# Beyond Proportional Hazards 

Technical Workshop
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ARC Research Programme - Use of Big Health and Actuarial Data for understanding Longevity and Morbidity Risks

Programme's webpage - http://bit.ly/arctechworkshop
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## Cox regression, the proportional hazards assumption and timevarying covariates

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#### Abstract

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## Objectives

- What is a hazard ratio and Cox proportional hazards model.
- Describe methods to check the assumption of proportional hazards in the Cox model
- Describe methods how to deal with non-proportional hazards in the Cox model


## Hazard aka "force of mortality" and "mortality intensity"

- Hazard is an instantaneous failure rate at time $t$
- Probability that an individual will experience the event at time $t$ given that the event has not yet occurred.




## Cox proportional hazards regression

- The type of regression model typically used in survival analysis in medicine is the Cox proportional hazards regression model.
- The Cox model estimates the hazard $\mu_{i}(t)$ for subject $i$ for time $t$ by multiplying the baseline hazard function $\mu_{0}(t)$ by the subject's risk score $r_{i}$ as

$$
\mu_{i}\left(t, \beta, Z_{i}\right)=\mu_{0}(t) r_{i}\left(\beta, Z_{i}\right)=\mu_{0}(t) e^{\beta Z_{i}}
$$

- The risk factors $Z$ have a log-linear contribution to the force of mortality which does not depend on time $t$.


## Hazard ratio (HR)

- Taking a ratio of the hazard functions for two subjects $i$ and $j$ who differ in one risk factor $z$ (with the values $z_{0}$ and $z_{1}$, respectively) but not in the other risk factors,

$$
\operatorname{HR}(t, \beta, Z)=\frac{\mu_{i}\left(t, \beta, Z_{i}\right)}{\mu_{j}\left(t, \beta, Z_{j}\right)}=\frac{\mu_{0}(t) e^{\beta Z_{i}}}{\mu_{0}(t) e^{\beta Z_{j}}}=\frac{e^{\beta_{z} z_{1}}}{e^{\beta_{Z} z_{0}}}=e^{\beta_{Z}\left(z_{0}-Z_{1}\right)} .
$$

- This means that the baseline hazard $\mu_{0}(t)$ does not have to be specified and the hazard ratio $\mathrm{e}^{\beta_{Z}\left(z_{0}-Z_{1}\right)}$ is constant with respect to time $t$.
- Because of this, the Cox model does not make any assumptions about the shape of the baseline hazard.
- $\mathrm{e}^{\beta_{z}\left(z_{0}-z_{1}\right)}$ is an adjusted HR, i.e. all other risks are already accounted for by the model.


## Hazard ratio

- Comparison of two hazard functions
- Cox model assumes constant hazard ratio over time




## Proportional hazards assumption

- Graphical methods:
- Comparison of Kaplan-Meier estimates by group
- Plot (minus the log cumulative baseline hazard) for each group against (log survival time)
- Formal tests:
- Grambsch and Therneau's test based on Schoenfeld residuals
- Include interaction between covariate and a function of time
- Log(time) often used but could be any function of time


## Example: Cox model for death from Parkinson's disease

- Data: parkison disease
- Sample of 520 patients
- Study period of 17 years
- Outcome: time to death (266 events)
- Exposure: new vs standard treatment
- Covariates:

Sex (baseline male / female)
Age (baseline 25-59 / 60-69 / 70-92)

```
                exp(coef) exp(-coef) 1ower .95 upper .95
treat 1.216 0.8221 0.9549 1.55
Concordance=0.527 (se = 0.016 )
```

|  | exp(coef) | $\exp ($ (-coef) | lower .95 upper .95 |  |
| :--- | ---: | ---: | ---: | ---: |
| treat | 1.216 | 0.8224 | 0.9545 | 1.549 |
| sex | 1.031 | 0.9701 | 0.8099 | 1.312 |

Concordance $=0.522 \quad(\mathrm{se}=0.018)$


## Kaplan-Meier plots by levels of a factor

- Estimated survival function
- Does not adjust for other covariates!
- Crossing of hazard lines indicates non-proportional hazards
- Otherwise, can be difficult to judge


Survival time by sex adjusted for treatment and age


## Complementary log-log plot of S(t;Z)

- From the hazard function of the PH model, we obtain the survivor function

$$
\mathrm{S}(\mathrm{t} ; Z)=\exp \left\{-M_{0}(\mathrm{t}) e^{\beta Z}\right\}
$$

where $M_{0}(\mathrm{t})$ is the cumulative hazard corresponding to $\mu_{0}(\mathrm{t})$.

- Hence $\ln \{-\ln S(t ; Z)\}=\ln \left(M_{0}(\mathrm{t})\right)+\beta Z$.
- Hence any two such functions, $S(t ; z 1)$ and $S(t ; z 2)$ for different values of the covariate vector z , will be parallel.
- Plot $\ln \{-\ln \mathrm{S}(\mathrm{t} ; \mathrm{Z})\}$ vs t or a function of t .


## Complementary log-log plot for Parkinson's data

- Can be unadjusted or adjusted (here adjusted for treatment and age group)
- Proportional hazards assumption violated if curves are not parallel to each other
- Plot vs log(t) shows straight lines for Weibull distribution.


This only works if there are few covariates and few distinct values, only then $\mathrm{S}(\mathrm{t} ; \mathrm{Z})$ is reliably estimated for each $Z$ value.

## Residuals

- Residual is the difference between an observed value and a predicted value.
- Due to censoring, this is not straightforward in survival analysis
- Therefore, there are many types of residuals
- Here we are going to concentrate on Cox-Snell residuals and Schoenfeld residuals


## Cox-Snell residuals

- In order to assess an overall goodness of fit of a model, we use Cox-Snell residuals
- Cox-Snell residuals are $-\log (\hat{S}(\mathrm{t}$; Z $)$ ), i.e. estimated cumulative hazards at the time of death or censoring
- If the model is correct, Cox-Snell residuals should have exponential distribution $\exp (1)$


## Cox-Snell residuals

- Overall goodness-of-fit
- The first survival model for Parkinson's data with treatment, sex, and age group. Graph indicates good fit.
- Plot of Cox-Snell residuals is just a QQ-plot for exponential distribution



## Schoenfeld residuals

- Schoenfeld residuals are the differences between the covariate value $Z_{i}$ of subject i who experienced an event at time $t_{i}$ and the weighted average of all covariate values across all subjects at risk at $t_{i}$
- Schoenfeld residuals are used for testing the proportionality of hazards assumption using Grambsh and Therneau's test


## Grambsch and Therneau test

- Testing correlation between Schoenfeld residuals and survival time
- Significant correlation indicates non-proportional hazards

|  | $r$ | rho | chisq |
| :--- | ---: | ---: | ---: |$\quad$ p



## Cox model with time-varying coefficients

$$
\mu(t, \beta, Z)=\mu_{0}(t) e^{\beta(t) Z}
$$

Write the time-varying coefficients as

$$
\beta_{j}(\mathrm{t})=\beta_{j}+\theta_{j} g_{j}(\mathrm{t}), \quad \mathrm{j}=1, \ldots, \mathrm{p}
$$

where $g_{j}(\mathrm{t})$ is known. A standard choice is $g_{j}(\mathrm{t})=\log (\mathrm{t})$.
Test $H_{0}: \theta=0$ (as a vector and for each component.).

## Testing interaction of covariate with time

- Significant correlation indicates non-proportional hazards
- NB: very sensitive
$n=520$, number of events $=266$

|  | coef | (coef) | se(coef) | z | $\operatorname{Pr}(>\|z\|)$ |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| treat | $4.078 \mathrm{e}+00$ | $5.905 \mathrm{e}+01$ | 5.989e-01 | 6.810 | $9.76 \mathrm{e}-12$ |  |
| sex | $3.109 \mathrm{e}+00$ | $2.239 \mathrm{e}+01$ | $4.942 \mathrm{e}-01$ | 6.290 | $3.17 \mathrm{e}-10$ |  |
| agegrp2 | $1.814 \mathrm{e}+01$ | $7.566 \mathrm{e}+07$ | $2.184 \mathrm{e}+00$ | 8.307 | $<2 e-16$ |  |
| agegrp3 | $1.903 \mathrm{e}+01$ | $1.843 \mathrm{e}+08$ | $2.149 \mathrm{e}+00$ | 8.857 | < 2e-16 |  |
| treat: $\log$ (time) | -2.054e+00 | $1.283 \mathrm{e}-01$ | $2.900 \mathrm{e}-01$ | -7.081 | $1.43 \mathrm{e}-12$ |  |
| sex:log(time) | $-1.590 \mathrm{e}+00$ | 2.040e-01 | $2.493 \mathrm{e}-01$ | -6.377 | $1.81 \mathrm{e}-10$ |  |
| agegrp2:log(time) | $-7.222 e+00$ | $7.300 \mathrm{e}-04$ | $8.989 \mathrm{e}-01$ | -8.035 | 8.88e-16 |  |
| agegrp3: 10 g (time) | -7.597e+00 | 5.019e-04 | 8.938e-01 | -8.500 | < 2e-16 |  |
| Signif. codes: | ** 0.001 | **, 0.01 | , 0.05 | 0.1 | , 1 |  |

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## What if the proportional hazards assumption is not met?

- Stratify the analysis on violating variable: $\mu_{s}\left(t, \beta, Z^{\prime}\right)=\mu_{0 s}(t) e^{\beta Z \prime}$ for Z' being all covariates but that one.
- Fit one model: allow baseline hazards to vary by group but assume covariate effects are the same across strata. Only if the variable is of no direct interest. (There should be no significant interactions between covariates and stratum variable)
- Fit separate models: allow both baseline hazards and hazard ratios to vary by group


## What if the proportional hazards assumption is not met?

- Include time-dependent effect
- Split follow-up time such that the hazards are proportional within these time bands
- Continuous (could be any function of time)


## Stratified analysis

- Check for interactions
- Fit one stratified Cox model ( $\mathrm{n}=520$, events=266)
- Fit separate models
- Male ( $\mathrm{n}=283$, events=141)
- Female ( $\mathrm{n}=237$, events=125)
- Easy procedure but comes at the cost of no estimate for the effect of the violated variable associated with the outcome
$\exp (c o e f) \exp (-c o e f)$ 1ower .95 upper .95

| treat | 1.0395 | 0.9620 | 0.4877 | 2.216 |
| :--- | :--- | :--- | :--- | :--- |


| sex | 0.7895 | 1.2666 | 0.2964 | 2.103 |
| :--- | :--- | :--- | :--- | :--- |


| agegrp2 | 2.1979 | 0.4550 | 0.7261 | 6.653 |
| :--- | :--- | :--- | :--- | :--- |

$\begin{array}{lllll}\text { agegrp3 } & 23.7526 & 0.0421 & 7.8517 & 71.855\end{array}$

| treat:sex | 1.0938 | 0.9142 | 0.6695 | 1.787 |
| :--- | :--- | :--- | :--- | :--- |


| sex:agegrp2 | 1.3487 | 0.7415 | 0.6348 | 2.865 |
| :--- | :--- | :--- | :--- | :--- |


|  | $\exp (c o e f)$ | exp(-coef) | lower .95 upper .95 |  |
| :--- | ---: | ---: | ---: | ---: |
| treat | 1.162 | 0.8605 | 0.9099 | 1.484 |
| agegrp2 | 3.392 | 0.2948 | 2.3549 | 4.887 |
| agegrp3 | 7.389 | 0.1353 | 5.0865 | 10.735 |


|  | exp(coef) | exp(-coef) | lower .95 upper .95 |  |
| :--- | ---: | ---: | ---: | ---: |
| treat | 1.126 | 0.88817 | 0.8067 | 1.571 |
| agegrp2 | 2.918 | 0.34272 | 1.8230 | 4.670 |
| agegrp3 | 10.540 | 0.09488 | 6.5101 | 17.063 |


|  | exp(coef) | exp (-coef) | lower .95 | upper .95 |
| :--- | ---: | ---: | ---: | ---: |
| treat | 1.258 | 0.7950 | 0.8737 | 1.811 |
| agegrp2 | 4.005 | 0.2497 | 2.2151 | 7.242 |
| agegrp3 | 5.335 | 0.1875 | 2.9578 | 9.622 |

## Schoenfeld Residuals plot of effect of sex over time



## Step-wise time-dependent hazards

- Split follow-up time in intervals in which the proportional hazards assumpation is no longer violated
- Create time dependent effect
- Here: $0=$ male's hazard (baseline),
1=female's hazard 0-9 years, 2=female's hazard 9+ years
- Fit mode with time dependent effect
- More time consuming procedure due to creating the most effective time intervals

|  | exp(coef) | $\exp (-$ coef) | lower .95 | upper .95 |
| :--- | ---: | ---: | ---: | ---: | ---: |
| treat | 1.1636 | 0.8594 | 0.9117 | 1.4852 |
| t_sex1 | 0.6887 | 1.4520 | 0.5162 | 0.9188 |
| t_sex2 | 0.9118 | 1.0968 | 0.5678 | 1.4641 |
| agegrp2 | 3.4215 | 0.2923 | 2.3750 | 4.9291 |
| agegrp3 | 7.5985 | 0.1316 | 5.2343 | 11.0305 |
|  |  |  |  |  |
|  |  |  |  |  |
|  |  | rho | chisq | p |
|  | treat | -0.06453 | 1.101428 | 0.2940 |
|  | t_sex1 | 0.09955 | 2.762015 | 0.0965 |
|  | t_sex2 | 0.02402 | 0.158846 | 0.6902 |
|  | agegrp2 | 0.00158 | 0.000657 | 0.9795 |
|  | agegrp3 | -0.07938 | 1.708571 | 0.1912 |
|  | GLoBAL | NA | 6.446771 | 0.2651 |

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## References

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The 'Use of Big Health and Actuarial Data for understanding Longevity and Morbidity Risks' research programme is being funded by the ARC.

## Questions

## Comments

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## Linking survival modelling results to life expectancy differentials

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#### Abstract

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## Quantifying Longevity Changes

- Medical and social advances are the major drivers in the longevity increase. But how to quantify this relationship?
- In medicine, Randomized Control Trials (RCTs) are considered to be the gold standard.
- RCTs estimate the hazard or force of mortality in a (selective) sample of people and summarised over the observed (limited) time period.
- New health interventions are usually based on these estimated hazards obtained from clinical trials. A lengthy lead time would be needed to observe their effect on population longevity.


## Our approach, 1

- Our research uses The Health Improvement Network (THIN) primary care data to develop statistical models of longevity.
- The advantage of using individual-level medical data is that it is possible to model both the uptake of medical treatment and the effect of that treatment on longevity conditional on the individual sociodemographic and health factors instead of the aggregated profile.
- We carefully design each observational study and match cases to controls. Survival models, usually the Cox regression, are fitted to such individual level data.
- The conclusions are generalisable to the general population.


## Hazard ratio

- The type of regression model typically used in survival analysis in medicine is the Cox proportional hazards regression model.
- The Cox model estimates the hazard $\mu_{i}(x)$ for subject $i$ at time $x$ as $\mu_{i}\left(x, \beta, Z_{i}\right)=\mu_{0}(x) \mathrm{r}_{i}\left(\beta, Z_{i}\right)=\mu_{0}(x) e^{\beta Z_{i}}$
- Taking a ratio of the hazard functions for two subjects $i$ and $j$ who differ in one risk factor $z$ and not in the other risk factors, $\mu(x, \beta, Z)=\frac{\mu_{i}\left(x, \beta, Z_{i}\right)}{\mu_{j}\left(x, \beta, Z_{j}\right)}=\frac{\mu_{0}(x) e^{\beta Z_{1}}}{\mu_{0}(x) e^{\beta Z_{0}}}=\frac{e^{\beta_{Z} Z_{1}}}{e^{\beta_{Z} Z_{0}}}=e^{\beta_{Z}\left(z_{0}-Z_{1}\right)}$


## From a hazard to effective age

- For simplicity, consider a binary risk factor with the reference value $\mathrm{y}=0$ and (at risk) $\mathrm{y}=1$.
- On the log scale, the loghazards are $\lambda_{1}(t)=\lambda_{0}(t)+\beta$. This means that the log-hazard lines differ only by an increment
- For a monotone-increasing hazard, find the (unique) time increment $\Delta(\mathrm{t})$ such that $\lambda_{1}(\mathrm{t})=$ $\lambda_{0}(\mathrm{t}+\Delta(\mathrm{t}))$


Value of $t+\Delta(t)$ is, by definition, the effective age of the person with risk $y=1$ at chronological age t .

## Our approach，2：for an individual

－For an individual，the hazard ratios obtained from the survival models are translated into effective age changes．
－Effective age at $y=1$ is the average chronological age with the same hazard as when $\mathrm{y}=0$ ．
－Effective ages are often used by insurers as a way of applying the correct rating to an underwritten life．

Log force of mortality for UK population based on 2010 period life table （Office for National Statistics 2017）．


## What does HR mean for an individual

- Using Gompertz law $\lambda_{0}(t)=a+b t$, the increase in annual hazard of mortality associated with ageing one year is approximately constant between ages 50 and 90 .
For $y=1, \lambda_{1}(t)=a+b t+\beta=a+b(t+\Delta) \Rightarrow \Delta=\beta / b$
- For England and Wales in 2010-2012, the increase in the hazard between those ages was approximately 1.1 per year.
- A HR can be translated to the numbers of years gained in effective age as $\Delta=\log (H R) / \log (1.1) \approx 10^{*} \log (H R)$. [Brenner, 1993; Spiegelhalter, 2016]
- For LE at age $\mathrm{t}, \mathrm{e}_{1}(\mathrm{t})=\mathrm{e}_{0}(\mathrm{t}+\Delta)$.



## Our approach, 3: Period life expectancy

- Consider a population consisting of J risk groups of prevalence $q_{j}, j=1, \ldots J ; \Sigma q_{j}=1$.
- Treatment of interest $(\mathrm{i}=0,1)$ is prevalent in the population from age T but its effects vary across risk groups.
- Prevalence of the treatment of interest in group $j$ at age $T$ is $p_{j, 1}$
- Then the overall survival function $S(T)$ at age $x=T$ is the weighted mean of the survival functions in the individual risk groups

$$
S(T)=\left[\sum_{j} q_{j} p_{j, 1} S_{1 j}(T)+\sum_{j} q_{j}\left(1-p_{j, 1}\right) S_{0 j}(T)\right] / \sum_{j} q_{j} .
$$

## The Cox model

- Assume that the hazards are proportional, so that the hazards $M_{i j}=M_{0}(x) M_{i j}(Y)$, where $M_{0}(x)$ is the baseline hazard at age $x$ and

$$
\log \left(\mu_{i j}(Y)\right)=a_{i j}=a_{0}(T)+\alpha_{i}+\beta_{j}+\gamma_{i j}+\beta^{T} Y
$$

where $a_{0}(T)$ is the baseline value which may depend on intervention time $T, \alpha_{i}, \beta_{j}$ and $\gamma_{i j}$ are the main effects and interaction of risk group j and treatment I, and the other covariates $Y$ have no interactions with the treatment or the risk of interest.

## Survival function under Gompertz-Cox model

- The log-hazards in a risk group $(\mathrm{i}, \mathrm{j})$ are just $\mathrm{a}_{\mathrm{ij}}+\mathrm{bx}$, i.e. the straight lines with the same slopes but differing intercepts.
- The survival functions are $S_{i j}(x)=\exp \left(-e^{a_{i j}} b^{-1}\left(e^{b x}-1\right)\right)$. Substituting the $\mathrm{a}_{\mathrm{ij}}$, the survival functions at age $\mathrm{x}>\mathrm{T}$ are

$$
S_{i j}(x \mid Y)=\exp \left(-e^{a_{0}(T)+\alpha_{i}+\beta_{j}+\gamma_{i j}+\beta^{T} Y} b^{-1}\left(1-e^{b x}\right)\right)
$$

- Assuming that the prevalences do not depend on Y, Y can be integrated out to obtain

$$
\begin{gathered}
S(x \mid T)=\sum_{j} q_{j} p_{j, 1} \exp \left(-e^{a_{0}(T)+\alpha_{1}+\beta_{j}+\gamma_{1 j}} b^{-1}\left(1-e^{b x}\right)\right)+ \\
\sum_{j} q_{j}\left(1-p_{j, 1}\right) \exp \left(-e^{a_{0}(T)+\beta_{j}} b^{-1}\left(1-e^{b x}\right)\right) .
\end{gathered}
$$

## Finding component survival functions

$$
\begin{gathered}
S(x \mid T)=\sum_{j} q_{j} p_{j, 1} \exp \left(-e^{a_{0}(T)+\alpha_{1}+\beta_{j}+\gamma_{1 j}} b^{-1}\left(1-e^{b x}\right)\right)+ \\
\sum_{j} q_{j}\left(1-p_{j, 1}\right) \exp \left(-e^{a_{0}(T)+\beta_{j}} b^{-1}\left(1-e^{b x}\right)\right)
\end{gathered}
$$

- This is a non-linear equation with one unknown, $a_{0}$. The lefthand side is given by the period life-table, and the slope b should be determined for a particular population of interest. As $S(x)$ is a decreasing function of $a_{0}$, it has a unique solution.
- After solving for $a_{0}(\mathrm{~T})$, we can find component survival functions $S_{i j}(x)$ for any set of prevalences $\left\{q_{j}\right\}$ and $\left\{p_{i, 1,2}\right\}$.


## Estimating changes in life expectancy

- For a Gompertz distribution $\mathrm{G}(\mathrm{a}, \mathrm{b})$, the LE is

$$
e_{G(a, b)}(z)=\frac{b^{-1} \exp \left(b^{-1} e^{a}\right) E_{1}\left(b^{-1} e^{a+b x}\right)}{\exp \left(-e^{a} b^{-1}\left(e^{b x}-1\right)\right)}
$$

So we can find component LEs $\mathrm{e}_{\mathrm{ij}}(z)$ for each component distribution $G\left(a_{i j}, b\right)$. Then, the life expectancy at age $z$ is

$$
e(z)=\frac{\int_{z}^{\infty} S(x) d x}{S(z)}=\frac{\sum_{k} w_{k} S_{k}(z) \int_{z}^{\infty} S_{k}(x) d x / S_{k}(z)}{\sum w_{k} S_{k}(z)}=\frac{\sum_{k} w_{k} S_{k}(z) e_{k}(z)}{\sum w_{k} S_{k}(z)}
$$

- Taking all $\mathrm{p}_{\mathrm{j}, 1}=0$, we obtain a hypothetical life expectancy $\mathrm{e}_{0}(\mathrm{z})$ if there were no intervention of interest, and, for all $p_{j, 1}=1, a$ hypothetical life expectancy $\mathrm{e}_{1}(z)$ with full uptake of the intervention.


## Case study: survival benefits of statins

- We used the data for QRISK2 groups $10-19 \%$ and $\geq 20 \%$ at ages 70 and 75 (yob 1920-1940, observed 1987-2011) from Gitsels et al. [2016]
- We fitted the same Cox models after adding the QRISK2 group to the predictors. The final models adjusted for sex, birth cohort, socioeconomic status, diabetes, hyper-cholesterolaemia, blood pressure regulating drugs, body mass index, and smoking status. The models included a random effect on general practice.
- Interactions between statins, QRISK2 groups and the other risk factors were tested, but none was significant.
- We also used the adjusted HRs for all-cause mortality of heart attack survivors, from Gitsels et al. [2017], as a substituteefor sonte
$\rightarrow$ HRs for CVD sufferers. The HRs are given in Table 1.


## Table 1. Population characteristics, statins study by Gitsels et al. 2016

| Cohort | Cardiac risk | Women \% <br> (Statins \%) | Men \% <br> (Statins \%) |
| :---: | :---: | :---: | :---: |
| Age 70 | QRISK2 10-19\% | $80(9.5)$ | $17(5.4)$ |
| N=247,149, FU=7 years | QRISK2>20\% | $20(28.2)$ | $83(17.4)$ |
| Age 75 |  |  | $0(0.0)$ |
| $\mathrm{N}=194,085, \mathrm{FU}=6$ years | QRISK2 10-19\% | $15(4.6)$ | $100(19.1)$ |

* FU= average follow-up

Table 2. Hazard ratios of statins and of cardiac risk groups

| Cardiac risk | Age | HR statins <br> (vs no statins) | Changes in effective <br> age (men) |  |
| :--- | :--- | :--- | :--- | :--- |
| No heart attack | 70 | $0.84(0.80,0.88)$ | Changes in effective <br> age (women) |  |
|  | 75 | $0.82(0.79,0.86)$ | $-1.92(-2.16,-1.24)$ | $-1.57(-2.01,-1.15)$ |
| Heart attack | 70 | $0.74(0.70,0.78)$ | $-2.91(-3.45,-2.40)$ | $-1.79(-2.97,-1.36)$ |
|  | 75 | $0.77(0.74,0.81)$ | $-2.53(-2.91,-2.04)$ | $-2.72(-3.22,-2.24)$ |
| Cardiac risk | Age | HR Cardiac <br> Risk | Changes in effective <br> age (men) | Changes in effective <br> age (women) |
| QRISK2 10-19\% | 70 | $0.80(0.77,0.83)$ | $-2.16(-2.53,-1.80)$ | $-2.01(-2.36,-1.68)$ |
|  | 75 | $0.87(0.80,0.94)$ | $-1.35(-2.16,-0.60)$ | $-1.26(-2.01,-0.56)$ |
| QRISK2>20\% | 70 | 1 | 0 | 0 |
| Heart attack | 75 | 1 | 0 | 0 |
|  | 70 | $1.50(1.42,1.59)$ | $3.92(3.39,4.48)$ | $3.66(3.17,4.19)$ |

${ }^{1}$ based on Gompertz distributions with $b=0.1034$ for men and 0.1108 for women fifuctanes sauty

## Info on the prevalences of the risk groups and the treatment

- Prevalence of risk groups (q's on slide 9): QRISK2 score increases with age and by age 70, there were practically no patients with a QRISK2 score of $<10 \%$ and by age 75 , there were no male patients with a QRISK2 score of < 20\%.
- Prevalence of treatment(p's on slide 9): At the end of study period in 2010, statins were prescribed in 20\% of patients with a QRISK2 score of < 20\%, in $45 \%$ of patients with a QRISK2 score of $\geq 20 \%$, and in $90 \%$ of patients with CVD.
- Given cardiac risk group, statins were prescribed more in women, in younger patients, and in patients from less deprived areas.


## Fitting Gompertz distribution to period life tables



Log-hazards between the ages 70-90 from the ONS period life table centered at 2010 (circles) and fitted regression lines by Townsend score quintiles and sex.

## Baseline hazard in the statins survival model



The baseline hazard is well approximated by the Gompertz hazard.

## Calculating component life expectancies

- Since the mortality rates, the cardiac risk distribution and the statin prescription rates differ by gender and by socioeconomic status, we analysed the life tables separately for each Townsend score quintile- by-gender combination.
- For each life table, we substitute the $S(x)$ at age $x=70$ or 75 (obtained from the fitted Gompertz distribution $G(a, b)$ ) into the left-hand side of the equation on top of slide 13, and solve for the value of $a_{0}(\mathrm{~T})$.
- These values were used to calculate period life tables for component cardiac risk by statin prescription subpopulations for each (i,j) combination.


## Results, 1

- Increase in individual LE due to statins depends on cardiac risk, and is highest for heart attack survivors (1.41-2.02 years), and is comparable in the two QRISK2 groups (1.14-1.35 years across ages 70 and 75). The effect of statins increases with deprivation.
- We also calculated the period LE and its increase due to statins in each cardiac risk group for the total England and Wales population by averaging the LE across all TS quintiles, a and plotted the results.


# Life expectancy by cardiac risk group with and without statins for ages 70 - 90 based on the ONS period life table centered at 2010 




## Results, 2

- We also calculated national life expectancy with and without statins, by averaging the LE across cardiac risk groups, taking $\mathrm{p}=0$ (for no statins) and $\mathrm{p}=1$ (for statins).
- The national life expectancy for women aged 70 or 75 would be increased by up to 0.91 or 0.79 years, respectively, if all eligible women under the current guideline of primary and secondary prevention of CVD were prescribed statins.
- Similarly, the national life expectancy for men aged 70 or 75 would be increased by up to 0.79 or 0.63 years. The most improvement would come from the areas of medium deprivation.


## An app for general public



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1. Brenner H, Gefeller O, Greenland S. (1993) Risk and rate advancement periods as measures of exposure impact on the occurrence of chronic diseases. Epidemiol Camb Mass. 4(3):229-36.
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## Questions

## Comments

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# Modelling non-proportional hazards: time-dependent coefficients, parametric "double Cox" regression and Landmark analysis 

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The 'Use of Big Health and Actuarial Data for understanding Longevity and Morbidity Risks' research programme is being funded by the Actuarial Research Centre.


#### Abstract

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## What if the proportional hazards assumption is not met?

- For a Cox model $\mu(t \mid \beta, Z)=\mu_{0}(t) \exp \left(Z^{\mathrm{T}} \beta\right)$ we discussed two ways to cope with non-proportionality:
- Stratify the analysis on violating variable: $\mu_{s}(t \mid \beta, Z)=\mu_{0 S}(t) e^{Z^{\mathrm{T}} \beta}$
- baseline hazards vary by strata s;
- Here we add an option of modelling shape of baseline hazards
- Include time-varying effects: $\mu(t, \mid \beta, Z)=\mu_{0}(t) e^{Z^{\mathrm{T}} \beta(t)}$
- Coefficients $\beta(t)$ are continuous functions of time
- Use landmark analysis


## Parametric "Double-Cox" regression

Components:

- A baseline hazard function (which changes over time).
- The risk factors Zhave a loglinear contribution to the force of mortality which does not depend on time $t$.

The Cox parametric regression model


Weibull or Gompertz baseline hazard function with scale $\lambda$ and shape $k$. Shape $k$ is modelled as $k=k(Z)$.

Additional regression model to allow varying shape depending on covariates

$$
\begin{aligned}
& \mu_{0}(t \mid Z)=\frac{k(Z)}{\lambda}\left(\frac{t}{\lambda}\right)^{k(Z)-1} \xrightarrow[\mathrm{k}(Z)=k_{0} e^{Z^{\mathrm{T}} \beta_{k}}]{\mu_{0}(t \mid Z)=\lambda \exp (k(Z) t)}
\end{aligned}
$$

## Cox model with shared frailty

## Proportional hazards model with frailty:

$$
\boldsymbol{\mu}(t \mid U, Z)=\boldsymbol{\mu}_{0}(t) U e^{Z^{\mathrm{T}} \beta},
$$

For mathematical convenience, it is frequently assumed that frailty U is gamma-distributed with mean 1 and unknown variance $\sigma^{2}$ :

$$
U \sim \operatorname{Gamma}\left(\sigma^{-2}, \sigma^{-2}\right)
$$

The frailty variance $\sigma^{2}$ characterizes heterogeneity in the population.
Shared frailty assumption:
All patients from the same unit /clients from the same company are in the same cluster $j, j=1, \ldots, J$ and share the same frailty $U_{j}$.

## "Double-Cox" model with shared frailty

- Standard shared frailty Cox model : $\boldsymbol{\mu}(t \mid U, Z)=\boldsymbol{\mu}_{0}(t) U e^{Z^{\mathrm{T}} \beta}$;
- Baseline hazard $\mu_{0}(t)=\mu_{0}(t ; \lambda, k)$;
- Cox-like parameterization for the shape of the baseline hazard function: $\mathrm{k}(\mathrm{Z})=k_{0} e^{\mathrm{Z}^{\mathrm{T}}} \mathrm{\beta}_{k}$;
- Frailty U ~ Gamma with mean 1 and variance $\sigma^{2}$.
- If needed, competing risks can be introduced through correlated shared frailty components.

Find MLE of the vector of unknown parameters $\theta=\left(\lambda, k_{0}, \sigma^{2}, \beta, \beta_{k}\right)$.
This model was introduced in [1] for analysis of time to revision/ time to death after hip replacement.

## Different shapes of cumulative hazards for revision surgery after hip replacement

Cumulative hazard function by type of bearing


## Extended Cox regression with time-varying covariates and regression effects

A model may include both constant and time-varying effects:

$$
\mu(t, \mid \beta, Z)=\mu_{0}(t) e^{Z(t)^{\mathrm{T}} \beta(t)+X(t)^{\mathrm{T}} \gamma}
$$

- Here $Z(t)$ and $X(t)$ are time-varying covariates (updated over time).
- $Z(t)$ are covariates with time-varying hazards $\beta(t)$, and $X(t)$ covariates have constant hazards $\gamma$.
- See Ch. 6 in the book by Martinussen\&Scheike [2] and their R package timereg for analysis of extended multiplicative hazards models.
- Their program timecox can test for and fit models with both constant and time-varying effects.


## Inference in extended Cox model

- It is easier to estimate cumulative regression coefficients $B(t)=\int_{0}^{t} \beta(s) d s$, their estimates are $\mathrm{n}^{1 / 2}$-consistent and asymptotically Normal.
- This allows to draw confidence bands for $\mathrm{B}(\mathrm{t})$ and to test hypotheses about them.
- A simple test of $\beta_{p}(t)=\beta_{p}$ is based on maximum deviation of the cumulative coefficient $B_{p}(t)$ from a straight line over an interval $[0, T]$.
- Similarly, cumulative residuals are used for various diagnostic purposes.


## Plots of cumulative coefficients for DM2 study



## Robustness of the Cox model

Consider once more the extended Cox model

$$
\mu(t \mid \beta, Z)=\mu_{0}(t) e^{Z^{\top} \beta(t)} .
$$

The cumulative hazard $M(t \mid Z)=-\ln (S(t \mid Z)$. The ratio

$$
\frac{M(t \mid z)}{M_{0}(t)}=\frac{\int \mu_{0}(s) \exp \left(\mathrm{z}^{\mathrm{T}} \beta(s)\right) \mathrm{ds}}{\int \mu_{0}(s) \mathrm{ds}} \approx \frac{\exp \int_{\mu_{0}(s)}\left(\mathrm{z}^{\mathrm{T}} \beta(s)\right) \mathrm{ds}}{\int_{\mu_{0}(s)} \mathrm{d} s}=\exp \left(\mathrm{Z}^{\mathrm{T}} \bar{\beta}(\mathrm{t})\right),
$$

where $\bar{\beta}(\mathrm{t})=\frac{\int \mu_{0}(s) \beta(s) \mathrm{ds}}{\int \mu_{0}(s) \mathrm{ds}}$, if the variance $\frac{\int \mu_{0}(s)\left(\mathrm{Z}^{\mathrm{T}}(\beta(s)-\bar{\beta}(\mathrm{t}))\right) 2 \mathrm{ds}}{\int \mu_{0}(s) \mathrm{ds}}$ is small. This means that the Cox model gives approximately correct predictions of surviving up to time t .

## What is landmark analysis

In the landmarking approach, dynamic predictions for the conditional survival after $\mathrm{t}=t_{L M}$ is used on current information for all patients still alive just prior to $t_{L M}$. [Van Houwelingen, H . and Putter, H., 2011]

The sliding landmark model is the simple Cox model

$$
h\left(t \mid x, t_{L M}, w\right)=h_{0}\left(t \mid t_{L M}, w\right) \exp \left(x^{T} \beta_{L M}\right), \quad s \leq t \leq s+w
$$

for the data set obtained by truncation at $s=t_{L M}$ and administrative censoring at $t_{L M}+\mathrm{W}$.
$h_{0}\left(t \mid t_{L M}, w\right)$ is the baseline hazard or force of mortality.
This is a convenient way to obtain a dynamic prediction without fitting a complicated model with time-varying effects.

## Super-prediction data set

- Fix the prediction window w; [say, w=5 years]
- Select a set of prediction time points $\left\{s_{1}, \ldots, s_{L}\right\}, 20 \leq L \leq 100$; [say, every 6 months.]
- Create a prediction data set for each $t_{L M}=s_{l}$ by truncation and administrative censoring;
- Stack all these data into a single "Super-prediction data set". The subsets corresponding to a given prediction time $t_{L M}=s_{l}$ are "strata".
- The risk set $\mathrm{R}\left(t_{i}\right)$ for an event time $t_{i}$ is present in all strata with $s \leq$ $t_{i} \leq s+w$. Passing from stratum s to $\mathrm{s}+1$ corresponds to sliding the window over the time range.
- Individual life $j$ contributes up to $w /\left|s_{l+1}-s_{l}\right|$ times in each prediction window. [10 times when $\mathrm{w}=5$ and the time shift $s_{l+1}-s_{l}$ is 6 months.]


## Sliding Cox model results (crude model)

Hazard of all-cause mortality associated with statin prescription


## Integrated partial log-likehood landmark model - ipl

The landmark super prediction model with window $w$ and letting the regression coefficients $\beta_{L M}$ depend on time $t_{L M}$ is given by
$h\left(t \mid x, t_{L M}=s, w\right)=h_{0}(t \mid s, w) \exp \left(x^{T} \beta_{L M}(s)\right), \quad s \leq t \leq s+w$ where

$$
\beta_{L M}(s)=\sum_{j=1}^{m} \gamma_{j} f_{j}(s) .
$$

- $f_{j}(s)$ are the basis functions, $f_{1}(s)=1, f_{j}(0)=0$ for $j>1$, and $\gamma_{j}$ are the parameters, with $\beta_{L M}(0)=\gamma_{1}$.
- The parameters of this model are estimated by maximizing the integrated (over s) partial log-likelihood introduced by van Houwelingen (2007).
- This approach is based on a stratified (on s) analysis with smooth landmark dependent effect $\beta_{L M}(s)$ and separate estimated baseline hazards for each stratum.


## Pseudo-partial log-likelihood landmark model <br> - ipl ${ }^{*}$

In the $\boldsymbol{i} \boldsymbol{p} \boldsymbol{l}^{*}$ model, the baseline hazard is modelled directly as

$$
h_{0}(t \mid s, w)=h_{0}(t) \exp (\theta(s)),
$$

where $\quad \theta(s)=\sum_{j=1}^{m} \eta_{j} g_{j}(s)$
for proper basis functions $g_{j}(s)$ with $g_{j}\left(s_{1}\right)=0$, resulting in

$$
h\left(t \mid x, t_{L M}=s, w\right)=h_{0}(t) \exp \left(x^{T} \beta_{L M}(s)+\theta(s)\right), \quad s \leq t \leq s+w,
$$

where $\beta_{L M}(s)$ and $\theta(s)$ are the $m$ th degree polynomials in $s$.

## Adjusted hazard of all-cause mortality associated with current statin prescription



## Predicted probabilities of survival in a window

Predictions for all $\mathrm{s} \in\left[s_{1}, s_{L}\right]$ in the $\boldsymbol{i p l} \boldsymbol{l}^{*}$ model are obtained from estimated cumulative hazards

$$
H\left(s+w \mid x, t_{L M}=s\right)=\exp \left(x^{T} \beta_{L M}(s)+\theta(s)\right)\left(H_{0}^{*}(\mathrm{~s}+\mathrm{w})-H_{0}^{*}(\mathrm{~s}-)\right)
$$

This is because in the $\boldsymbol{i p l} \boldsymbol{l}^{*}$ model

$$
h\left(t \mid x, t_{L M}=s, w\right)=h_{0}(t) \exp \left(x^{T} \beta_{L M}(s)+\theta(s)\right), \quad s \leq t \leq s+w
$$

only the baseline hazard $h_{0}(t)$ depends on $t$.

## Probabilities of death for 1936-1940 cohort

Dynamic prediction with 10 year window


## Baseline hazard in the statins landmark model



The baseline hazard is well approximated by the Gompertz hazard

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## The ipl*landmark model in actuarial research

In the $\boldsymbol{i p l} \boldsymbol{l}^{*}$ model, the hazards are modelled as

$$
h\left(t \mid x, t_{L M}=s, w\right)=h_{0}(t) \exp \left(x^{T}(s) \beta_{L M}(s)+\theta(s)\right), \quad s \leq t \leq s+w,
$$

where $\beta_{L M}(s)$ and $\theta(s)$ are the $k$ th and the ( $k-1$ )th degree polynomials of $s=t-t_{0}$.
The log-hazards are $\lambda\left(t \mid x, t_{0}\right)=\lambda_{0}(\mathrm{t})+x^{T}(s) \beta_{L M}(s)+\theta(s)$.
For Gompertz baseline hazard, $\lambda_{0}(\mathrm{t})=a+b t$.
Values of $a$ and $b$ can be estimated from the estimated baseline hazard or substituted for a particular population. Next, we can obtain cumulative hazards, survival and period life expectancy for various scenarios of changing risks $x(s)$.

## Discussion and conclusions

- The most general form of extended Cox regression with timedependent effects is difficult to use. To make it relevant to actuarial research we also need to consider the shape of the baseline hazards.
- Parametric "double-Cox" model is a useful replacement for the stratified Cox model which also models shape of baseline hazards and can be easily used for actuarial purposes.
- Landmark analysis is a convenient way to model dynamically changing survival data. The ipl* model conveniently lends itself to actuarial modelling.
- Extra development is required to use the results for population LE projections using methodology similar to that in Kulinskaya et al. (2019).


## References:

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6. Kulinskaya E., Gitsels, LA. and Bakbergenuly, I., 2019. Calculation of changes in individual and period life expectancy based on proportional hazards model of an intervention. Insurance Mathematics and Economics, under review.

## Questions

## Comments

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## Landmark analysis of survival benefits of statin prescription

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The 'Use of Big Health and Actuarial Data for understanding Longevity and Morbidity Risks' research programme is being funded by the Actuarial Research Centre.


#### Abstract

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## Introduction

- We aim to demonstrate the use of landmark analysis in actuarial research using the statin survival benefits as a case study.
- Statins have been widely prescribed for cardiac prevention
- Clinical trials have demonstrated the survival benefits of statin prescription
- The threshold of cardiac risk at which to prescribe statins is still controversial, especially at older ages where everyone would be eligible solely due to their age.
- Little is known about the effect of long-term prescription in the general population, where sequential treatment decisions are made according to the latest clinical guidelines.


## The Health Improvement Network (THIN) data

- Anonymised electronic primary care medical records (Vision)
- Data collection began in 2003 using Read codes
- 11 million patients, 3.7 million active patients
- 562 general practices, covering $6.2 \%$ of the UK population

- Diagnoses, prescriptions, consultations, postcode deprivation


## Subset of THIN selected for our research:

- 110,243 patients who turned 60 between 1990 and 2000 and did not have a previous statin prescription or a cardiovascular disease diagnosis


## Primary prevention of CVD

Primary prevention: no previous history of CVD

- Example: lipid-lowering therapy - statins

National Institute of Health and Clinical Excellence (NICE):

- Offer atorvastatin 20 mg for the primary prevention of CVD to people who have a $10 \%$ or greater 10-year risk of developing CVD.
- Estimate the level of risk using the QRISK2 assessment tool
- www.nice.org.uk/guidance/cg181/
- www.qrisk.org/2016/

Up to 17 million UK residents eligible for statins


Clinical information
Smoking status: non-smoker

$$
v
$$

Diabetes status: none v

Angina or heart attack in a 1st degree relative $<60$ ? $\square$
Chronic kidney disease? $\square$
Atrial fibrillation?
On blood pressure treatment? $\square$
Rheumatoid arthritis?
Leave blank if unknown
Cholesterol/HDL ratio: $\square$
Systolic blood pressure ( mmHg ): $\square$
-Body mass index-


Calculate risk over 10 vears. Calculate risk

## Prevalence of statin prescription



Prevalence of statin prescription differs by calendar year, age, sex and cardiac risk group

## Statistical Analysis Options

- Objective: dynamically predict the survival benefits associated with statin therapy over the course of 25 years.
- The original plan was to develop a model with the following states: S0 not eligible for statins, S1 eligible for statins, S2 prescribed statins, and S3 death.

- Alternatively, develop a survival model with time-dependent predictors and parameters.
- Or use landmark analysis.


## Adherence to statin prescription

| Number of arm <br> switches | $\mathbf{0}$ | $\mathbf{1}$ | $\mathbf{2}$ | $\mathbf{3}$ | $\mathbf{4}$ | $\mathbf{5 +}$ |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| \% of patients | 51.1 | 40.7 | 6.2 | 1.5 | 0.4 | 0.1 |

- $51.1 \%$ were never prescribed statins;
- $40.7 \%$ were prescribed at some age and stayed on statins;
- 6.2\% dropped off statins permanently;
- $1.5 \%$ dropped off statins and then came back on to stay;
- 0.5\% had 4 or more switches;
- the maximum was 9 switches for 1 person


## Data preparation and analysis

Data: Medical history was updated every half a year (landmark) until end of follow-up (death, deregistered or end of study).

Imputation: Due to missing data at early ages, multiple imputation was performed using joint modelling at age 60. The method of last observation carried forward was used for missingness in follow up.

Analysis: Landmark analyses were carried out by fitting Cox proportional hazards regression of all cause mortality associated with current statin prescription at each landmark from age 60 to 85 and adjusted for medical history.

We separately conducted three landmark analyses: with window widths 5, 10 and 30 years.

## The four stages of modelling process

- A Cox model was fitted on complete cases at baseline age to inform the imputation model. Both models included all medical history if prevalent.
- Cox models were fitted on the imputed datasets at ages $65,70,75$, 80 and 85 to inform the final landmark model. These models included all medical history and tested for interactions between statin prescription, sex, year of birth and cardiac risk.
- The final, fully adjusted, Cox landmark models were fitted at 10 imputed datasets. The landmarking was smoothed with an integrated partial log-likelihood (ipl) and with Pseudo-partial loglikelihood (ipl*).
- Ten landmark models pooled using Rubin's rules.


## The statistical model for survival benefits of statins was adjusted for:

- Cardiac risk at three levels: low (QRISK2 $\leq 20 \%$ ), medium (QRISK2 of 20-39\%) and high (QRISK2 $\geq 40$ or CVD diagnosis)
- Sex, birth cohort, Townsend deprivation quintile, chronic kidney disease, diabetes, treated hypertension, hypercholesteromia, aspirin, BMI, alcohol consumer status, smoking status and general practice


# Hazard of all-cause mortality associated with statin prescription (30 years window) 

Hazard of all-cause mortality associated with statin prescription


## Why statins are more beneficial in younger cohort: better drugs?

$20 \%$ to $30 \%$ : low-intensity statin
$31 \%-40 \%$ medium-intensity statin
Above $40 \%$ : high-intensity statin

|  | 5mg | 10mg | 20mg | 40mg | 80mg |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Fluvastatin | - | - | $\bigcirc$ | $\bigcirc$ | - |
| Pravastatin | - | - | - | - | - |
| Simvastatin | - | - | - | - | $\bigcirc$ |
| Atorvastatin | - | - | - | - | $\bigcirc$ |
| Rosuvastatin | - | - | - | - | - |

Source: National I Istitute for Heath and Care Excellence

Atorvastatin vs simvastatin
Items dispensed in England (millions)
${ }_{50 \mathrm{~m}}$ Simvastatin Atorvastatin


## GPs set for mass drug switch to

 atorvastatin after analysis shows price could fall by 95\%22 February 2012

```
&
```

f SHARE ON FACEBOOK
Exclusive GPs are set to be enrolled in schemes to switch patients en masse to atorvastatin in the wake of an analysis for the Government's

Cerivastatin was withdrawn from the world market in 2001 and the clinical guidelines changed from simvastatin to atorvastatin in 2014. But in 2014 our patients were 79-89 years old.


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## Length of prior prescription for patients on statins at age s



## Average length of prior prescription for patients not on statins at age s



## Proportion of patients on statins at age s with at least 75\% adherence at follow up



## HRs of all-cause mortality estimated in 5, 10 and 30 years window

Born in 1930-1935


## HRs of all-cause mortality estimated in 5, 10 and 30 years window

Born in 1936-1940


## Probabilities of death for 1936-1940 cohort

Dynamic prediction with 10 year window


## Do survival benefits really increase at older ages? Here controls never were on statins:

We also performed an analysis keeping only patients who never were prescribed statins in the control group. Younger patients do better!


Similar HRs ( $0.74,0.63$ vs $0.74,0.61$ here) only from age $80!$

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## Summary of results on statins

- The prevalence of statin prescription increased substantially by age with nearly half of the study population having had a prescription by age 75 and $57 \%$ by age 85 at the end of the study.
- The adherence to statin prescription was high, with $77 \%$ adhering more than $75 \%$ of the time and only $5 \%$ adhering less than $25 \%$ of the time
- In "current knowledge" landmark analysis, statin prescription was associated with increasing survival benefits at older ages and was significant at the earliest from age 62 onward. Benefits seemed to decrease with age in our sensitivity analysis based on the full knowledge of statin history.
- Statin prescription was more effective in patients born in later years due to the changing availability and recommended dosages of statin types resulting in more effective treatment but did not differ by sex or cardiac risk.
- Therefore, age alone can be used to decide on initiating and staying on statin therapy based on the predicted overall effect (which tallied up benefits and harms).


## Discussion and conclusions on statins

- After adjustment for cardiac risk and related medical history, it appears that statin therapy is especially beneficial at older ages and in people born at later years in a realistic "current knowledge" scenario. The benefits of statins in earlier ages may be underestimated as more people will get statin prescription later.
- This study adjusted for cardiac risk groups defined by the changing clinical guidelines on the eligibility of statin prescription. However we did not distinguish between recommended types and doses of statins. This might partly explain why statin prescription was associated with greater survival benefits in patients born in later years.
- We used statin prescription as a proxy for statin intake. Lower intake than prescription would result in more conservative findings and thus imply that statins could be even more beneficial.


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1. Gitsels, L.A.,Kulinskaya, E. and Steel, N., 2016. Survival benefits of statins for primary prevention: a cohort study. PloS one, 11(11), p.e0166847.
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## Questions

## Comments

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## Stroke Mortality and Morbidity in the UK

## Padma Chutoo (PhD candidate) University of East Anglia

The 'Use of Big Health and Actuarial Data for understanding Longevity and Morbidity Risks' research programme is being funded by the Actuarial Research Centre.

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## Overview

- Stroke definition and statistics
- Study description
- Patient Numbers
- Kaplan Meier plots
- Checking the Cox's Proportional hazard Assumption
- Parametric regression fits
- Double Cox-Weibull model specification
- IS model and hazard plots
- Overview of Multiple Imputation
- Future works


## What is Stroke?

- Ischemic stroke is caused by a blood clot that blocks or plugs a blood vessel in the brain.
- Haemorrhagic stroke is caused by a blood vessel that breaks and bleeds into the brain


A clot forms and blocks blood flow to part of the brain.

Haemorrhagic Stroke


A weakened blood vessel ruptures and causes bleeding in or around the brain.

- Transient Ischemic Attacks or TIAs, are "mini-strokes" whereby the symptoms from the clot appear temporarily. TIAs are warning signs that should be taken seriously.


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## Stroke Statistics

Stroke is the fourth single leading cause of death in the UK.


Reference: Heath and Social Care information Centre Quality and Outcomes Framework (QOF) - 2014-2015.

## The NHS and social care costs of stroke are around $£ 1.7$ billion a year in England




Stroke is the biggest single cause of major disability in the United Kingdom. Almost two-thirds of stroke survivors leave hospital with disability.

Stroke burden is projected to rise from around 38 million DisabilityAdjusted Life Years (DALYs) globally in 1990 to 61 million DALYs in 2020.

## Stroke study: brief description

- Objective: impact of $1^{\text {st }}$ ischaemic stroke and transient ischaemic attack (TIA) on longevity and morbidity risks.
- The study period is from 1986 up to 2017.
- Design: case/control 1:3
- Exclusion criteria: prior major cancers, dementia, chronic kidney disease stages 3+ and haemorrhagic stroke.
- The primary outcome is all-cause mortality. The secondary outcomes are further strokes, dementia (Alzheimer's and vascular dementia), heart failure, myocardial infarction, pulmonary arterial disease.


## Stroke study: brief description

## Variables of interest:

- Drugs: Antihypertensive drugs, Anticoagulant drugs, Lipid regulating drugs and antidiabetic drugs.
- Medical conditions: Asthma, Atrial Fibrillation, CKD, CHD, PAD, Hypothyroidism, COPD, Diabetes, Hypercholesterolemia, Hypertension, Depression.
- Demographical and lifestyle conditions: BloodPressure, Cholesterol, BMI, gender, date of birth, age at entry, smoking status, alcohol status and IMD Decile.


## Patient numbers

## IS dataset



Multiple Imputation dataset

$$
(N=75,769)
$$

Cases $=20,250$
Controls $=55,519$

## TIA dataset

Full case dataset
( $N=24,797$ )
Cases $=9,377$
Controls $=15,420$

Multiple Imputation dataset
( $N=74,037$ )
Cases $=20,633$
Controls $=53,374$

## Unadjusted Kaplan Meier plot IS cases and controls



## Unadjusted Kaplan Meier plot TIA cases and controls



## Violations to Cox's Proportional hazard assumption ( $\alpha=0.05$ )

|  | rho | chisq | p |
| :---: | :---: | :---: | :---: |
| birth_cohort1921 to 1930 | -0.0305 | 4.6059 | $0.0318614 / 08 / 697$ |
| birth_cohort1931 to 1940 | -0.04986 | 11.4182 | 0.00072727164999 |
| birth_cohort1941 to 1960 | -0.08358 | 32.0438 | 0.00000001507344 |
| age_cat2 | 0.00991 | 0.4616 | 0.49688725441191 |
| age_cat3 | -0.01266 | 0.7385 | 0.39013103374282 |
| aqe_cat4 | -0.02933 | 3.9631 | 0.04650827842605 |
| sexMale | 0.00256 | 0.0294 | 0.86394990495609 |
| groupscases | -0.03331 | 4.7344 | 0.02956567737229 |
| IMD_Quintile2 | 0.01582 | 1.2685 | 0.26005731908003 |
| IMD_Quintile3 | 0.00982 | 0.5247 | 0.46886479768015 |
| IMD_Quintile4 | 0.02516 | 3.5033 | 0.06124845077876 |
| IMD_Quintile5 | 0.02632 | 4.0789 | 0.04342093793658 |
| BMI catobese | 0.03568 | 5.6952 | 0.01701099437364 |
| BMI_catoverweight | 0.01743 | 1.3773 | 0.24055963462973 |
| BMI_catUnderweight | -0.01279 | 0.7491 | 0.38677422168589 |

## Comments

Covariates violating the Cox's PH assumption : Birth cohort, Age category, case/control, BMI, IMD, hypertension and antiplatelet.

The global test was highly significant providing evidence of non-proportionality.

| AF_factorYes and Treated | -0.00210 | 0.0205 | 0.88620238544372 |
| :--- | ---: | ---: | ---: |
| AF_factorYes and Untreated | 0.01561 | 1.1125 | 0.29153432590237 |
| hypertension_factorYes and Treated | -0.04421 | 8.7999 | 0.00301247436989 |
| hypertension_factorYes and Untreated | -0.00589 | 0.1542 | 0.69459488132253 |
| age_cat2:groupscases | -0.01262 | 0.6992 | 0.40306144688028 |
| age_cat3:groupscases | -0.00481 | 0.1024 | 0.74901958328828 |
| age_cat4:groupscases | 0.00344 | 0.0526 | 0.81864457985083 |
| sexMale:groupscases | 0.00573 | 0.1442 | 0.70412354400852 |
| groupscases:hypertension_factorYes and Treated | 0.02637 | 3.1294 | 0.07689249209760 |
| groupscases:hypertension_factorYes and_Untreated | 0.01609 | 1.1510 | 0.28334103952037 |
| GLOBAL | NA | 134.1296 | 0.00000000000228 |



Graphical diagnostics based on the scaled Schoenfeld residuals.

A covariate which does not violate the Cox's PH assumption


## Comments:

There is no distinct pattern of the residuals with time, so this covariate is not time-dependent.

Graphical diagnostics based on the scaled Schoenfeld residuals.

.... Reference line for null effect

-     - Average hazard over time
- Time-varying hazard




## Comments:

A non-zero slope is evidence against proportionality.

## Distribution fitting : IS

Parametric Regression Fits
IS cases


Parametric Regression Fits
IS controls


## Parametric "Double-Cox" regression

Components:

- A baseline hazard function (which changes over time).
- The risk factors $Z$ have a loglinear contribution to the force of mortality which does not depend on time $t$.

The Cox parametric regression model


Weibull baseline hazard function with scale $\lambda$ and shape $k$. Shape $k$ is modelled as $k=k(Z)$.

$$
\mu_{0}(t \mid Z)=\frac{k(Z)}{\lambda}\left(\frac{t}{\lambda}\right)^{k(Z)-1}
$$

Additional regression model to allow varying shape depending on covariates

$$
\mathrm{k}(Z)=k_{0} e^{Z^{\mathrm{T}} \beta_{k}}
$$

## IS model

The scale model includes the following main effects and interactions :

- Birth cohort
- IMD in Quintiles
- Body Mass index
- Antiplatelet therapy
- Chronic Pulmonary Disorder
- Chronic Kidney Disease ( stages 1-3)
- Heart Failure
- Myocardial Infarction
- Peripheral Arterial Disease
- Atrial fibrillation
- Diabetes
- Anticoagulant therapy
- Smoking
- Interaction of IS diagnosis with Antihypertensive treatment
- Interaction of IS diagnosis with sex
- Interaction of IS diagnosis with age

The shape model includes the following main effects :

- Birth cohort
- Antiplatelet therapy


## Overview of Multiple Imputation



## Step 1 :

Generate multiple sets of imputed values to produce multiple imputed datasets.

## Step 2 :

Perform survival analysis on each dataset.

Step 3 :
Pool the results using Rubin's rules.

Hazard curves demonstrating the birth cohort effect : IS


Hazard curves for healthy cases and controls, aged 39-60 years with IMD Quintile = 1 across different birth cohorts and APL( antiplatelet intake).

## Forest plot : IS

## Adjusted Hazard Ratio



## Forest plot : IS model

Adjusted Hazard ratios


## Future Works:

- Write up two papers: on TIA and on IS
- Translation of models into actuarial analysis


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The 'Use of Big Health and Actuarial Data for understanding Longevity and Morbidity Risks' research programme is being funded by the ARC.

# Impact of Diabetes Mellitus II on Longevity and Morbidity Risks: Full Case Analysis 

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#### Abstract

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## Presentation Outline

Dintroduction

- Purpose of the Study
- Why Diabetes Mellitus II?
$\square S t u d y$ Design
- Selection Criteria
- Study Sample
- Statistical Models
$\square$ Results
-Further Data Modelling


## Introduction

Purpose of the Study
$\square$ To derive, analyse and model the impact of diabetes mellitus II (DM-II) on longevity and morbidity risks.
$\square$ Primary Outcome: all-cause mortality.
$\square$ Secondary Outcomes: amputation, cognitive impairment, Chronic Kidney Disease (CKD) Stages 3 to 5, heart failure (HF), myocardial infarction (MI), pulmonary vascular disease (PVD), stroke, cancer and cognitive impairment including dementia.

## Why Diabetes Mellitus II (DM-II)



Source: WHO (2018)

DM-II: Rankings among the Top Ten

| Year | All <br> Ages | $\mathbf{5 0 - 5 9}$ | $\mathbf{6 0 - 6 9}$ | $\mathbf{7 0 +}$ |
| :--- | :--- | :--- | :--- | :--- |
| 2016 | 7 | 6 | 5 | 6 |
| 2015 | 7 | 6 | 5 | 6 |
| 2010 | 10 | 7 | 5 | 7 |
| 2000 | 15 | 9 | 6 | 7 |

## Why DM-II (cntd.)



Source: ONS (2017)

## Study Design

## Selection Criteria

-UUK THIN database.

- Patients diagnosed with DM-II (cases) from 1984 and, aged 40 years and above were matched (1:3) to non - diabetics (controls) by practice, age and sex.
- Excluded patients with severe medical conditions diagnosed (e.g. cancer) before entry date.
- The follow up period is from 1984 up to 2017.


## Study Design

$\square$ Variables of Interest - at entry

| Demographic |
| :--- |
| 1. Age Group |
| 2. Birth Year |
| 3. Gender |
| 4. General Practice <br> (Frailty) |



1. Smoking Status
2. Townsend Deprivation Index
3. Body Mass Index (BMI)

| Medical Conditions |
| :--- |
| 1. Case-Control Indicator |
| 2. Angina |
| 3. Atrial Fibrillation (AF) |
| 4. HF |
| 5. Hypercholesterolemia |
| 6. Hypertension |
| 7. MI |
| 8. PVD |

Interactions e.g. Age Group and Gender, Case-Control and Smoking status

## Study Design

Full Case Analysis - Selection Criteria
Included Patients with complete records on

- Smoking status,
- Alcohol consumption status,
- Townsend deprivation score,
- BMI,
- Blood Pressure (BP),
- Blood lipid ratio and
- High-density lipoproteins (HDL).


## Study Sample

Total Study Sample
$\square 108282$ (57\% Males) Cases.
Full Case Study Sample

- 20213 (57.7\% Males) Cases.
$\square 253800$ ( $55 \%$ Males) Controls.
$\square 28693$ (56.2\% Males) Controls.
Distribution of the Study Sample by Age Group, Sex and Case-Control Status


Prevalence of Some Medical Conditions at Entry Date


## Statistical Models for All-Cause Mortality

- Cox Regression for DM - II

Backward elimination was used for variable selection ( $\alpha_{\text {main }}=0.05$,
$\alpha_{\text {interactions }}=0.01$ )

- Case-control indicator,
- Age group,
- Birth Year,
- Gender,
- Smoking status,
- Townsend deprivation index,
- HF,
- Hypercholesterolemia,
- Hypertension,
- MI,
- PVD,
- BMI
and interactions


## Assessing PH Assumption

$$
(\alpha=0.05)
$$



Variables violating the PH Assumption

- Year of Birth
- Hypercholesterolemia
- Hypertension

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## Validating PH Assumption results using timecox ( $\alpha=0.05$ )

Test for Time Invariant Effects

|  | Kolmogorov-Sminorv <br> Test | p -value: $\mathrm{H}_{0}: \beta(t)=\beta$ |
| :--- | :--- | :--- |
| Intercept | 2.72 | 0.207 |
| Birth Year [1930-1939] | 2.99 | 0.25 |
| Birth Year [1940-1949] | 2.53 | 0.217 |
| Hypercholesterolemia [Treated] | 2.52 | 0.735 |
| Hypercholesterolemia [Untreated] | 3.16 | 0.029 |
| Hypertension [Treated] | 4.9 | 0.159 |
| Hypertension [Untreated] | 2.31 | 0.558 |
| Birth Year [1930-1939]:const(Gender) <br> [Male] | 5.2 | 0.127 |
| Birth Year [1940-1949]:const(Gender) <br> [Male] | 4.5 | 0.324 |

## Only hypercholesterolemia has time variant effects

## Estimating the Baseline Function using flexsurvreg package



## Gompertz-Cox Regression

- Distribution
- Gompertz distribution.
- Shape Model
- Hypercholesterolemia.
- Scale Model
- All covariates and interactions as in Cox Model.


## Adjusted Hazard Ratios

Adjusted Hazard Ratios for Scale Cox Model


## Adjusted Hazard Function



## Further Work

1. Imputed Data Model (Mortality)
2. Translation into Actuarial Models (Mortality)
3. Morbidity Models (Cancer, CKD Stages 3-5)
4. Translation into Actuarial Models
5. Publish at least 2 papers

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## Hormone Replacement Therapy and its effects on Morbidity and Longevity of Women

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The 'Use of Big Health and Actuarial Data for understanding Longevity and Morbidity Risks' research programme is being funded by the Actuarial Research Centre.


#### Abstract

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## Outline

- Brief description of Hormone Replacement Therapy
- Study design and selection criteria
- Distribution of the study population
- Hazards of selected medical conditions at follow-up
- Complete case analysis
- Results


## Menopause and its Symptoms:



## Brief Description of Hormone Replacement Therapy (HRT)

## What is HRT?

- HRT is mainly used to relieve women from menopausal symptoms
- It has been used for more than sixty years
- HRT contains female sex hormones estrogen and/or progesterone
- First available in the United Kingdom in 1965


## Routes of Administration

- Oral tablets, transdermal patches, injections, topical gels, and ointments.


## Study design and patients selection criteria

- Cases are patients of age 46 years and above who received any kind of HRT.
- Controls are matched with cases by year of birth and general practice (GP).
- Patients with all kinds of cancer, acute myocardial infarction (AMI), serious heart failure, stroke (except TIA), chronic kidney disease (CKD) stage 3-5, dementia, oophorectomy before 45, premature ovarian insufficiency, premature menopause and surgical menopause are excluded.
- Primary outcome of interest is all-cause mortality. Secondary outcomes are osteoporosis, dementia, cardiovascular disease, type II diabetes, and hormonal cancers.
- Follow up period between 1984 to 2017.
- Working data consists of 112,354 cases and 245,320 matched controls.


## Age distribution at first HRT prescription and death experience at follow-up

Proportion of Study Population by Age Category at Baseline


Death Experience of Study Population by Age Category


- Majority of women started HRT between 46-55 years of age
- There are more death in controls than cases in all age category

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## Hazard ratios and 95\% confidence intervals of the conditions developed at follow up



## Time to diagnosis of Breast cancer at follow up by age category at HRT and its type <br> KM plot of time to diagnosis of Breast cancer at follow up



KM plot of time to diagnosis of Breast cancer at follow up




- In all age category HRT users developed more breast cancer than non-user at follow up


## Survival model of all-cause mortality

> The following predictors were used in the survival modelling:

- Socio-economic status: Townsend score
- Lifestyle: Smoking status, body mass index (BMI)
- Health: Type II diabetes, hypertension, hypercholesterolaemia, peripheral vascular disease (PVD)/peripheral arterial disease (PAD), coronary heart disease (CHD), oophorectomy/hysterectomy status, systolic and diastolic blood pressure
- Demography: Age category at first HRT and birth cohort
- Medication: HRT (estrogen-only, estrogen and progesterone), antihypertensive drugs
> Patients with complete information for all of the above covariates has been selected for full case analysis
$>$ Final model also included interactions of smoking with BMI and type II diabetes


## Selection of patients with complete records:



## Grambsch and Therneau test

hrt_cat_1Combined
hrt_cat_10estrogen-only
Age.cat51-55
Age.cat56-60
Age.cat61-65
B. cohort1931-1940
B. cohort1941-1950
B. cohort1951-1960
hypertension_cat_treated
hypertension_cat_untreated
bmi_cat0bese
bmi_cat0verweight
smoking_cat_current
smoking_cat_ex
townsend_2
townsend_3
townsend_4
townsend_5
diabetes_type2
osteoporosis
CHD
opho.hysboth_removed opho.hysopho_without_hys bmi_catObese: smoking_cat_current bmi_cat0verweight:smoking_cat_current bmi_cat0bese: smoking_cat_ex bmi_cat0verweight:smoking_cat_ex smoking_cat_current:diabetes_type2 smoking_cat_ex:diabetes_type2 GLOBAL
rho
-0.002697
-0.000269
-0.031085
-0.027581
-0.0.040494
-0.026251
-0.046838
-0.042161
-0.014381
0.012651
0.003277
-0.004197
-0.051673
-0.023847
0.001919
-0.004281
$-0.003795$
-0.007716
-0.006944
0.004521
-0.004256
0.008301
0.001018
0.025841
0.014928
0.016734
0.023806
0.005911
$-0.01673$
chisq
0.0744110 .785020029057
0.0007530 .978111154356
10.0572560 .001517490554
7.9891510 .004705847114
17.268775
0.000032447539
7.1310650 .007575972010
22.712986 0.000001880925
0.000021284617
2.1787000 .139932572339
1.6554910 .198213197224
0.1102940 .739809895849
0.1816530 .669956369590
27.3010120 .000000174120
5.8539030 .015542544963
0.0380610 .845320438510
0.1889000 .663833458455
0.1485320 .699942607104
0.6151870 .432841333884
0.5224230 .469809744403
0.2300370 .631496621577
0.1889710 .663774173883
0.7195020 .396307206913
0.0107130 .917564502212
6.9060910 .008590260141
2.3017000 .129232523293
2.8980470 .088686922137
5.8631010 .015461528170
0.3620350 .547378311009

NA 103.6045950 .000000000257

A significant
p-value(<0.05)
is an indication of violation of the proportional hazard assumption in the Cox PH model

## Plots of residuals:



## HRT model, Forest plot 1

| Risk factors | Subgroups |  | Adjusted hazard ratio(95\% CI) |
| :---: | :---: | :---: | :---: |
| HRT type | Non-user (reference group) |  |  |
|  | Combined HRT | $\square$ | 0.93(0.89-0.97) |
|  | Estrogen-only | - | 0.93(0.84-1.03) |
| Townsend score | 1 (reference group) |  |  |
|  | 2 | 星 | 1.03(0.96-1.09) |
|  | 3 | 든 | 1.17(1.11-1.24) |
|  | 4 | - | 1.39(1.31-1.47) |
|  | 5 | -最- | 1.51(1.42-1.62) |
| BMI | Healthy weight (reference group) |  |  |
|  | Overweight | - | 1.01(0.95-1.08) |
|  | Obese | - | 1.41(1.32-1.51) |
|  | $\bigcirc$ | $\begin{array}{cccccccccccc} \hline 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0.2 & 0.4 & 0.6 & 0.8 & 1 & 1.2 & 1.4 & 1.6 & 1.8 & 2 \\ \text { Adjusted } & \text { HR and } & 95 \% & \text { Confidence Interval } \end{array}$ |  |

## HRT model, Forest plot 2

| Risk factors | Subgroups | - Time 1 - Time 2 | Adjusted hazard ratio(95\% Cl) |
| :---: | :---: | :---: | :---: |
|  |  |  | Time 1/Time 2 |
| Age category | 46-50 (reference group) |  |  |
|  | 51-55 | n-n | 1.71 (1.56-1.87)/1.36(1.24-1.50) |
|  | 56-60 |  | 2.86(2.58-3.18)/2.11(1.90-2.35) |
|  | 61-65 | $\square-\longrightarrow$ | $5.23(4.65-5.89) / 3.16(2.78-3.60)$ |
| Smoking category | Non-smoker (reference group) |  |  |
|  | Ex-smoker | - - | 1.87(1.64-2.13)/1.50(1.31-1.71) |
|  | Current-smoker | - - - | 3.83(3.52-4.17)/2.86(2.63-3.10) |
| Birth cohort | 1921-1930 (reference group) |  |  |
|  | 1931-1940 | - ${ }^{\text {暏 }}$ | 1.02(0.91-1.16)/0.77(0.69-0.85) |
|  | 1941-1950 | $\square$ | 1.11(0.96-1.28)/0.61(0.53-0.70) |
|  | 1951-1960 | - - - | 1.38(1.15-1.64)/0.51(0.36-0.72) |
|  |  | $00.40 .81 .21 .622 .42 .83 .23 .644 .44 .85 .25 .6$ Adjusted $H R$ and $95 \%$ Confidence Inteval |  |

## Baseline hazard function fitted with different parametric distributions:



## Future Work:

- Multiple imputation
- Models for imputed data.
- Translation of models into actuarial analysis
- Landmark analysis


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