

# PERSUADE BC\_OS

2025-08-26

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[Link to PERSUADE GitHub page](#)

## 1. Kaplan-Meier

The Kaplan–Meier (KM) curves provide a non-parametric estimate of the survival function, based solely on the observed data, without assuming any particular hazard shape or distribution. These plots allow visual comparison of survival experience between groups, highlighting differences in survival patterns and potential crossing of curves, which may later inform the choice of stratified vs. non-stratified models (see Section 2). The accompanying table summarises key KM estimates (e.g., median survival, survival probabilities at selected time points). These observed data serve as the benchmark against which all parametric, spline-based, and cure model fits will be assessed.

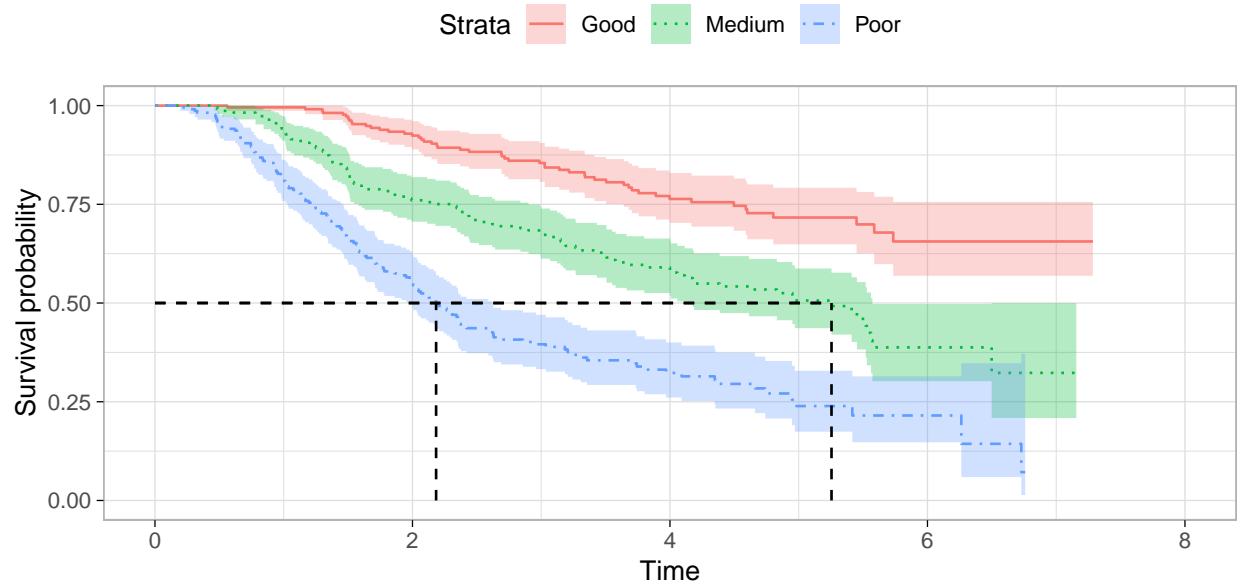


Table 1: Observed survival data

	records	n.max	n.start	events	rmean	se(rmean)	median	0.95LCL	0.95UCL
group=Good	229	229	229	51	5.934330	0.1616003	NA	NA	NA
group=Medium	229	229	229	103	4.600852	0.1856699	5.254795	4.115068	5.572603
group=Poor	228	228	228	145	3.101736	0.1772520	2.183562	1.978082	2.619178

## 2. Proportional hazards assumption

### Should stratified parametric survival models be used?

To decide whether stratified or non-stratified parametric survival models should be applied, it is important to assess whether the **proportional hazards (PH) assumption** holds. This assumption means that the hazard ratio between two (or more) groups remains constant over time.

- **If the PH assumption holds:** Non-stratified parametric models can be used, with group effects included as covariates in a single model.
- **If the PH assumption does not hold:** It is advised to fit separate (stratified) parametric survival models for each group.

This section presents plots for assessing the PH assumption **over the observed data period only**. Even if the PH assumption appears valid here, it might be violated beyond the observed follow-up. For further details, see [NICE DSU TSD 14](#).

### How to interpret the figures:

- **Figure A** plots the log of time against the log of the cumulative hazard for each group. Parallel lines suggest that the PH assumption holds.
- **Figures B and C** show scaled Schoenfeld residuals over time, with a smoothed spline (cyan) overlaid. If the spline systematically deviates from a horizontal line, this suggests a time-varying covariate effect and a potential PH violation ([Grambsch & Therneau, 1994](#)).
- **Crossing survival curves** in the Kaplan–Meier plot (previous page) may also indicate that the PH assumption is not satisfied.

**Caution:** These diagnostics only apply to the observed data period. Towards the end of follow-up, results may be unreliable due to sparse data, so the tail of curves should be interpreted with care.

**A: LN(cumulative hazard)**



**B: Scaled Schoenfeld residuals**



**C: Scaled Schoenfeld residuals**



### 3. Hazard function

#### 3.1 Shape of the observed smoothed hazard function

The **hazard function** represents the instantaneous rate at which an event occurs at a specific time, conditional on survival until that time. Its shape varies depending on the assumed distribution (parametric survival model). When selecting an appropriate model, the plausibility of different hazard function shapes should be considered in light of:

- The shape of the *observed* hazard function (shown below).
- Known hazard shapes from standard parametric models (see Table).
- Relevant *external data* (not shown here).

Below is an overview of the potential hazard shapes for standard parametric survival models:

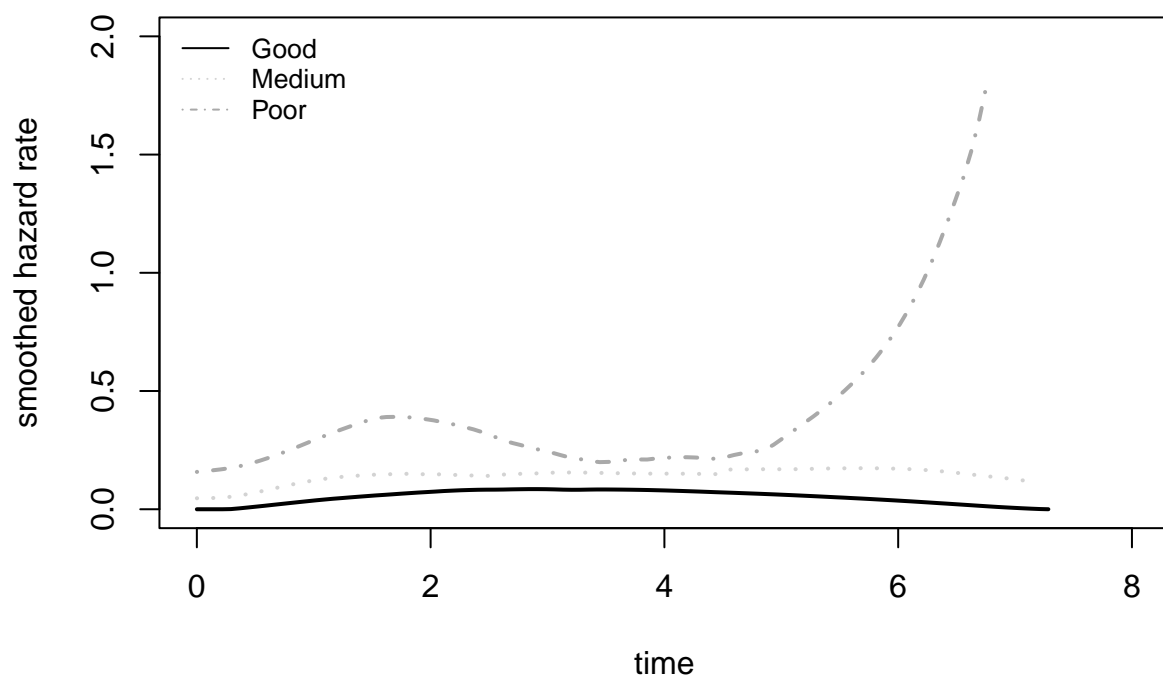
No	Distribution	Hazard function shape
1	Exponential	Constant hazard
2	Weibull	Monotonically increasing or decreasing hazards
3	Gompertz	Monotonically increasing or decreasing hazards
4	Log-normal	Arc-shaped or monotonically decreasing hazards
5	Log-logistic	Arc-shaped or monotonically decreasing hazards
6	Gamma	Monotonically increasing or decreasing hazards
7	Generalised Gamma	Arc-shaped, bathtub-shaped, monotonically increasing, or monotonically decreasing

Because **spline-based** and **(non-)mixture cure models** are derived from these standard parametric forms, their hazard functions can be interpreted in relation to the table above.

- For **spline-based models** using the *hazard scale*, the baseline hazard is Weibull, so hazards are monotonic within each spline segment (between knots).
- For **spline-based models** using the *odds scale* (log-logistic) or *normal scale* (log-normal), the baseline hazard follows the corresponding parametric form.
- For **(non-)mixture cure models**, the hazard shape applies separately to the cure and non-cure fractions.

For more details and visualisations of hazard function shapes across parametric survival models, see [Incerti \(2019\)](#).

**Caution:** These plots apply only to the *observed* data period and cannot directly inform the hazard shape beyond this range. Additionally, hazard estimates near the end of follow-up may be unstable due to sparse data. Interpret the tails of the curves with care.



### 3.2 Shape of the predicted hazard function

The following plots show how the hazard rate is estimated under each fitted parametric survival model. These curves reflect the model-based *predicted* hazard functions over time, which may extend beyond the observed data period (see *Extrapolation Section*). By comparing these predicted hazard shapes, together with the known hazard function form for each parametric model, to:

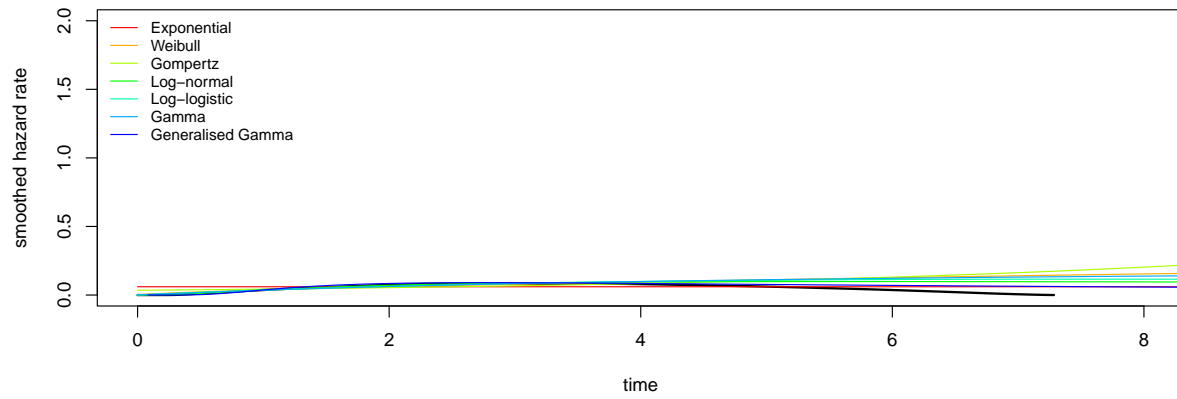
- The **observed smoothed hazard functions**, and
- Prior knowledge or external evidence on plausible hazard behaviour,

you can assess whether each model's functional form provides a reasonable representation and extrapolation of the underlying event process.

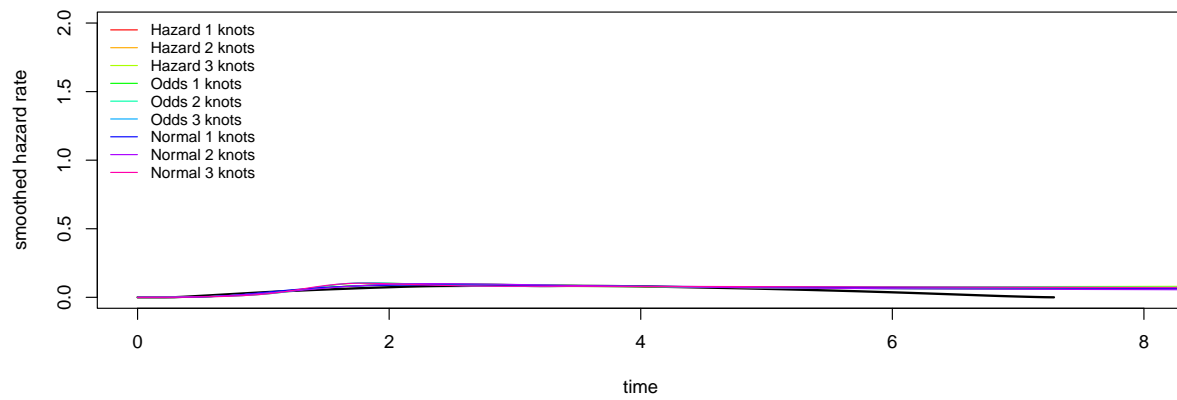


## 4 Parametric survival models

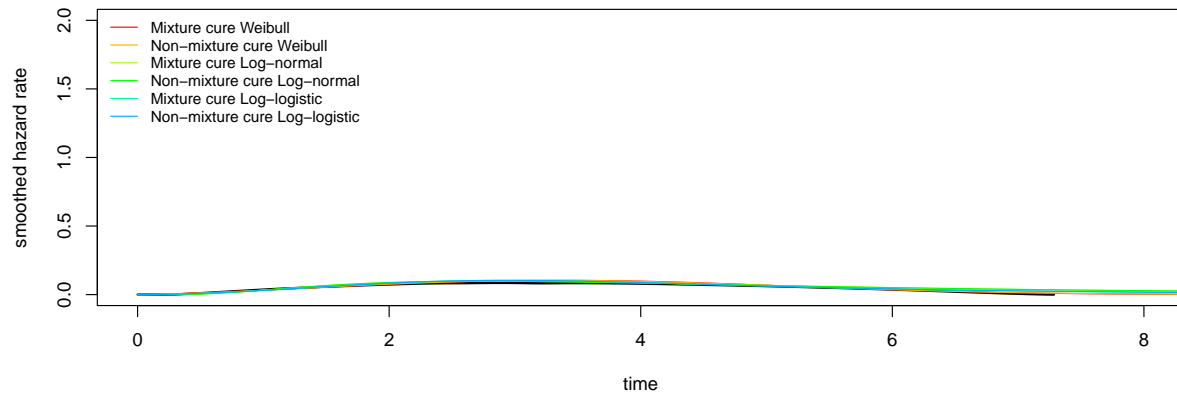
Standard parametric models, Group: Good



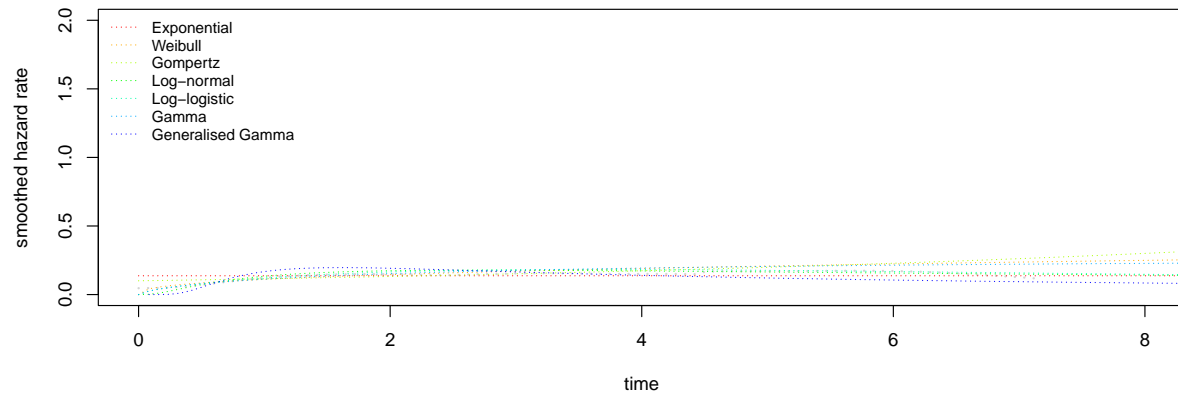
Spline models, Group: Good



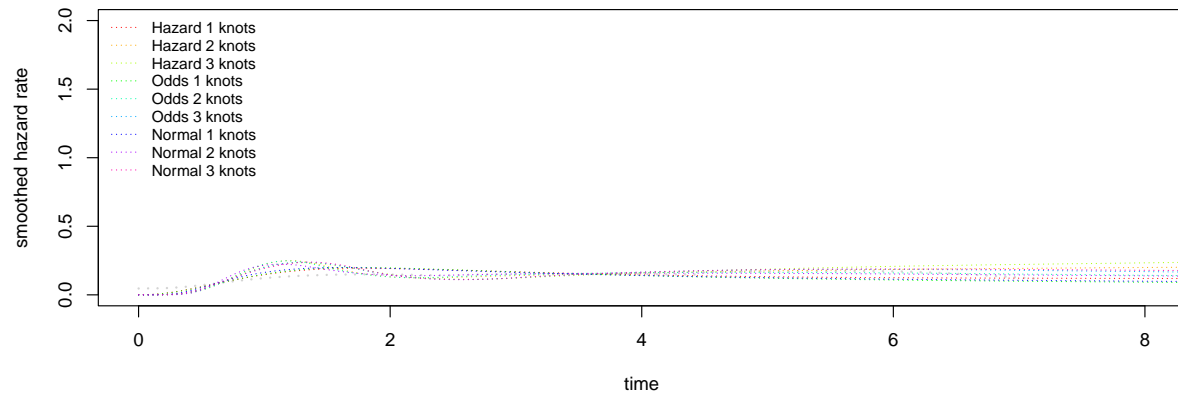
Cure models, Group: Good



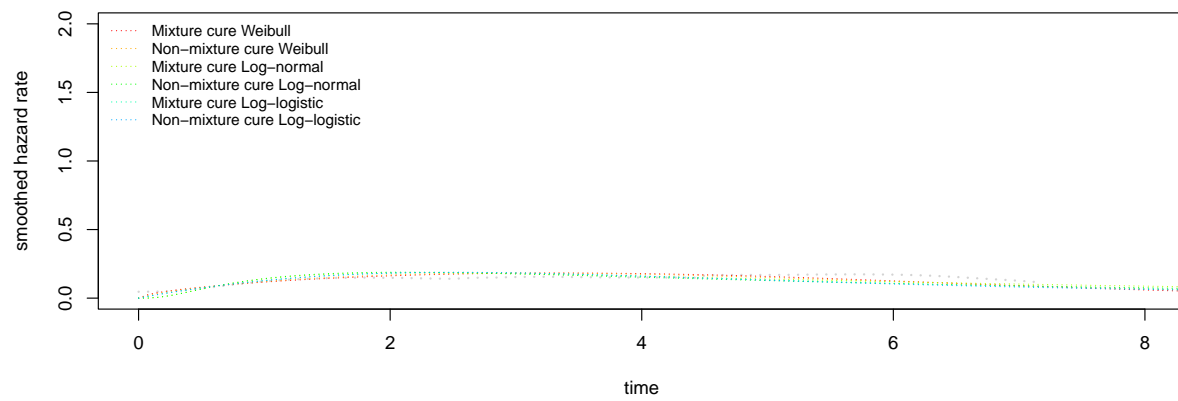
Standard parametric models, Group: Medium



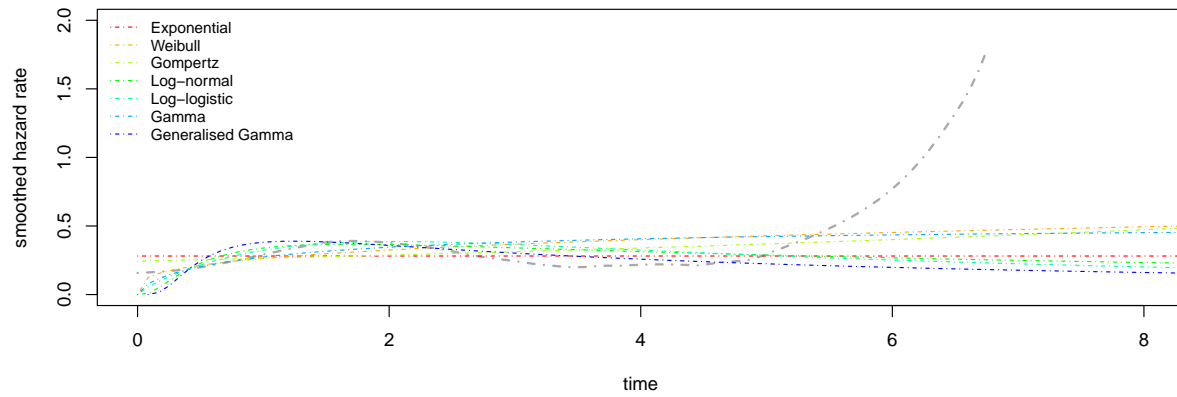
Spline models, Group: Medium



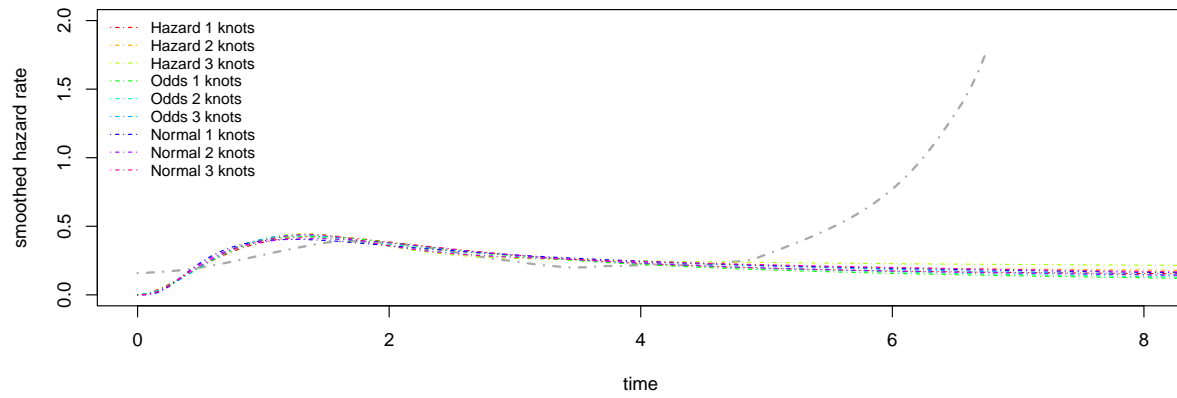
Cure models, Group: Medium



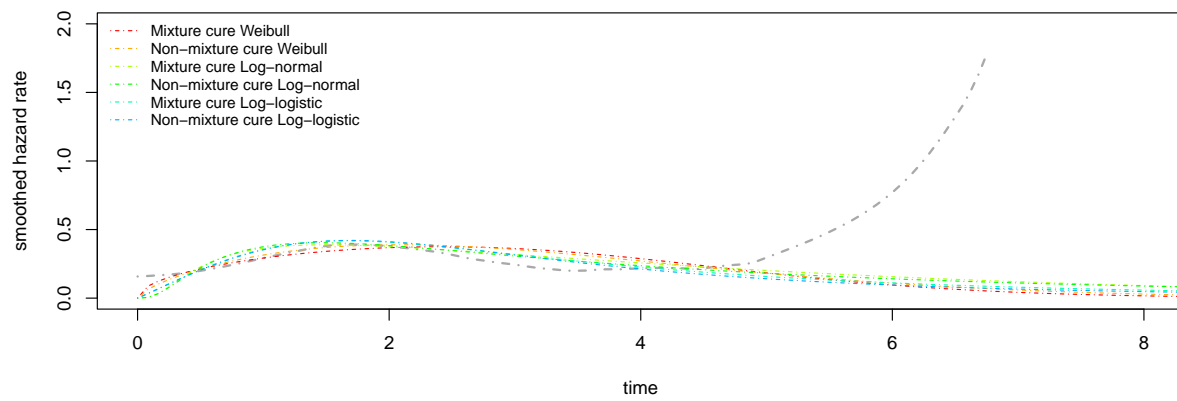
Standard parametric models, Group: Poor



Spline models, Group: Poor



Cure models, Group: Poor



## 4.1 Standard parametric models

The Table below displays the goodness-of-fit statistics for each parametric survival model, ordered from ‘best’ fitting to less well fitting based on the Akaike Information Criterion (AIC). The AIC and Bayesian Information Criterion (BIC) provide a measure of the relative fit of each model to the observed data, while penalising for the number of parameters included in the fitted models. The lower the AIC or BIC, the better the relative fit of a model compared to other fitted models.

### Rules of thumb for model selection:

- **Burnham and Anderson** (1998) suggest that models with an AIC within 4 points of the lowest AIC can be considered as having substantial support from the data [Burnham and Anderson, 1998](#).
- **Raftery** (1995) suggests that models with a BIC within 2 points of the lowest BIC can be considered the best-fitting models [Raftery et al., 1995](#).

In the following pages, three plots per fitted parametric survival model are displayed to support visual inspection of the fit of the models to the observed data:

- **Figure A:** Kaplan–Meier curves (black and grey) versus fitted parametric survival models (colour).
- **Figure B:** Diagnostic plot specific to each fitted parametric survival model (see graphical test in Table 1 of [Ishak et al., 2013](#)).
- **Figure C:** Comparison of smoothed hazard rates based on empirical data (black and grey) versus estimated transition probabilities (colour).

In Figures A and C, the Kaplan–Meier curves and smoothed hazard rates are identical across models; only the coloured fitted curves change.

The guiding rule is: the closer the coloured lines are to the black and grey lines, the better the fit.

Notably:

- Weibull (shape = 1), Gompertz (shape = 0) and gamma (shape = 1) distributions simplify to the exponential distribution.
- The generalised gamma distribution simplifies to:
  - Log-normal ( $Q = 0$ )
  - Weibull ( $Q = 1$ )
  - Exponential ( $Q = 1$  and scale = 1)
  - Gamma ( $Q = \text{scale}$ )

Information regarding parameterisation of parametric survival models can be found [here](#).

### CAUTION:

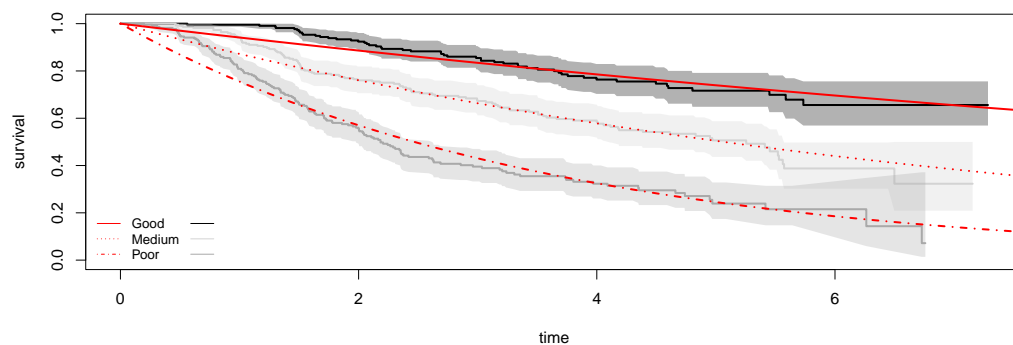
These goodness-of-fit statistics apply only to the *observed* data period. They do not indicate the suitability of extrapolated survival beyond this period. Additionally, the tail of the observed data period may be affected by a low number of observations, which should be considered when interpreting model performance.

Table 3: Goodness of fit statistics

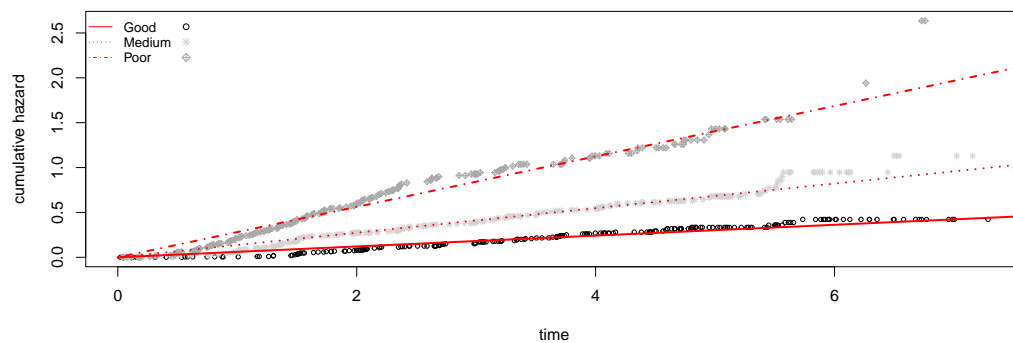
Model	AIC	BIC
Generalised Gamma	1589.049	1629.826
Log-normal	1592.880	1620.066
Log-logistic	1609.294	1636.479
Gamma	1621.982	1649.167
Weibull	1632.618	1659.803
Gompertz	1660.954	1688.140
Exponential	1668.212	1681.805

## Exponential

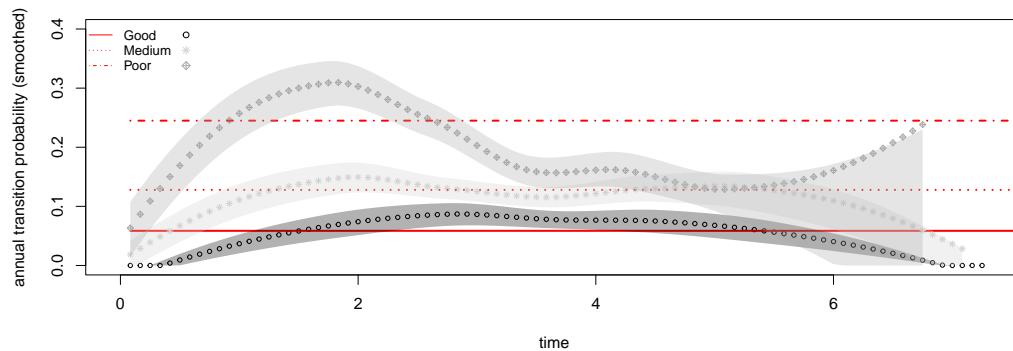
A: Kaplan–Meier (Exponential)



B: Diagnostic plot (Exponential)

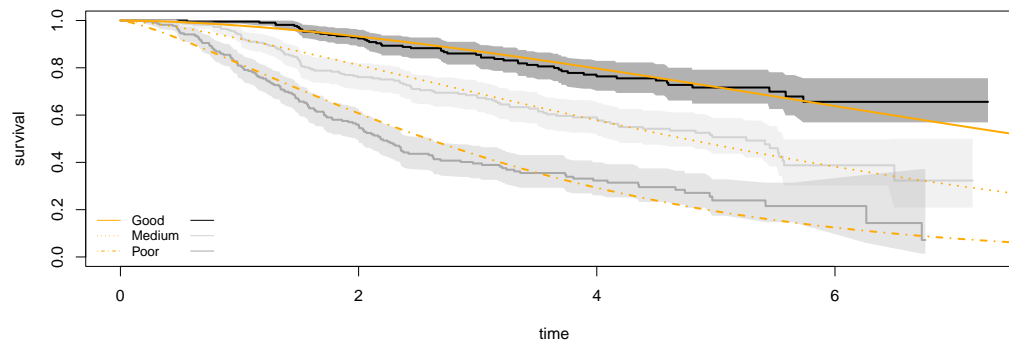


C: Annual transition probability (Exponential)

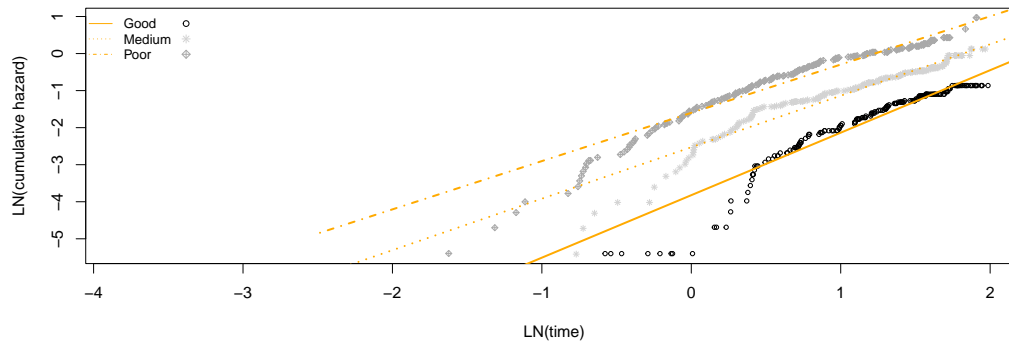


## Weibull

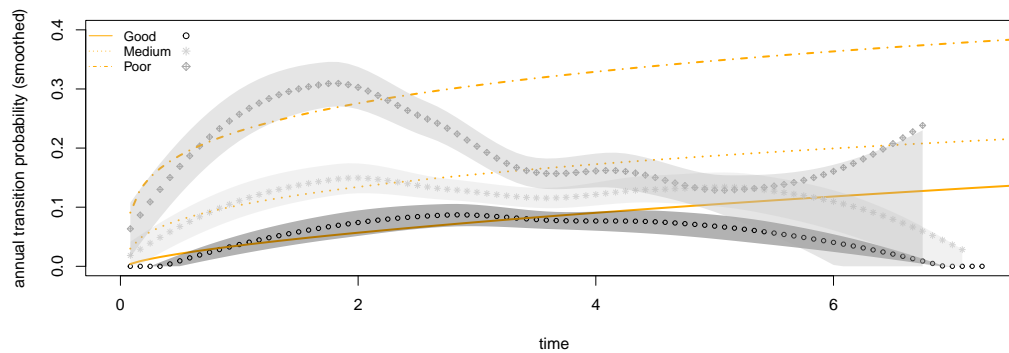
**A: Kaplan–Meier (Weibull)**



**B: Diagnostic plot (Weibull)**

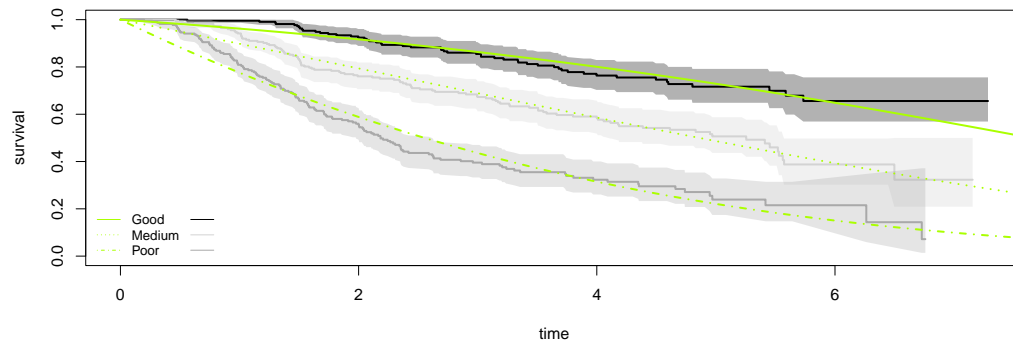


**C: Annual transition probability (Weibull)**

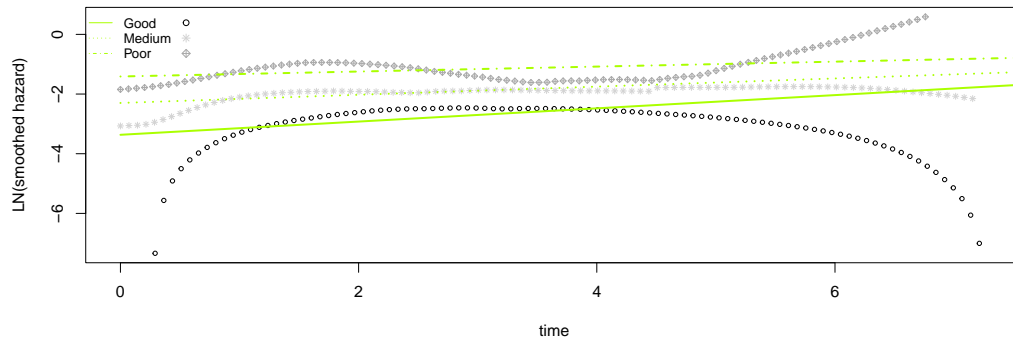


## Gompertz

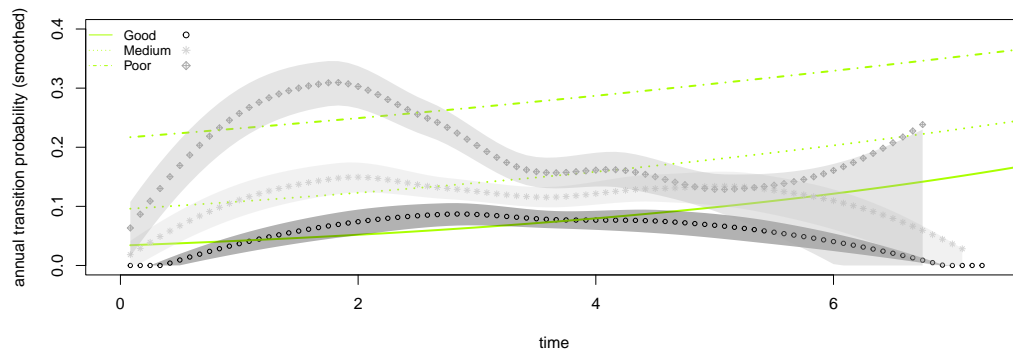
A: Kaplan-Meier (Gompertz)



B: Diagnostic plot (Gompertz)

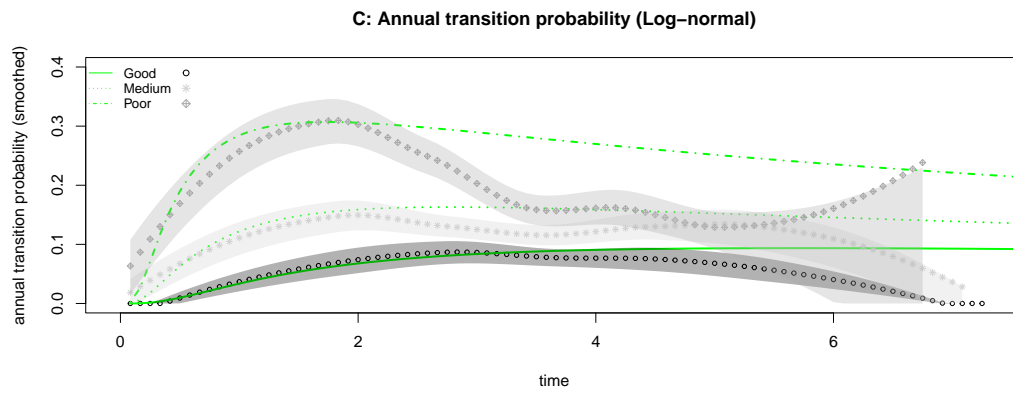
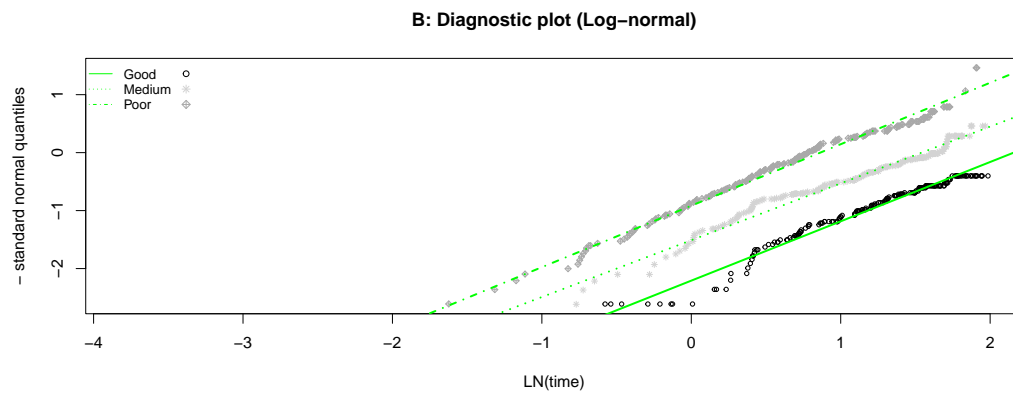
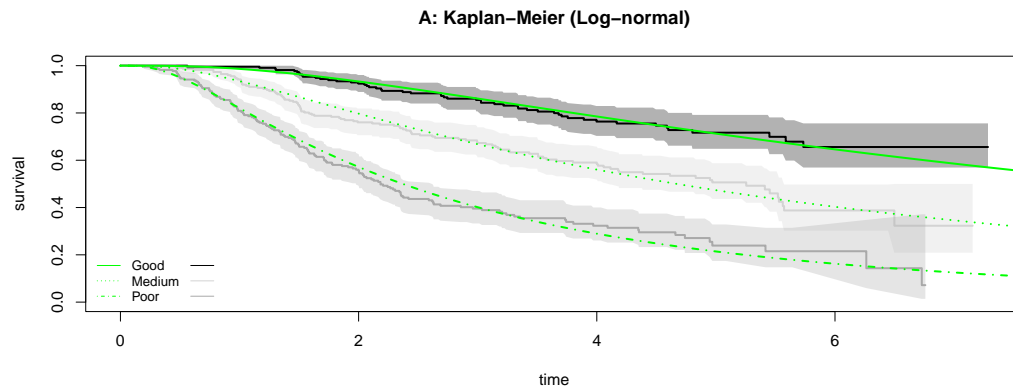


C: Annual transition probability (Gompertz)



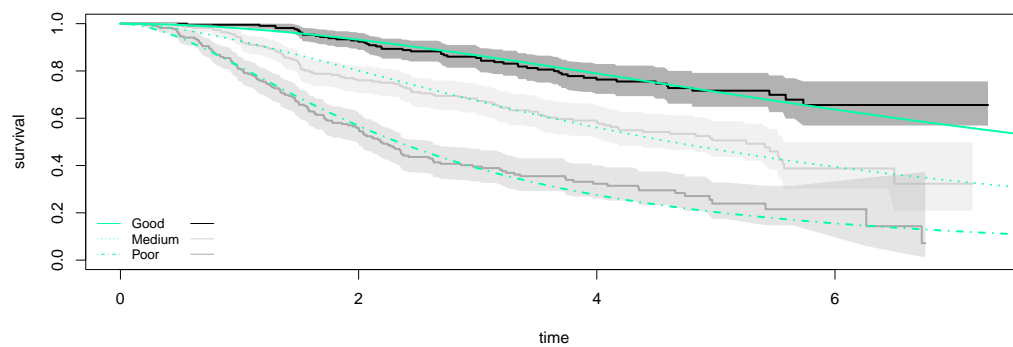


## Log-normal

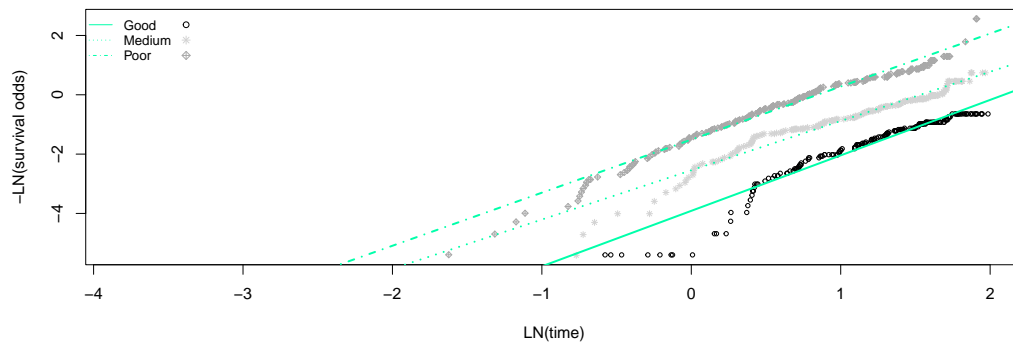


## Log-logistic

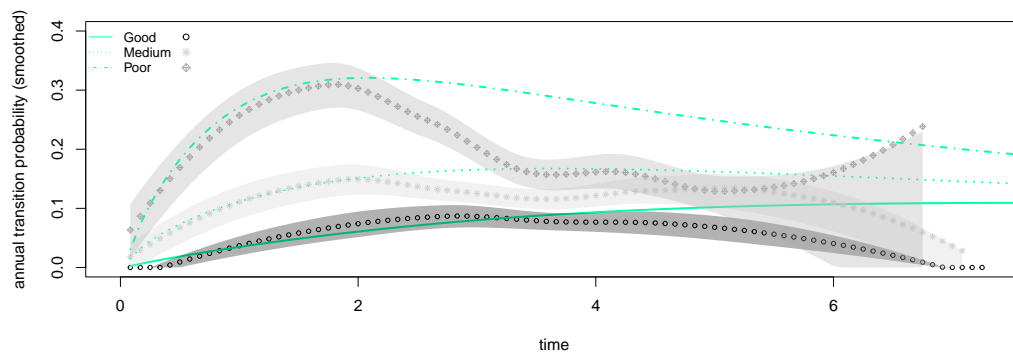
A: Kaplan-Meier (Log-logistic)



B: Diagnostic plot (Log-logistic)

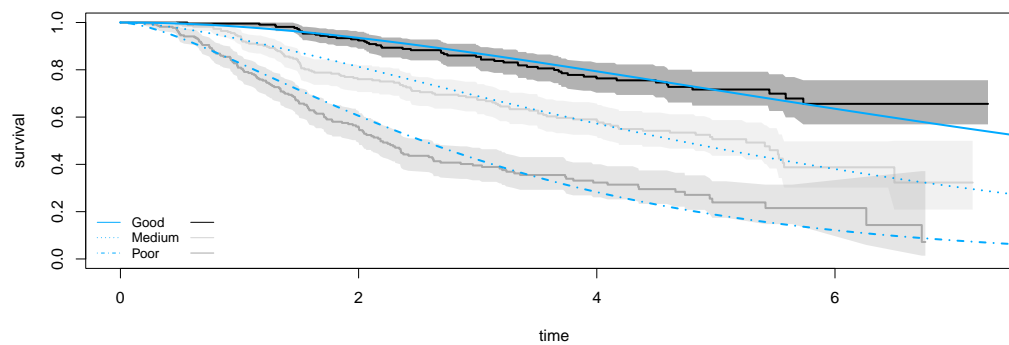


C: Annual transition probability (Log-logistic)

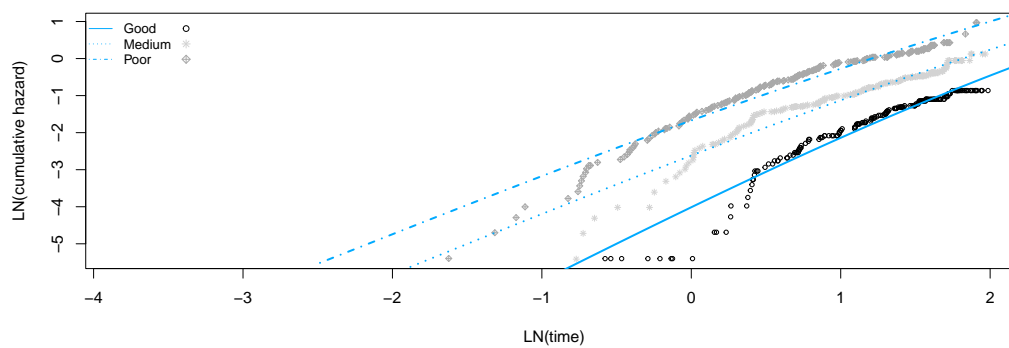


## Gamma

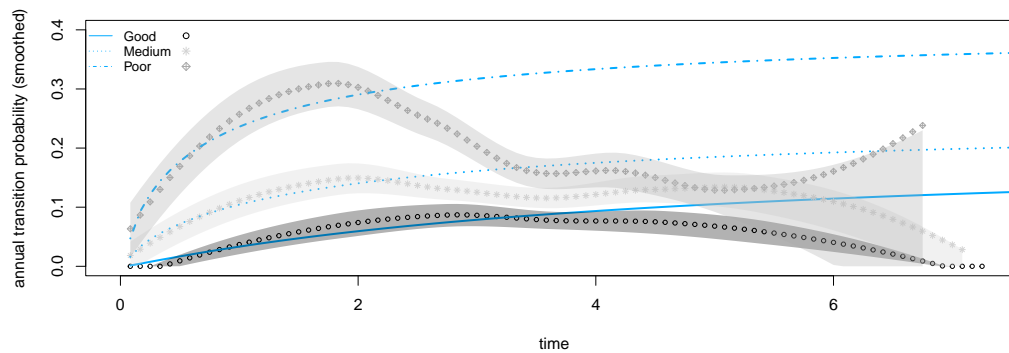
A: Kaplan-Meier (Gamma)



B: Diagnostic plot (Gamma)

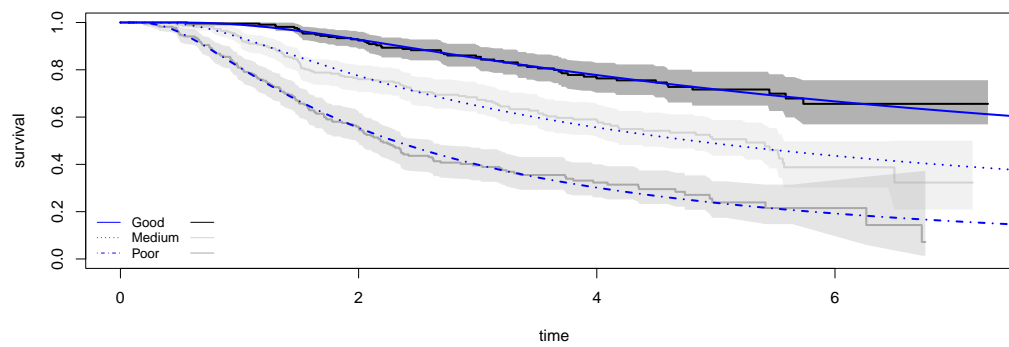


C: Annual transition probability (Gamma)

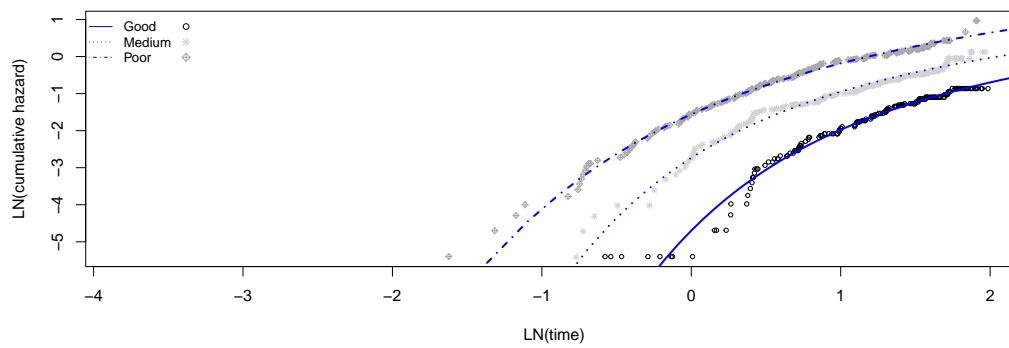


## Generalised Gamma

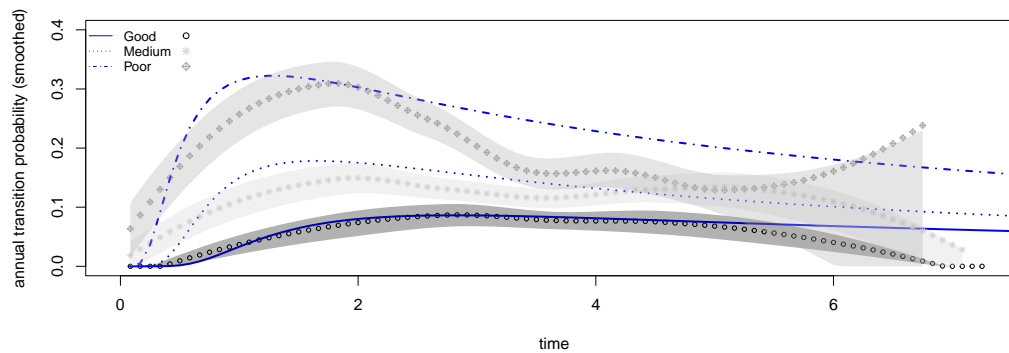
A: Kaplan–Meier (Generalised Gamma)



B: Diagnostic plot (Generalised Gamma)



C: Annual transition probability (Generalised Gamma)



## 4.2 Parametric natural cubic spline models

If standard parametric models do not provide a satisfactory fit to the data (based on the visual assessments and goodness-of-fit statistics presented in the previous section or extrapolations presented in the next section), spline-based models may provide a more flexible alternative. An explanation of these natural cubic spline models, henceforth referred to as spline-based models, is provided in [Royston and Parmar \(2002\)](#).

### Model complexity and parsimony

Following the principle of *Occam's Razor* and the recommendations in [NICE TSD 21](#), the preferred approach is to select the simplest model (e.g., a standard parametric model) that provides an adequate fit to the data and clinically plausible extrapolations. However, when simpler models do not provide a satisfactory fit, particularly in terms of long-term extrapolations and consistency with external evidence, more flexible models, such as spline-based models, can be considered.

### Relationship to standard parametric models

Spline-based models extend standard parametric survival models by allowing the hazard, odds, or normal scale to vary flexibly over time:

- **Hazard scale** spline models extend the Weibull distribution.
- **Odds scale** spline models extend the log-logistic distribution.
- **Normal scale** spline models extend the log-normal distribution.

### Model assessment and rules of thumb

The same goodness-of-fit statistics (AIC and BIC) used in Section 4.1 are presented here, and the same *rules of thumb* apply:

- **Burnham & Anderson (1998)**: Models within 4 AIC points of the lowest AIC are considered to have substantial support from the data [Burnham and Anderson, 1998](#).
- **Raftery (1995)**: Models within 2 BIC points of the lowest BIC are considered among the best-fitting models [Raftery et al., 1995](#).

### Plots

As in Section 4.1, the following pages display three plots for each fitted spline-based survival model:

- **Figure A**: Kaplan–Meier curves (black and grey) versus the fitted spline model (colour).
- **Figure B**: Model-specific diagnostic plots (see [Ishak et al., 2013](#)).
- **Figure C**: Smoothed hazard rates from empirical data (black and grey) versus model-based estimates (colour).

### CAUTION:

These statistics and plots apply only to the *observed* data period and do not directly inform the appropriateness of extrapolations beyond this period.

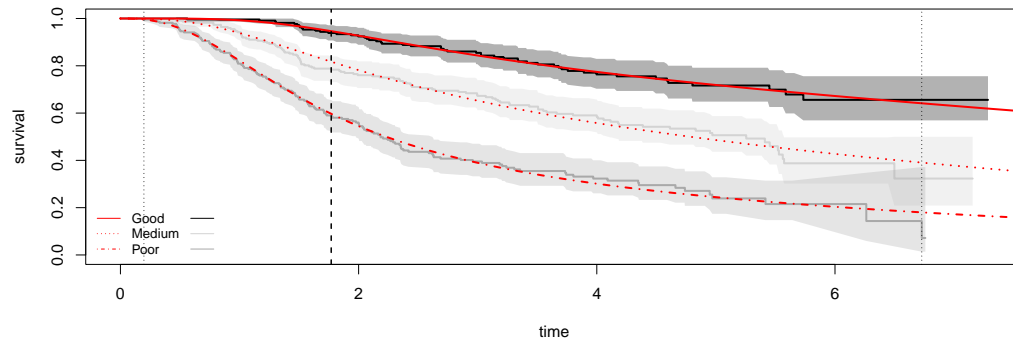
Additionally, the tail of the observed data may be affected by a low number of events, which should be considered when interpreting model performance.

Table 4: Goodness of fit statistics (including standard parametric and spline models)

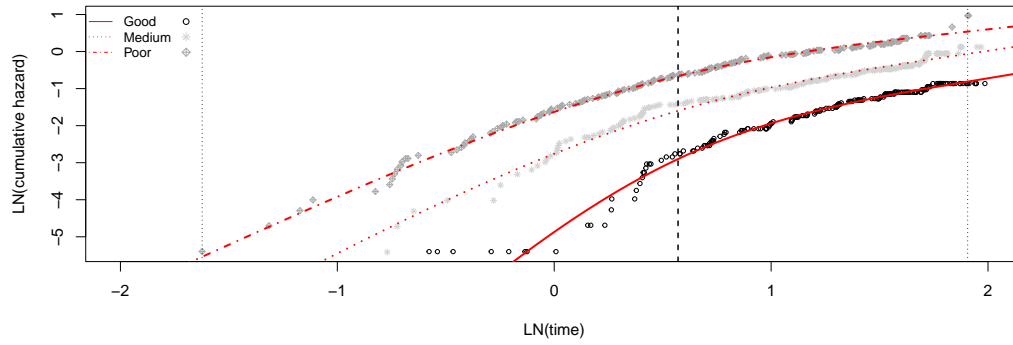
Model	AIC	BIC
Hazard 2 knots	1585.894	1640.264
Odds 2 knots	1587.289	1641.659
Normal 1 knots	1587.682	1628.460
Normal 2 knots	1588.344	1642.714
Generalised Gamma	1589.049	1629.826
Hazard 1 knots	1589.327	1630.105
Normal 3 knots	1589.832	1657.795
Hazard 3 knots	1589.875	1657.838
Odds 1 knots	1590.221	1630.999
Odds 3 knots	1590.718	1658.681
Log-normal	1592.880	1620.066
Log-logistic	1609.294	1636.479
Gamma	1621.982	1649.167
Weibull	1632.618	1659.803
Gompertz	1660.954	1688.140
Exponential	1668.212	1681.805

## Hazard 1 knots

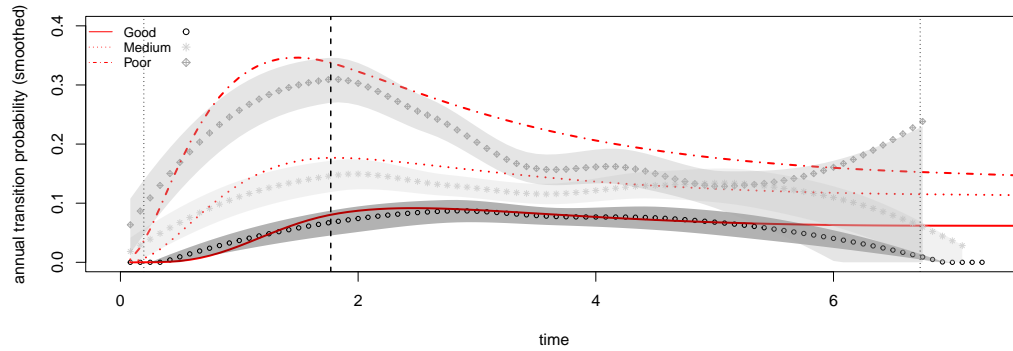
A: Kaplan–Meier (Hazard 1 knots)



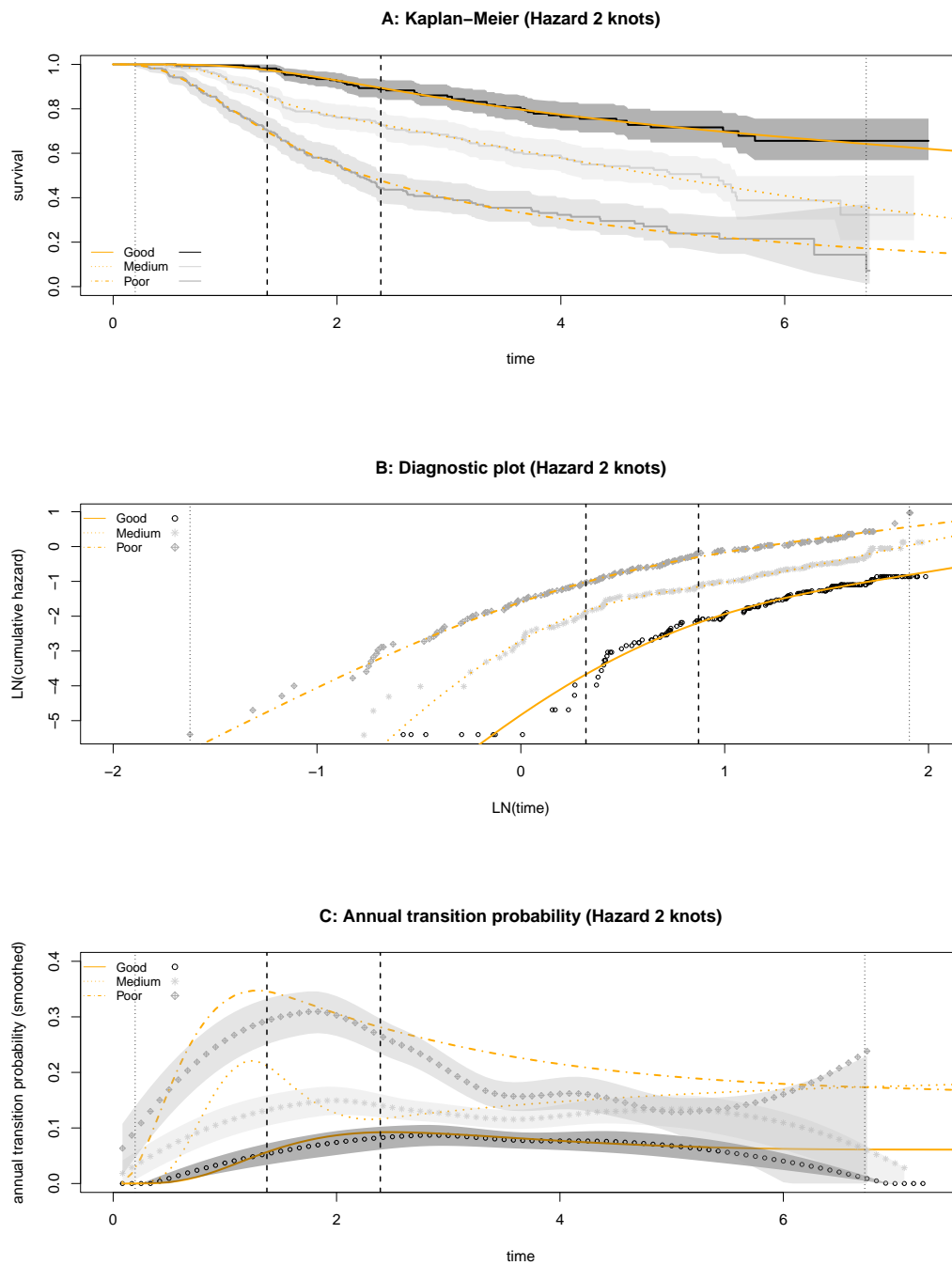
B: Diagnostic plot (Hazard 1 knots)



C: Annual transition probability (Hazard 1 knots)



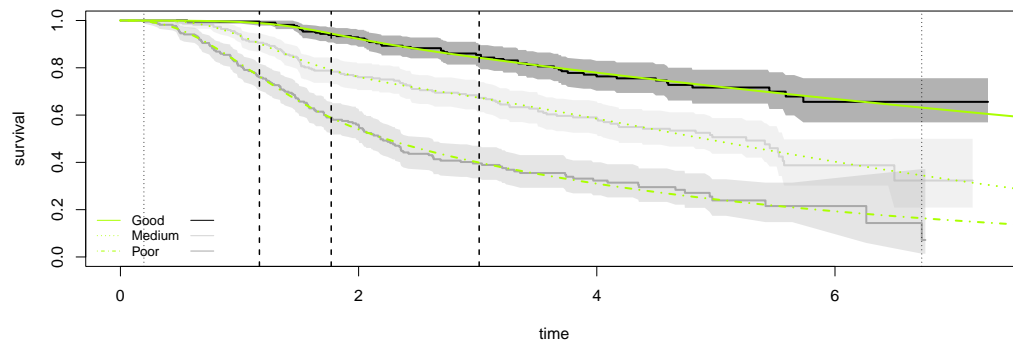
## Hazard 2 knots



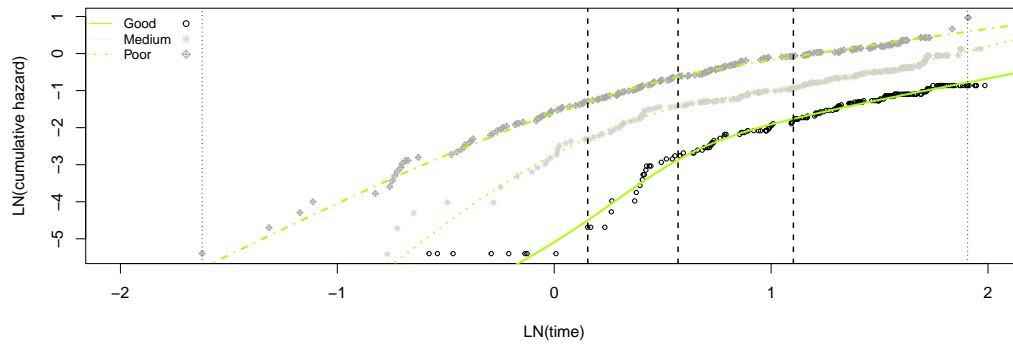


## Hazard 3 knots

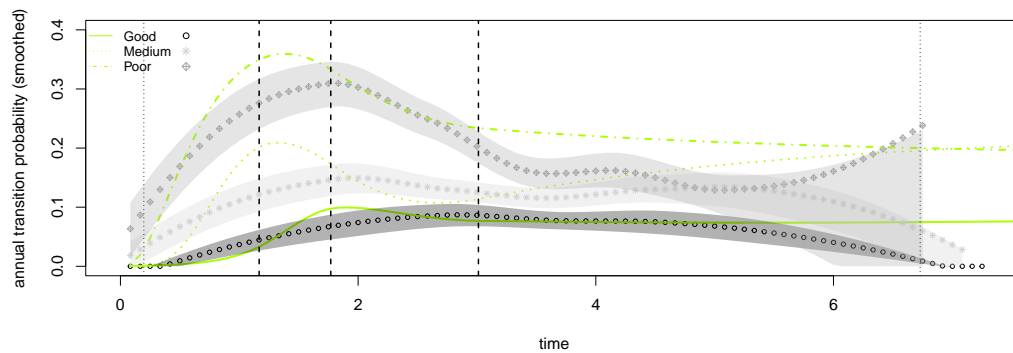
A: Kaplan-Meier (Hazard 3 knots)



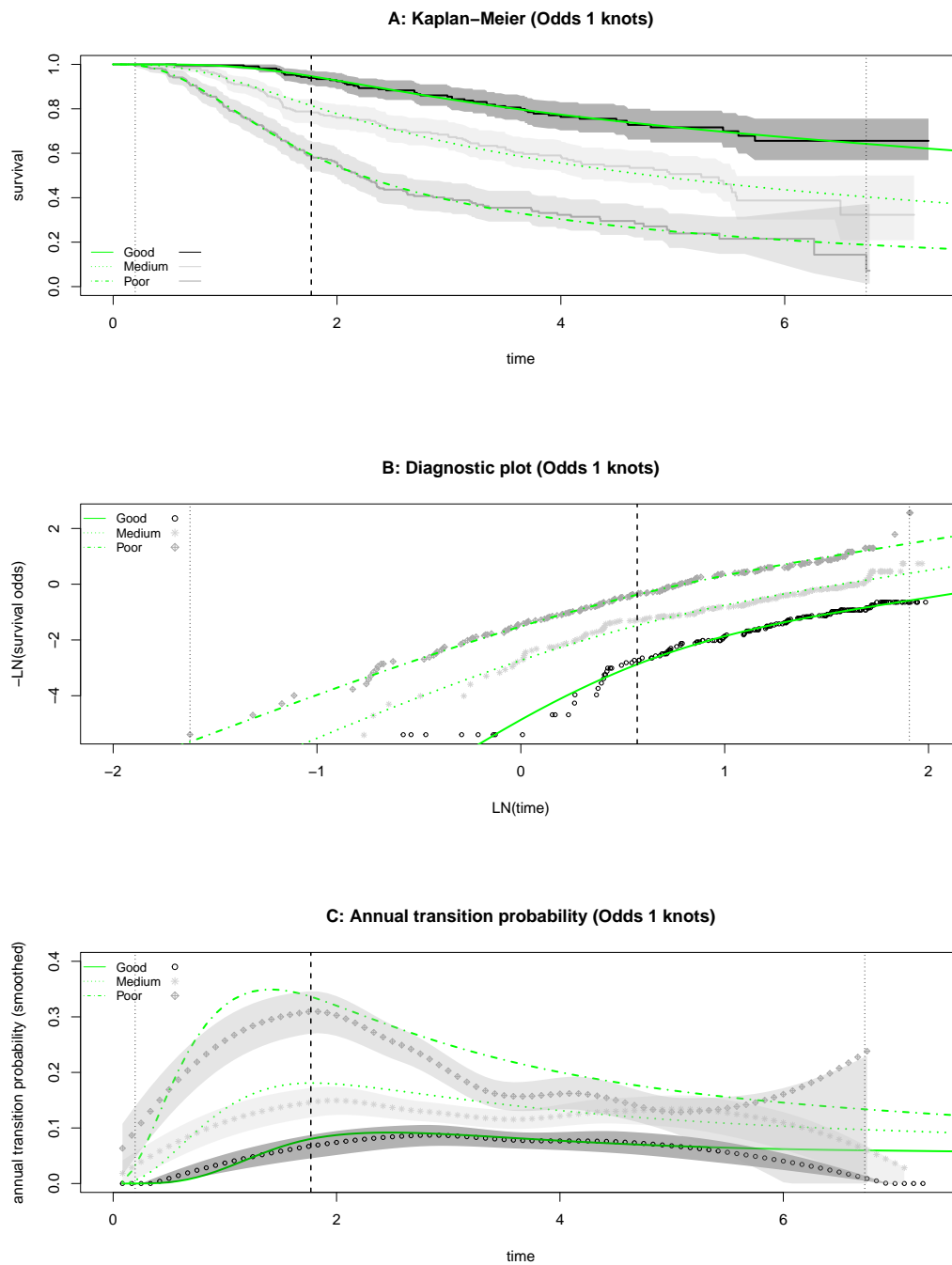
B: Diagnostic plot (Hazard 3 knots)



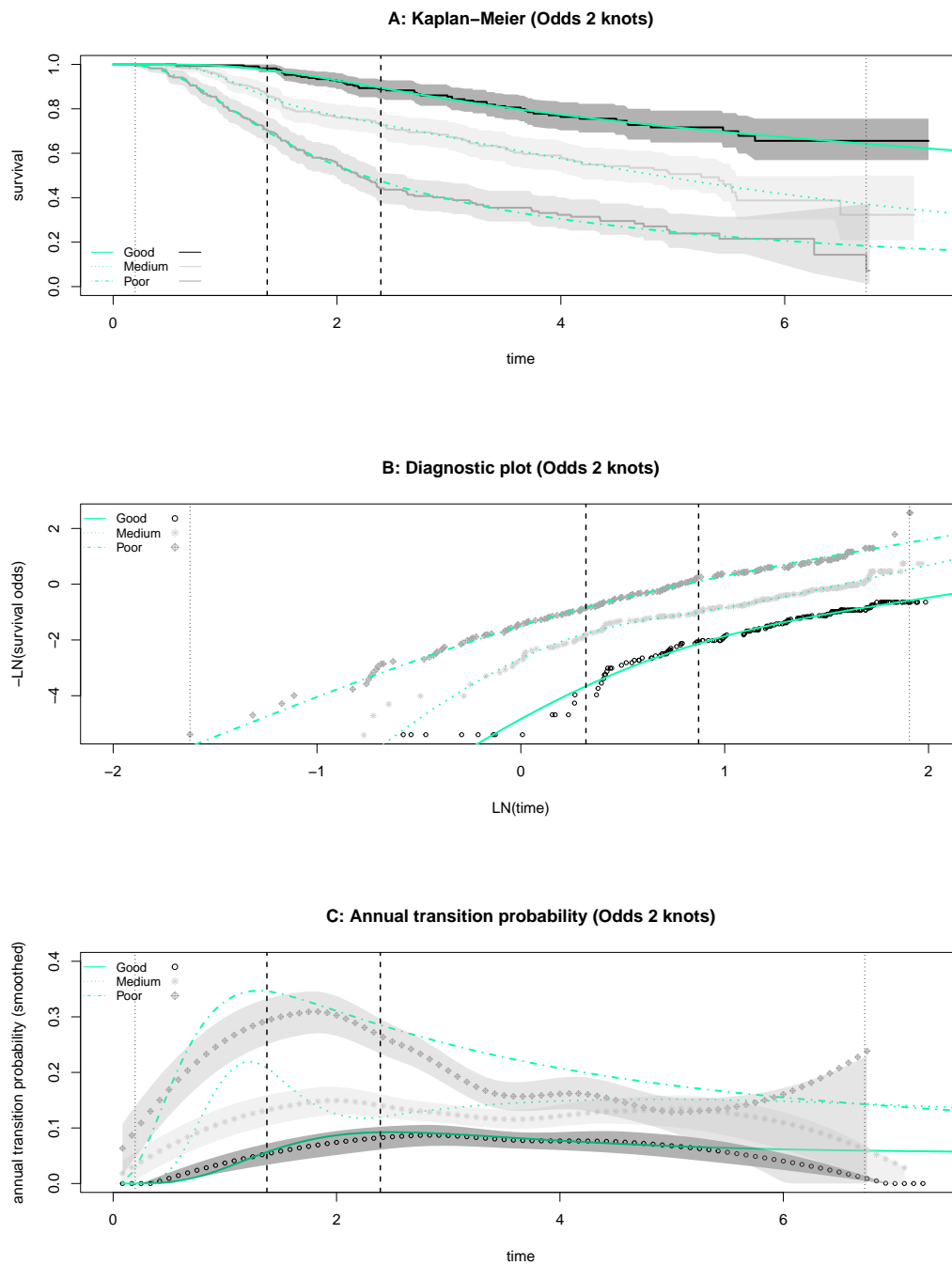
C: Annual transition probability (Hazard 3 knots)



## Odds 1 knots

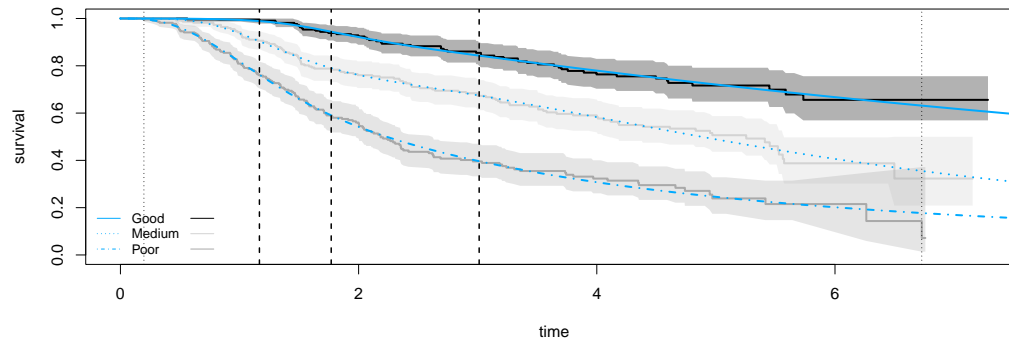


## Odds 2 knots

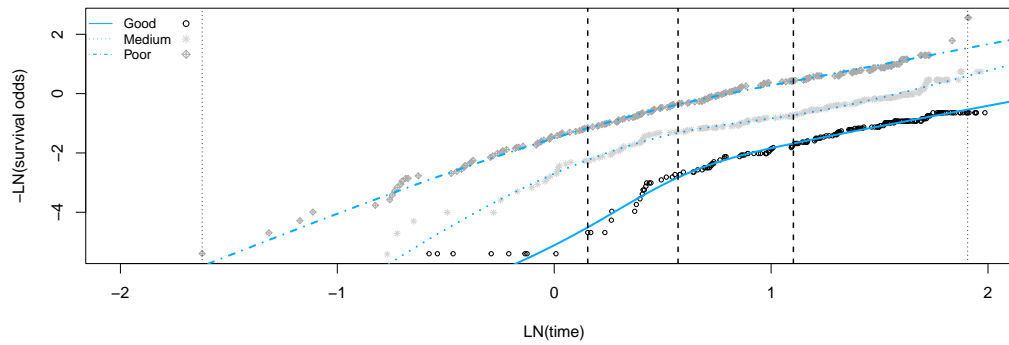


## Odds 3 knots

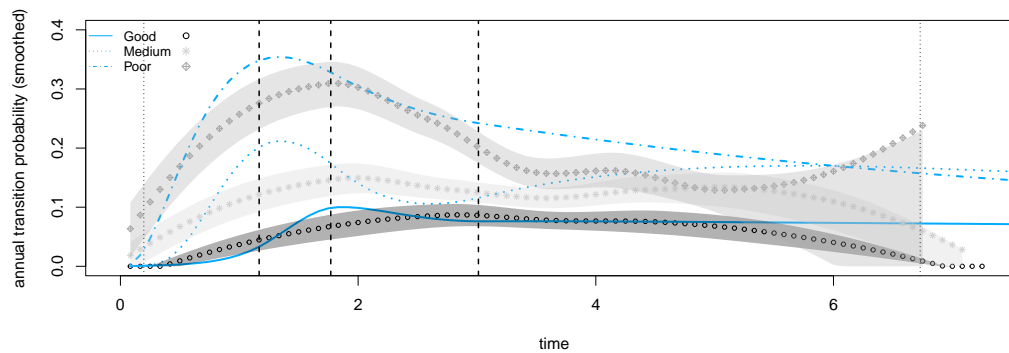
A: Kaplan-Meier (Odds 3 knots)



B: Diagnostic plot (Odds 3 knots)

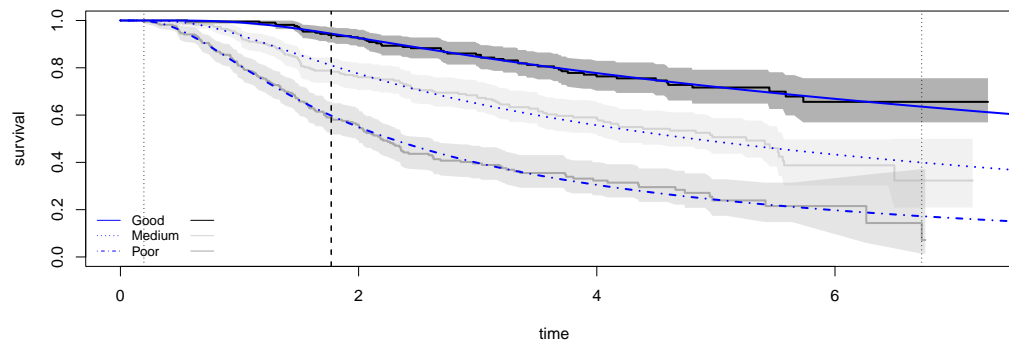


C: Annual transition probability (Odds 3 knots)

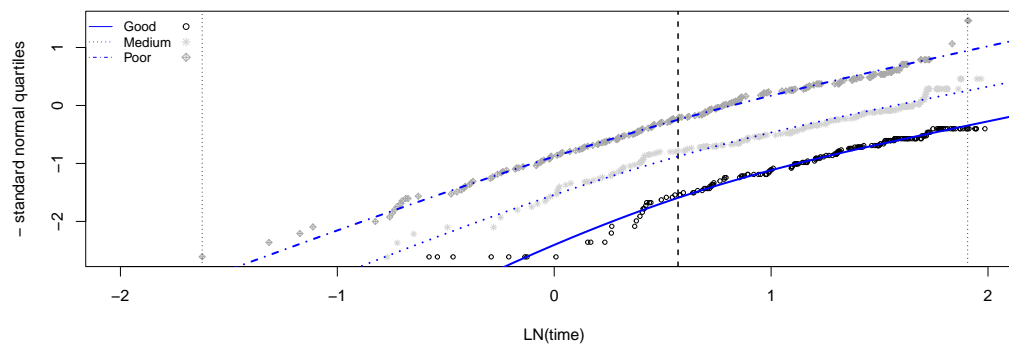


## Normal 1 knots

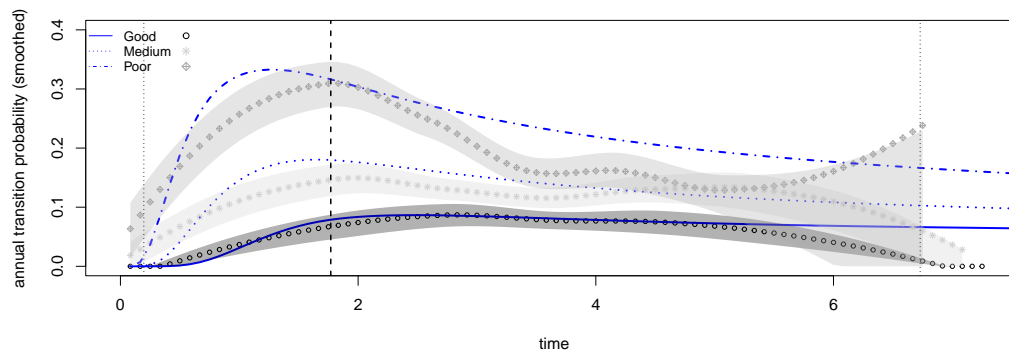
**A: Kaplan–Meier (Normal 1 knots)**



**B: Diagnostic plot (Normal 1 knots)**

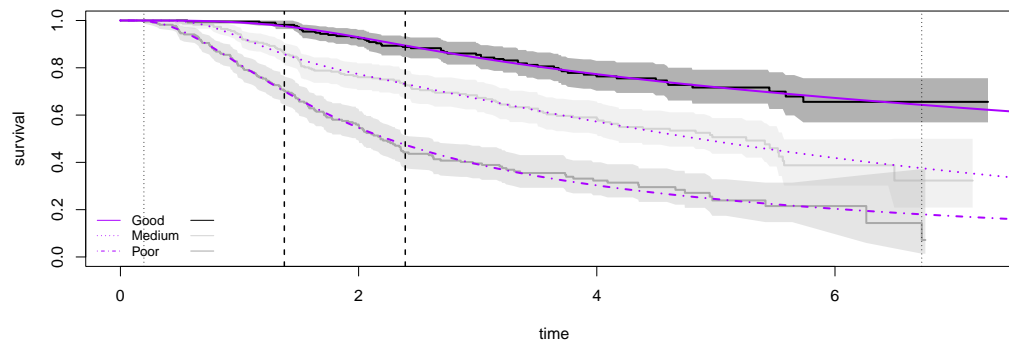


**C: Annual transition probability (Normal 1 knots)**

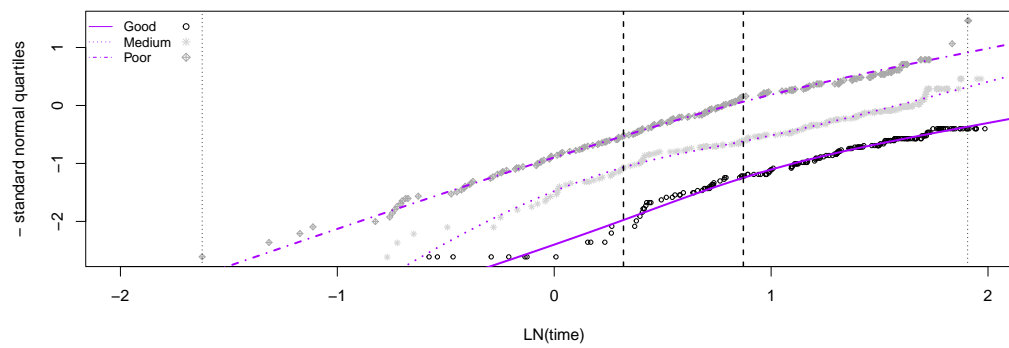


## Normal 2 knots

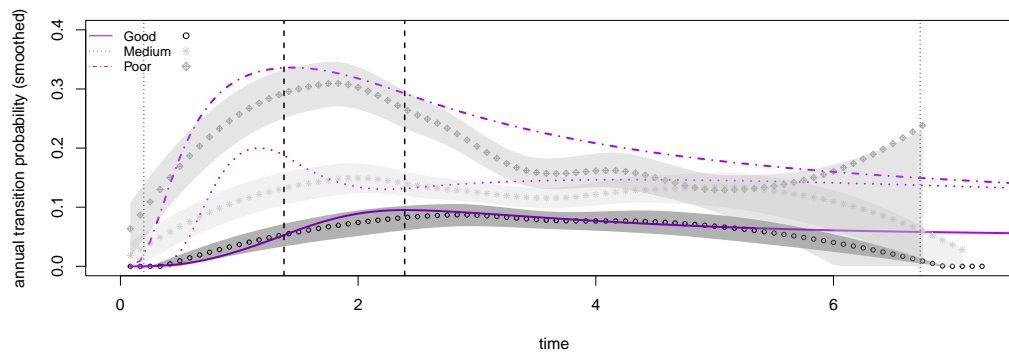
A: Kaplan–Meier (Normal 2 knots)



B: Diagnostic plot (Normal 2 knots)

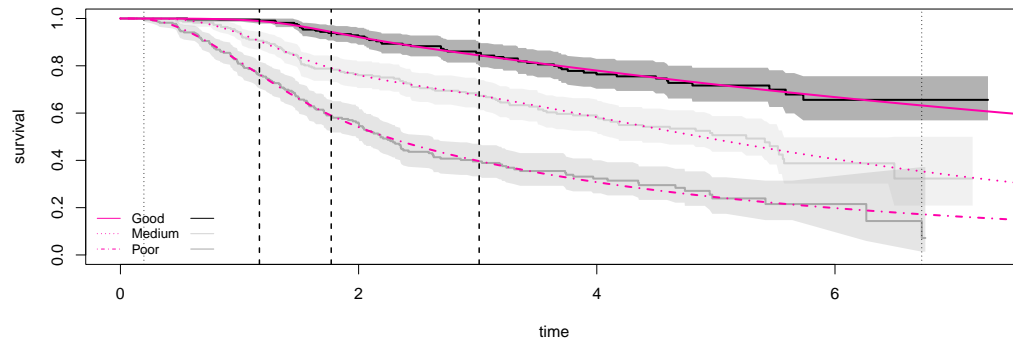


C: Annual transition probability (Normal 2 knots)

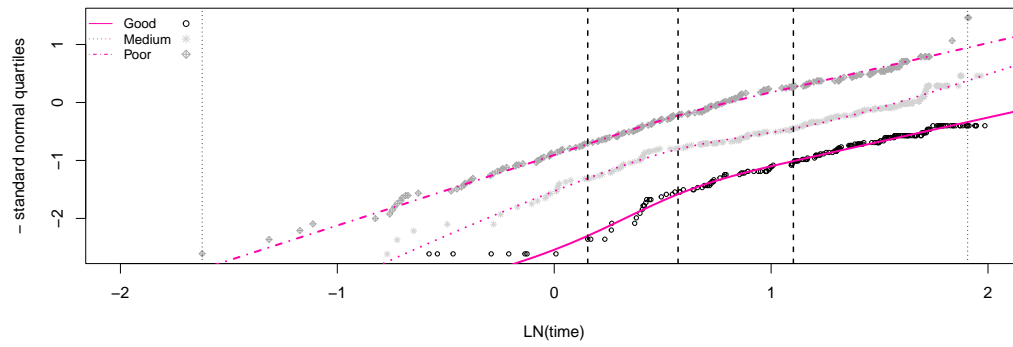


## Normal 3 knots

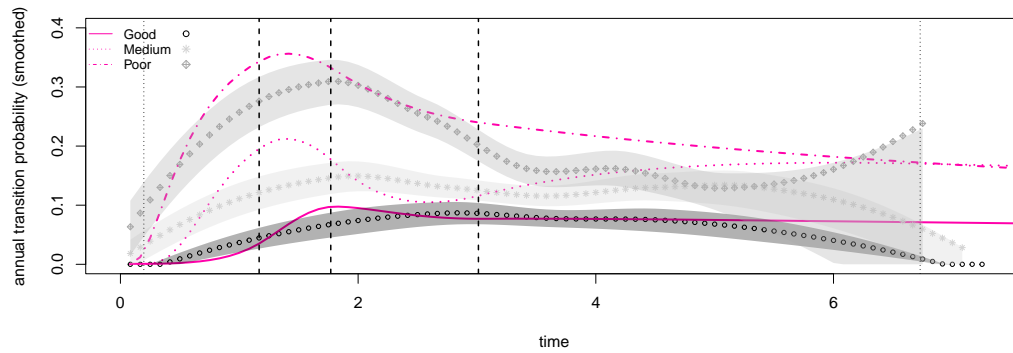
**A: Kaplan–Meier (Normal 3 knots)**



**B: Diagnostic plot (Normal 3 knots)**



**C: Annual transition probability (Normal 3 knots)**



### 4.3 Parametric (non-)mixture cure models

In some disease areas, a proportion of patients may be considered “cured,” meaning they have the same mortality risk as the general population (or a background hazard). Cure models explicitly allow for this possibility and estimate both the cure fraction and the survival of the uncured fraction.

- *Mixture cure models*: Assume the population is composed of a cured fraction and an uncured fraction, each with its own survival curve. The overall survival curve is a weighted mixture of the two. This means the survival curve approaches a horizontal asymptote at the estimated cure fraction.
- *Non-mixture cure models*: Directly model the hazard function so that it approaches zero over time for the cured fraction, without explicitly separating the two subpopulations in the survival function.

Both approaches can be fitted using standard parametric distributions (i.e., Weibull, log-normal or log-logistic).

The *link function* relates the linear predictor to the estimated cure fraction.

The most commonly used link function is the *logistic*, but others are available:

- "logistic": Ensures the cure fraction is between 0 and 1 via the logistic transformation.
- "loglog": Uses the complementary log-log link, which can be more appropriate if cure proportions are very close to 0 or 1.
- "identity": Fits the cure fraction directly on the probability scale (must remain in  $[0,1]$ ).
- "probit": Uses the cumulative normal distribution as the link.

#### Model complexity and parsimony

Following *Occam's Razor* and [NICE TSD 21](#), standard parametric models should be preferred when they provide an adequate and clinically plausible fit. Cure models should be considered only when there is strong clinical or empirical evidence supporting the presence of a long-term cured fraction.

#### Model assessment and rules of thumb

The same goodness-of-fit statistics (AIC and BIC) used in Section 4.1 are presented here, and the same *rules of thumb* apply:

- **Burnham & Anderson (1998)**: Models within 4 AIC points of the lowest AIC are considered to have substantial support from the data [Burnham and Anderson, 1998](#).
- **Raftery (1995)**: Models within 2 BIC points of the lowest BIC are considered among the best-fitting models [Raftery et al., 1995](#).

#### Plots

As in Section 4.1, the following pages display three plots for each fitted spline-based survival model:

- **Figure A**: Kaplan–Meier curves (black and grey) versus the fitted spline model (colour).
- **Figure B**: Model-specific diagnostic plots (see [Ishak et al., 2013](#)).
- **Figure C**: Smoothed hazard rates from empirical data (black and grey) versus model-based estimates (colour).



**CAUTION:**

These statistics and plots apply only to the *observed* data period and do not directly inform the appropriateness of extrapolations beyond this period.

Additionally, the tail of the observed data may be affected by a low number of events, which should be considered when interpreting model performance.

Table 5: Goodness of fit statistics (including standard parametric and cure models)

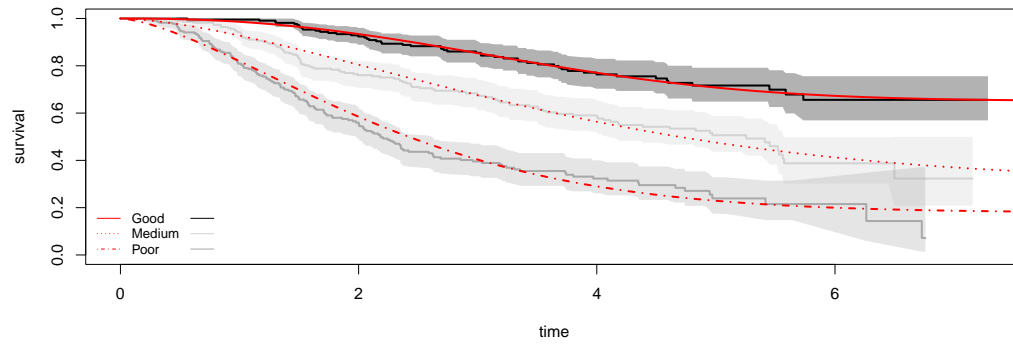
Model	AIC
Generalised Gamma	1589.049
Log-normal	1592.880
Mixture cure Log-normal	1593.762
Non-mixture cure Log-normal	1593.793
Mixture cure Log-logistic	1604.290
Non-mixture cure Log-logistic	1605.960
Log-logistic	1609.294
Non-mixture cure Weibull	1615.016
Gamma	1621.982
Mixture cure Weibull	1622.730
Weibull	1632.618
Gompertz	1660.954
Exponential	1668.212

Table 6: Cure proportions per group (lower and upper 95CI)

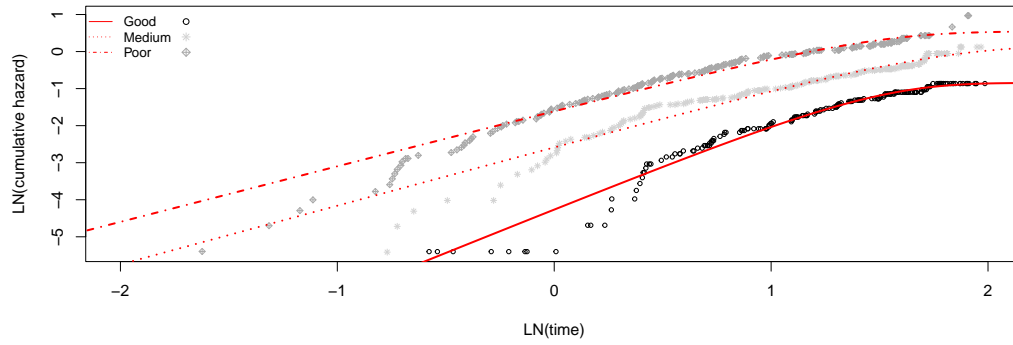
Model	CureFraction
Mixture cure Weibull	65% (54%–75%), 31% (15%–53%), 18% (10%–29%)
Non-mixture cure Weibull	65% (53%–75%), 30% (13%–55%), 17% (9%–29%)
Mixture cure Log-normal	57% (35%–77%), 19% (3%–66%), 11% (3%–35%)
Non-mixture cure Log-normal	56% (33%–77%), 20% (5%–57%), 10% (3%–30%)
Mixture cure Log-logistic	60% (45%–74%), 23% (7%–54%), 14% (6%–30%)
Non-mixture cure Log-logistic	60% (45%–74%), 25% (10%–51%), 15% (8%–28%)

## Mixture cure Weibull

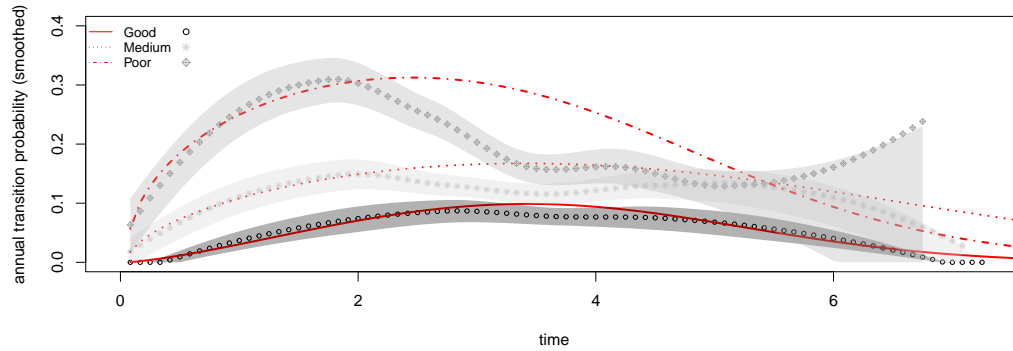
A: Kaplan–Meier (Mixture cure Weibull)



B: Diagnostic plot (Mixture cure Weibull)

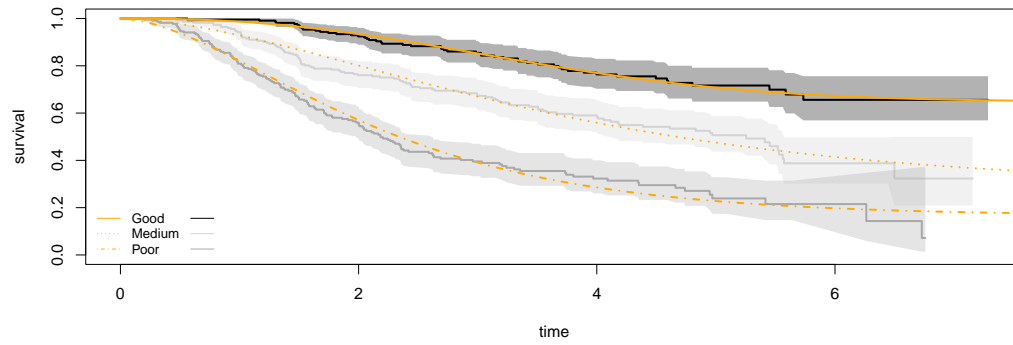


C: Annual transition probability (Mixture cure Weibull)

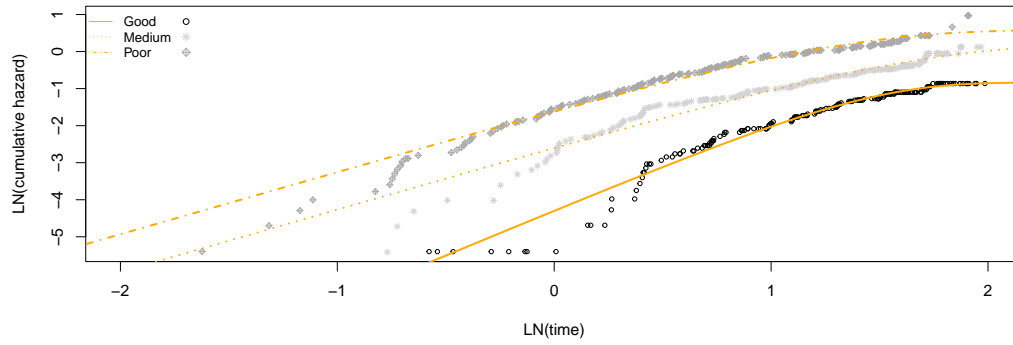


## Non-mixture cure Weibull

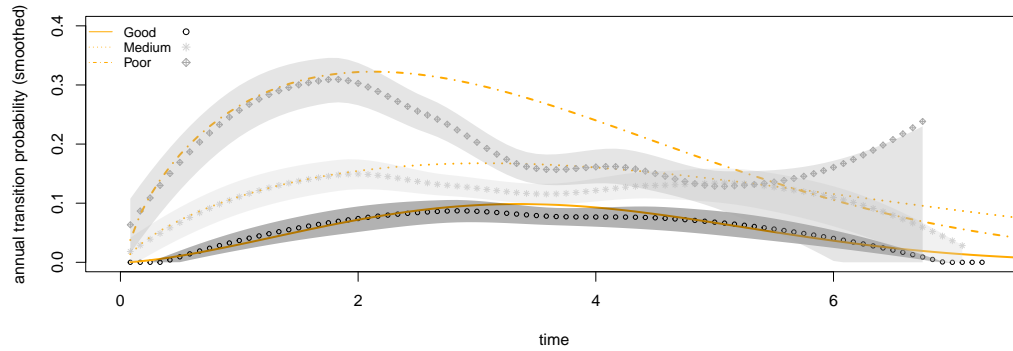
A: Kaplan-Meier (Non-mixture cure Weibull)



B: Diagnostic plot (Non-mixture cure Weibull)

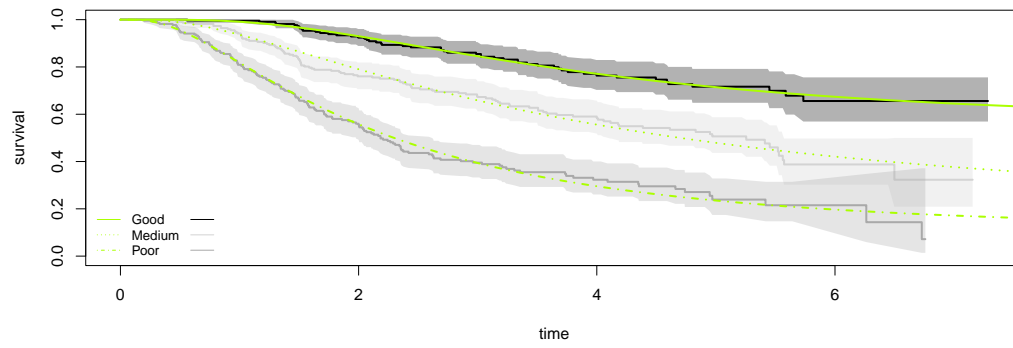


C: Annual transition probability (Non-mixture cure Weibull)

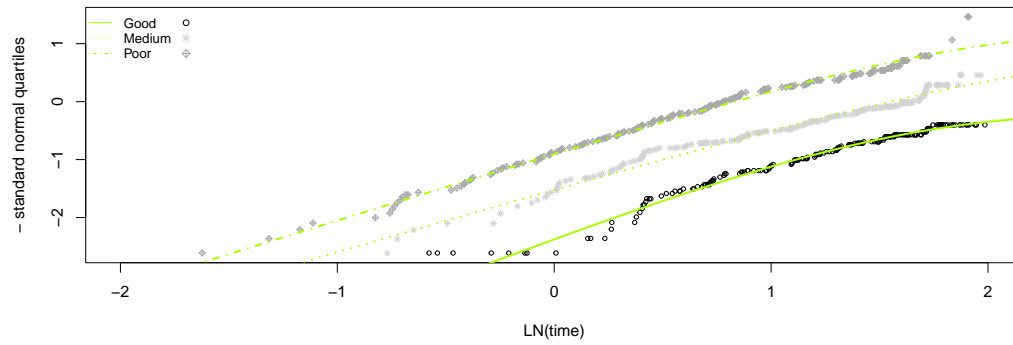


## Mixture cure Log-normal

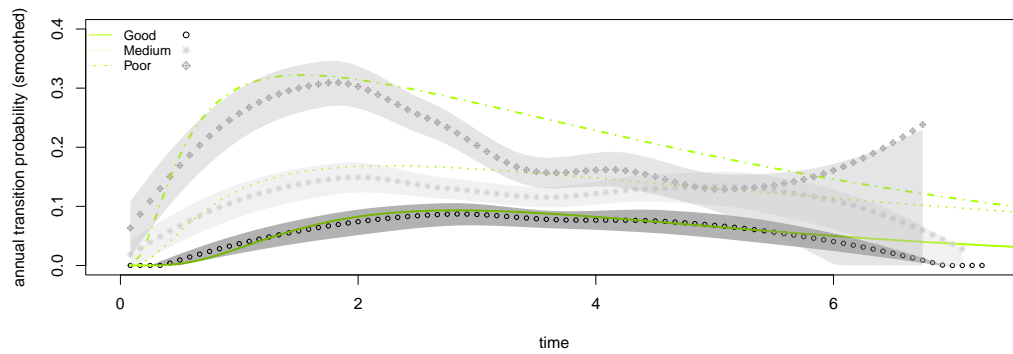
A: Kaplan-Meier (Mixture cure Log-normal)



B: Diagnostic plot (Mixture cure Log-normal)

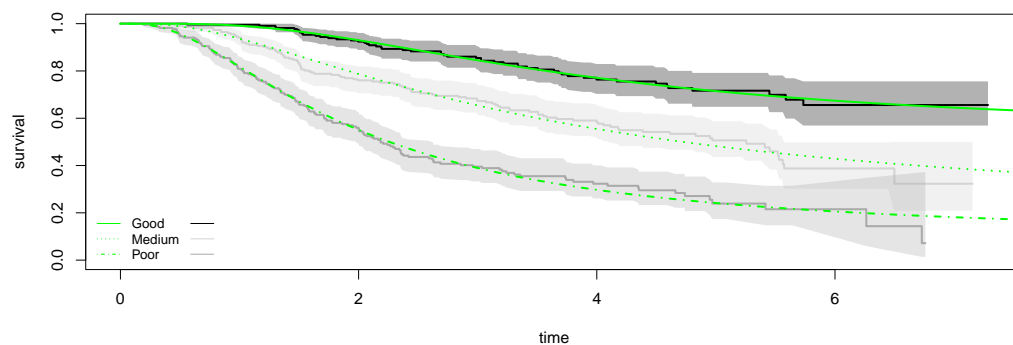


C: Annual transition probability (Mixture cure Log-normal)

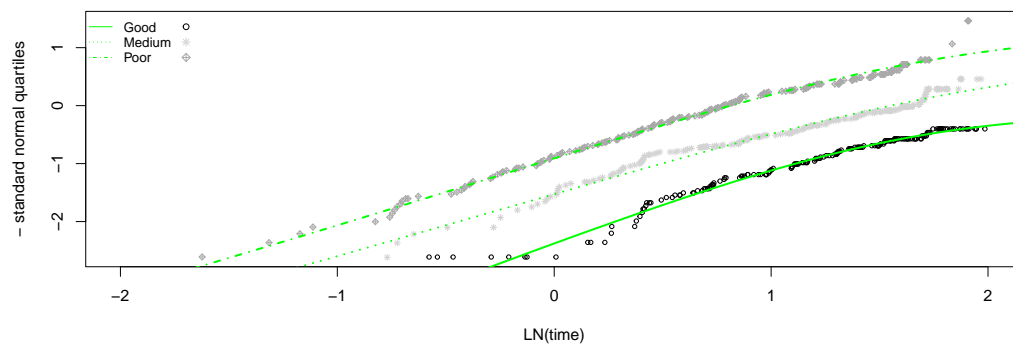


## Non-mixture cure Log-normal

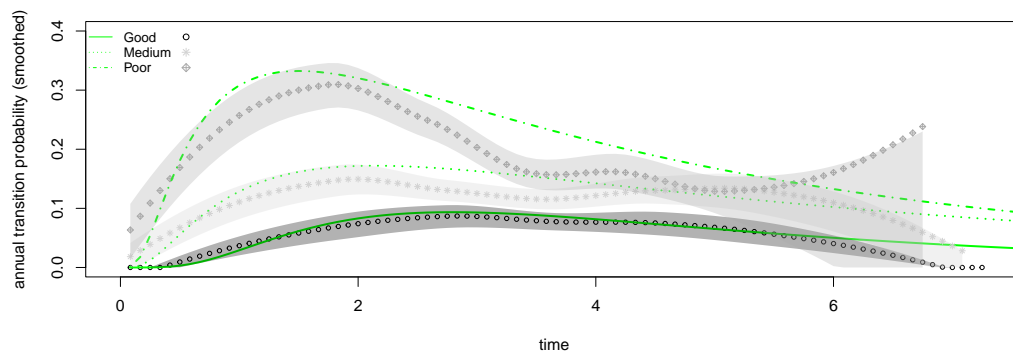
**A: Kaplan-Meier (Non-mixture cure Log-normal)**



**B: Diagnostic plot (Non-mixture cure Log-normal)**

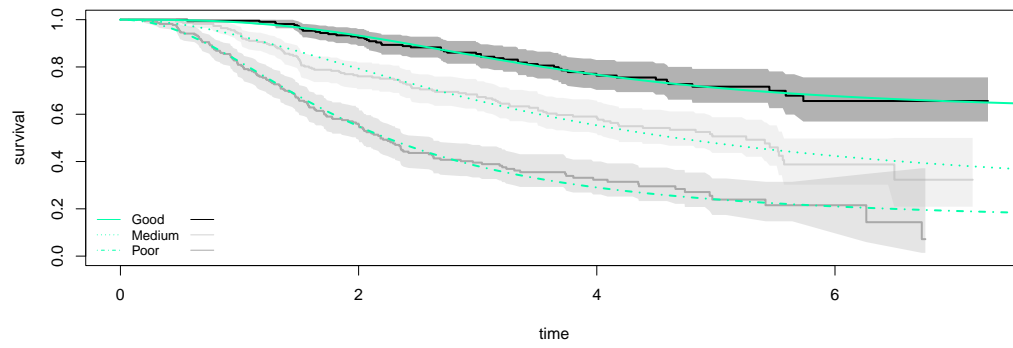


**C: Annual transition probability (Non-mixture cure Log-normal)**

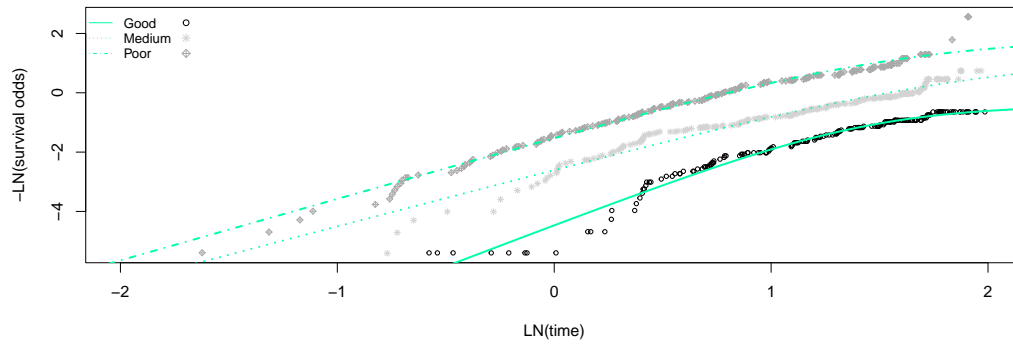


## Mixture cure Log-logistic

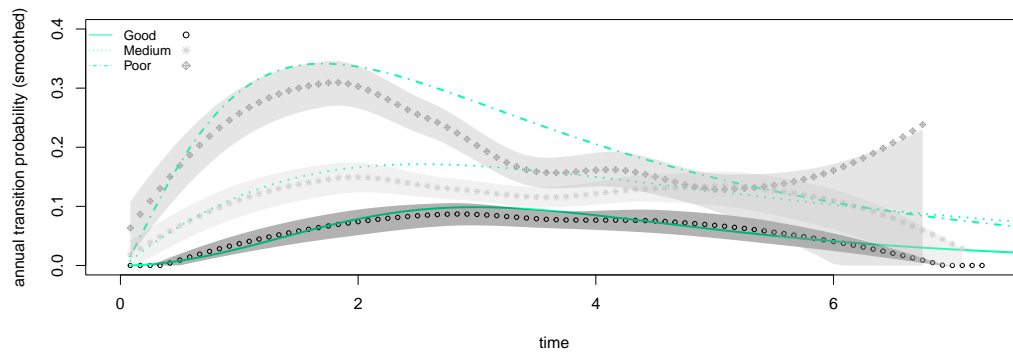
A: Kaplan-Meier (Mixture cure Log-logistic)



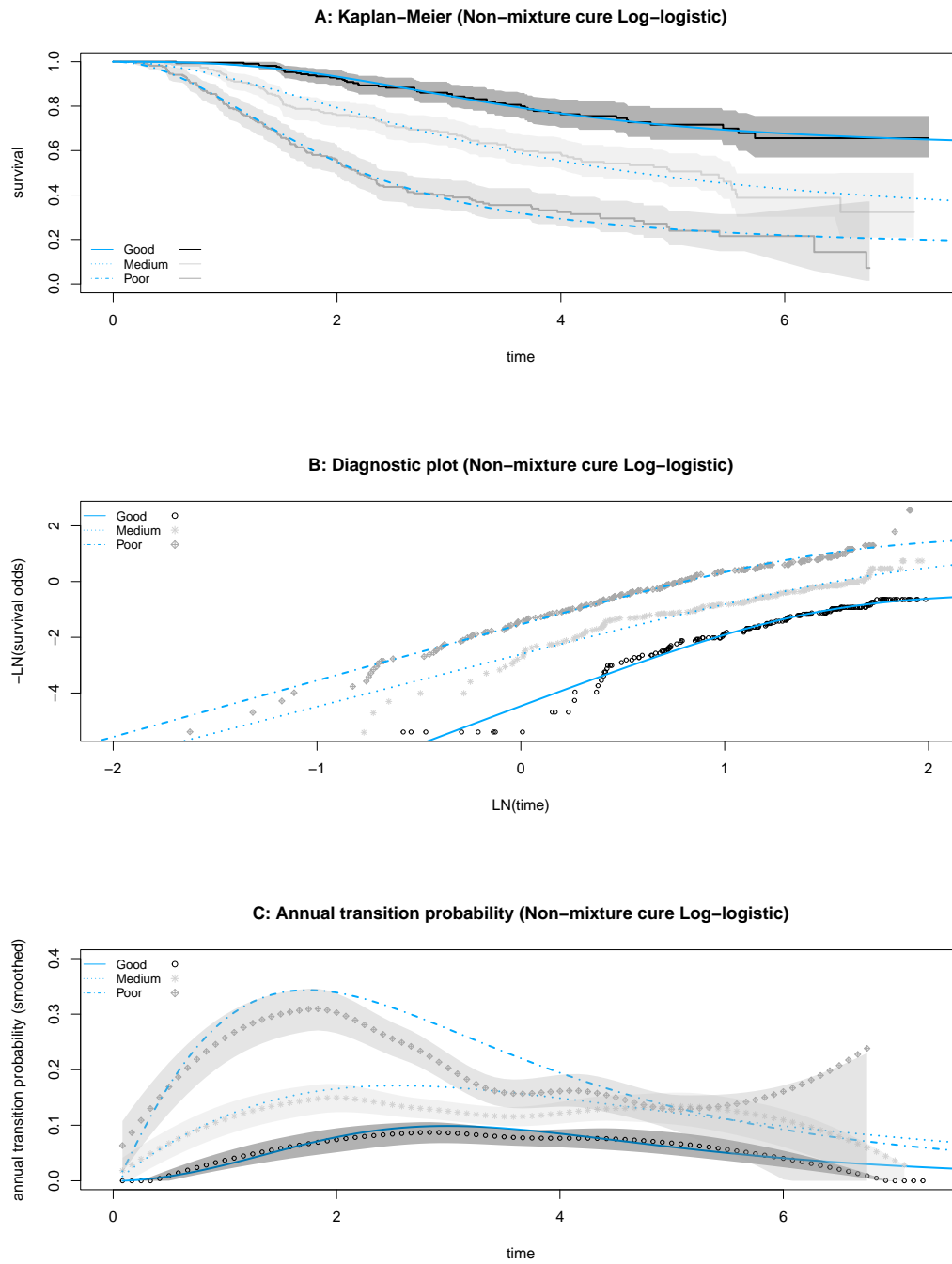
B: Diagnostic plot (Mixture cure Log-logistic)



C: Annual transition probability (Mixture cure Log-logistic)



## Non-mixture cure Log-logistic





## 5 Extrapolation

The plausibility of estimated survival beyond the observed data period is often a critical driver in health economic models. As highlighted in [NICE TSD 14](#) and [NICE TSD 21](#), model choice for extrapolation should consider whether the estimated long-term survival is consistent with **external data** (e.g., observational studies, registry data, or general population mortality).

In this section, extrapolation is examined by:

1. *Plotting survival curves* (Figures A) over the observed and extrapolated periods.
2. *Plotting annual transition probabilities* (Figures B) over the observed and extrapolated periods.
3. *Plotting hazard functions* (Figures C) over the observed and extrapolated periods.
4. *Tabulating survival probabilities* at multiple user-specified time points (first table).
5. *Summarising annual transition probabilities* (second table).

All outputs are presented *per group*.

### Assessing plausibility

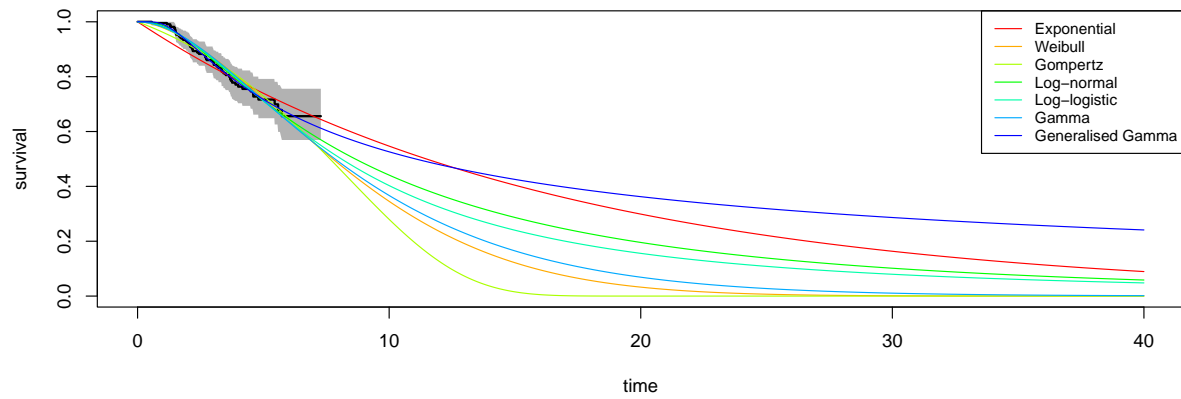
- Compare survival probabilities at specific time points with *external data* (e.g., registry data, literature, expert opinion).
- Compare annual transition probabilities with *general population mortality* (e.g., from national life tables).
- If a model predicts conditional transition probabilities more favourable than the general population, this may be implausible unless clinically justified.
- In such cases, alternative models should be considered, or adjustments made (e.g., incorporating background mortality).

**Note:** These checks are consistent with the guidance in NICE TSD 14 and TSD 21, which recommend:

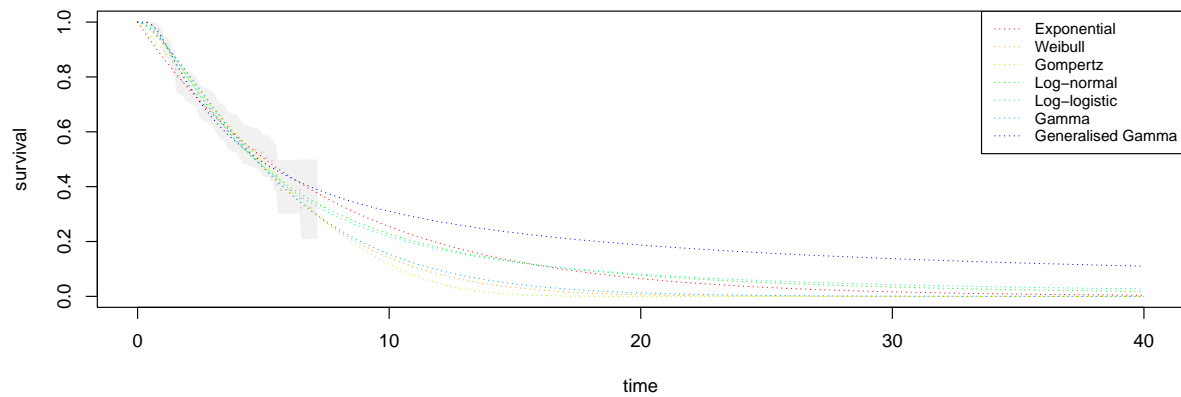
- Using *external evidence* to validate extrapolations.
- Keeping models as simple as possible (Occam's Razor), but adopting more flexible approaches when standard parametric models do not align with external evidence or long-term expectations.

## 5.1 Extrapolated survival

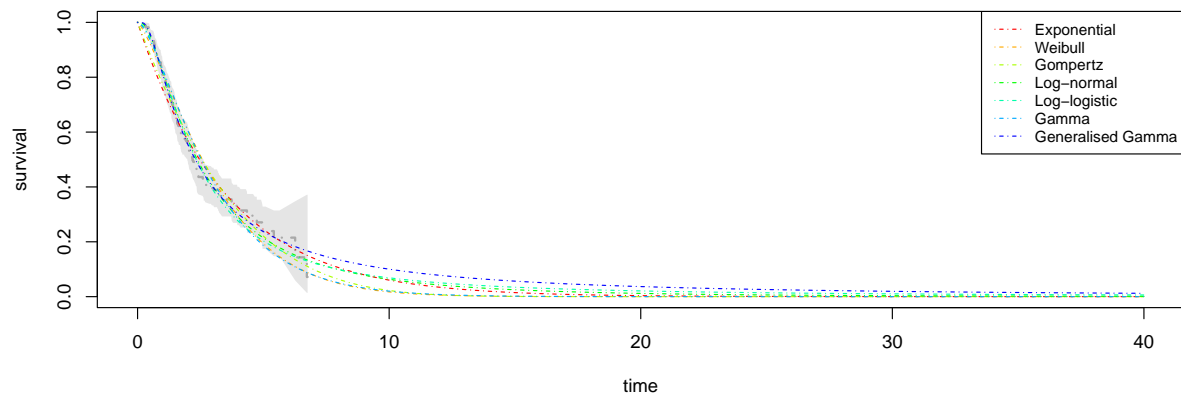
**A: Kaplan–Meier (parametric curves), Group: Good**



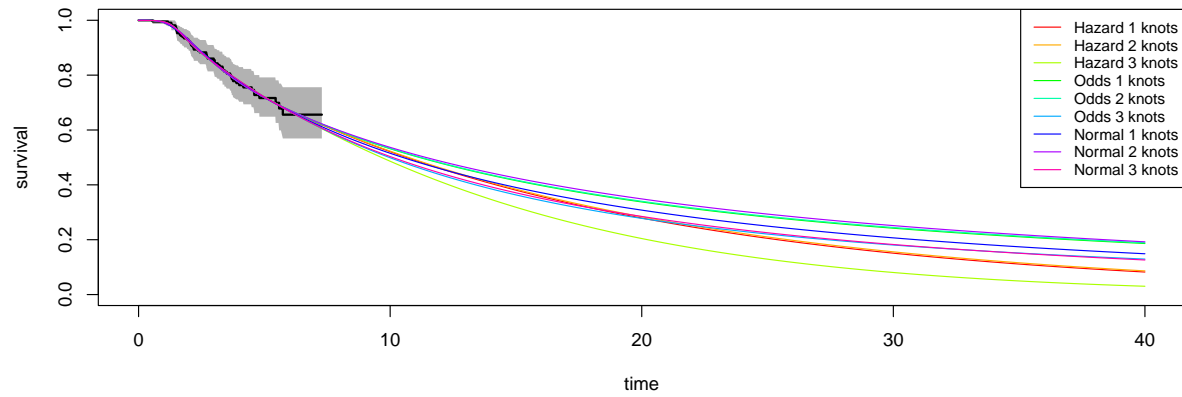
**A: Kaplan–Meier (parametric curves), Group: Medium**



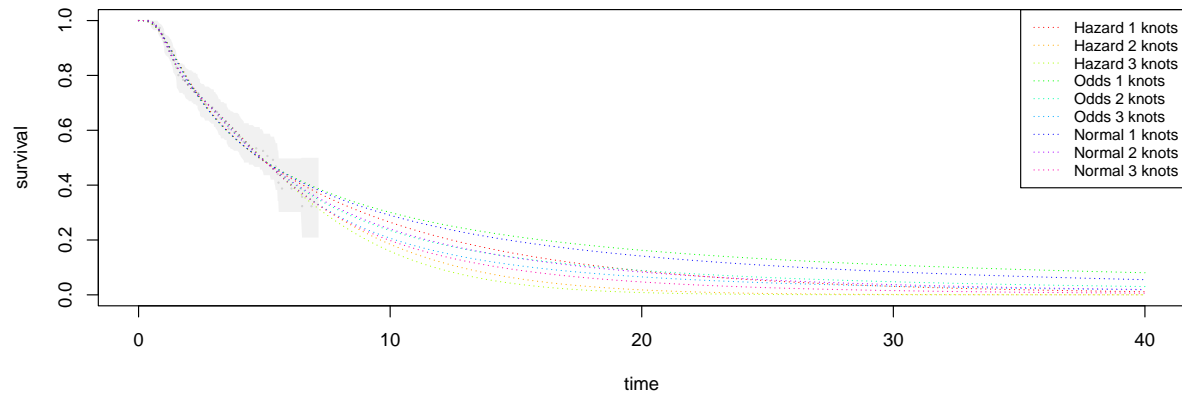
**A: Kaplan–Meier (parametric curves), Group: Poor**



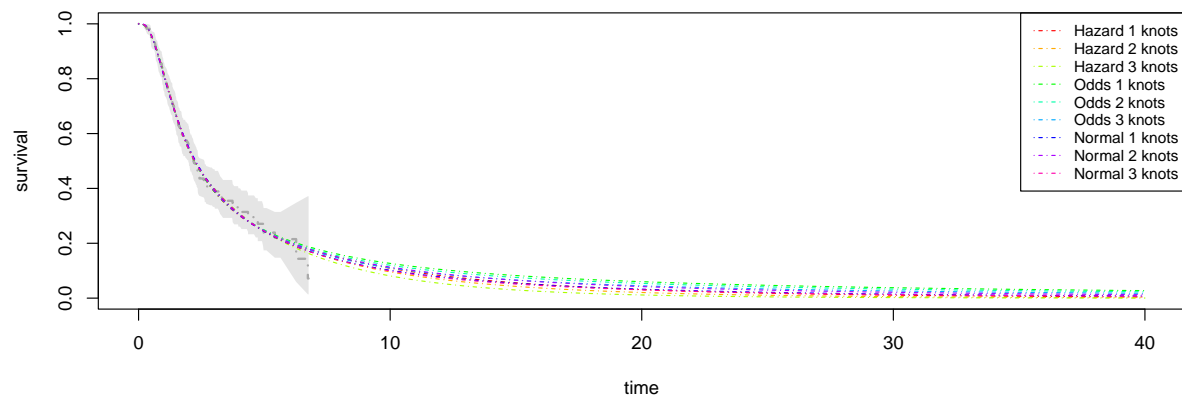
**A: Kaplan–Meier (spline curves), Group: Good**



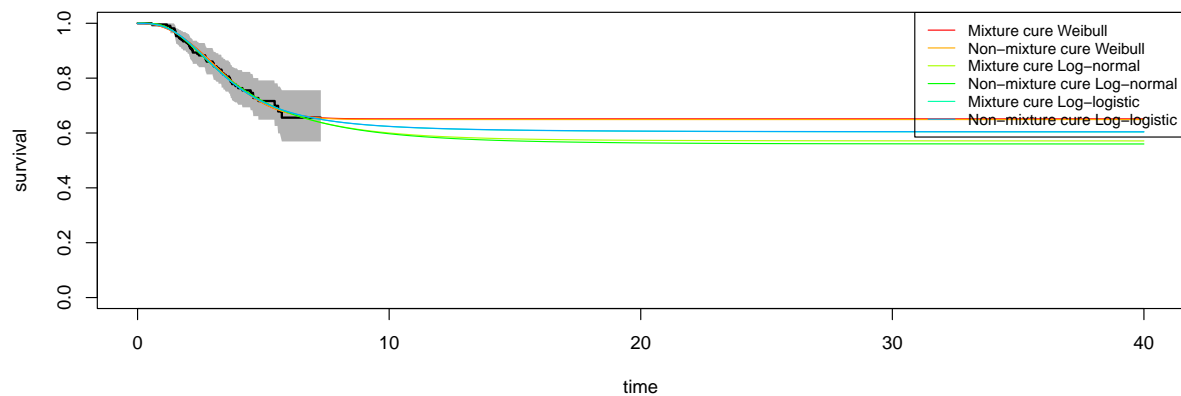
**A: Kaplan–Meier (spline curves), Group: Medium**



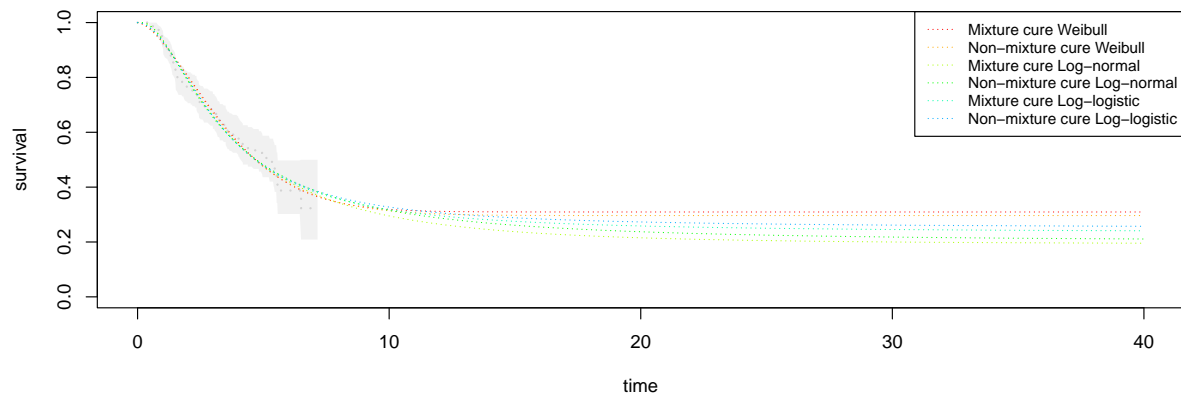
**A: Kaplan–Meier (spline curves), Group: Poor**



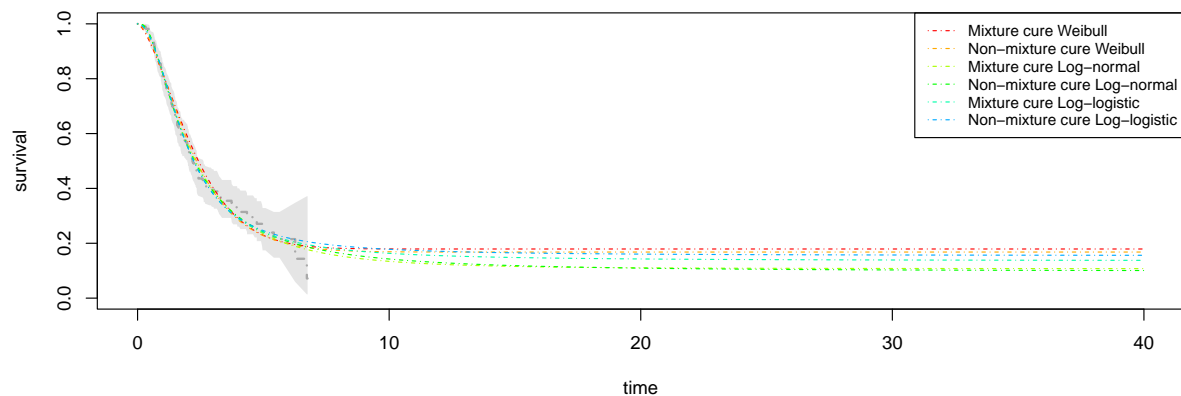
**A: Kaplan–Meier (cure curves), Group: Good**



**A: Kaplan–Meier (cure curves), Group: Medium**

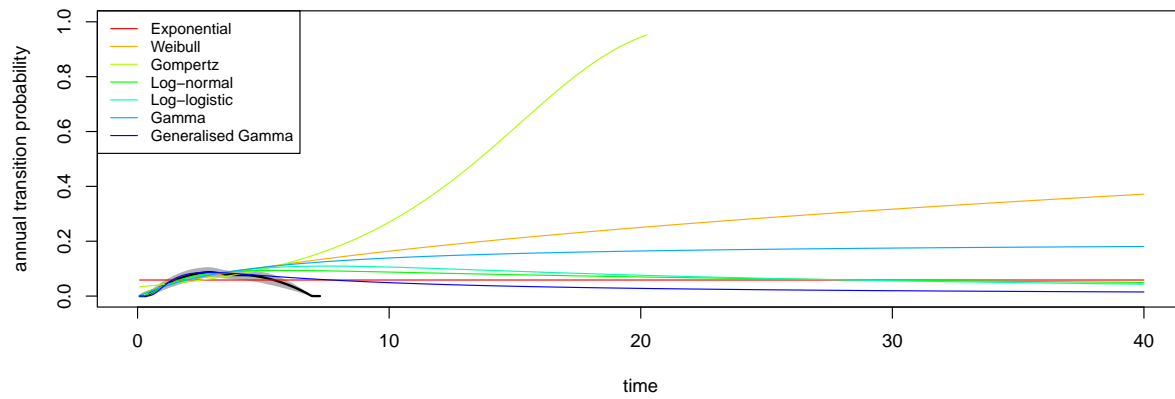


**A: Kaplan–Meier (cure curves), Group: Poor**

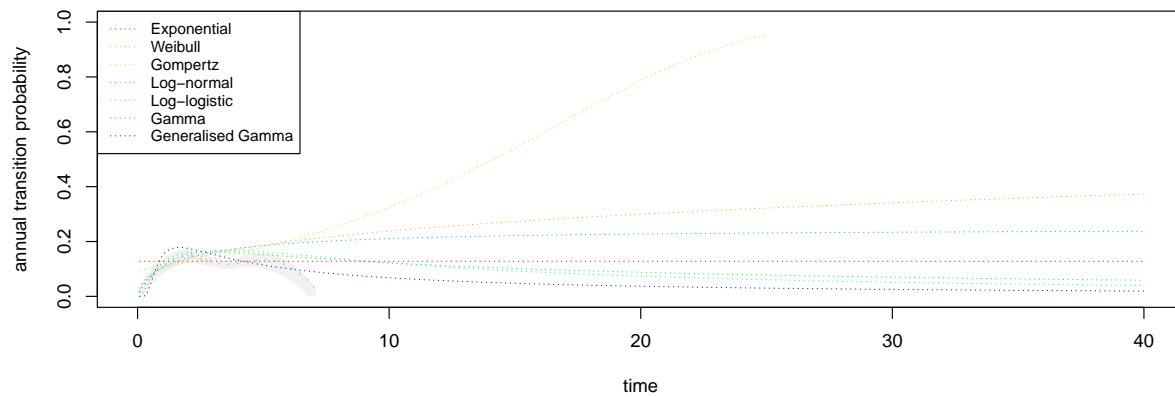


## 5.2 Extrapolated transition probabilities

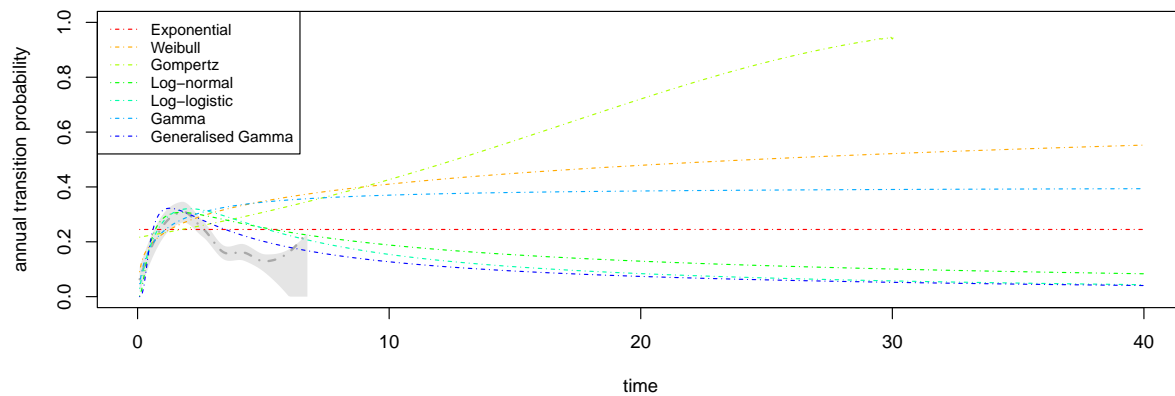
**B: Annual transition probability (parametric curves), Group: Good**



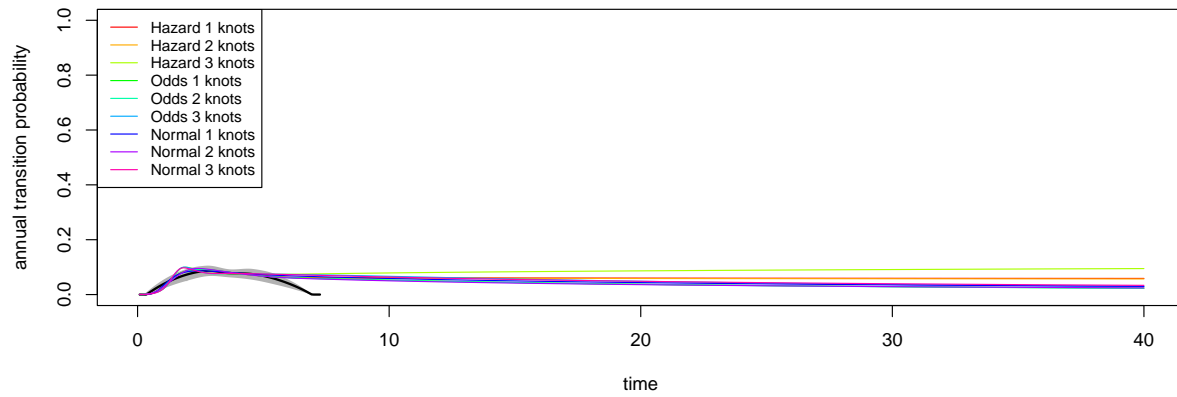
**B: Annual transition probability (parametric curves), Group: Medium**



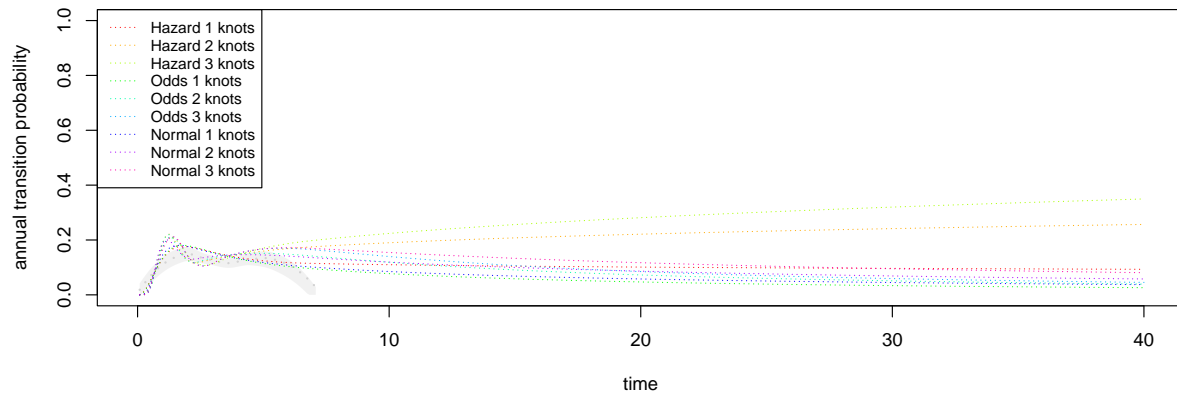
**B: Annual transition probability (parametric curves), Group: Poor**



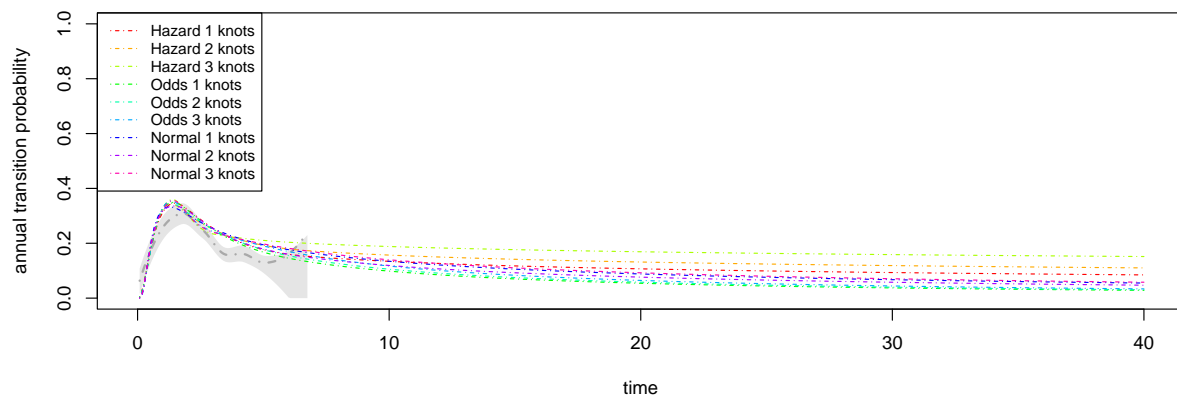
**B: Annual transition probability (spline curves), Group: Good**



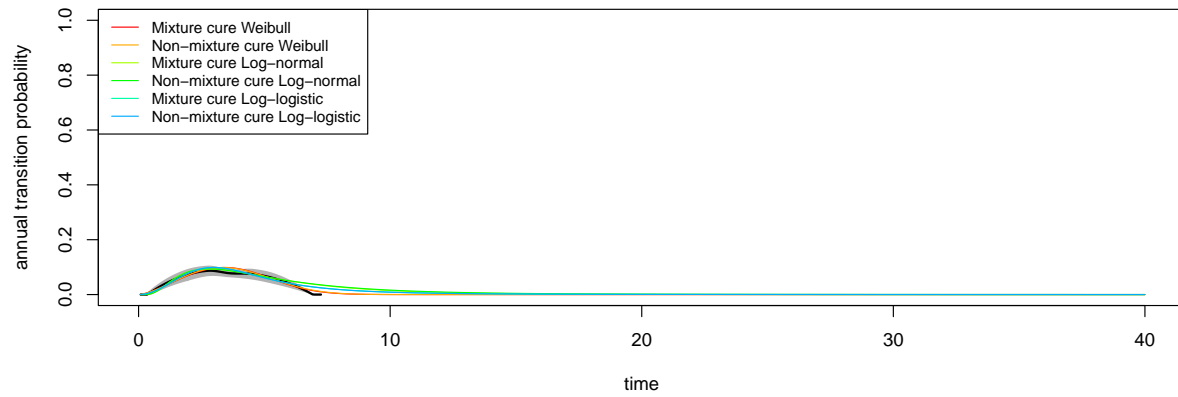
**B: Annual transition probability (spline curves), Group: Medium**



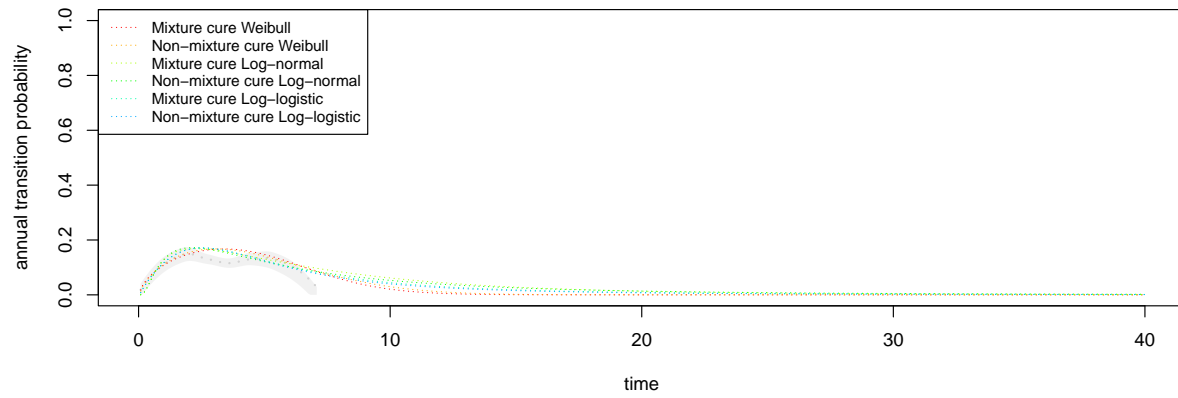
**B: Annual transition probability (spline curves), Group: Poor**



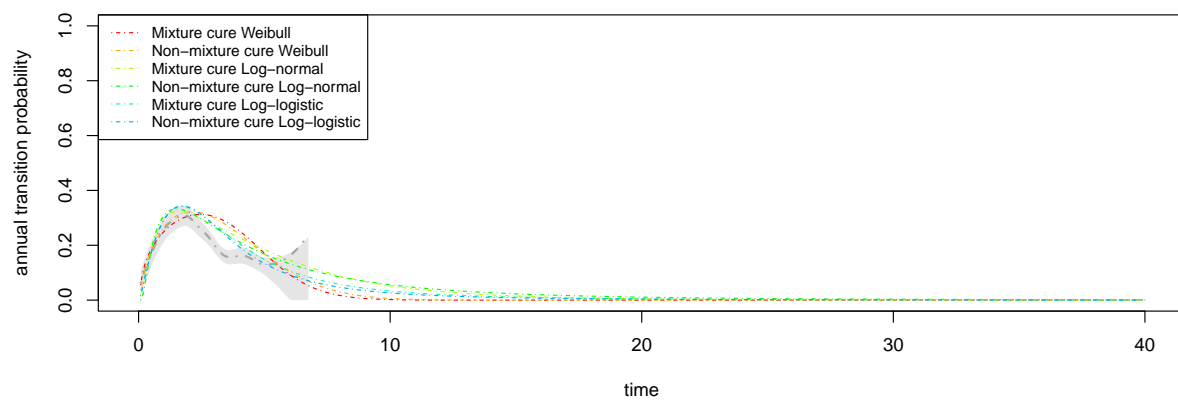
**B: Annual transition probability (cure curves), Group: Good**



**B: Annual transition probability (cure curves), Group: Medium**

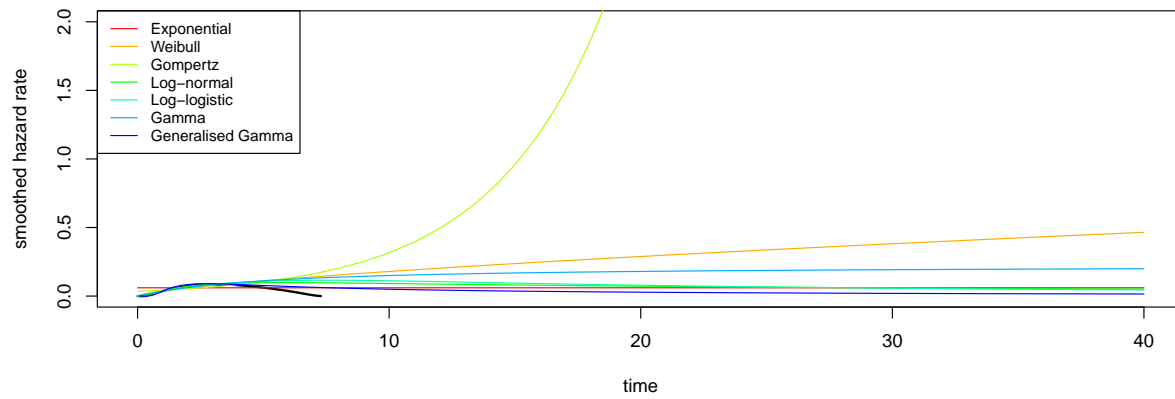


**B: Annual transition probability (cure curves), Group: Poor**

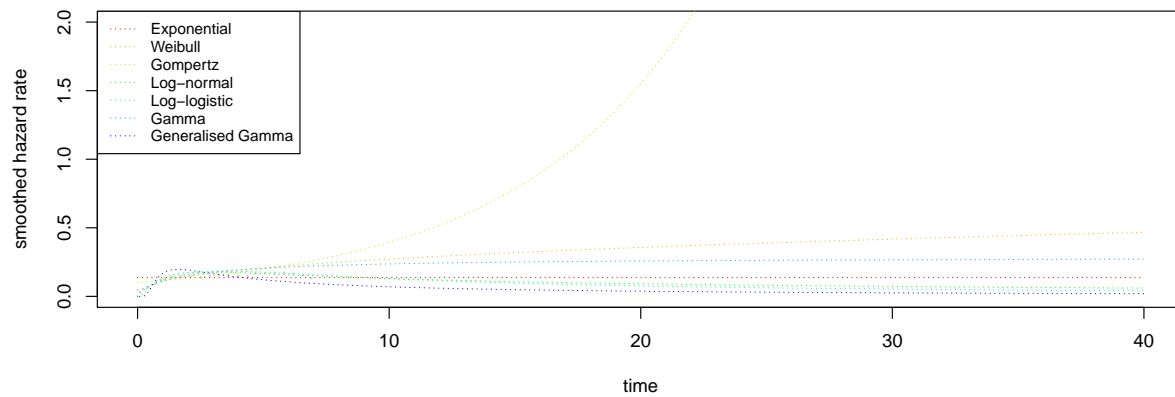


### 5.3 Extrapolated hazard function

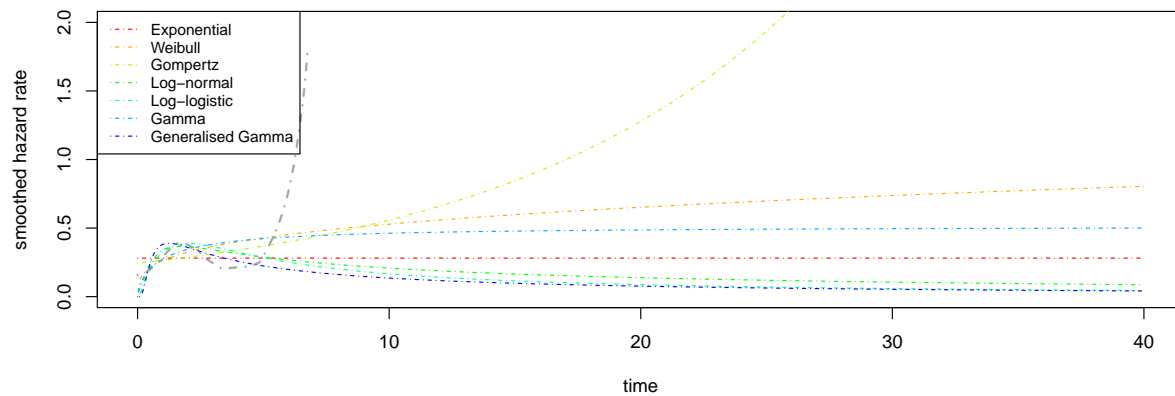
C: Hazard function (parametric curves), Group: Good



C: Hazard function (parametric curves), Group: Medium

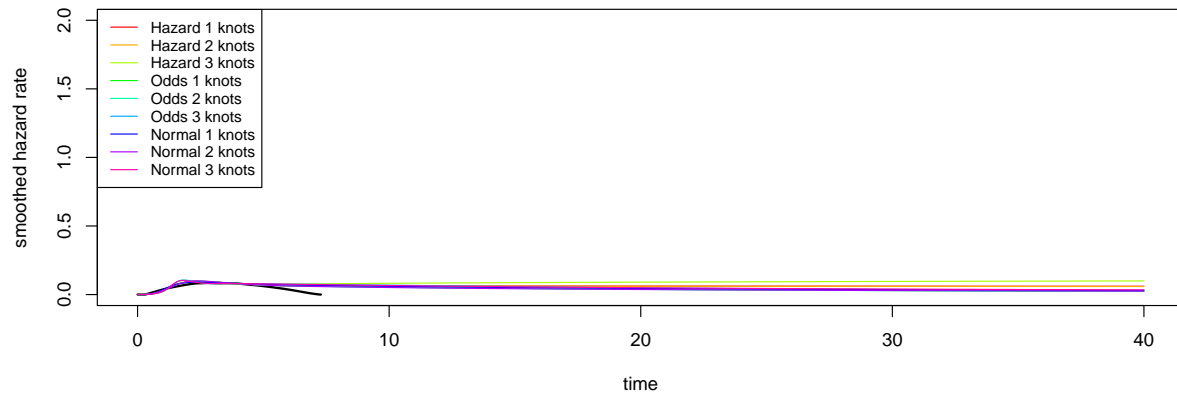


C: Hazard function (parametric curves), Group: Poor

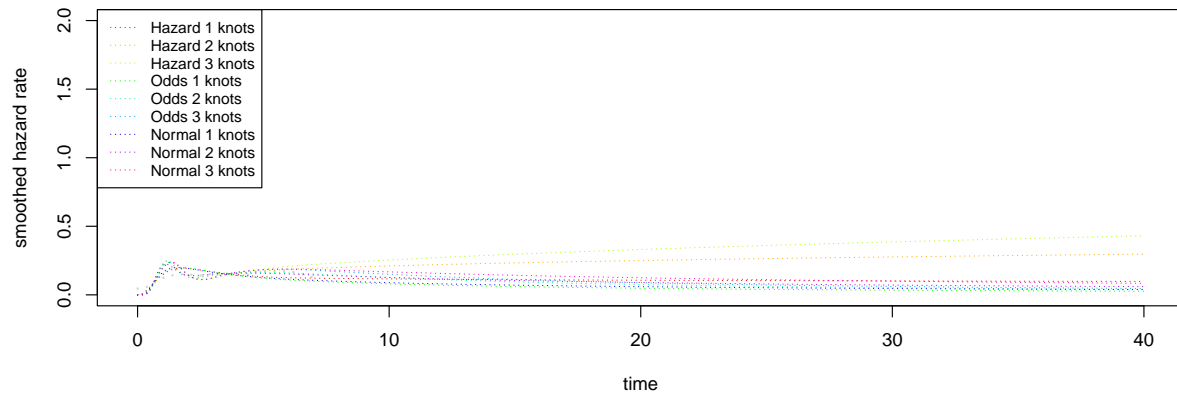




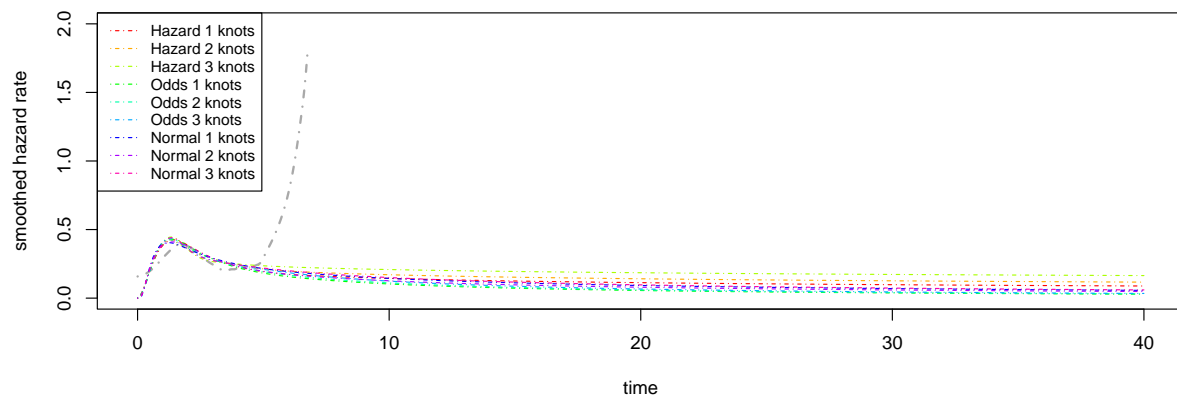
**C: Hazard function (spline curves), Group: Good**



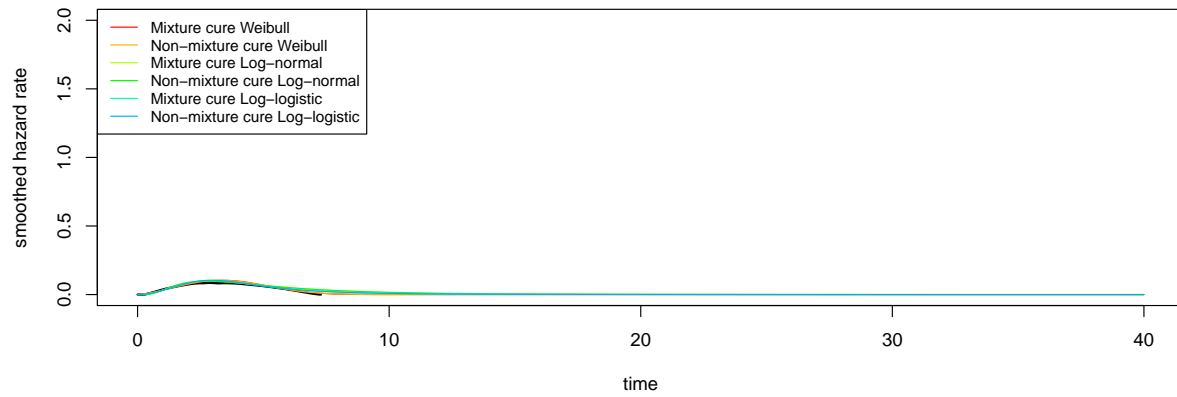
**C: Hazard function (spline curves), Group: Medium**



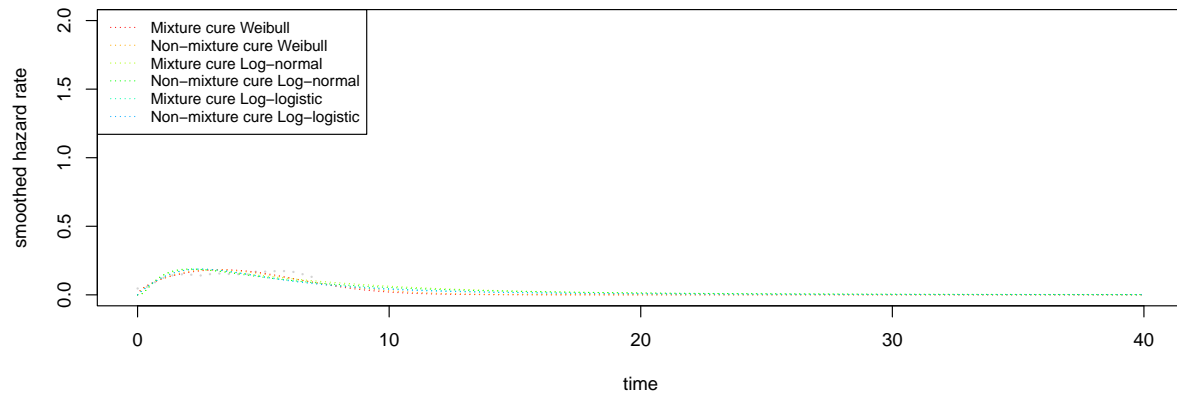
**C: Hazard function (spline curves), Group: Poor**



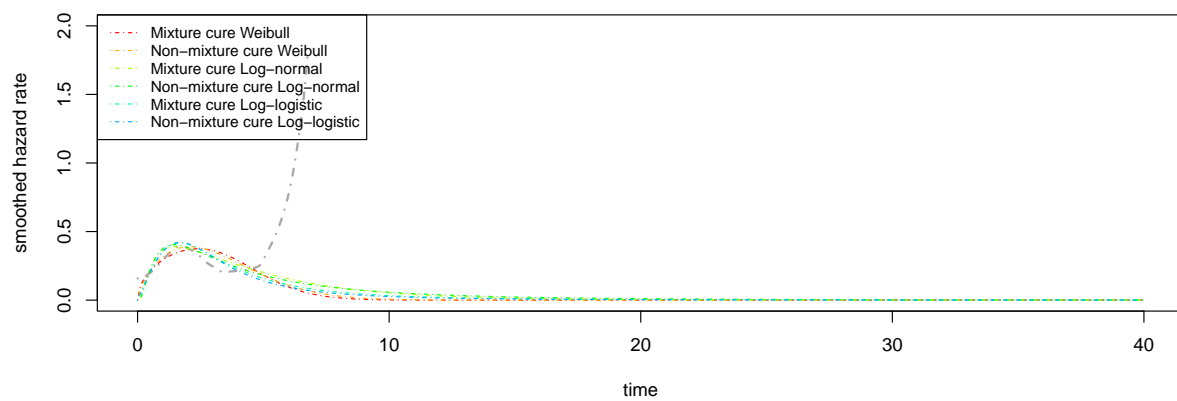
**C: Hazard function (cure curves), Group: Good**



**C: Hazard function (cure curves), Group: Medium**



**C: Hazard function (cure curves), Group: Poor**



## 5.4 Tabulated results

### Group Good

Table 7: Survival probability at different time points

	T= 0	T= 1	T= 2	T= 5	T= 10	T= 20	T= 30	T= 40
Exponential	1	0.941	0.886	0.739	0.547	0.299	0.163	0.089
Weibull	1	0.978	0.932	0.719	0.345	0.033	0.001	0.000
Gompertz	1	0.962	0.917	0.729	0.280	0.000	0.000	0.000
Log-normal	1	0.986	0.933	0.713	0.441	0.196	0.102	0.059
Log-logistic	1	0.980	0.932	0.712	0.403	0.156	0.080	0.048
Gamma	1	0.982	0.935	0.714	0.367	0.069	0.011	0.001
Generalised Gamma	1	0.991	0.928	0.717	0.526	0.362	0.286	0.241
Hazard 1 knots	1	0.992	0.927	0.719	0.521	0.279	0.151	0.082
Hazard 2 knots	1	0.992	0.928	0.719	0.523	0.284	0.156	0.086
Hazard 3 knots	1	0.994	0.922	0.721	0.486	0.204	0.080	0.030
Odds 1 knots	1	0.992	0.927	0.718	0.532	0.338	0.242	0.186
Odds 2 knots	1	0.992	0.928	0.718	0.533	0.340	0.245	0.189
Odds 3 knots	1	0.994	0.922	0.721	0.499	0.278	0.181	0.129
Normal 1 knots	1	0.992	0.926	0.719	0.515	0.308	0.207	0.149
Normal 2 knots	1	0.992	0.929	0.718	0.537	0.349	0.251	0.192
Normal 3 knots	1	0.994	0.921	0.721	0.503	0.285	0.182	0.126
Mixture cure Weibull	1	0.986	0.934	0.708	0.652	0.652	0.652	0.652
Non-mixture cure Weibull	1	0.987	0.934	0.708	0.649	0.649	0.649	0.649
Mixture cure Log-normal	1	0.991	0.930	0.715	0.600	0.573	0.571	0.571
Non-mixture cure Log-normal	1	0.991	0.930	0.715	0.597	0.564	0.561	0.560
Mixture cure Log-logistic	1	0.989	0.933	0.712	0.624	0.606	0.604	0.604
Non-mixture cure Log-logistic	1	0.989	0.933	0.712	0.624	0.607	0.605	0.604

Table 8: Summary statistics of annual transition probabilities

	Mean	Std.Dev	Min	Q1	Median	Q3	Max	IQR
Exponential	0.059	0.000	0.059	0.059	0.059	0.059	0.059	0.000
Weibull	0.235	0.096	0.004	0.164	0.251	0.317	0.371	0.153
Gompertz	0.374	0.300	0.034	0.101	0.278	0.631	0.952	0.530
Log-normal	0.068	0.017	0.000	0.056	0.067	0.082	0.094	0.025
Log-logistic	0.073	0.023	0.002	0.053	0.070	0.094	0.109	0.040
Gamma	0.149	0.038	0.001	0.139	0.164	0.175	0.181	0.036
Generalised Gamma	0.035	0.021	0.000	0.019	0.027	0.045	0.086	0.026
Hazard 1 knots	0.061	0.011	0.000	0.059	0.060	0.061	0.092	0.002
Hazard 2 knots	0.059	0.011	0.000	0.058	0.058	0.060	0.092	0.002
Hazard 3 knots	0.084	0.015	0.000	0.080	0.087	0.091	0.100	0.011
Odds 1 knots	0.041	0.017	0.000	0.028	0.036	0.050	0.092	0.022
Odds 2 knots	0.041	0.017	0.000	0.028	0.036	0.050	0.092	0.022
Odds 3 knots	0.050	0.018	0.000	0.036	0.047	0.064	0.100	0.028
Normal 1 knots	0.046	0.016	0.000	0.035	0.042	0.056	0.087	0.021
Normal 2 knots	0.040	0.017	0.000	0.028	0.035	0.048	0.095	0.019
Normal 3 knots	0.050	0.016	0.001	0.039	0.047	0.061	0.098	0.023
Mixture cure Weibull	0.010	0.025	0.000	0.000	0.000	0.000	0.099	0.000
Non-mixture cure Weibull	0.010	0.025	0.000	0.000	0.000	0.000	0.099	0.000
Mixture cure Log-normal	0.014	0.025	0.000	0.000	0.001	0.012	0.093	0.011
Non-mixture cure Log-normal	0.014	0.025	0.000	0.000	0.001	0.013	0.093	0.013
Mixture cure Log-logistic	0.012	0.025	0.000	0.000	0.001	0.007	0.099	0.007
Non-mixture cure Log-logistic	0.012	0.025	0.000	0.000	0.001	0.007	0.099	0.007

## Group Medium

Table 9: Survival probability at different time points

	T= 0	T= 1	T= 2	T= 5	T= 10	T= 20	T= 30	T= 40
Exponential	1	0.872	0.761	0.505	0.255	0.065	0.016	0.004
Weibull	1	0.923	0.811	0.474	0.141	0.006	0.000	0.000
Gompertz	1	0.898	0.794	0.486	0.117	0.000	0.000	0.000
Log-normal	1	0.935	0.797	0.473	0.228	0.077	0.034	0.018
Log-logistic	1	0.927	0.801	0.468	0.218	0.081	0.043	0.027
Gamma	1	0.930	0.813	0.469	0.154	0.013	0.001	0.000
Generalised Gamma	1	0.937	0.774	0.488	0.310	0.187	0.138	0.110
Hazard 1 knots	1	0.939	0.782	0.486	0.265	0.087	0.031	0.011
Hazard 2 knots	1	0.935	0.766	0.490	0.184	0.018	0.001	0.000
Hazard 3 knots	1	0.936	0.761	0.491	0.159	0.008	0.000	0.000
Odds 1 knots	1	0.939	0.778	0.489	0.301	0.162	0.109	0.081
Odds 2 knots	1	0.935	0.769	0.489	0.235	0.089	0.048	0.030
Odds 3 knots	1	0.937	0.761	0.489	0.206	0.065	0.032	0.019
Normal 1 knots	1	0.938	0.775	0.488	0.290	0.141	0.084	0.055
Normal 2 knots	1	0.930	0.773	0.489	0.240	0.083	0.037	0.019
Normal 3 knots	1	0.937	0.761	0.489	0.198	0.047	0.015	0.006
Mixture cure Weibull	1	0.928	0.804	0.475	0.319	0.309	0.309	0.309
Non-mixture cure Weibull	1	0.929	0.801	0.475	0.314	0.296	0.296	0.296
Mixture cure Log-normal	1	0.936	0.790	0.479	0.295	0.215	0.200	0.196
Non-mixture cure Log-normal	1	0.937	0.787	0.482	0.315	0.237	0.218	0.211
Mixture cure Log-logistic	1	0.931	0.793	0.477	0.318	0.258	0.246	0.241
Non-mixture cure Log-logistic	1	0.931	0.793	0.479	0.327	0.273	0.262	0.257

Table 10: Summary statistics of annual transition probabilities

	Mean	Std.Dev	Min	Q1	Median	Q3	Max	IQR
Exponential	0.128	0.000	0.128	0.128	0.128	0.128	0.128	0.000
Weibull	0.282	0.073	0.030	0.238	0.300	0.341	0.373	0.103
Gompertz	0.470	0.278	0.096	0.210	0.425	0.726	0.951	0.515
Log-normal	0.095	0.032	0.000	0.069	0.086	0.117	0.163	0.048
Log-logistic	0.085	0.040	0.015	0.051	0.072	0.115	0.167	0.063
Gamma	0.214	0.034	0.016	0.211	0.227	0.234	0.237	0.023
Generalised Gamma	0.053	0.040	0.000	0.025	0.036	0.064	0.178	0.039
Hazard 1 knots	0.106	0.020	0.001	0.096	0.101	0.109	0.177	0.013
Hazard 2 knots	0.211	0.042	0.000	0.192	0.221	0.241	0.257	0.049
Hazard 3 knots	0.265	0.070	0.000	0.224	0.282	0.320	0.350	0.096
Odds 1 knots	0.060	0.038	0.000	0.033	0.046	0.074	0.181	0.041
Odds 2 knots	0.083	0.040	0.000	0.050	0.071	0.113	0.219	0.063
Odds 3 knots	0.094	0.042	0.000	0.058	0.082	0.126	0.212	0.067
Normal 1 knots	0.069	0.035	0.000	0.045	0.057	0.082	0.180	0.038
Normal 2 knots	0.093	0.032	0.000	0.068	0.085	0.116	0.201	0.048
Normal 3 knots	0.119	0.032	0.000	0.094	0.113	0.143	0.212	0.049
Mixture cure Weibull	0.027	0.052	0.000	0.000	0.000	0.019	0.167	0.019
Non-mixture cure Weibull	0.028	0.052	0.000	0.000	0.000	0.028	0.168	0.028
Mixture cure Log-normal	0.039	0.050	0.000	0.004	0.013	0.057	0.168	0.053
Non-mixture cure Log-normal	0.037	0.048	0.000	0.005	0.013	0.049	0.172	0.044
Mixture cure Log-logistic	0.034	0.049	0.001	0.003	0.009	0.042	0.171	0.039
Non-mixture cure Log-logistic	0.032	0.048	0.001	0.002	0.007	0.037	0.171	0.035

## Group Poor

Table 11: Survival probability at different time points

	T= 0	T= 1	T= 2	T= 5	T= 10	T= 20	T= 30	T= 40
Exponential	1	0.755	0.570	0.245	0.060	0.004	0.000	0.000
Weibull	1	0.817	0.608	0.193	0.017	0.000	0.000	0.000
Gompertz	1	0.776	0.588	0.221	0.022	0.000	0.000	0.000
Log-normal	1	0.820	0.572	0.214	0.063	0.012	0.004	0.001
Log-logistic	1	0.819	0.568	0.203	0.069	0.021	0.010	0.006
Gamma	1	0.829	0.605	0.187	0.020	0.000	0.000	0.000
Generalised Gamma	1	0.810	0.555	0.237	0.100	0.037	0.019	0.012
Hazard 1 knots	1	0.822	0.545	0.244	0.109	0.031	0.011	0.004
Hazard 2 knots	1	0.817	0.545	0.243	0.096	0.021	0.005	0.002
Hazard 3 knots	1	0.819	0.539	0.243	0.081	0.012	0.002	0.000
Odds 1 knots	1	0.820	0.542	0.248	0.127	0.060	0.038	0.027
Odds 2 knots	1	0.817	0.544	0.246	0.120	0.054	0.033	0.023
Odds 3 knots	1	0.818	0.542	0.246	0.110	0.045	0.026	0.018
Normal 1 knots	1	0.811	0.549	0.242	0.102	0.033	0.015	0.008
Normal 2 knots	1	0.815	0.546	0.245	0.113	0.042	0.021	0.012
Normal 3 knots	1	0.818	0.541	0.244	0.099	0.030	0.013	0.007
Mixture cure Weibull	1	0.819	0.585	0.229	0.179	0.179	0.179	0.179
Non-mixture cure Weibull	1	0.820	0.570	0.228	0.169	0.168	0.168	0.168
Mixture cure Log-normal	1	0.818	0.558	0.235	0.134	0.111	0.108	0.108
Non-mixture cure Log-normal	1	0.818	0.551	0.241	0.143	0.109	0.103	0.101
Mixture cure Log-logistic	1	0.822	0.549	0.240	0.163	0.143	0.139	0.138
Non-mixture cure Log-logistic	1	0.823	0.549	0.246	0.178	0.161	0.157	0.156

Table 12: Summary statistics of annual transition probabilities

	Mean	Std.Dev	Min	Q1	Median	Q3	Max	IQR
Exponential	0.245	0.000	0.245	0.245	0.245	0.245	0.245	0.000
Weibull	0.454	0.087	0.091	0.411	0.479	0.522	0.553	0.111
Gompertz	0.579	0.231	0.217	0.366	0.572	0.794	0.952	0.428
Log-normal	0.150	0.063	0.002	0.100	0.128	0.184	0.307	0.084
Log-logistic	0.116	0.078	0.031	0.057	0.083	0.149	0.321	0.092
Gamma	0.370	0.042	0.047	0.370	0.385	0.391	0.394	0.020
Generalised Gamma	0.101	0.071	0.000	0.052	0.073	0.124	0.322	0.072
Hazard 1 knots	0.125	0.056	0.005	0.093	0.106	0.132	0.346	0.039
Hazard 2 knots	0.147	0.049	0.003	0.118	0.131	0.155	0.347	0.037
Hazard 3 knots	0.179	0.039	0.003	0.158	0.168	0.187	0.359	0.028
Odds 1 knots	0.083	0.072	0.004	0.037	0.053	0.095	0.349	0.058
Odds 2 knots	0.087	0.072	0.003	0.040	0.057	0.102	0.347	0.063
Odds 3 knots	0.093	0.072	0.003	0.044	0.064	0.113	0.354	0.069
Normal 1 knots	0.111	0.065	0.000	0.067	0.087	0.131	0.333	0.065
Normal 2 knots	0.101	0.067	0.000	0.058	0.076	0.116	0.336	0.059
Normal 3 knots	0.115	0.064	0.001	0.070	0.091	0.136	0.356	0.066
Mixture cure Weibull	0.037	0.087	0.000	0.000	0.000	0.002	0.312	0.002
Non-mixture cure Weibull	0.039	0.088	0.000	0.000	0.000	0.006	0.322	0.006
Mixture cure Log-normal	0.050	0.087	0.000	0.001	0.005	0.049	0.322	0.048
Non-mixture cure Log-normal	0.051	0.084	0.001	0.003	0.011	0.054	0.332	0.050
Mixture cure Log-logistic	0.044	0.085	0.001	0.001	0.005	0.032	0.341	0.031
Non-mixture cure Log-logistic	0.041	0.084	0.000	0.001	0.004	0.025	0.343	0.024



## 6. PERSUADE object information

```
## List of 7
## $ name          : chr "BC_OS"
## $ input          :List of 11
## ..$ years       : num [1:686] 3.68 4.32 4.82 3.16 2.65 ...
## ..$ status      : num [1:686] 0 0 0 0 0 0 0 1 0 0 ...
## ..$ group       : Factor w/ 3 levels "Good","Medium",...: 1 1 1 1 1 1 1 1 1 1 ...
## ..$ strata      : logi TRUE
## ..$ spline_mod  : logi TRUE
## ..$ cure_mod    : logi TRUE
## ..$ cure_link   : chr "logistic"
## ..$ time_unit   : num 0.0833
## ..$ time_horizon : num 40
## ..$ time_pred_surv_table: num [1:8] 0 12 24 60 120 240 360 480
## ..$ time_pred   : num [1:481] 0 0.0833 0.1667 0.25 0.3333 ...
## $ surv_obs      :List of 6
## ..$ km          :List of 24
## .. ..- attr(*, "class")= chr [1:2] "npsurv" "survfit"
## ..$ km_names: int [1:646] 1 1 1 1 1 1 1 1 1 1 ...
## ..$ cum_haz : 'data.frame': 256 obs. of 9 variables:
## ..$ haz      :List of 3
## ..$ tp       :List of 4
## ..$ cox_reg  :List of 21
## .. ..- attr(*, "class")= chr "coxph"
## $ surv_model   :List of 6
## ..$ param_models:List of 7
## ..$ param_ic    : 'data.frame': 7 obs. of 3 variables:
## ..$ spline_models:List of 9
## ..$ spline_ic   : 'data.frame': 9 obs. of 3 variables:
## ..$ cure_models :List of 6
## ..$ cure_ic     : 'data.frame': 6 obs. of 3 variables:
## $ surv_pred    :List of 3
## ..$ model:List of 9
## ..$ gr       :List of 3
## ..$ tp_gr:List of 3
## $ surv_model_excel: 'data.frame': 24 obs. of 150 variables:
## ..$ rate      : chr [1:24] "expo" "rate" "-2.80703426596042" "-3.08148411925748" ...
## ..$ groupMedium : chr [1:24] "expo" "groupMedium" "0.818021897705403" "0.482435189564671" ...
## ..$ groupPoor   : chr [1:24] "expo" "groupPoor" "1.53752320421143" "1.21843772753164" ...
## ..$ shape       : chr [1:24] "weib" "shape" "0.522842941227738" "0.285099322690929" ...
## ..$ scale       : chr [1:24] "weib" "scale" "2.26626166011077" "2.02632949004802" ...
## ..$ groupMedium : chr [1:24] "weib" "groupMedium" "-0.447145140906987" "-0.732231654626038" ...
## ..$ groupPoor   : chr [1:24] "weib" "groupPoor" "-1.0384947611494" "-1.30926136509352" ...
## ..$ shape(groupMedium) : chr [1:24] "weib" "shape(groupMedium)" "-0.193739409990849" "-0.484038444" ...
## ..$ shape(groupPoor) : chr [1:24] "weib" "shape(groupPoor)" "-0.258211641329158" "-0.53041017496" ...
## ..$ shape       : chr [1:24] "gom" "shape" "0.221650478494696" "0.0571597766378877" ...
## ..$ rate       : chr [1:24] "gom" "rate" "-3.36564422440594" "-3.90407851702435" ...
## ..$ groupMedium : chr [1:24] "gom" "groupMedium" "1.06685398302701" "0.423029806773669" ...
## ..$ groupPoor   : chr [1:24] "gom" "groupPoor" "1.9540432716812" "1.35352047967122" ...
## ..$ shape(groupMedium) : chr [1:24] "gom" "shape(groupMedium)" "-0.0847240786449626" "-0.289307606" ...
## ..$ shape(groupPoor) : chr [1:24] "gom" "shape(groupPoor)" "-0.138758583249691" "-0.340847146615" ...
## ..$ meanlog     : chr [1:24] "lnorm" "meanlog" "2.15766237442877" "1.89389741374292" ...
## ..$ sdlog       : chr [1:24] "lnorm" "sdlog" "-0.0231614685999281" "-0.240079127188789" ...
```

```

## ..$ groupMedium      : chr [1:24] "lnorm" "groupMedium" "-0.616405276964592" "-0.931509869641886"
## ..$ groupPoor        : chr [1:24] "lnorm" "groupPoor" "-1.29461457120387" "-1.59148086932483" ..
## ..$ sdlog(groupMedium) : chr [1:24] "lnorm" "sdlog(groupMedium)" "0.0430707930704261" "-0.22024713"
## ..$ sdlog(groupPoor)  : chr [1:24] "lnorm" "sdlog(groupPoor)" "-0.035860060637656" "-0.2847543784"
## ..$ shape            : chr [1:24] "llog" "shape" "0.626215586614288" "0.391807869444117" ...
## ..$ scale            : chr [1:24] "llog" "scale" "2.09213155981541" "1.85991061112256" ...
## ..$ groupMedium      : chr [1:24] "llog" "groupMedium" "-0.559250078304111" "-0.843377495291217"
## ..$ groupPoor        : chr [1:24] "llog" "groupPoor" "-1.24675818981847" "-1.51563436942317" ...
## ..$ shape(groupMedium) : chr [1:24] "llog" "shape(groupMedium)" "-0.119014027328347" "-0.404025558"
## ..$ shape(groupPoor)  : chr [1:24] "llog" "shape(groupPoor)" "-0.0445926446637765" "-0.3150356240"
## ..$ shape            : chr [1:24] "gam" "shape" "0.730152742986698" "0.405934219745528" ...
## ..$ rate             : chr [1:24] "gam" "rate" "-1.49809910454757" "-2.03166884973234" ...
## ..$ groupMedium      : chr [1:24] "gam" "groupMedium" "0.24690520822162" "-0.392738296363486" ..
## ..$ groupPoor        : chr [1:24] "gam" "groupPoor" "0.834663901724156" "0.234149853810018" ...
## ..$ shape(groupMedium) : chr [1:24] "gam" "shape(groupMedium)" "-0.22379661876854" "-0.62506526205"
## ..$ shape(groupPoor)  : chr [1:24] "gam" "shape(groupPoor)" "-0.245015909581633" "-0.628451036394"
## ..$ mu               : chr [1:24] "ggam" "mu" "1.81202668453465" "1.21730209478661" ...
## ..$ sigma            : chr [1:24] "ggam" "sigma" "0.232571933902732" "-0.016741543388701" ...
## ..$ Q               : chr [1:24] "ggam" "Q" "-1.22829849620357" "-2.75400037606476" ...
## ..$ groupMedium      : chr [1:24] "ggam" "groupMedium" "-0.703779456085614" "-1.46345284222943"
## ..$ groupPoor        : chr [1:24] "ggam" "groupPoor" "-1.15639058358082" "-1.81090501002432" ...
## ..$ sigma(groupMedium) : chr [1:24] "ggam" "sigma(groupMedium)" "-0.111742534466758" "-0.400994984"
## ..$ sigma(groupPoor)  : chr [1:24] "ggam" "sigma(groupPoor)" "-0.251806027157588" "-0.52934875428"
## ..$ Q(groupMedium)    : chr [1:24] "ggam" "Q(groupMedium)" "0.130949690012828" "-1.7041062478985"
## ..$ Q(groupPoor)      : chr [1:24] "ggam" "Q(groupPoor)" "0.706102215543455" "-0.924489391519342"
## ..$ gamma0           : chr [1:24] "spl_hazard_1" "gamma0" "-4.00166824461331" "-4.73804895372434"
## ..$ gamma1           : chr [1:24] "spl_hazard_1" "gamma1" "5.68413827144086" "2.64680689857505"
## ..$ gamma2           : chr [1:24] "spl_hazard_1" "gamma2" "0.536346985941307" "0.150091211344567"
## ..$ groupMedium      : chr [1:24] "spl_hazard_1" "groupMedium" "1.64701334654769" "0.82121480514"
## ..$ groupPoor        : chr [1:24] "spl_hazard_1" "groupPoor" "2.73852858210568" "1.9573725458295"
## ..$ gamma1(groupMedium) : chr [1:24] "spl_hazard_1" "gamma1(groupMedium)" "-2.61371799384606" "-5.8"
## ..$ gamma1(groupPoor)  : chr [1:24] "spl_hazard_1" "gamma1(groupPoor)" "-3.04969394511859" "-6.150"
## ..$ gamma2(groupMedium) : chr [1:24] "spl_hazard_1" "gamma2(groupMedium)" "-0.286595121633603" "-0."
## ..$ gamma2(groupPoor)  : chr [1:24] "spl_hazard_1" "gamma2(groupPoor)" "-0.310481705247366" "-0.70"
## ..$ gamma0           : chr [1:24] "spl_odds_1" "gamma0" "-4.0491737654773" "-4.80121937987566" .
## ..$ gamma1           : chr [1:24] "spl_odds_1" "gamma1" "5.58348971192191" "2.4370507805455" ...
## ..$ gamma2           : chr [1:24] "spl_odds_1" "gamma2" "0.503676257390164" "0.0982702028126948"
## ..$ groupMedium      : chr [1:24] "spl_odds_1" "groupMedium" "1.68509095473313" "0.8293319359502"
## ..$ groupPoor        : chr [1:24] "spl_odds_1" "groupPoor" "2.81726297700326" "1.99594335877646"
## ..$ gamma1(groupMedium) : chr [1:24] "spl_odds_1" "gamma1(groupMedium)" "-2.44366892055128" "-5.781"
## ..$ gamma1(groupPoor)  : chr [1:24] "spl_odds_1" "gamma1(groupPoor)" "-2.85991639069175" "-6.08715"
## ..$ gamma2(groupMedium) : chr [1:24] "spl_odds_1" "gamma2(groupMedium)" "-0.27699989500101" "-0.711"
## ..$ gamma2(groupPoor)  : chr [1:24] "spl_odds_1" "gamma2(groupPoor)" "-0.328459513919301" "-0.7506"
## ..$ gamma0           : chr [1:24] "spl_normal_1" "gamma0" "-2.18021330994335" "-2.50676494276407"
## ..$ gamma1           : chr [1:24] "spl_normal_1" "gamma1" "2.00305993955204" "0.754967846287642"
## ..$ gamma2           : chr [1:24] "spl_normal_1" "gamma2" "0.139244131569558" "-0.03107801496562"
## ..$ groupMedium      : chr [1:24] "spl_normal_1" "groupMedium" "0.781203417379839" "0.3858841960"
## ..$ groupPoor        : chr [1:24] "spl_normal_1" "groupPoor" "1.39918475049402" "1.0136686890126"
## ..$ gamma1(groupMedium) : chr [1:24] "spl_normal_1" "gamma1(groupMedium)" "-0.474093975078312" "-1.8"
## ..$ gamma1(groupPoor)  : chr [1:24] "spl_normal_1" "gamma1(groupPoor)" "-0.634060434239667" "-1.92"
## ..$ gamma2(groupMedium) : chr [1:24] "spl_normal_1" "gamma2(groupMedium)" "-0.0508253646904045" "-0"
## ..$ gamma2(groupPoor)  : chr [1:24] "spl_normal_1" "gamma2(groupPoor)" "-0.0772462585348352" "-0.2"
## ..$ gamma0           : chr [1:24] "spl_hazard_2" "gamma0" "-3.98129140079743" "-6.29287630646042"
## ..$ gamma1           : chr [1:24] "spl_hazard_2" "gamma1" "5.57246906818651" "-3.04982227896694"

```

```

## ..$ gamma2          : chr [1:24] "spl_hazard_2" "gamma2" "0.256338265058247" "-3.08497801538128"
## ..$ gamma3          : chr [1:24] "spl_hazard_2" "gamma3" "0.289633438971024" "-2.6933860504839"
## ..$ groupMedium     : chr [1:24] "spl_hazard_2" "groupMedium" "2.91628215953512" "0.447765119203"
## ..$ groupPoor       : chr [1:24] "spl_hazard_2" "groupPoor" "2.88242174914437" "0.52158214984163"
## ..$ gamma1(groupMedium): chr [1:24] "spl_hazard_2" "gamma1(groupMedium)" "0.783631054627367" "-8.21"
## ..$ gamma1(groupPoor) : chr [1:24] "spl_hazard_2" "gamma1(groupPoor)" "-2.64531056845819" "-11.32"
## ..$ gamma2(groupMedium): chr [1:24] "spl_hazard_2" "gamma2(groupMedium)" "1.65006763421488" "-1.89"
## ..$ gamma2(groupPoor) : chr [1:24] "spl_hazard_2" "gamma2(groupPoor)" "0.0774625317935244" "-3.31"
## ..$ gamma3(groupMedium): chr [1:24] "spl_hazard_2" "gamma3(groupMedium)" "-1.90693272459592" "-5.1"
## ..$ gamma3(groupPoor) : chr [1:24] "spl_hazard_2" "gamma3(groupPoor)" "-0.404156251325355" "-3.45"
## ..$ gamma0          : chr [1:24] "spl_odds_2" "gamma0" "-4.02185633708958" "-6.3825076933676" .
## ..$ gamma1          : chr [1:24] "spl_odds_2" "gamma1" "5.51052878336718" "-3.19361337561952" .
## ..$ gamma2          : chr [1:24] "spl_odds_2" "gamma2" "0.253140292086233" "-3.16417940172001"
## ..$ gamma3          : chr [1:24] "spl_odds_2" "gamma3" "0.26119991232863" "-2.81390126847145" .
## ..$ groupMedium     : chr [1:24] "spl_odds_2" "groupMedium" "3.02298542925585" "0.4777940040656"
## ..$ groupPoor       : chr [1:24] "spl_odds_2" "groupPoor" "2.89341134948443" "0.46717570677471"
## ..$ gamma1(groupMedium): chr [1:24] "spl_odds_2" "gamma1(groupMedium)" "1.0315946008094" "-8.13093"
## ..$ gamma1(groupPoor) : chr [1:24] "spl_odds_2" "gamma1(groupPoor)" "-2.61699779061024" "-11.3869"
## ..$ gamma2(groupMedium): chr [1:24] "spl_odds_2" "gamma2(groupMedium)" "1.80086631783035" "-1.8636"
## ..$ gamma2(groupPoor) : chr [1:24] "spl_odds_2" "gamma2(groupPoor)" "-0.0115893063326446" "-3.506"
## ..$ gamma3(groupMedium): chr [1:24] "spl_odds_2" "gamma3(groupMedium)" "-2.0827061335566" "-5.4192"
## ..$ gamma3(groupPoor) : chr [1:24] "spl_odds_2" "gamma3(groupPoor)" "-0.339047547656046" "-3.5245"
## ..$ gamma0          : chr [1:24] "spl_normal_2" "gamma0" "-2.47954443170845" "-3.33706504973905"
## ..$ gamma1          : chr [1:24] "spl_normal_2" "gamma1" "1.1528048973128" "-1.19034788985897"
## ..$ gamma2          : chr [1:24] "spl_normal_2" "gamma2" "-0.360056185826704" "-1.4568534247492"
## ..$ gamma3          : chr [1:24] "spl_normal_2" "gamma3" "0.489377045312761" "-0.58778806367312"
## ..$ groupMedium     : chr [1:24] "spl_normal_2" "groupMedium" "1.56460781348189" "0.58035562978"
## ..$ groupPoor       : chr [1:24] "spl_normal_2" "groupPoor" "1.63775064239602" "0.7237866888568"
## .. [list output truncated]
## $ misc          :List of 7
## ..$ form        :Class 'formula' language survival::Surv(years, status) ~ group
## .. .. attr(*, ".Environment")=<environment: 0x0000024a94002878>
## ..$ group_names: chr [1:3] "Good" "Medium" "Poor"
## ..$ ngroups     : int 3
## ..$ lbls        : chr [1:7] "Exponential" "Weibull" "Gompertz" "Log-normal" ...
## ..$ lbls_spline: chr [1:9] "Hazard 1 knots" "Hazard 2 knots" "Hazard 3 knots" "Odds 1 knots" ...
## ..$ lbls_cure   : chr [1:6] "Mixture cure Weibull" "Non-mixture cure Weibull" "Mixture cure Log-norm"
## ..$ cols_tp     : num 23
## - attr(*, "class")= chr "PERSUADE"
## NULL

```

## 7. Session information

```
## R version 4.4.2 (2024-10-31 ucrt)
## Platform: x86_64-w64-mingw32/x64
## Running under: Windows 11 x64 (build 26100)
##
## Matrix products: default
##
##
## Random number generation:
## RNG:      Mersenne-Twister
## Normal:   Inversion
## Sample:   Rejection
##
## attached base packages:
## [1] stats      graphics  grDevices  utils      datasets  methods   base
##
## other attached packages:
## [1] PERSUADE_0.0.0.9000
##
## loaded via a namespace (and not attached):
## [1] RColorBrewer_1.1-3  rstudioapi_0.17.1  jsonlite_2.0.0      magrittr_2.0.3      TH.data_1.1-3
## [7] SuppDists_1.1-9.8  farver_2.1.2       rmarkdown_2.29      fs_1.6.5            vctrs_0.6.5
## [13] RCurl_1.98-1.16    base64enc_0.1-3    rstatix_0.7.2       htmltools_0.5.8.1  usethis_3.0.0
## [19] curl_6.4.0         broom_1.0.9        deSolve_1.40        Formula_1.2-5       sass_0.4.10
## [25] pracma_2.4.4       KernSmooth_2.23-24 bslib_0.9.0         htmlwidgets_1.6.4  desc_1.4.3
## [31] zoo_1.8-12         cachem_1.1.0       commonmark_1.9.5    mime_0.12           lifecycle_1.0.3
## [37] Matrix_1.7-1       R6_2.6.1           fastmap_1.2.0       shiny_1.10.0        digest_0.6.37
## [43] colorspace_2.1-1   ps_1.8.1           pkgload_1.4.0       Hmisc_5.2-0         ggpubr_0.6.1
## [49] flexsurvcure_1.3.3 km.ci_0.5-6        abind_1.4-8         compiler_4.4.2      remotes_2.5.0
## [55] htmlTable_2.4.3    backports_1.5.0    carData_3.0-5       pkgbuild_1.4.5      ggsignif_0.6.4
## [61] quantreg_5.99      sessioninfo_1.2.2  tools_4.4.2         foreign_0.8-87      mstate_0.3.3
## [67] nnet_7.3-19        glue_1.8.0         quadprog_1.5-8      callr_3.7.6         nlme_3.1-166
## [73] gridtext_0.1.5     grid_4.4.2         rsconnect_1.4.1     checkmate_2.3.2     cluster_2.1.6
## [79] gtable_0.3.6       fda_6.3.0          KMSurv_0.1-6        tidyr_1.3.1         survminer_0.5.0
## [85] xml2_1.3.6         car_3.1-3          markdown_2.0         pillar_1.11.0       stringr_1.5.1
## [91] splines_4.4.2      ggtext_0.1.2       dplyr_1.1.4         lattice_0.22-6      survival_3.7-0
## [97] ks_1.14.3          tidyselect_1.2.1   fds_1.8             rms_6.8-2           miniUI_0.1.1.1
## [103] knitr_1.50         gridExtra_2.3      litedown_0.7        svglite_2.1.3       xfun_0.52
## [109] devtools_2.4.5     sft_2.4            stringi_1.8.4       yaml_2.3.10         boot_1.3-31
## [115] evaluate_1.0.4     codetools_0.2-20   tibble_3.2.1        cli_3.6.3           rpart_4.1.23
## [121] xtable_1.8-4       processx_3.8.4     jquerylib_0.1.4     survMisc_0.5.6      dichromat_2.0-0
## [127] MatrixModels_0.5-4 ellipsis_0.3.2     ggplot2_3.5.2       mclust_6.1.1        profvis_0.4.0
## [133] bitops_1.0-9       viridisLite_0.4.2 mvtnorm_1.3-2       flexsurv_2.3.2      scales_1.4.0
## [139] purrr_1.0.4        rlang_1.1.6        multcomp_1.4-28
```