

# Parametric Estimation of The Mean Number of Events in The Presence of Competing Risks

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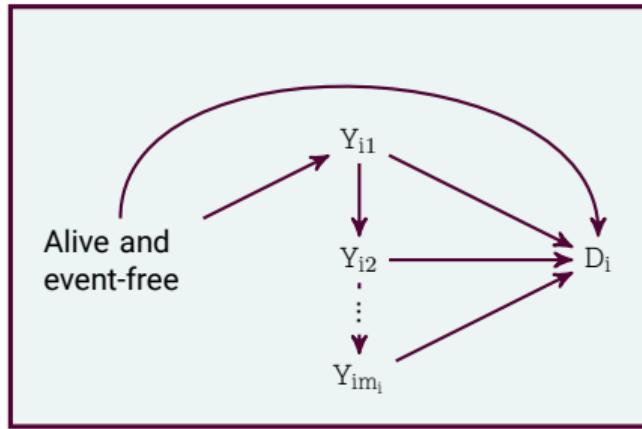
Presentation at the 11<sup>th</sup> NordicEpi conference in Copenhagen, 2024



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# Background

- ▶ Recurrent events are common in time-to-event data, e.g., cardiovascular events, hospital admissions, childbirths, etc.
- ▶ The mean number of events is one useful summary measure in these situations.
- ▶ Estimation of the mean number of events in the presence of competing events is more challenging



**Figure 1.** Illustration of the event process where the nodes symbolise different states of the event process.

# Estimating The Mean Number of Events

## Mean Number of Events Function

$$\mathbb{E}[N(t)] = \int_0^t S(u)\lambda(u)du \quad (1)$$

where  $S(t)$  is the survival function of the competing event and  $\lambda(t)$  the intensity function of the recurrent event process.

- ▶ Cook and Lawless suggested using the Kaplan-Meier and Aalen-Johansen estimate for estimating  $S(t)$ , and  $\lambda(t)$  respectively.
- ▶ We instead suggest using a flexible parametric model (FPM) to jointly model the recurrent and competing event process.

## The Joint Flexible Parametric Model

We define one model for the log cumulative hazard function of the  $j^{\text{th}}$  recurrent event ( $\Lambda_{ij}$ ) and the competing event ( $H_i$ ):

$$\begin{aligned}\log \Lambda_{ij}(t|x_{1ij}) &= s[\log(t)|\gamma_1, l_1] + x_{1ij}^T \beta_1, \\ \log H_i(t|x_{2i}) &= s[\log(t)|\gamma_2, l_2] + x_{2i}^T \beta_2.\end{aligned}\tag{2}$$

Both models are jointly estimated using a combined likelihood  $L_i$ , where  $L_{1i}$  and  $L_{2i}$  are the contributions of the  $i^{\text{th}}$  individual to the likelihood of the recurrent and competing event process, respectively.

$$\begin{aligned}\log L_i(\theta|x_i, t_{ij}, t_i) &= \log L_{1i}(\theta_1|x_{1ij}, t_{ij}) + \log L_{2i}(\theta_2|x_{2i}, t_i) \\ &= \sum_{j=1}^{m_i} \left\{ \delta_{ij} \log[\lambda(t_{ij}|x_{1ij})] - \Lambda(t_{ij}|x_{1ij}) + \Lambda(t_{ij-1}|x_{1ij}) \right\} \\ &\quad + \delta_i \log[h(t_i|x_{2i})] - H(t_i|x_{2i})\end{aligned}\tag{3}$$

# Implementation

The model is implemented in the R package `JointFPM`

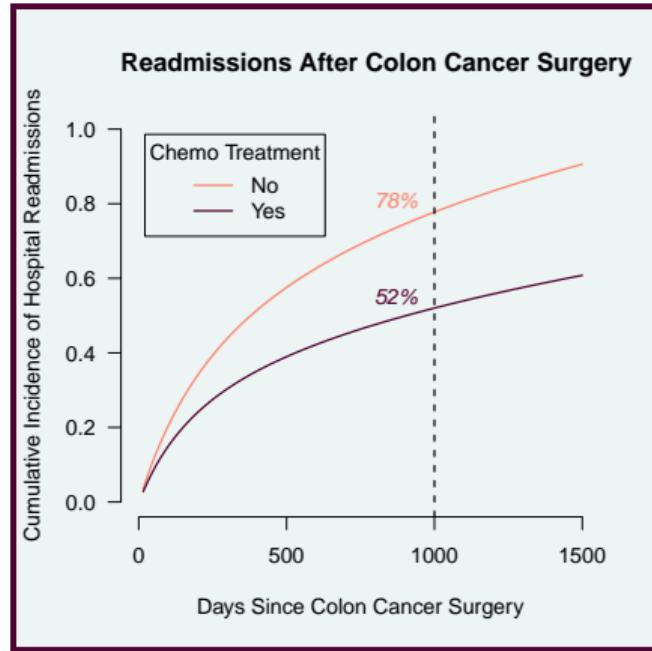
- ▶ Available on CRAN
- ▶ Based on the `rstpm2` package for estimating FPMs
- ▶ Currently supports predictions of  $\mathbb{E}[N(t)]$  and differences thereof, as well as standardised estimates



Link to `JointFPM` package

# Example: Readmission After Colon Cancer Surgery

- ▶ Aim: Investigate hospital readmission patterns in patients that underwent colon cancer surgery by chemotherapy status.
- ▶ Data: Based on the readmission dataset included in the `frailtypack` package for R
- ▶ Follow-up: Followed for hospital readmission from the date of surgery until the date of censoring, death, or a maximum follow-up of 1500 days.



**Figure 2.** CIF of hospitalisation after colon cancer surgery.

# JointFPM Data Set-Up

**Table 1.** Data setup for the joint likelihood.  $t.start$ : time at the start of follow-up;  $t.stop$  is time at the end of follow-up;  $re$ : indicator for rows contributing to  $L_1$ ;  $ce$ : indicator for rows contributing to  $L_2$ ;  $x$ : a vector of covariates for modelling the intensity function of the recurrent ( $x_1$ ) and the competing event ( $x_2$ ).

<b>id</b>	<b>t.start</b>	<b>t.stop</b>	<b><math>\delta</math></b>	<b>ce</b>	<b>re</b>	<b>x</b>
i	0	$t_{i1}$	$\delta_{i1}$	0	1	$X_{1ii1}$
i	$t_{i1}$	$t_{i2}$	$\delta_{i2}$	0	1	$X_{1ii2}$
i	$t_{ij-1}$	$t_{ij}$	$\delta_{ij}$	0	1	$X_{1ij}$
:	:	:	:	:	:	:
i	$t_{im_i-1}$	$t_{im_i}$	$\delta_{im_i}$	0	1	$X_{1im_i}$
i	0	$t_i$	$\delta_i$	1	0	$X_{2i}$

## JointFPM Data Set-Up (Cont'd)

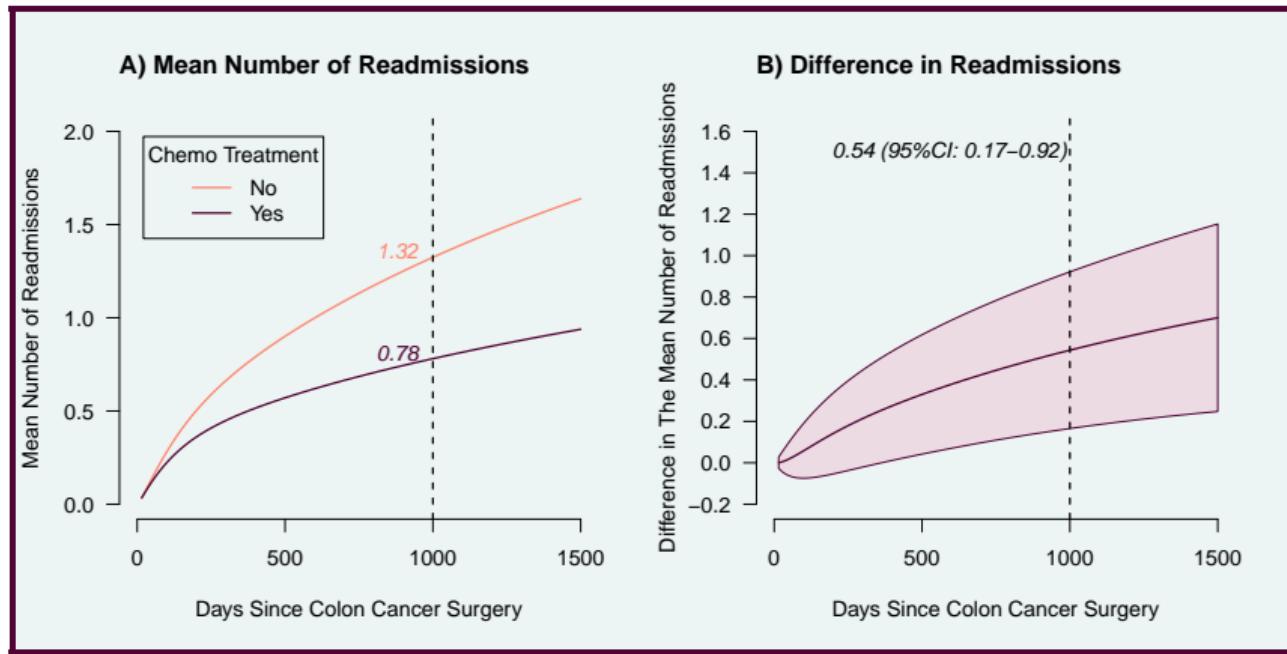
**Table 2.** Example of a dataset in stacked long format for the first 3 individuals in the readmission dataset included in the *frailtypack* package for R. *chemo*: chemotherapy treatment indicator

<b>id</b>	<b>t.start</b>	<b>t.stop</b>	<b>event</b>	<b>ce</b>	<b>re</b>	<b>chemo</b>
1	0	24	1	0	1	1
1	24	457	1	0	1	1
1	457	1037	0	0	1	1
1	0	1037	0	1	0	1
2	0	489	1	0	1	0
2	489	1182	0	0	1	0
2	0	1182	0	1	0	0
3	0	15	1	0	1	0
3	15	783	0	0	1	0
3	0	783	1	1	0	0

# Model Specification in JointFPM

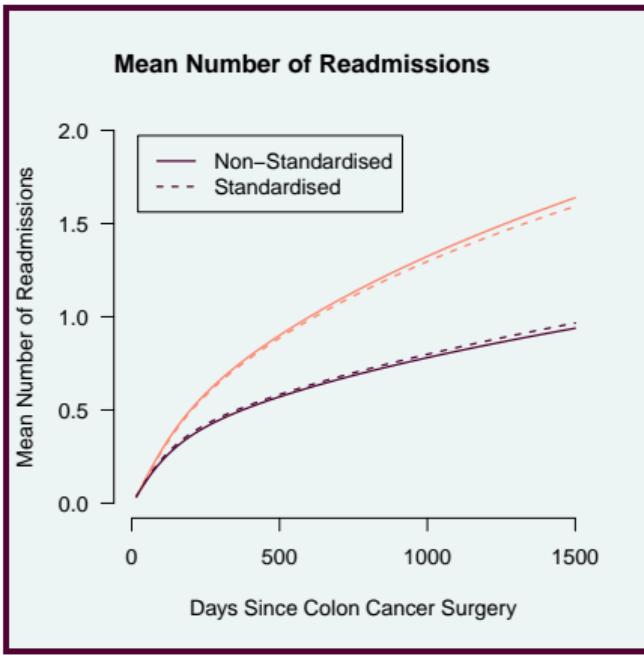
```
> JointFPM(surv = Surv(t.start, t.stop, event,
+                         type = "counting") ~ 1,
+                         re_model = ~ chemo,
+                         ce_model = ~ chemo,
+                         re_indicator = "re",
+                         ce_indicator = "ce",
+                         df_ce = 2,
+                         df_re = 3,
+                         tvc_re_terms = list(chemo = 1),
+                         tvc_ce_terms = list(chemo = 2),
+                         cluster = "id",
+                         data = data)
```

# Mean Number of Events



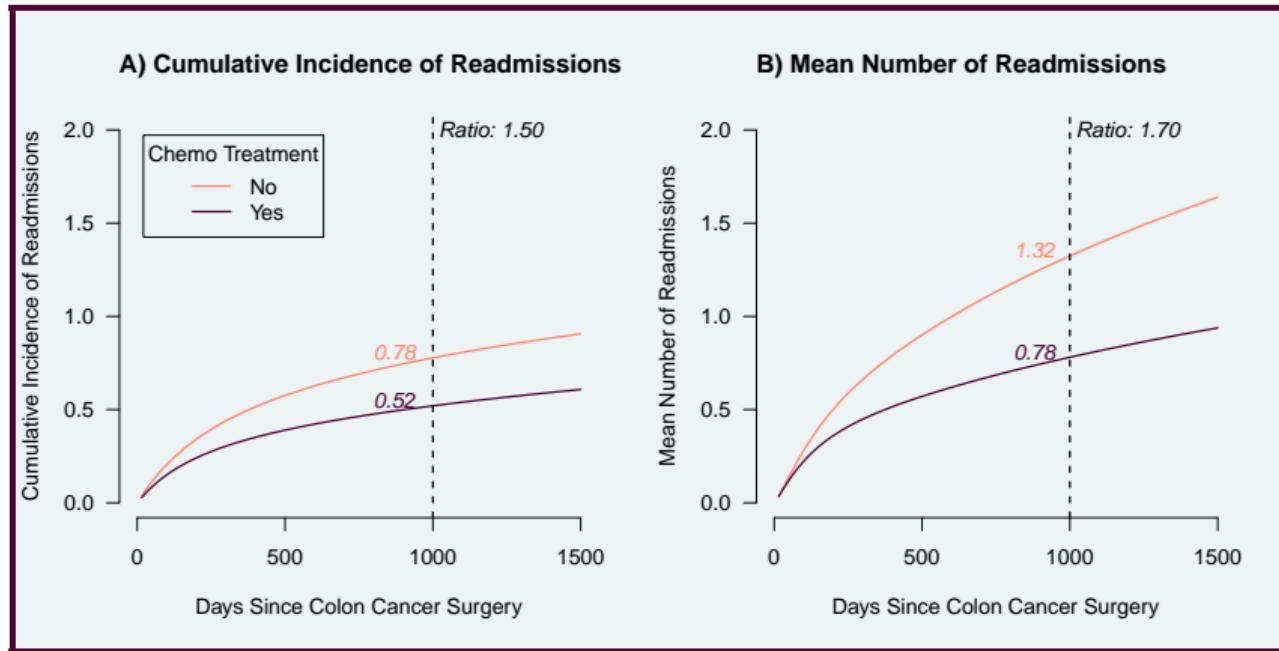
**Figure 3.** Mean number of hospital readmission after surgery for colon cancer, by chemotherapy treatment (A) and differences thereof (B).

# Standardised Mean Number of Events



**Figure 4.** Comparison of non-standardised and standardised estimates of the mean number of events after colon cancer surgery in patient treated and not treated with neoadjuvant chemotherapy.

# Comparison of CIF and Mean Number of Events



**Figure 5.** Comparison of the CIF of hospitalisation (A) with the mean number of hospitalisation (B).

# Discussion

## Strengths:

- ▶ Easy estimation of functions of  $\mathbb{E}[N(t)]$
- ▶ Use of delta method for obtaining confidence intervals
- ▶ Possibility obtaining standardised estimates

## Limitations

- ▶ Summary measure of the recurrent event process
- ▶ So far limited to one competing event
- ▶ Computationally intensive



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Link to the presentation slides