[Development of a log-normal accelerated failure time model for survival of Dutch dairy cows under altering agricultural policy]

[Kulkarni P.S.\*, Mourits M.C.M., Nielen M., van den Broek J., Hogeveen H., Steeneveld W.]

summary

Changes in agricultural policy such as milk-quota abolishment impact herd size and might influence culling decisions of dairy farmers. The purpose of this study was to develop a modelling strategy for studying the relevant cow-level risk factors for survival of Dutch dairy cows representing production, reproduction and metabolic health performances under perturbations due to agricultural policy changes. An interval-censored Accelerated Failure Time (AFT) model was developed on a large national level database between years 2009 and 2019 association with time-varying relevant risk factors under three different policy periods. Results show that the productive lifetime survival of dairy cows reduced over time and changed under the influence of different policies. However, the relevance of associated cow-level risk factors remained the same.

introduction

Replacement of dairy cows is a fundamental part of dairy farm management. The replacement decisions involve culling of underperforming dairy cows and subsequent replacement by suitable heifers. On average, 25-30% of Dutch dairy cows are replaced annually (Nor et al., 2014; CRV, 2018) indicating a cow-longevity of 6 to 7 years (Nor et al., 2014) which is much lower than the natural biological longevity. Culling on individual cow level was shown to be associated with older parity/ age, older age at first calving, calving complications and longer calving intervals, lower relative production level, and health indicators like high somatic cell count in milk, and very high or very low fat-protein ratios in early lactation(Schukken et al., 2003; Huijps et al., 2008; Nielsen et al., 2010; Pritchard et al., 2013; Gussmann et al., 2019; Rilanto et al., 2020). These factors can be termed as associated cow-level risk factors for culling.

Changes in national agricultural policies can influence farmers’ culling decisions. Dairy farmers might change their strategy either in anticipation or as a result of changes in agricultural policies of the country. Failure to respond to such policy changes might negatively affect the future profitability of the dairy farms (McDonald et al., 2013). So, in combination with the changing policy climate, the culling strategy of dairy farms operates in a dynamic environment where the relevance of associated risk factors and replacement criteria might change periodically. Literature on risk factors influencing culling decisions and their trade-offs representing the changed Dutch farming policy climate is, however, lacking. There is a need for a study of effects of policy and associated risk factors related to the voluntary culling of dairy cows.

Risk of culling and its relevant factors can be studied epidemiologically by looking at survival of individual producing cows on dairy farms. Survival in terms of productive longevity can be studied with survival analysis models such as cox-proportional hazards, semi-parametric models or parametric Accelerated Failure Time models (AFT) depending on nature of data and interpretation (Kleinbaum and Klein, 2010). Time-varying effects or hazards of associated risk factors can be analysed with censored longitudinal survival data with appropriate survival models (Klein and Moeschberger, 2006). A large-scale survival analysis of such nature in the Dutch dairy farming system is pertinent.

The purpose of this study was to develop a modelling strategy for studying the relevant cow-level risk factors for survival of Dutch dairy cows representing production, reproduction and health performances under perturbations due to agricultural policy changes.

MATERIALS and methods

Data

Anonymized production data on individual Dutch dairy cow-level were obtained from the Cattle Improvement Cooperative- CRV (CRV Holding BV, the Netherlands). This data comprised of 4 subsets, containing 1) Milk Production Registration (MPR) test records, 2) cow removal/exit data records, 3) lactation records and 4) insemination records (see Table 1 for details). The data spanned from years 2009 to 2019 and included information on approximately 80% of all the milk-producing cows in the Netherlands. The raw data files included repeated measures of 6,033,922 dairy cows from 19,885 farms.

Table 1. Overview original data (sub)sets

|  |  |  |
| --- | --- | --- |
| No. | Names of data (sub)sets | Contents |
| 1 | Milk Production Registration (MPR data) | Test-day records of producing cows on milk, fat%, protein%, somatic cell count, number of lactations, parity, etc. |
| 2 | Animal removal/ exit from herd records (Exit data) | Exit date of animals, code of exit (dead, alive/no exit, slaughter, export) |
| 3 | Lactation records data (Lactation data) | Lactation records on 305-milk, 305-fat, 305-protein, calving date, etc. |
| 4 | Insemination records (Insemination data) | Records of inseminations per parity, total inseminations, type of insemination, etc |

Only data from commercial farms were selected. A commercial Dutch dairy farm was defined as a farm having (a) records (being active) for at least 5 years between 2009 and 2019, (b) an average of at least 30 producing cows (with a minimum of 25 in any given year) and (c) an average of 4 test-day observations per year for all cows (with a minimum of 3 observations in any given year). Furthermore, for farms that ended their farming operations, the records from the year of closure were omitted. Cow-level records containing missing birth dates, missing test records, etc. as well as records containing unrealistic values were omitted. Records on cows which changed farms more than twice in their production lifetime were also excluded. Moreover, cows which were exported to other countries were excluded completely from the data as the information on their survival was not available. The four data (sub)sets were merged per cow in a single final dataset, consisting of repeated records on 4,779,676 dairy cows from 13,936 commercial farms.

Based on the literature, variables representing the associated risk factors for culling were selected from the merged data. The final factors and their levels are presented in Table 2. Parity was categorised into 4 levels, Lactation value (LV), which denotes the relative milk production level of a cow in a herd, in 3 levels. Details of how LV is calculated can be found at CRV (2020). Fat and protein percentages in the first 100 days of lactation were converted to fat-protein ratios (FPR). The proportion of test-days with ratios above 1.5 and below 0.9 were determined in each parity per cow, representing very high and very low FPR, respectively. The two factors representing very high and very low FPR were split in two levels representing small proportion (less than 50%) and large proportion (more than/ equal to 50%) of low/high-FPR values in first 100 lactation days. Individual somatic cell counts in test-day milk were classified in 4 levels, whereas the rolling average number of inseminations per parity was factorized in 3 levels. A factor for policy periods was generated based on calendar year with three levels representing the targeted policy periods, namely the Milk Quota period 2009-2013 (MQ), the Post-Milk Quota period 2014-2016 (PMQ) and the Phosphate regulation period 2017-2019 (PH).

Table 2. Selected risk factors and their levels with number of observations

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Factor | Abbrev. | Explanation | Levels | No. of test-day records |
| Lactation value | LV | Relative milk production level on test-day in comparison to the herd average of 100.  Three levels represent less than 90, between 91 and 110, more than 110 LV | below average | 26,023,175 |
|  | average | 65,532,040 |
|  | above average | 22,950,930 |
| Parity | - | Parity number of cows | 1st parity | 34,517,660 |
|  | 2nd parity | 28,438,152 |
|  | 3-4th parities | 35,092,020 |
|  | > 4 parities | 16,458,313 |
| Very high-fat protein ratio | highFPR | Indicator for subclinical ketosis, reflected by the proportion of tests in first 100 days of lactation resulting in FPR>1.5 | < 50% | 112,705,286 |
|  | ≥ 50% | 1,800,859 |
| Very low-fat protein ratio | lowFPR | Indicator for Sub-acute Rumen Acidosis. reflected by the proportion of tests in first 100 days of lactation resulting in  FPR < 0.9 | < 50% | 114,436,777 |
|  | ≥ 50% | 69,368 |
| Test day-Somatic cell count (x 1,000) | SCC | Somatic cell count in thousands per millilitre of milk on test-day | < 200 | 91,912,692 |
|  | ≥ 200 and < 600 | 15,257,987 |
|  | ≥ 600 and < 1000 | 3,202,567 |
|  | ≥ 1,000 | 4,132,899 |
| Insemination | Insem | Rolling average of total number of inseminations per parity | < 2 | 63,753,449 |
|  |  | ≥ 2 and < 5 | 47,408,119 |
|  |  | ≥ 5 | 3,344,577 |
| Policy Periods | Period | Time periods of test-day records MQ (Milk quota): 2009-2013,  PMQ (post-milk quota): 2014-2016,  PH (Phosphate regulation): 2017-2019 | MQ | 49,613,372 |
|  |  | PMQ | 33,652,664 |
|  |  | PH | 31,240,109 |

The data were transformed into survival data with start time, stop time and event variables (removal/exit) representing left-truncated (initial start time was difference between the test date and birth date of the cows), and interval-censored repeated measures data according to Klein and Moeschberger (2006). Each interval represented the time period between two test-days of MPR recording. Start and stop times for the intervals were represented in weeks of survival. Event “1” represented removal of cows from MPR records as where the cow can be considered as “culled (voluntarily)” or “sold alive to another herd” and the event of “0” represented cows which were still producing, censored, or those which died naturally during the period between 2009 and 2019. Factors were time-varying variables with observations per interval.

Statistical analysis

Time-varying effects or hazards of associated risk factors can be analysed with censored longitudinal survival data with appropriate survival models (Klein and Moeschberger, 2006). Given the nature of the data, a parametric survival model with appropriate distribution for survival time was to be chosen. An AFT model with an underlying theoretical distribution assumes a specific distribution for time-to-event or survival time that is analysed log-linearly against covariates or in this case, factors with distinct levels. Interval censored data of animals can be utilized in such a model along with time-dependent factor levels (Klein and Moeschberger, 2006; Kleinbaum and Klein, 2010).

Several AFT models with different underlying distributions for time-to-event (the dependent variable) were tested graphically. To check the validity of the assumptions of the AFT models, residuals from the AFT models were plotted. This was done to visually appreciate the conformity of residuals to the expected error distribution of the AFT. However, since the residuals were estimated from censored data, they were censored as well. To circumvent this issue, the Kaplan-Meier estimates of the AFT residuals were computed and then plotted against the survival probability. The expected error distribution curves were superimposed on this graph to visually validate the conformity of the AFT models to the assumptions. The expected error distributions corresponding to the distributions of the dependent variable are presented in Table 3.

Table 3. Underlying error distributions for the AFT models that were tested

|  |  |  |
| --- | --- | --- |
| No. | AFT model distribution | Expected error distribution |
| 1 | Weibull | Extreme value distribution |
| 2 | Exponential | Extreme value distribution |
| 3 | Log-Logistic | Logistic distribution |
| 4 | Logistic | Logistic distribution |
| 5 | Log-normal | Normal distribution |

Out of these tests, the lognormal AFT model was selected based on a visual conformation of the residuals and expected residual distribution as well as lowest Akaike-Information Criterion (AIC) (see Results description). Logarithm of time-to-event was linearly regressed against these associated time-dependent factor-levels which were assumed to linearly increase or decrease time-to-event based on their effect.

Selected relevant factors (Table 2) were added to the model as fixed time-varying effects along with a random (shared variance) term of farm corrected by clustering,

(1)

Where, β is a vector of time ratio (TR) estimates ( being the transpose), is a matrix of factor levels with “i” clusters and “j” observations per cluster and are random errors within cluster (not independent inside cluster). This structure represents correcting for cluster dependence by marginalizing the TR estimates similar to the method used in Fan and Datta (2011).

Consequently, the model was refined by using the AIC-based stepwise backward selection protocol. The final model was defined as follows,

(2)

Where, ‘*Ftime*’ represents time-to-event, , , , , , ’ represent the factors as denoted Table 3 and ‘’ denotes the cluster/random effects of the farms in which cows are producing. In this model, the ‘’ is representative of survival intervals between previous and next testing date in the MPR records. The interaction terms represent the proportion of effect of the factors under different policy periods. Interaction terms ‘*Period:lowFPR*’ and ‘*Period:Insem*’ were removed from the final model by AIC-backwards selection. Estimates of the factor levels were calculated ‘inside’ the levels of the period term with their standard errors.

RESULTS

Descriptive statistics

The data spanned from year 2009 to 2019 with a maximum of 13,590 farms and minimum of 11,737 farms per year (Table 4). However, the majority of the selected farms (~78%) continued production for the entire span of 11 years. Producing cows from the selected herds in the MPR data were tested on an average of 10 times per year.

Table 4. Recorded number of commercial farms and producing cows between 2009 and 2019

|  |  |  |
| --- | --- | --- |
| Year | Cows | Farms |
| 2009 | 1,308,083 | 13,375 |
| 2010 | 1,371,412 | 13,450 |
| 2011 | 1,405,444 | 13,531 |
| 2012 | 1,443,133 | 13,590 |
| 2013 | 1,492,813 | 13,453 |
| 2014 | 1,536,476 | 13,407 |
| 2015 | 1,600,403 | 13,355 |
| 2016 | 1,695,173 | 13,176 |
| 2017 | 1,634,629 | 12,732 |
| 2018 | 1,529,185 | 12,244 |
| 2019 | 1,388,810 | 11,737 |

Between 2010 and 2019, 337,754 new primiparous cows were introduced to the farms with a maximum of 396,909 cows in year 2016 and a minimum of 253,251 cows in year 2019 (Figure 1). Similarly, on average 268,206 cows had an event i.e., they were voluntarily culled or sold alive with a maximum of 338,076 and a minimum of 230,002 cows in years 2017 and 2015, respectively (Figure 1).

Figure 1. Total Influx and Efflux of cows in years 2010 to 2019.

Note: influx-efflux figures for year 2009 are not displayed as they were biased due to left-truncation of cows that were already producing. X- axis divided in three policy periods viz., Milk Quota (MQ, 210-2013), Post-Milk Quota (PMQ, 2014-2016) and Phosphate regulation (PH, 2017-2019)

Model selection

In order to select a parametric model, a graphical procedure for testing the residuals was employed. The same model was fitted with different AFT variations of distributions for log-survival time such as Weibull, Loglogistic, Logistic and exponential. It was shown that although none of the Kaplan-Meier (KM) estimates of residuals follow the exact expected error distribution, the KM estimates of the lognormal AFT model and log-logistic AFT model reasonably follow the expected error distribution (Figure 2). This showed that the AFT model assumptions of lognormal distribution for the dependent variable (time-to-event) were sound. Out of all the variations, lognormal distribution had the lowest AIC thus validating the choice of the model assumptions (Table 5). The graphical procedure and AIC estimation showed that the AFT model assumptions of lognormal distribution for the dependent variable (time-to-event) were sound. Lowest AIC also meant that the selected model had the least out-of-sample variance.

Diagram

Description automatically generated

Figure 2. Graphical test for Kaplan-Meier (KM) estimates of residuals from AFT models against five different expected error distributions±

±On x-axes, residuals from respective AFT distributions; on y-axes, survival probabilities from 0% 🡪100% are plotted

Table 5. Comparison of different AFT models and their AIC scores

|  |  |  |
| --- | --- | --- |
| Model distribution type | Degrees of Freedom | Akaike-Information Criterion (AIC) |
| Lognormal | 34 | 46881680 |
| LogLogistic | 34 | 47397611 |
| Weibull | 34 | 47832641 |
| Logistic | 34 | 50139935 |
| Exponential | 33 | 57346377 |

Survival Analysis using AFT model

Table 6 shows the effects of associated risk factors in the final model under the levels of policy periods in terms of survival time in weeks. All main effects of the associated factors were significant based on 95% confidence intervals. In terms of difference between the policy period, the median survival of the cows decreased by 2.7 weeks and 15.3 weeks in PMQ and PH, respectively, compared to MQ (Table 6). Hence, the lowest median survival for cows under policy period was found in PH period. Based on the results of the AFT model (Table 6), it was shown that estimated survival increased with higher parities, above average LV, higher proportion of HighFPR and higher Insem and lower SCC and lower proportion of lowFPR within all three policy periods.

Table 6. Estimates of survival time (in weeks) based on Accelerated Failure Time model

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Factor± | Survival time in weeks | 95% CI | | | | | | |
|  | exp(ß) | LOW | | UP | | | | |
| Intercept | 246.7 | 244.7 | | 248.6 | | | | |
| Log(scale) | +0.3 |  | |  | | | | |
| Policy Periods | |  | |  | | | | |
| MQ ± | Ref |  | |  | | | | |
| PMQ | -2.7 | -2.7 | | -1.2 | | | | |
| PH | -15.3 | -15.3 | | -11.4 | | | | |
|  |  |  | |  | | | | |
|  | MQ | PMQ | | PH | | | | |
| Factor | Survival time in Weeks § | | | | | | |
| Parity |  |  | |  | |  | | |
| 1st parity | Ref | Ref | | | Ref | | | |
| 2nd parity | +85.0 | +83.3 | +87.0 | | | |
| 3-4 parities | +217.4 | +215.1 | +222.1 | | | |
| > 4 parities | +459.6 | +441.5 | +451.2 | | | |
| LV |  |  |  | | | |
| below average | -29.8 | -30.3 | -29.5 | | | |
| average | Ref | Ref | Ref | | | |
| above average | +25.1 | +25.2 | +20.6 | | | |
| SCC (X 1,000) | |  |  | | | |
| < 200 | Ref | Ref | Ref | | | |
| ≥ 200 and < 600 | -11.8 | -9.7 | -9.2 | | | |
| ≥ 600 and < 1000 | -18.5 | -14.8 | -12.3 | | | |
| ≥ 1,000 | -32.4 | -29.2 | -24.4 | | | |
| highFPR |  |  |  | | | |
| < 50% | Ref | Ref | Ref | | | |
| ≥ 50% | +9.8 | +9.6 | +6.0 | | | |
| lowFPR |  |  |  | | | |
| < 50% | Ref | Ref | Ref | | | |
| ≥ 50% | -12.0 | -10.9 | -5.1 | | | |
| Insem |  |  |  | | | |
| < 2 | Ref | Ref | Ref | | | |
| ≥2 and < 5 | +18.9 | +17.4 | +15.3 | | | |
| ≥ 5 | +29.2 | +24.6 | +24.6 | | | |

± Abbreviations in the table: Ref (reference level of factor), MQ (milk quota), PMQ (post-milk quota), PH (phosphate regulation), LV (lactation value), SCC (test-day somatic cell count), highFPR (very high test-day fat-protein ratio), lowFPR (very low test-day fat-protein ratio), Insem (rolling avg. of inseminations per parity)

§ 95% confidence intervals for Parity, LV, SCC, low/highFPR and Insem were too small to report (< ±1 week)

DISCUSSION

The purpose of this study was to develop a modelling strategy for studying the relevant cow-level risk factors for survival of Dutch dairy cows representing production, reproduction and health performances under perturbations due to agricultural policy changes. In this study, it was shown that lognormal AFT model was appropriate for determining the associations between the risk factors and the survival of dairy cows under changing agricultural policy. The survival analysis of the cows was utilized to gain insight in the culling/ sale pattern of the dairy cows in the different policy periods.

Survival in terms of productive longevity can be studied with survival analysis models such as cox-proportional hazards, semi-parametric models or parametric AFT models (Wei, 1992) depending on nature of data and interpretation (Kleinbaum and Klein, 2010). Frequently, survival analysis of dairy cows was done on basis of age-longevity in herds (Gröhn and Rajala-Schultz, 2000; Gussmann et al., 2019; Rilanto et al., 2020) or on basis of stages of lactation per parity (Roxström et al., 2003; Rocha et al., 2018). The distribution of dependent variable assumed under AFT models depend on the nature of data. Log-normal and log-logistic distribution AFTs are most commonly utilized models in biological studies (Klein and Moeschberger, 2006).

In this study, the AFT model was developed per policy over calendar years which signified major changes to agricultural policy. Unlike the non-parametric survival methods, use of AFT model involved assumption of underlying log-normal distribution of “time-to-event” variable which was reasonable given the nature of the data. Due to the parametric nature of the model, AFT models are more robust for incorporating multiple covariates, fixed factors and random components (Keiding et al., 1997; Lambert et al., 2004). In this study, the shared random variance of farm effect was controlled for using clusters from R package ‘Survival’ (R Core Team, 2020). The collinearity between repeated records for the dairy cows was also addressed in due to the design of interval censoring of survival times. Moreover, the estimates of the associated factor levels in the AFT model are in form of log-time ratios which are easy to interpret in terms of ‘acceleration’ in log-time towards event (Wei, 1992). Besides that, AFT models are flexible towards neglected covariates and factors (Hougaard, 1999) such as disease indicators for mastitis, lameness, etc. in dairy cattle which influence culling decisions and were not recorded in the data.

In this study, a largescale national level database was utilized for the analysis. This enabled very precise estimation of associated effects of the relevant factors with small 95% confidence intervals. However, based on the results of the AFT model, no large-scale differences in the survival of cows were found between the different policy periods. Based on these results, it was speculated that the adjustments made by the farmers under the changing policy climates might not be strictly within the bounds of particular periods. Some farmers make early changes while others have delayed reactions.

The factors selected in this model encompassed production, reproduction and metabolic heath performances based on the literature. Based on the results, there were no changes in the ‘pattern’ of estimated survival under the levels of associated risk factors within different policy periods. This showed that there were no differences in the relevancy of associated risk factors between the three policy periods. Hence, survival analysis of dairy cows under changing policy was not straightforward. Under continuously changing policy climate the perturbations caused in culling patterns of the farms could be treated as a continuum rather than discrete changes per year or per period in future research. In conclusion, this study demonstrated that parametric AFT model can be used to analyse the survival of dairy cows in association with risk factors.

ACKNOWLEDGEMENTS

Special thanks to Dr. Miel Hostens, and Rene Janssen of Utrecht University and Dr. Ies Nijman of UMC-Utrecht for their help in big data analysis and high performance computing.

REFERENCES

CRV, 2018. Jaarstatistieken-NL. [www.crv.nl](file:///C:\Users\steen053\AppData\Local\Microsoft\Windows\INetCache\Content.Outlook\VMQQGWF8\www.crv.nl).

CRV, 2020. (in Dutch) netto-opbrengst-en-lactatiewaarde. <https://www.crv4all.nl/download/netto-opbrengst-en-lactatiewaarde/>

Fan, J., Datta, S., 2011. Fitting marginal accelerated failure time models to clustered survival data with potentially informative cluster size. Computational statistics & data analysis55, 3295-3303.

Gröhn, Y.T., Rajala-Schultz, P.J., 2000. Epidemiology of reproductive performance in dairy cows. Animal Reproduction Science60-61, 605-614.

Gussmann, M., Denwood, M., Kirkeby, C., Farre, M., Halasa, T., 2019. Associations between udder health and culling in dairy cows. Preventive veterinary medicine171, 104751.

Hougaard, P., 1999. Fundamentals of survival data. Biometrics55, 13-22.

Huijps, K., Lam, T., Hogeveen, H., 2008. Costs of mastitis: facts and perception. Journal of Dairy Research75(1).

Keiding, N., Andersen, P.K., Klein, J.P., 1997. THE ROLE OF FRAILTY MODELS AND ACCELERATED FAILURE TIME MODELS IN DESCRIBING HETEROGENEITY DUE TO OMITTED COVARIATES. Statistics in Medicine16, 215-224.

Klein, J.P., Moeschberger, M.L., 2006. Survival analysis: techniques for censored and truncated data. Springer Science & Business Media.

Kleinbaum, D.G., Klein, M., 2010. Survival analysis. Springer.

Lambert, P., Collett, D., Kimber, A., Johnson, R., 2004. Parametric accelerated failure time models with random effects and an application to kidney transplant survival. Statistics in Medicine23, 3177-3192.

McDonald, R., Shalloo, L., Pierce, K.M., Horan, B., 2013. Evaluating expansion strategies for startup European Union dairy farm businesses. Journal of Dairy Science96, 4059-4069.

Nielsen, C., Østergaard, S., Emanuelson, U., Andersson, H., Berglund, B., Strandberg, E., 2010. Economic consequences of mastitis and withdrawal of milk with high somatic cell count in Swedish dairy herds. Animal: an international journal of animal bioscience4, 1758.

Nor, N.M., Steeneveld, W., Hogeveen, H., 2014. The average culling rate of Dutch dairy herds over the years 2007 to 2010 and its association with herd reproduction, performance and health. Journal of dairy research81, 1-8.

Pritchard, T., Coffey, M., Mrode, R., Wall, E., 2013. Genetic parameters for production, health, fertility and longevity traits in dairy cows. Animal: an international journal of animal bioscience7, 34.

R Core Team, 2020. R: A language and evironment for statistical computing. R Foundation for Statistical Computing, Vienna, Austia.

Rilanto, T., Reimus, K., Orro, T., Emanuelson, U., Viltrop, A., Mõtus, K., 2020. Culling reasons and risk factors in Estonian dairy cows. BMC Veterinary Research16, 1-16.

Rocha, J.F., Lopez-Villalobos, N., Burke, J.L., Sneddon, N.W., Donaghy, D.J., 2018. Factors that influence the survival of dairy cows milked once a day. New Zealand Journal of Agricultural Research61, 42-56.

Roxström, A., Ducrocq, V., Strandberg, E., 2003. Survival analysis of longevity in dairy cattle on a lactation basis. Genetics Selection Evolution35, 305.

Schukken, Y.H., Wilson, D.J., Welcome, F., Garrison-Tikofsky, L., Gonzalez, R.N., 2003. Monitoring udder health and milk quality using somatic cell counts. Veterinary research34, 579-596.

Wei, L.J., 1992. The accelerated failure time model: A useful alternative to the cox regression model in survival analysis. Statistics in Medicine11, 1871-1879.