) = \lambda_0(t) \cdot e^{\beta z + \gamma_1 a_0 + \gamma_2 a_0^2}$

Adjusted for  $a_0$  with quadratic covariate

**Model 3:**  $\lambda(t, Z, a_0) = \lambda_0(t) \cdot e^{\beta z + \gamma_1 a_{65}}$

Adjusted for  $a_0$  as binary ( $\geq 65$  years)

**Model 4:**  $\lambda_g(t, Z, a_0) = \lambda_{0g}(t) \cdot e^{\beta z}$

Stratified by  $a_0$  or birth cohort,  $g=1, \dots, s$

# Age as Time-Scale

**Model 5:**  $\lambda(a, Z) = \lambda_0(a) \cdot e^{\beta z}$

Unadjusted for left truncation at  $a_0$

**Model 6:**  $\lambda(a, Z) = \lambda_0(a|a_0) \cdot e^{\beta z}$

Adjusted for left truncation at  $a_0$

**Model 7:**  $\lambda_g(a, Z) = \lambda_{0g}(a|a_0) \cdot e^{\beta z}$

Adjusted for left truncation at  $a_0$  and stratified by birth cohort,  $g=1, \dots, s$

# Comparisons among the estimated HR

HR estimates ( $\text{BMI} \geq 25$  vs  $\text{BMI} < 25$ ) adjusted for age

Follow-up as Time-Scale		Age as Time-Scale	
Model	HR	Model	HR
(0) Unadjusted	1.286	(5) Unadjusted truncation	1.137
(1) Linear age	1.082	(6) Adjusted truncation	1.117
(2) Quadratic age	1.102	(7) Adjusted and stratified	1.109
(3) Binary age	1.112		
(4) Stratified on age	1.107		

# Comparisons among the estimated HR

HR estimates (Smoke vs Non-Smoke) adjusted for age

Follow-up as Time-Scale		Age as Time-Scale	
Model	HR	Model	HR
(0) Unadjusted	1.036	(5) Unadjusted truncation	1.513
(1) Linear age	1.374	(6) Adjusted truncation	1.401
(2) Quadratic age	1.391	(7) Adjusted and stratified	1.400
(3) Binary age	1.299		
(4) Stratified on age	1.385		

# What if age is an effect modifier?

- Follow-up as time scale (Stratified analysis):

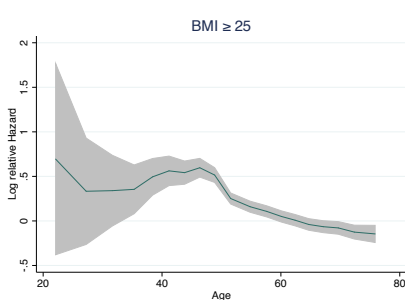
	Age < 65			Age ≥ 65		
	HR	se	p - value	HR	se	p - value
BMI ≥ 25	1.81	0.10	< 0.001	0.90	0.03	0.005

- Follow-up as time scale (Interaction term):

Var	HR	se	p - value
BMI ≥ 25	1.35	0.085	< 0.001
Centered Age	1.12	0.002	< 0.001
Interaction	0.99	0.003	< 0.001

# What if age is an effect modifier?

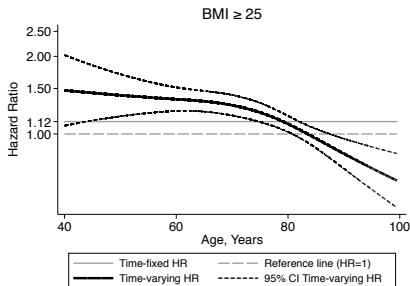
## STEPP procedure:



# What if age is an effect modifier?

## ● Age as time scale:

If the effect of a risk factor changes with age the hazards would not be proportional.



# Conclusions

- When analysing epidemiologic cohort data is better to use age as time-scale
- If adjustment for age at entry is made correctly the difference among the estimated regression coefficients depending on the time-scale chosen is minimal
- Pay attention to the calendar-period and/or birth cohort effects (stratified models)





# References

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