The POINT Conditional Recovery Rate (CRR) Model

We updated our Conditional Recovery Rate (CRR) model in Barclays Capital's POINT platform. The CRR model is used to calculate loss given default in the Global Risk Model (GRM) for corporate debt instruments. The recovery rate estimates are forward-looking and time-varying in relation to the state of the economy. The model performs much better than historical averages in predicting future recovery rates and accounts for well established empirical regularities; recoveries vary with the economic cycle and subordination level, and depend on the overall health of the industry in which the firm operates. The updates include use of the aggregate default rate forecasts and distance-to-default measures from the POINT CDP model.

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1. Introduction

The recent turmoil in credit markets has once again brought into focus the concerns of portfolio managers, risk managers, and other market participants surrounding issuer default risk (i.e., the risk to portfolio values and asset returns caused by uncertainty regarding a firm's ability to fulfill its obligations with respect to its debt and obligations).

In order to reliably measure default risk at the security level, we need accurate estimates of the default probability of the issuing firm and a measure of loss given default of the security. In addition, measurement of default risk at the portfolio level requires default correlations. Our earlier publication of the POINT CDP[1] model discusses how we estimate forward-looking default probabilities. Here we discuss our approach to estimating the loss given default (LGD).

Our Conditional Recovery Rate (CRR) model is a dynamic statistical model that predicts recovery rates on corporate debt instruments using different categories of predictive information. It contains conditioning variables related to the seniority of the instrument, industry, and economic environment. Our default probability and recovery rate models were developed coherently such that they have common on the state of the economy. Both models are used in the Barclays Capital's Global Risk Model to capture the risk of default-related portfolio loss.

The CRR model is calibrated to a one-month prediction horizon on a large sample of post-default prices of US bonds. The empirical performance of the model constitutes a significant improvement over more commonly used approaches to recovery rate estimation.

[1] See Asvanunt and Staal (2009).

2. Recovery Rates

Recovery rates are an important variable in credit-related modeling and financial decision making, and as such, have been the topic of a substantial literature in both industry and academia. Accurate modeling of recovery rates is especially important in the context of risk management, where sensible measurement of portfolio loss distributions is crucial.

The importance of modeling recovery rates is clear from the expression for the expected loss on a defaultable obligation:

Expected loss = exposure at default x default probability x LGD

The expected loss is symmetrical in default probabilities and LGD, and therefore the same proportional error in either of these variables will have the same effect on the projected loss of the security. While the expected loss is symmetrical in default probabilities and recovery rates, the distributions of recovery rates and default probabilities are very different. Observed and predicted recovery rates are much more widely dispersed than estimated default probabilities, which suggests that an increase in the accuracy of predicted recovery rates has a relatively large impact on the uncertainty surrounding the expected loss estimate.

Common practice is to extract estimates of recovery rates from historical averages within categories of obligations (e.g., senior unsecured corporate bonds). The static and backward-looking nature of this approach can lead to significant biases in estimates of expected credit losses, especially around the turning points in the business cycle. We address the shortcomings of the standard approach by conditioning estimates of future recovery rates on forward-looking indicators.

What drives debt recovery? We investigate several categories of information with respect to their relationship with realized recovery rates based on existing literature and our own analysis of a large sample of defaulted bond data. The most important determinant of the recovery on a defaulted claim is whether or not it is secured, i.e., backed by some sort of collateral, and where it falls in the capital structure of the obligor, i.e., the degree to which the claim is subordinated to other securities of the firm. Another important finding is that recoveries are systematically related to the state of the economy; losses are systematically higher in recessions than expansions. In addition, the health of the industry in which the firm operates captures common tendencies of recovery rates on firm obligations[2]. We measure this last variable through the average distance-to-default for a particular industry as given by the POINT CDP model[3]. Additional information on future recovery rates might come from firm-level information. We found little evidence of improved out-of-sample predictability using this type of information[4]. We briefly discuss each of the components of the conditioning information set that drives the CRR model.

A recurring theme in the literature on default recoveries is that seniority and the presence of collateral are perhaps the most important determinants of recovery rates. To illustrate, in their study on corporate bank loans, Gupton, Gates and Carty (2000) report that syndicated loan recoveries for senior secured debt average 70%, while those for senior unsecured debt

[2] This categorization is in line with recent academic research. Acharya et al (2007) conclude that contract-specific characteristics such as seniority and security, industry of defaulting firm, and macroeconomic condition are likely to play an important role in explaining variation in recoveries.
[3] Asvanunt and Staal (2009) discuss the POINT CDP model and the distance-to-default variable in detail.
[4] The fit of a model estimated with firm-specific conditioning variables such as leverage was only marginally better in sample; out-of-sample this slight improvement was found to be irrelevant.

average only 52%. For our purposes, we take into account collateral by distinguishing secured from unsecured obligations. Seniority is then combined with collateral to provide a standard classification of corporate obligations.

Figure 1: Recovery rates by subordination of defaulted US corporate bonds (1973 – 2008)

Lien Position	Historical Average
Senior Super Secured[5]	61.4%
Senior Secured	58.6%
Senior Unsecured	38.6%
Senior Subordinated	34.1%
Subordinated	33.2%
Junior Subordinated	16.4%
Preferred Stock	9.0%

Source: Barclays Capital, Moody's

Figure 1 clearly illustrates the impact of lien position on recovery rates: all else being equal, lower seniority leads to a lower recovery rate, while the presence of collateral tends to increase the recovery rate.

As is well understood by now, a large component of credit risk is systematic[6]. In recessions, or more generally bad economic times, the number of firms defaulting on their obligations rises. At the same time, the amount recovered on those defaulted obligations tends to decrease[7]. This joint behavior of default and recovery rates amounts to a compounding of credit risk that is often ignored in models of portfolio credit risk[8]. The credit risk models in Barclays Capital's Global Risk Model incorporate this compounding of credit risk through the negative correlation of recovery rates and default probabilities over the business cycle through joint dependence of recovery rates and firm default probabilities on indicators of the state of the economy. In effect, we assume that the same underlying economic conditions that cause default rates to rise also cause recovery rates to decline[9].

Figure 2 shows the density of recovery rates in a large sample of observed prices on corporate bonds 30 days after the default event. The unconditional sample distribution of recoveries is far from symmetrical, with low recoveries being significantly more common. It is interesting to note the substantial difference in recovery distributions over time. It has been noted before that recoveries are lower (and default rates higher) in bad economic times, and the aggregation of the recovery distribution in good and bad times results in the different sample distribution. We illustrate this by plotting the density of recovery rates in NBER dated recessionary and expansionary periods separately in Figure 3.

While the average recovery rate over our whole sample is 39.9%, it is only 28.9% during recessions versus 42.5% during expansions. Clearly, we see proportionally many more cases of lower recoveries in recessions. During expansionary periods, recoveries are more evenly distributed.

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5 Senior Super Secured debts are Equipment Trust Certificates and Enhanced Equipment Trust Certificates.

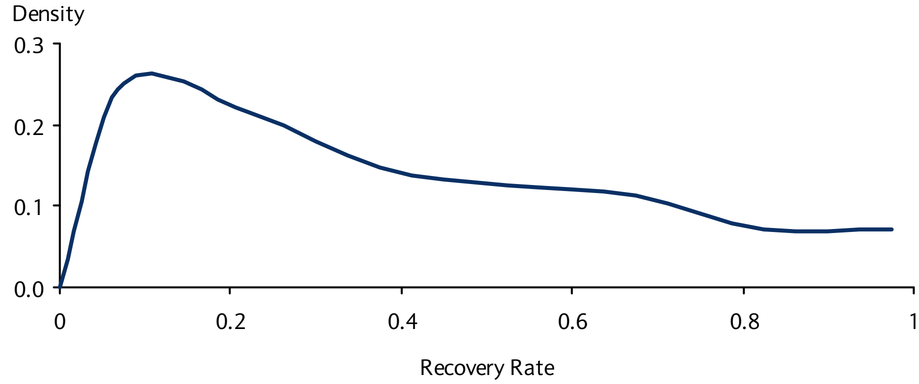
6 A common observation is that only up to half of corporate credit spreads can be explained by expected loss. A significant part of the remainder of spreads could be explained by default risk premia required by investors for bearing systematic default related loss risk.

7 See Altman et al. (2005) for a more detailed discussion.

8 Frye (2000) describes one of the first econometric models in which recovery and default likelihood depend on the same systematic factor.

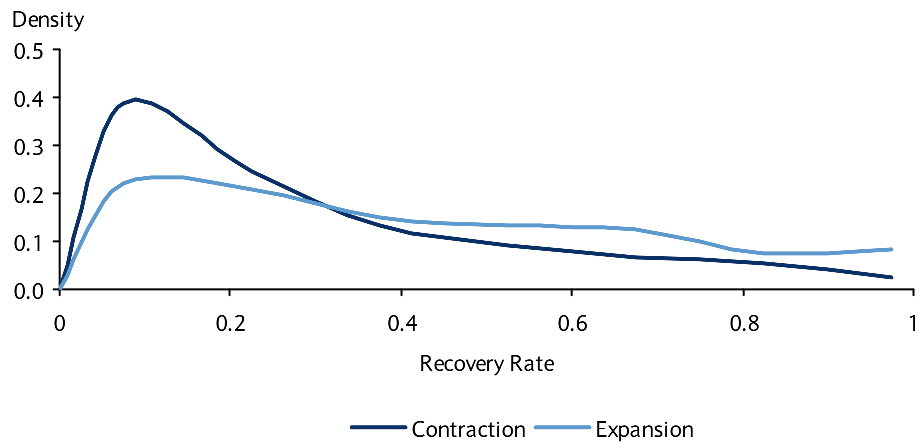
9 Of course, it is possible that to some extent the higher default rate itself drives the lower recovery rates through diminished recovery value in a saturated market for specific assets.

Figure 2: Density of historical recovery rates on US corporate debt (1973-2008)



Source: Barclays Capital, Moody's

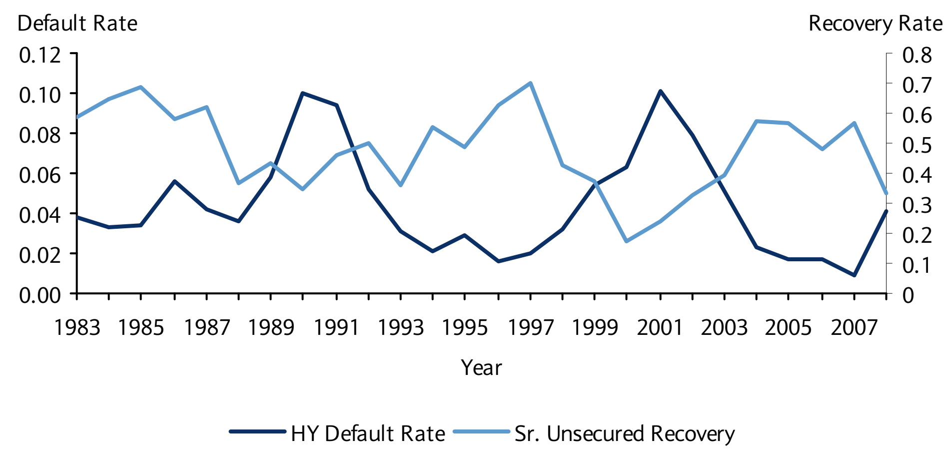
Figure 3: Density of historical recovery rates during NBER contractions and expansions on US corporate debt (1973-2008)



Source: Barclays Capital, Moody's

Further inspection of the data confirms that recovery rates vary significantly over time, both within a subordination class and over the whole sample. Average recovery rates over time are strongly correlated with the business cycle, in particular with the realized aggregate default rate. Figure 4 compares the high-yield default rates and the average recovery rates of senior unsecured bonds each year.

Figure 4: US high-yield default rates versus average recovery rates over senior unsecured bonds (1983-2008)



Source: Barclays Capital, Moody's

Finally, there are differences in recovery rates between industries related to factors such as asset specificity and concentration (Acharya et al (2007) stress the importance of industry effects on recovery rates). We use the 10 economic sectors defined in the GICS I classification to incorporate industry-specific effects into the CRR model[10]. In the CRR model, the importance of industry membership in explaining recovery is dependent on the overall level of distress in the industry.

3. Modeling Recovery

Before we discuss the details of our modeling approach, we explain how recovery is defined and measured for our purposes. The price at default is defined as the 30-day post-default observed price[11]. The recovery rate is then defined as the fraction of face value recovered by the price observed 30 days after the default event:

$$RR_t = \frac{P_t^{default}}{100}$$

Recovery rates should be expected to lie in the interval [0,1][12]. Loss given default (LGD) is then simply defined as *(1-RR)*[13]. To incorporate recovery rates into a model of return distributions, we can translate *RR* into return space as follows:

$$R_{default,t} = \frac{RR_t}{P_{t-1}} \times 100 - 1 .$$

[10] The sectors in this classification are: energy, materials, industrials, consumer discretionary, consumer staples, health care, financials, information technology, telecommunications, and utilities.

[11] A default event is defined by the occurrence of the following credit events: Chapter 7 or Chapter 11 bankruptcy, a missed payment or delayed disbursement of interest or principal, and some occurrences of distressed exchange. See Emery et al. (2009) for more detail on definition of default.

[12] A very small number of observed recovery rates are larger than one. This might reflect the value of coupons or restructuring events. We ignore these values for modeling purposes.

[13] The Global Risk Model in POINT reports LGD as $\left(1-\frac{RR_t}{P_t}\right)+\frac{YTW}{12}$

This definition focuses on the loss of principal and payments foregone, and ignores the workout expenses of the default process[14]. For our purposes it is the most relevant definition of recovery, since it reflects the goal of the majority of investors and portfolio managers to avoid, or sell, positions in newly defaulted debt. Accurate modeling of recovery rates is an important tool in the decision-making process of such investors.

In order to model the conditional distributions of recovery rates over time, we employ a statistical framework that links the conditioning information set to recovery rates. The CRR model is based on a dynamic Beta regression[15] approach for modeling recovery rates RR:

$$RR_t \sim Beta(\alpha_t, \gamma_t),$$

Where we express expected recovery rates through a monotonic transformation of a linear expression:

$$E\left[RR_t \mid x_{t-1}\right] = g(x_{t-1}'\beta),$$

And we use the link function:

$$g(z) = \frac{\exp(z)}{1+\exp(z)}.$$

The beta distribution provides us with a flexible modeling tool that respects the natural domain of recovery rates. The choice of the link function g together with the choice of the predictive variables x, allows for a dynamic model of expected recovery rates. We transform raw predictive variables to increase their explanatory power in the model (that is, the variables x are themselves subject to some "pre-modeling"). The logit function above was found to perform best in terms of forecasting performance. The model is estimated using maximum likelihood techniques, and all the standard machinery associated with standard statistical theory applies. The approach described here allows us to model the entire conditional distribution of recovery rates, including the variance of the beta distribution. This is useful since it allows us to incorporate this parameter as a random variable in simulations of portfolio distributions, and portfolio credit loss in particular.

4. Empirical Results

Our model is based on a sample that consists of almost 2,500 unique observations on post default bond prices and data on over 800 separate corporate default events over the period from 1984 to 2008. The final estimation sample is constructed to reflect par-debt value weighted recovery rates for each seniority class for each firm. That is, we create a value weighted recovery observation for each subordination class for each firm, and use these as the primary modeling object. While our model is fitted to bond data, loans are treated in the same framework as well; the predicted recovery rates on loans used in our risk models are calibrated in the framework of the CRR model in a second modeling step based on loan-specific data[16].

[14] Alternatively, we can interpret the recovery upon default as the value of the suitably discounted expected ultimate recovery (i.e., the recovery realized at the resolution of the default). An entirely different approach to estimating recovery rates is to imply recovery rates from liquid credit instrument prices. This approach is not suitable for portfolio risk modeling since it effectively produces risk-neutral quantities through assumptions on risk premia and pricing models.

[15] See' *http://en.wikipedia.org/wiki/Beta_distribution*' for a detailed description of the Beta distribution.

[16] Loans are typically senior to bonds, and typically have higher recovery rates since (they are far more likely to be collateralized).

Most of the content of the model lies in the choice of the information set, or predictive variables x. Ideally, we would have liked to link recovery rates to firm-specific circumstances such as leverage and asset specificity, as well as industry- and economy-wide indicators. Unfortunately, results from a model with individual firm variables were not convincing in terms of statistical fit and economic intuition. While disappointing, these results are not surprising given the relatively small sample size that results when individual firm data are required leading up to the default event with a prediction horizon of one month[17].

The final model specification is relatively simple but accounts for well established empirical findings. The predictive variable used to account for the state of the economy is our forward-looking high-yield aggregate default rate forecast developed for the POINT CDP model, which in turn is driven by macro-variables such as the tightening of commercial and industrial loan standards[18] and the percentage of corporate bonds rated high yield. The industry effects are captured through the average level of distance-to-default from the POINT CDP model and indicator variables for the GICS I industry classifications. Debt subordination is also captured through indicator variables for the seven levels of classification.

Estimated coefficients of the variables in the CRR model are significant at the 5% level, except for three of the industry indicators (which we include nonetheless since they do improve the fit of the model in a sensible way). The effect of subordination, industry, and the state of the economy is as expected. For example, as of the end of 2008, average predicted recovery rates are significantly higher for utilities (48.2% for senior unsecured debt), and lower for financial, information technology, and telecommunication firms (26.6%, 25.0%, and 27.5% for senior unsecured debt, respectively). Recovery rates are negatively correlated with the default probabilities from our POINT CDP model through their opposite dependence on the aggregate default rate forecasts and average distance-to-default. This agrees with empirical evidence that default and recovery rates are significantly negatively correlated over the economic cycle. Figure 5 shows the predicted recovery rates for selected industries. The inclusion of industry average distance-to-default allows us to capture the time-variant impact of the state of individual industries. Intuitively, a lower distance-to-default within an industry predicts lower recoveries due to an increased risk of industry-wide distress. For instance, historical recovery rates for information technology and telecommunication firms were more significantly affected during the dot-com bust in 2000 than for other industries. Using industry average distance-to-default as a predictor allowed us to anticipate this phenomenon in the CRR model.

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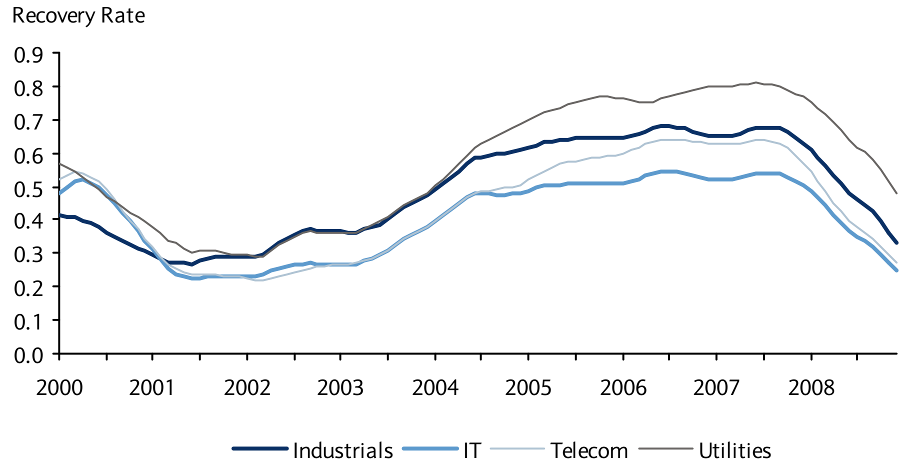
17 Using predictive variables with a longer historical lag did not improve the statistical fit significantly. A compromise using aggregate firm variables at the industry level performed better in terms of significance of coefficients, but did not lead to significant improvement in statistical fit, and most importantly, out-of-sample forecasting performance.
18 Tightening of C&I loan standard is obtained from the Federal Reserves' senior loan officer opinion survey.

Figure 5: Predicted recovery rates for senior unsecured bond by industry (2000-2008)



Source: Barclays Capital

The CRR model performs markedly better than the historical average approach in predicting recovery rates. We performed out-of-sample tests between 1997 and 2008 to compare the results. The mean squared prediction error (MSPE[19]) of the backward-looking historical average model (which we implement by taking the 12-month trailing average of recovery by subordination category) over our sample is 774. The CRR model improves substantially upon this with an MSPE of 625. The (pseudo) R2 in a beta regression is 0.16 for a model based on the 12-month trailing recovery rate and subordination, versus 0.28 for the CRR model. The correlation between our predicted and realized recovery rate at issuer level is 53% across all subordination levels. The correlation between average predicted and realized recovery rate on senior unsecured debt is 85%.

It is interesting to note that the difference between the CRR model estimates and those from historical averages is particularly significant around the turning points of economic cycles. For example, as of the end of 2007, the 12-month trailing average of recovery rates for senior unsecured bonds was 69.6%, while the CRR model estimate was 60.3%. After years of historically low default rates and high recovery rates, the backward-looking approach predicts relatively high recovery rates. The CRR model takes into account the current state of the economy, and the level of distress in individual industries, and adjusts predicted recovery rates downwards accordingly: recovery rate predictions by subordination are below trailing averages because the economic indicators are reflecting a worse-than-average state of the economy. In contrast, the historical average approach predicts high recoveries based on the favorable (and few) observed recoveries in the past 12 months.

5. Conclusions

Barclays Capital's Conditional Recovery Rate (CRR) model is a proprietary statistical model that is used to predict recovery rates on corporate debt instruments. The recovery rate estimates provided by the model are one of the essential determinants of portfolio credit risk in Barclays Capital's Global Risk Model in POINT. The model provides forward-looking recovery rate estimates of corporate debt instruments based on predictive information in three different categories: subordination, industry, and the state of the economy.

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19 $MSPE = \frac{\sum \left(RR_t^{predicted} - RR_t^{actual}\right)^2}{n-1}$, which measures the average distance between predicted recoveries and realized recoveries.

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Appendix

This appendix provides details about the Beta regression model used in our recovery rate model[20]. The model uses a parameterization of the Beta distribution that is indexed by mean and dispersion parameters. The advantage of using Beta distributions to model conditional distributions of recovery rates is that they are very versatile in capturing differently shaped distributions while respecting the natural domain of recovery rate outcomes [0,1]. We model time-varying recovery rate distributions by linking the mean and variance of these distributions to economically relevant determinants of recovery rates.

We assume recovery rates $0 < RR_t < 1$ follow a Beta distribution with time-varying parameters:

$$RR_t \sim Beta(\alpha_t, \gamma_t) \,,\ \alpha_t, \gamma_t > 0$$

Notice that the time-varying nature of our model can capture empirical features (such as multi-modality) of unconditional recovery distributions through aggregation of conditional Beta distributions. We re-parameterize the beta distribution to be expressed in terms of a mean and dispersion parameter:

$$RR_t \sim Beta(\mu_t, \sigma_t)$$

where

$$\mu_t = E_{t-1}[RR_t] = \frac{\alpha_t}{\alpha_t + \gamma_t}$$

and

$$\sigma_t = V_{t-1}(RR_t) = \frac{\mu_t(1-\mu_t)}{1+\varphi_t}.$$

φ_t can be interpreted as a dispersion parameter because the variance of recovery rates RR_t is decreasing in φ_t for a fixed value of μ_t,

The model is specified by assuming that the conditional mean of RR_t can be written as:

$$\mu_t = g(X_{t-1}\beta)$$

Where beta is a vector of regression parameters and X_{t-1} is a matrix of covariates observed in the current information set at each point in time, and the link function g is specified by

$$g(z) = \frac{\exp(z)}{1+\exp(z)}.$$

Additionally, we can specify the dispersion parameter in a similar fashion as

$$\varphi_t = h(Z_t\delta),$$

for some suitable differentiable monotonic link function h and a set of (possibly different) regression parameters Z_t. For our purposes, we set $\varphi_t = \varphi$, since our analysis does not support a more complex specification.

[20] See Ferrai and Cribari-Neto (2004) for a full exposition of the statistical theory on which we build here.

The log-likelihood function for a sample of conditionally independent observations is:

$$l(\beta,\delta)=\sum_{t=1}^{N}\left(\log\Gamma(\varphi_t)-\log\Gamma(\mu_t\varphi_t)-\log\Gamma((1-\mu_t)\varphi_t)+(\mu_t\varphi_t-1)\log RR_t\right.$$
$$\left.+((1-\mu_t)\varphi_t-1)\log(1-RR_t)\right),$$

where μ_t and φ_t are specified as above, and Γ denotes the gamma function. Since the corresponding estimating equations do not admit a closed-form solution, the maximum likelihood estimates of all parameters are found through numerical optimization of the log-likelihood. Using standard statistical theory, the asymptotic distribution of these estimators can be derived and used in creating test statistics. A bootstrap approach was employed to further investigate the properties of the model.

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