

**THE ROLE OF FRAILTY MODELS AND
ACCELERATED FAILURE TIME MODELS
IN DESCRIBING HETEROGENEITY
DUE TO OMITTED COVARIATES**

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SUMMARY

In survival analysis, deviation from proportional hazard may sometime be explained by unaccounted random heterogeneity, or frailty. This note recalls the literature on omitted covariate in survival analysis and how in a case study how untably frailty model might behave when added to account for unobserved heterogeneity in standard survival analysis with no replication per heterogeneity unit. Accelerated failure time modelling seem to avoid the difficulties and also to yield easily interpretable results.

We propose that it would be advantageous to upgrade the accelerated failure time approach alongside the hazard modelling approach to survival analysis.

1. INTRODUCTION

Statistical modelling of heterogeneity may be based on stratification according to factor , regression on covariate , or by assuming a probability distribution of

time framework for interpretation of covariate effect in survival analysis with random heterogeneity.

The purpose of this note is to briefly recapitulate the above framework and to present another case study which, like that of Hougaard et al.¹⁶, indicates that accelerated failure model may be preferable in accounting for (residual) heterogeneity in univariate (“single-pell”) survival time due to “missing” (omitted, unrecorded) covariate.

Section 2 presents a brief partial survey on approaches to the study of omitted covariate in the 1980s, and Section 3 briefly recalls the proportional hazard frailty model with a perspective of current techniques for inferential analysis. Section 4 presents and lightly extends the Struthers-Kalbfleisch heuristic on omitted covariate in survival analysis based on a normal-theory linear model equivalent to the accelerated failure time model. Section 5 presents a preliminary discussion of the PROPORTIONALS0TDFDf(to)TOjfl1721TDFDf(to)THEjfl17291failureac200(e

parameter , maximum li

Let W have a standard extreme value distribution of a minimum, that is, the density of W is $p(w - e^w)$, $-\infty < w < \infty$. Then T follows the above Weibull distribution, where

$$Y = \log T = -\frac{\log \kappa}{\nu} - \frac{\beta_1}{\nu}x_1 - \frac{\beta_2}{\nu}x_2 + \frac{W}{\nu}.$$

This is an *accelerated failure time model*: an ordinary regression problem of $\log(\text{survival time})$ on x_1 and x_2 with extreme value distributed residual with scale parameter ν^{-1} , regression coefficient $-\beta_1/\nu$ and $-\beta_2/\nu$ and intercept $-\nu^{-1} \log \kappa$. Borrowing experience from normal-theory linear regression (i.e. assuming W standard normal $(0,1)$), it is seen that the regression coefficient and intercept are estimated by the usual regression estimate, in particular $E(\widehat{\beta_1/\nu}) = \beta_1/\nu$, ν^{-1} is estimated by the usual residual empirical variance s^2 , and for large

above, $\beta\tau$ is estimated by the usual regression estimate, so $E(\widehat{\beta\tau}) = \beta\tau = \beta_1/\nu$ (= the theoretical regression of Y on x_1). Therefore $\hat{\beta} \xrightarrow{P} \beta = \beta_1\nu^{-1/2}/\tau$, which is closer to 0 than β_1 : there is the well-known *attenuation due to an omitted covariate*. Furthermore

$$\text{a.s. var.}(\hat{\beta}) = \frac{1}{n} \left(\frac{1}{\sigma_{x_1}^2} + \frac{\beta_1^2}{2\nu\tau^2} \right) < \text{a.s. var.}(\hat{\beta}_1) \quad ;$$

the standard error is also attenuated, indeed if $\sigma_{x_1}^2$ is large, the Wald 57031111413899879206111311

bution has changed, now being that of $(W + U)/\nu$. In gain borrowing experience from normal-theory linear regression, $-\beta_1/\nu$ would be estimated by the usual regression estimate, $E(\widehat{\beta_1/\nu}) = \beta_1/\nu$, but if we had erroneously assumed no frailty ($U = 0$), $\nu - 1$ would have been overestimated by the factor $\eta = (\text{Var}W + \text{Var}U)/\text{Var}W$ and the hazard model regression parameter $\beta_1 = (\beta_1/\nu)/\nu^{-1}$ similarly underestimated by the factor η^{-1} , leading to *attenuation by di regarding frailty*.

Conclusion. For the Weibull model the accelerated failure time parametrization conveniently separates regression coefficient from dispersion parameter, allowing unchanged estimation of regression coefficient under the frailty-amended model, which only contributes to the dispersion. This was previously pointed out by Hougaard et al.¹⁶.

5. EXAMPLE

Anderson et al.² considered in their Example VII.3.1, VII.3.4 and IX.4.3 survival after operation for malignant melanoma for 205 patients.

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imilar way of incorporating the e covariate . If the covariate are included in a tandard Co model the e timated regre ion coefficient and tandard error were

$$\begin{aligned} \log(\text{tumour thickness}) & 0.610 (0.176) \\ \text{ulceration} & 0.971 (0.321) \end{aligned}$$

but graphical chec (nder en et al.², Fig . VII.3.3 and VII.3.6) rai ed ome u picion that hazard for patient without and with ulceration, were not proportional but rather converging. Therefore a time-dependent covariate to account for po ible time \times covariate interaction wa added:

$$\begin{aligned} \log(\text{tumour thickness}) & 0.607 (0.177) \\ \text{ulceration} & 1.082 (0.357) \\ \text{ulceration} \cdot (\log(t) - 7) & -1.198 (0.589); \end{aligned}$$

here t i mea ured in day and $7 \sim \log(3 \times 365)$. li elihood ratio te t of no effect of the latter variable yielded $p = .02$, giving ome evidence to uport the u pected deviation from proportionality.

Semiparametric frailty model.

Becau e thi deviation might be interpreted a a election effect in a heterogeneous population ari ing from important unmea ured confounder not being included in the analy i , a frailty model wa po tulated. To the

Cox regression model specification of the death intensity with the two covariate was multiplied a frailty factor Z , assumed gamma distributed with $E(Z) = 1, \text{Var}(Z) = \delta$. The fitted parameters were (with the no-frailty model estimate attached for comparison)

	Frailty	No frailty
log(tumour thickness)	1.370 (0.472)	0.610 (0.176)
ulceration	1.696 (0.686)	0.971 (0.321)
frailty variance	4.215 (2.266)	0 (-)

with likelihood ratio test statistic of no frailty variance yielding $p = .007$. For details on estimating the standard error under the frailty model, cf. Andersen et al.²⁷.

It is thus seen that incorporation of unmeasured population heterogeneity in this case *deattenuate* the effect of the measured covariate (as well as of their standard error) by a factor of about 2.

Weibull frailty model.

Andersen et al.² noted that the underlying intensity of the fitted Cox regression model varied so regularly that a hypothesis of Weibull underlying intensity should be acceptable. In order to study the

vey by Klein et al.⁴, as well as the power variance family (α, ψ, δ) due to Hougaard³², of which all of the are special cases. Hougaard's model is more easily characterized by the Laplace transform

$$E \exp \left\{ -\frac{\psi}{\alpha} [(t + s)^\alpha - t^\alpha] \right\}.$$

Our gamma distribution is $(0, \delta^{-1}, \delta^{-1})$, while $(\alpha, \psi, 0)$ ($0 < \alpha < 1$) are the positive stable distribution and $(\frac{1}{2}, \psi, \delta)$ the inverse Gaussian distribution. As well known, the positive stable frailty distribution lead to unidentifiability in the present case of observing only one event per individual. For the other frailty model, with the no frailty model included for comparison, the estimates are given in Table 1.

It is seen that the results from the all-inclusive power variance frailty model are virtually indistinguishable from that of the gamma frailty model, which in turn fit significantly better than the inverse Gaussian frailty and the no frailty/positive stable frailty (the latter two having the same likelihood).

Also, the estimates for no frailty and gamma frailty are well compatible with the semiparametric estimate quoted above, and also there is a deattenuation factor of 2 to 3 on the regression parameter when considering the gamma frailty model. The assumption of inverse Gaussian frailty yield intermediate results, and judging from the likelihood also a less effective accounting for the heterogeneity.

Table 2 record the estimated correlation between the estimated frailty parameter (indicating the spread of the frailty distribution) and the estimate of the regression coefficient and the Weibull shape parameter. The positive

correlation reflect the inherent negative correlation between two alternative way of describing the observed heterogeneity in survival time : either by a large frailty parameter (wide frailty distribution), or by a “flat” underlying intensity (small Weibull shape parameter). Indeed, while the underlying Weibull distribution in the no-frailty model is significantly different from an exponential distribution (shape parameter=1), a much more concentrated underlying distribution is estimated for the gamma and inverse Gaussian frailty model .

The positive correlation between estimated frailty parameter and estimated regression parameter reflect the deattenuation effect described in Section 3. Intuitively: The interindividual variation is *either* described by covariate (high regression coefficient) *or* frailty (large frailty parameter).

Accelerated failure time interpretation.

Alternatively, we may start from the accelerated failure time (AFT) interpretation outlined toward the end of Section 3. We then obtain the result of Table 3, accounting for the multiplicative indeterminacy in the positive table frailty distribution and still assuming underlying Weibull distribution.

It is seen that in the AFT interpretation, the various model agree. Let

$$\begin{aligned} \log(\text{survival time}) = \text{const.} & - 0.60 \times \log \text{tumour thickness} \\ & - 0.75 \times \text{ulceration} \\ & + \text{noise} . \end{aligned}$$

That is, for fixed value of ulceration, if tumour thickness increase by a factor α , survival time will decrease by a factor $\alpha^{0.60}$. Similarly, for fixed value of tumour thickness, ulceration of the tumour will decrease life by a factor of $e^{-0.75} \approx 0.47$ compared to what it would have been if the tumour was not ulcerated.

6. DISCUSSION

naïve interpretation: individual or population risk. The original impetus for the frailty concept such as defined by Vaupel et al.¹ was to clarify the behaviour of the *mean hazard among the survivor* in a heterogeneous population. In our example we observed a (slight) deviation from

the only slightly worse fitting inverse Gaussian frailty distribution deattenuation was halved, and for the positive stable frailty model it (the parameter above) is inherently unidentifiable. (Motivated in part by this feature of the positive stable frailty distribution, Robin and Greenland^{14,15} discussed consequences of such unidentifiability problem for compensation scheme). It is well known that ratios of regression coefficients are much less sensitive to model misspecification than the regression coefficients themselves, see Solomon¹⁹ for example from the present context and Li and Duan³¹ for a careful general discussion with review of earlier work. This is also very apparent in our example.

A conceptual explanation may be obtained from the observation above about strong positive correlation between the estimate of the Weibull shape parameter ν and the spread of the frailty distribution. The single-pell data contain only limited power to distinguish the random variation as within-individual (large ν) or between-individual (large frailty spread), and therefore interpretations based only on the within-individual hazard are unstable.

Accelerated failure time interpretation: Seen above the FT interpretation (which was here feasible starting from log-Weibull error distribution) avoids the unidentifiability problem by shifting attention of the dependence on covariates from the elusive concept of 'individual hazard' to the acceleration factor of the lifetime itself, thereby combining the within- and between-individual components of variation into much more stably determined functional forms. The heterogeneity is conveniently relegated to an overdispersion

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Table 1. Estimate for Weibull frailty

Table 2. Weibull frailty model . Correlation between estimated frailty parameter and parameter estimate specified.

	Gamma frailty semiparametric	Gamma frailty Weibull	Inverse Gaussian frailty Weibull
Weibull shape parameter	—	.882	.793
log(tumour thickness)	.632	.598	.323
ulceration	.532	.511	.430

Table 3. Weibull frailty model . Hazard rate regression coefficient contrasted to accelerated failure time regression coefficient .

	Gamma frailty	Inverse Gaussian frailty	No frailty (assumed=1) or Poitive table frailty (indeterminate)
Weibull shape parameter	2.917 (0.718)	1.747 (0.299)	1.150 · (0.131 ·)
log(tumour thickness)	1.754 (0.592)	0.932 (0.281)	0.577 · (0.175 ·)
ulceration	2.180 (0.875)	1.512 (0.518)	1.020 · (0.322 ·)
$\frac{\log(\text{tumour thickness})}{\text{Weibull shape parameter}}$	0.60 (0.15)	0.53 (0.18)	0.50 (0.16)
$\frac{\text{ulceration}}{\text{Weibull shape parameter}}$	0.75 (0.25)	0.87 (0.28)	0.89 (0.29)