## A NONLINEAR REGRESSION MODEL OF INCURRED BUT NOT REPORTED LOSSES by Scott Stelljes

### Discussion by Jeffrey H. Adams, FCAS

The paper by Stelljes [1] the subject of this discussion is a welcome addition to the Casualty Actuarial Society literature on nonlinear regression for loss reserving. This discussion will predominantly concern a key assumption made in [1]. In particular, on page 361:

"Based on the assumption that the incremental pure premiums for different development intervals are independent, the variance of IBNR pure premium is the sum of the variances of the incremental pure premiums for the remaining development intervals."

It may be true that the *historical* incremental pure premiums can be considered independent, but it does not follow that the future *fitted* incremental pure premiums are independent. An analogous situation exists for ordinary linear regression, where the *hat* matrix provides for the covariance of the fitted values. Since the variance of the sum of random variables depends on covariance between the random variables, the variance of the reserve will depend on the covariance of the incremental IBNRs.

After providing a brief review on traditional nonlinear regression in section 2, the bulk of this discussion is concerned with two issues. First, modifying the methods of [1] to reflect covariance among the fitted values and is described in section 3. Second, there are times when a reliable insurance trend factor is not available. In such circumstances the actuary needs to derive the trend as part of the model, as in the model on page 359 of [1]. [1] succinctly describes the problems with such an approach. Section 4 discusses this latter model and shows simulation is not required to calculate confidence intervals. The last section, section 5 will discuss some miscellaneous issues.

## 2. BRIEF REVIEW OF NON LINEAR REGRESSION BASED ON THE BOOK BY MYERS, MONTGOMERY, VINING [4].

Let y be the dependent variable. Let x be a vector of explanatory variables, and **B** a vector of parameters. We then assume the following function:

(2.1)  $y = f(x, B) + \varepsilon$ 

 $\epsilon$  are the errors and are assumed to be independent normal, with the means  $\mbox{ zero}$  and constant variance  $\sigma^2.$ 

(When fitting the data, this assumption should be checked to see if the error assumption is tenable since insurance claim data is often skewed or the errors may be heteroscedastic. [1] notes the heteroscedasticity and thus modifies the error term).

(2.2)  $E(y) = f(x, \mathbf{B})$ , denotes the expectation of y.

For example let  $y = x_1^*B_1/(B_3 + x_2^*B_2) + \text{error}$ . The expectation of y is  $f(x, \mathbf{B})$  and is  $x_1^*B_1/(B_3 + x_2^*B_2)$ .

Typically, **B** is unknown and replaced with parameter estimates. Based on significance tests (see (2.7) below), it is possible fewer parameters are necessary. Insignificant parameters can be discarded and the function refit.

The parameters may be estimated through nonlinear least squares using the iterative Gauss-Newton method (or other methods).

The (asymptotic) variance covariance matrix of parameter estimators **b** is (2.3) var(**b**)  $\cong \stackrel{\wedge}{\sigma}{}^2 (\mathbf{D}^T \mathbf{D})^{-1}$ 

(2.4) Dij =  $\partial f(x_i, \mathbf{B})/\partial B_i$ ) is evaluated at final parameter estimates.

In (2.4) i refers to the vector of explanatory variables for observation i, and the j refers to the j'th parameter.

An estimate of the error variance is

(2.5)  $\hat{\sigma}^2 = \hat{\epsilon}^T \hat{\epsilon}/(n-p)$ , n is the number of observations fit, and p the number of parameters in **B**.

(2.6) 
$$\stackrel{\wedge}{\boldsymbol{\varepsilon}} = \mathbf{y} - \mathbf{f}(\mathbf{x}, \mathbf{b})$$

(2.7) A parameter significance test is ( $\mathbf{b} \div$  (standard error of the parameter)), which is asymptotically the normal distribution. The denominator is the square root of the appropriate element from the diagonal of the asymptotic variance covariance matrix of the parameters (2.3), or for weighted regression (2.11).

Let  $g(\mathbf{b})$  be a function of the parameter estimators and observations. Then

 $(2.8) \operatorname{E}(\operatorname{g}(\mathbf{b})) \cong \operatorname{g}(\mathbf{B})$ 

The approximate (asymptotic) variance covariance matrix of  $g(\mathbf{b})$  is

(2.9)  $\operatorname{var}(\mathbf{g}(\mathbf{b})) \cong \mathbf{d}^{\mathrm{T}} \operatorname{var}(\mathbf{b}) \mathbf{d}$ , where

(2.10)  $\mathbf{d}^{\mathrm{T}} = [\partial g(\mathbf{B})/\partial B_{1},...,\partial g(\mathbf{B})/\partial B_{\mathrm{p}}]$  is evaluated at the estimated parameters.

Equations (2.9) emphasizes the discussion in section 1 regarding the non-independence of fitted values. (Take  $g(\mathbf{b})$  as the predicted values, then (2.9) can be used to derive the covariance of the predicted values).

If weighted non linear regression is used with a diagonal matrix  $\mathbf{V} = var(y_i) = diag\{\sigma_1^2, \dots, \sigma_n^2\}; \ \sigma_i^2 = \sigma^2 / w_i$ , and  $w_i$  are the weights then

$$(2.11) \quad \operatorname{var}(\mathbf{b}) \cong (\mathbf{D}^{\mathrm{T}}\mathbf{V}^{-1} \mathbf{D})^{-1}$$

Weighted non linear regression may be used in the presence of heteroscedasticity.

Let  $\mathbf{W} = \text{diag}\{w_1, \dots, w_n\}$ , then

- (2.12)  $\hat{\sigma}^2 = \hat{\epsilon}^T (\mathbf{W}) \hat{\epsilon} / (n-p)$  is the mean square error, and
- (2.13)  $\hat{\sigma}_i^2 = \hat{\sigma}^2 / w_i$ , provides an estimate for V.

After the fit, the model assumptions must be checked. Checks include the usual regression error plots.

For loss reserving, errors should also be checked by accident quarter. The accident quarter fitted values by age, should be plotted against the dependent variable pure premium values. This will appraise the fit and the homogeneity of the accident quarters.

### 3. THE EQUATIONS APPLIED TO LOSS RESERVING WHEN EXTERNAL TREND IS USED

Let  $c_i$  represent the accident quarter exposures for observation i. In [1], the exposures are not inflation sensitive and external inflation factors were utilized to trend the incremental pure premiums. If the exposures are inflation sensitive, no additional inflation adjustment is generally required. (However, you may statistically test whether an additional trend factor is required by fitting (4.1) and (4.2). This will be discussed in section 4). If no additional inflation adjustment is required, the methods in section 4 may be applied, and no simulation is required for confidence intervals.

Start with the basic equation given in [1] for future observation(s) y, the future incremental pure premium(s). There is only one explicit explanatory variable x, the valuation age.

(3.0)  $f(x, B) = B_1 \exp(xB_2) + B_3 \exp(xB_4)$ 

(3.1)  $y = f(x,b) + \varepsilon / (w^{1/2})$ 

Multiply (3.1) by exposure c gives

(3.2) cy = cf(x,b) + c 
$$\epsilon / (w^{1/2})$$

Taking the variance of (3.2) gives

(3.3) variance(cy) = variance(cf(x,b)) + variance(c  $\varepsilon/w^{1/2}$ )

Now take  $g(\mathbf{b}) = cf(x, \mathbf{b})$ , and then apply (2.9), (2.10), and (2.11) giving,

(3.4) variance(c y)  $\cong$  **d**<sup>T</sup> var(**b**) **d** + (c<sup>2</sup>) $\overset{\wedge}{\sigma}$ <sup>2</sup>/w

For equation (3.4) use equation (2.12) to valuate  $\hat{\sigma}^2$ .

The second term on right hand side of (3.4) is a diagonal matrix, diag = { $c_i^2 \sigma_i^2$  }.

The expectation of (3.2) is

(3.5)  $E(cy) \cong c f(x,b) = g(b)$ 

(3.5) provides the vector of means, and (3.4) provides the variance covariance matrix, for a multinormal distribution. It is that distribution that must be sampled to provide an IBNR array. Then, each IBNR value is multiplied by the simulated trend factor, as explained in [1]. Doray [6] page 648 explains a method for simulating the multinormal. The simulations in this discussion were performed in R version 2.4.1 (2006-12-18) (C) 2006 The R Foundation for Statistical Computing.

Exhibit 1 displays a summary and the key results of this discussion. The first four columns are reproduced from Table 3.2.1 of [1]. Columns (7) and (8) are calculated assuming all off diagonal elements of the matrix of (3.4) are set to zero, and then doing 1000 simulations of the multinormal distribution, after which simulated trend factors (using the [1] trending approach) are applied. That is essentially the method in [1]. Columns (5) and (6) are also based on 1000 simulations but incorporate covariance terms of the full matrix (3.4). Although the expected total IBNR are essentially the same in columns (3), (5), (7), and the standard deviations of the total IBNR of (4) and (8) are essentially the same, the standard deviations of the total IBNR in column (6) is significantly higher. Column (6) is the appropriate standard deviation.

Exhibit 2 column (5) and (10) provides a partial listing of the vector of 780 means (3.5) used to simulate the pre- trended IBNRs (these are at calendar quarter 40 level). Exhibit 3 provides a portion of the 780 by 780 variance covariance matrix (3.4).

Accident quarter variances are estimated as a by-product of simulating the entire southeast portion of the loss "triangle", and should not add up to the variance of total IBNR.

# 4. THE EQUATIONS APPLIED TO LOSS RESERVING WHEN NO EXTERNAL TREND IS USED

Let y be the incremental losses divided by an inflation or non inflation sensitive exposure base. We use the rejected trend model on page 359 of [1] shown as (4.1) below. (See section 5 paragraph g regarding the extrapolation issue briefly discussed in [1]).

Let  $B_5$  be the trend, u the calendar quarter, and age be the accident quarter valuation age. If an inflation sensitive exposure base is used,  $B_5$  provides for excess trend. (I have assumed the same weights as in [1]. Normally the appropriate weights need to be individually selected for each model).

After the fit, significance levels of the parameters can be checked. If  $B_5$  is not significant then there is no trend other than what is contemplated by the exposure base and age, then  $exp(uB_5)$  may be dropped from equation (4.1) and the model refit.

(4.1) 
$$f(age,u,\mathbf{B}) = (B_1 \exp(B_2 age) + B_3 \exp(B_4 age))\exp(uB_5)$$

(Denote u and age by the explanatory variable vector x.)

(4.2)  $y = f(x, B) + \epsilon / (w^{1/2})$ 

Assume (4.1), (4.2) have been fit to the historical incremental pure premiums. The focus will now be on the future incremental pure premiums.

Using the estimated parameters  $\mathbf{b}$  in (4.2), multiply (4.2) by c to get the future incremental losses:

(4.3) c y = cf(x,b) + c  $\epsilon / (w^{1/2})$ 

Taking the variance of (4.3) gives

(4.4) variance(cy) = variance(cf(x,b)) + variance(c 
$$\varepsilon/w^{1/2}$$
)

Now take g(b) = cf(x, b) and apply (2.9), (2.10), and (2.11) giving

(4.5) variance(c y)  $\cong$  **d**<sup>T</sup> var(**b**) **d** + (c<sup>2</sup>) $\overset{\wedge}{\sigma}$ <sup>2</sup>/w

For equation (4.5), use equation (2.12) to evaluate  $\hat{\sigma}^2$ . The second term on the right hand side of (4.5) is a diagonal matrix, diag = { $c_i^2 \hat{\sigma}_i^2$  }.

The expectation of (4.3) are the expected future incremental losses (4.6)  $E(cy) \cong g(x, b)$ 

Now form the sum of the future incremental losses denoted by R for reserve giving

(4.7)  $R = \Sigma$  cy, the sum taken over the southeast portion of the loss "triangle".

The expectation of R is the mean total reserve and is given by

(4.8)  $E(R) \cong \sum g(x, \mathbf{b})$ , the sum taken over the southeast portion of the loss "triangle".

The variance of R denoted by var(R) is

(4.9)  $\operatorname{var}(R) = \sum \operatorname{cov}(c_i y_i, c_j, y_i)$ 

In (4.9), the sum is taken over all future observations (i,j) in the southeast portion of the loss triangle. The covariance terms in (4.9) are from (4.5).

Using the normality assumption, the confidence interval for the reserve becomes

(4.10)  $E[R] \pm z \cdot var(R)^{1/2}$ , z is the appropriate standard normal value.

Applying section 4 equations to Exhibit A data from [1] provides the following:

The estimated parameters for  $b_1$ ,  $b_2$ ,  $b_3$ ,  $b_4$ ,  $b_5$  are 2.364885501 -0.077678377 21.611842502 -0.566532596 0.009735732. The MSE is 2759171.

The parameter variance covariance matrix derived from equation (2.11) is

|                | $\mathbf{b}_1$ | $b_2$         | <b>b</b> <sub>3</sub> | $b_4$         | <b>b</b> <sub>5</sub> |
|----------------|----------------|---------------|-----------------------|---------------|-----------------------|
| $\mathbf{b}_1$ | 0.308171765    | -3.248550e-03 | 2.13645749            | -2.257342e-02 | -2.046082e-03         |
| $b_2$          | -0.003248550   | 8.684792e-05  | -0.01130499           | 4.756396e-04  | -5.492841e-06         |
| $b_3$          | 2.136457489    | -1.130499e-02 | 31.07109676           | -2.940411e-01 | -1.983273e-02         |
| $b_4$          | -0.022573418   | 4.756396e-04  | -0.29404108           | 6.488308e-03  | -1.960661e-05         |
| $b_5$          | -0.002046082   | -5.492841e-06 | -0.01983273           | -1.960661e-05 | 3.016662e-05          |

The parameter standard deviations are the square roots of the diagonal:

0.555132205, 0.009319223, 5.574145384, 0.080550033, 0.005492415.

The 95% confidence intervals using t(.025,590-5) are

|       | $\mathbf{b}_1$ | $b_2$        | b <sub>3</sub> | $b_4$        | <b>b</b> <sub>5</sub> |
|-------|----------------|--------------|----------------|--------------|-----------------------|
| Lower | 1.274593134    | -0.095981606 | 10.664076447   | -0.724735018 | -0.001051543          |
| Upper | 3.45518287     | -0.05937519  | 32.55962508    | -0.40833007  | 0.02052296            |

The trend parameter  $b_5$  is just shy of significance at the 95% level, but will be used.

Exhibit 1, column (9) displays the estimated IBNRs and corresponds to equation (4.6) summed over the accident quarter's IBNRs. The IBNR, by accident quarter and in total, compare favorably with columns (3), (5), and (7), although a bit higher probably due to the higher trend (.0097 versus .005 used by the author). The total IBNR standard deviation calculated using the square root of (4.9) is 3782848, and using (4.10) with z = 1.96 provides a 95% reserve confidence interval of : (25254267, 40083031).

Simulation may also be used to determine confidence intervals. (4.6) provides the vector of means, and (4.5) provides the variance covariance matrix for a multinormal distribution. Exhibit 2 columns (4) and (9) provides a partial listing of the vector of 780 means that may be used to simulate the IBNRs. Exhibit 2 columns (4) and (5) are not comparable, since column (4) already includes trend, while column (5) is still at calendar quarter 40 level. The same applies for columns (9) and (10).

If confidence intervals are desired by accident quarter, the multinormal distribution can be simulated. Accident quarter variances are estimated as a by-product of simulating the entire southeast portion of the triangle, and of course will not add up to the variance of total IBNR. Alternatively, equation (4.9) may be used limiting the summation to the appropriate accident quarter ages. For example, consider accident quarter 4. The portion of the variance covariance matrix (4.5) corresponding to the fourth accident quarter's three IBNR elements is

| age | <u>38</u> | <u>39</u> | <u>40</u> |
|-----|-----------|-----------|-----------|
| 38  | 605880842 | 3367957   | 3291128   |
| 39  | 3367957   | 582719205 | 3225207   |
| 40  | 3291128   | 3225207   | 560981739 |

Adding up these nine figures provide the variance for the fourth accident quarter IBNR, which is 1769350371, and a standard deviation of 42064. The diagonal elements are the individual IBNR variances. For example, the variance of the incremental IBNR for accident quarter 4 age 39 is 582719205. Exhibit 1, column (10) displays the standard deviations for the accident quarter IBNRs calculated in such a fashion.

Exhibit 4 displays a partial portion of the variance covariance matrix as calculated in (4.5).

### 5. MISCELLANEOUS ISSUES

a) On page 354 of [1] "Furthermore, Narayan...remarks that dollar based regression models do not take into account changing levels of exposure. This is a serious flaw because the amount of loss in an accident period is highly correlated to the number of earned exposures." I would concur with this assessment and would suggest incorporating exposure as an explanatory variable in GLM or regression methods, or perhaps an offset in GLM. England and Verrall [2] discuss incorporating exposure in stochastic loss reserving. Incorporating exposure should act to reduce the number of parameters in a GLM or regression type model.

b) Page 231 of [1] formula (2.3.1) should have included the weight function in the minimization since weighted least squares is being performed i.e minimize

 $\begin{array}{l} n \\ \sum w_i(y_i \ \text{-} \ f(x_i, \textbf{B}))^2 \\ i=1 \end{array}$ 

This must have been a typo, and conversations with Stelljes has confirmed this.

c) Page 371 of [1] "Some of the models could be applied to cumulative instead of incremental data." (Page 370 in [1] does note that if autocorrelation occurs other models exist). In my limited experience fitting a single curve to an array of cumulative accident year or report year data results in autocorrelation which violates linear and nonlinear regression assumptions. In addition, heteroscedasticity tends to occur. A plot of the cumulative data for each incurred year versus the

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fitted curve will help detect autocorrlation as well as detect non-homogeneity of the accident years. A further problem with fitting cumulative data occurs when the estimated ultimate pure premium for a particular incurred year is below the actual emerged pure premium for that year. One way around these problems may be to fit a separate curve to each accident year as in Clark [3] and Kazenski[5]. Kazenski asserts he has detected no autocorrelation using such an approach.

d) Traditional nonlinear regression assumes the error terms are normal which is a symmetric distribution with a range  $-\infty$  to  $+\infty$ . Incremental pure premium data may actually be skewed and can hardly ever be highly negative, therefore, using the normal distribution is approximation at best.

e) Page 358 of [1] formula (2.2.2) should use the square root of the weight, not just the weight. This appears to have been a typo, and conversations with Stelljes has confirmed this. See equation (3.1) above.

f) A note regarding the parameter estimates and the data used for fitting.

[1] excluded the first evaluation of an accident quarter and all evaluations prior to the twenty first calendar quarter when fitting the equation. The same was done in this discussion, both in section 3 and section 4 and section 5 paragraph g. Also, Stelljes [1] has informed me the raw incremental pure premiums (Exhibit A in [1]) are first trended to calendar quarter 40 using a constant trend factor of exp(.005) per calender quarter prior to fitting them. The same was done for the section 3 calculations. Using Exhibit A data (kindly supplied by Stelljes as a computer file), I was able to replicate the following from [1]: parameters on page 362, matrix inversion of (FWF)<sup>-1</sup> on page 363, the confidence interval of (-40259,56186) for accident quarter 2 on page 364, and finally, the mean square error of 2987236 on page 364. The parameters in [1] on page 362: 3.1994, -.0754, 29.4446, -.5480 correspond to estimates of B<sub>1</sub>, B<sub>2</sub>, B<sub>3</sub>, B<sub>4</sub> in equation (3.0) of this discussion and are used in section 3.

Keeping within the limited scope of this paper, various diagnostics for the section 4 or section 5 paragraph g fittings have not been performed. Those diagnostic procedures are widely discussed in nonlinear regression texts and should be applied in practice. No claim is made that the fitted parameters are actually the best. Nonlinear regression requires initial starting values, and there is no guarantee the solution will converge, let alone converge to the global minimum mean square error.

### g) Extrapolating

In section 4, if  $B_5$  is significant, formula (4.5) extrapolates beyond the fitting space, (in the example for calendar quarters past 40). Discussions with Stelljes, and page 359 in [1] cautions against extrapolating. Pages 86-88 in [4] provides for a confidence interval of a "future observed response", and seems silent on the issue of extrapolating. Using the approaches in section 4, an alternative model is:

(5.1)  $f(age,aqtr, \mathbf{B}) = (B_1 \exp(B_2 age) + B_3 \exp(B_4 age))\exp(B_5 aqtr)$ 

where aqtr the accident quarter. Using the same data as in section 4, results from (5.1) were very close to those of (4.1), but even (5.1) will also extrapolate beyond the fitting space when  $B_5$  is significant.

If the variances as calculated by (4.5) appear unreasonable in the extrapolated region, perhaps a ceiling or floor may be required after some point. This seems to be an area requiring further research.

h) On the one hand, the approach in [1] (and section 3), assume the availability of an external trend and that the estimates of the parameter in the model are independent of the trend. On the other hand, it's nonlinear regression model is not extrapolated, only the trend needs to be extrapolated. The section 4 model allows for estimation of internal trend and allows for covariance among all the parameters (including trend), but does require extrapolation when  $B_5$  is significant. Neither method is perfect.

#### REFERENCES

[1] Scott Stelljes, "A Nonlinear Regression Model of Incurred But Not Reported Losses", Casualty Actuarial Society Forum, Fall 2006 Featuring Reserves Call Papers, pp. 353-377.

[2] Peter D. England and Richard J. Verrall, "A flexible Framework for Stochastic Claims Reserving", Proceedings of the Casualty Actuarial Society 2001 Volume LXXXVIII, pp. 1-38.

[3] Harold E. Clarke, "Recent Developments in Reserving for Losses in the London Reinsurance Market", Proceedings of the Casualty Actuarial Society 1988 Volume LXXV, pp. 1-48.

[4] Raymond H. Myers, Douglas C. Montgomery, G. Geoffrey Vining, Generalized Linear Models With Applications in Engineering and the Sciences, 2002 John Wiley and Sons, Inc., pp. 63-92 discuss nonlinear regression. This book also provides accessible explanations of linear regression, GLM, GEE and GAM.

[5] Paul M. Kazenski, "A Nonlinear Modeling Approach to Assessing the Accuracy of Property-Liability Insurer Loss Reserves", University of Hawaii - Manoa, February 1994.

[6] Louis Doray, "IBNR Reserve Under a Loglinear Location-Scale Regression Model", Casualty Actuarial Society Forum Spring 1994, Volume Two, pp. 607-652.

| HIBIT I  |          |            |           |            |            |            |           |            |            |
|----------|----------|------------|-----------|------------|------------|------------|-----------|------------|------------|
| (1)      | (2)      | (3)        | (4)       | (5)        | (6)        | (7)        | (8)       | (9)        | (10        |
| ( )      | ( )      |            | ( )       | Discussion | Discussion |            |           | Discussion | Discussior |
|          |          |            |           | Paper      | Paper      |            |           | Paper      | Pape       |
|          |          | [1]        | [1]       | section 3  | section 3  | Check [1]  | Check [1] | section 4  | section 4  |
| Accident |          | Expected   | Standard  | Expected   | Standard   | Expected   | Standard  | Expected   | Standard   |
| Quarter  | Exposure | Value      | Deviation | Value      | Deviation  | Value      | Deviation | Value      | Deviatior  |
| 2        | 50,801   | 8,190      | 24,518    | 7,489      | 24,719     | 7,616      | 24,912    | 8,010      | 23,601     |
| 3        | 51,187   | 16,643     | 35,835    | 16,767     | 36,204     | 16,816     | 33,944    | 16,872     | 33,922     |
| 4        | 51,146   | 26,310     | 44,192    | 28,985     | 45,415     | 24,058     | 44,909    | 26,443     | 42,064     |
| 5        | 51,527   | 36,541     | 51,941    | 33,429     | 51,328     | 37,975     | 52,022    | 37,157     | 49,402     |
| 6        | 52,348   | 49,099     | 58,839    | 49,399     | 59,053     | 48,470     | 60,416    | 49,380     | 56,446     |
| 7        | 52,480   | 61,528     | 65,232    | 60,100     | 69,592     | 60,716     | 65,327    | 62,191     | 62,790     |
| 8        | 53,148   | 75,340     | 71,800    | 75,401     | 72,824     | 76,815     | 72,159    | 76,954     | 69,266     |
| 9        | 53,924   | 91,671     | 78,552    | 93,025     | 79,352     | 90,003     | 80,072    | 93,486     | 75,738     |
| 10       | 54,403   | 109,065    | 85,433    | 112,127    | 88,895     | 108,506    | 87,839    | 111,208    | 81,966     |
| 11       | 54,557   | 124,874    | 91,436    | 126,736    | 94,084     | 125,926    | 91,494    | 129,920    | 87,919     |
| 12       | 55,083   | 144,622    | 96,258    | 149,578    | 100,674    | 141,166    | 94,407    | 151,342    | 94,22      |
| 13       | 55,292   | 168,450    | 103,341   | 175,839    | 107,340    | 166,273    | 101,628   | 173,891    | 100,296    |
| 14       | 55,899   | 192,189    | 108,233   | 189,828    | 117,084    | 183,868    | 108,754   | 199,906    | 106,864    |
| 15       | 56,067   | 215,948    | 115,108   | 218,495    | 119,945    | 218,185    | 113,886   | 226,736    | 113,10     |
| 16       | 57,025   | 247,643    | 123,187   | 245,486    | 126,152    | 249,288    | 119,610   | 259,542    | 120,393    |
| 17       | 57,071   | 279,736    | 129,481   | 277,633    | 136,171    | 279,801    | 129,502   | 291,148    | 126,81     |
| 18       | 57,317   | 311,248    | 134,933   | 305,717    | 133,675    | 311,388    | 134,122   | 326,584    | 133,66     |
| 19       | 57,907   | 346,819    | 143,714   | 346,509    | 143,603    | 336,674    | 140,549   | 367,375    | 141,22     |
| 20       | 58,285   | 388,878    | 149,405   | 383,582    | 151,327    | 387,150    | 152,150   | 410,598    | 148,78     |
| 21       | 59,096   | 433,974    | 157,772   | 435,640    | 164,002    | 427,185    | 163,959   | 461,162    | 157,349    |
| 22       | 59,193   | 479,592    | 165,473   | 474,623    | 173,326    | 478,486    | 161,765   | 510,590    | 165,193    |
| 23       | 59,524   | 530,342    | 173,337   | 524,379    | 177,440    | 528,747    | 169,566   | 566,470    | 173,823    |
| 24       | 59,745   | 583,879    | 177,894   | 585,037    | 183,270    | 573,480    | 175,996   | 626,235    | 182,74     |
| 25       | 60,427   | 645,944    | 188,083   | 652,774    | 204,720    | 639,599    | 194,014   | 696,579    | 193,11     |
| 26       | 60,155   | 705,701    | 195,557   | 709,139    | 199,170    | 706,895    | 193,614   | 761,641    | 202,28     |
| 27       | 60,568   | 776,239    | 207,953   | 776,419    | 222,299    | 788,439    | 203,526   | 841,356    | 213,58     |
| 28       | 60,708   | 852,632    | 215,059   | 863,905    | 225,281    | 844,677    | 209,276   | 924,383    | 225,21     |
| 29       | 60,262   | 925,896    | 222,578   | 921,837    | 235,006    | 924,073    | 229,328   | 1,005,182  | 236,46     |
| 30       | 60,606   | 1,012,197  | 233,755   | 1,015,105  | 247,787    | 1,016,063  | 247,362   | 1,107,100  | 250,82     |
| 31       | 60,580   | 1,109,304  | 251,368   | 1,099,773  | 268,201    | 1,094,682  | 247,988   | 1,212,155  | 265,68     |
| 32       | 60,648   | 1,213,637  | 258,802   | 1,227,733  | 267,445    | 1,221,054  | 254,047   | 1,330,473  | 282,51     |
| 33       | 61,159   | 1,344,114  | 277,079   | 1,325,154  | 281,107    | 1,348,687  | 269,254   | 1,473,989  | 302,86     |
| 34       | 61,462   | 1,492,000  | 292,032   | 1,470,864  | 296,064    | 1,509,526  | 298,480   | 1,633,463  | 325,28     |
| 35       | 61,934   | 1,660,873  | 312,021   | 1,664,619  | 328,967    | 1,665,426  | 304,419   | 1,826,677  | 351,85     |
| 36       | 61,716   | 1,858,275  | 333,112   | 1,867,446  | 348,580    | 1,863,920  | 337,684   | 2,040,965  | 380,44     |
| 37       | 61,837   | 2,123,409  | 361,113   | 2,128,841  | 352,122    | 2,140,963  | 343,229   | 2,330,037  | 417,18     |
| 38       | 62,285   | 2,514,004  | 394,000   | 2,499,739  | 392,466    | 2,521,633  | 404,654   | 2,738,893  | 466,09     |
| 39       | 62,728   | 3,055,695  | 450,062   | 3,069,822  | 465,666    | 3,061,935  | 443,104   | 3,329,815  | 532,473    |
| 40       | 63,180   | 3,892,584  | 522,958   | 3,892,268  | 515,975    | 3,878,801  | 501,528   | 4,232,741  | 633,498    |
| tals     |          | 30,105,085 | 1,350,093 | 30,101,242 | 2,210,162  | 30,104,966 | 1,348,733 | 32,668,649 | 3,782,84   |

| Exhibit 2 |          | <u> </u>       |              |              |          |          |                |                |             |
|-----------|----------|----------------|--------------|--------------|----------|----------|----------------|----------------|-------------|
| (1)       | (2)      | (3)            | (4)          | (5)          | (6)      | (7)      | (8)            | (9)            | (10)        |
|           | ( )      | ( )            | Section 4    | Section 3    | ( )      | ( )      | ( )            | Section 4      | Section 3   |
|           |          |                | Incremental  | Incremental  |          |          |                | Incremental    | Incremental |
| aqtr      | age      | expos          | IBNR         | IBNR         | aqtr     | age      | expos          | IBNR           | IBNR        |
| 2         | 40       | 50801          | 8010         | 7964         | 40       | 2        | 63180          | 846121         | 795568      |
| 3         | 39       | 51187          | 8723         | 8653         | 40       | 3        | 63180          | 553745         | 520639      |
| 3         | 40       | 51187          | 8150         | 8024         | 40       | 4        | 63180          | 381677         | 357292      |
| 4         | 38       | 51146          | 9420         | 9323         | 40       | 5        | 63180          | 278847         | 258771      |
| 4         | 39       | 51146          | 8801         | 8646         | 40       | 6        | 63180          | 215972         | 198022      |
| 4         | 40       | 51146          | 8223         | 8018         | 40       | 7        | 63180          | 176251         | 159387      |
| 5         | 37       | 51527          | 10256        | 10128        | 40       | 8        | 63180          | 150042         | 133789      |
| 5         | 38       | 51527          | 9583         | 9392         | 40       | 9        | 63180          | 131801         | 115967      |
| 5         | 39       | 51527          | 8953         | 8710         | 40       | 10       | 63180          | 118339         | 102858      |
| 5         | 40       | 51527          | 8365         | 8077         | 40       | 11       | 63180          | 107812         | 92679       |
| 6         | 36       | 52348          | 11261        | 11095        | 40       | 12       | 63180          | 99153          | 84382       |
| 6         | 37       | 52348          | 10522        | 10289        | 40       | 13       | 63180          | 91736          | 77348       |
| 6         | 38       | 52348          | 9831         | 9542         | 40       | 14       | 63180          | 85192          | 71207       |
| 6         | 39       | 52348          | 9185         | 8849         | 40       | 15       | 63180          | 79299          | 65733       |
| 6         | 40       | 52348          | 8582         | 8206         | 40       | 16       | 63180          | 73920          | 60784       |
| 7         | 35       | 52480          | 12202        | 11994        | 40       | 17       | 63180          | 68967          | 56268       |
| 7         | 36       | 52480          | 11400        | 11004        | 40       | 18       | 63180          | 64381          | 52123       |
| 7         | 37       | 52480          | 10651        | 10315        | 40       | 19       | 63180          | 60120          | 48304       |
| 7         | 38       | 52480<br>52480 | 9952         | 9566         | 40       | 20       | 63180          | 56153          | 40304       |
| 7         | 39       | 52480<br>52480 | 9952         | 8871         | 40       | 20       | 63180          | 52454          | 44770       |
| 7         | 40       | 52480<br>52480 | 9298<br>8687 | 8227         | 40       | 21       | 63180          | 49002          | 38491       |
| 8         | 40<br>34 | 53148          | 13355        | 13098        | 40       | 22       | 63180          | 49002          | 35692       |
| 8         | 35       | 53148<br>53148 | 12478        | 12147        | 40       | 23       | 63180          | 43780          | 33092       |
| 8         | 36       | 53148<br>53148 | 12478        | 12147        | 40       | 24<br>25 | 63180          | 39960          | 30693       |
| 8         | 37       | 53148<br>53148 | 1038         | 10446        | 40       | 25       | 63180          | 37335          | 28463       |
| 8         | 38       | 53148<br>53148 | 10093        | 9688         | 40       | 20       | 63180          | 34882          | 26395       |
| 8         | 39       | 53148<br>53148 | 9509         | 9088<br>8984 | 40       | 28       | 63180          | 32591          | 20393       |
| 8         | 40       | 53148<br>53148 | 8884         | 8332         | 40       | 20       | 63180          | 30450          | 24478       |
| 9         | 33       | 53924          | 14645        | 14330        | 40       | 30       | 63180          | 28450          | 22700       |
| 9         | 33<br>34 | 53924<br>53924 | 13683        | 14330        | 40       | 31       | 63180          | 26581          | 19522       |
| 9         | 35       | 53924<br>53924 | 12784        | 12324        | 40       | 32       | 63180          | 24835          | 18104       |
| 9         | 36       | 53924<br>53924 | 12784        | 12324        | 40       | 33       | 63180          | 24833          | 16789       |
| 9         | 37       | 53924<br>53924 | 11944        | 10599        | 40       | 34       | 63180          | 23203          | 15570       |
| 9         | 38       | 53924<br>53924 | 10427        | 9829         | 40<br>40 | 34<br>35 | 63180          |                | 14439       |
|           |          |                |              |              |          |          |                | 20255          | 13391       |
| 9<br>9    | 39<br>40 | 53924<br>53924 | 9742<br>9102 | 9115<br>8453 | 40<br>40 | 36<br>37 | 63180<br>63180 | 18925<br>17682 | 13391       |
|           |          |                |              |              |          |          |                |                |             |
| 10<br>10  | 32       | 54403          | 15968        | 15589        | 40<br>40 | 38       | 63180<br>63180 | 16520<br>15425 | 11516       |
| 10        | 33       | 54403          | 14919        | 14457        | 40       | 39       | 63180<br>63180 | 15435          | 10680       |
| 10        | 34<br>25 | 54403          | 13939        | 13407        | 40       | 40       | 63180          | 14421          | 9904        |
| 10        | 35       | 54403          | 13024        | 12433        |          |          |                |                |             |
| 10        | 36       | 54403          | 12168        | 11530        |          |          |                |                |             |
| 10        | 37       | 54403          | 11369        | 10693        |          |          |                |                |             |
| 10        | 38       | 54403          | 10622        | 9916         |          |          |                |                |             |
| 10        | 39       | 54403          | 9924         | 9196         |          |          |                |                |             |
| 10        | 40       | 54403          | 9273         | 8528         |          |          |                |                |             |

| Exhibit 3     |    |             |             |             |             |             |             |  |  |  |
|---------------|----|-------------|-------------|-------------|-------------|-------------|-------------|--|--|--|
| aqtr          |    | 2           | 3           | 3           | 4           | 4           | 4           |  |  |  |
| <u>aqtr</u> a | ge | 40          | 39          | 40          | 38          | 39          | 40          |  |  |  |
| 2             | 40 | 602,854,869 | 3,112,619   | 3,014,973   | 3,204,500   | 3,110,126   | 3,012,558   |  |  |  |
| 3             | 39 | 3,112,619   | 631,054,179 | 3,136,270   | 3,334,387   | 3,235,699   | 3,133,757   |  |  |  |
| 3             | 40 | 3,014,973   | 3,136,270   | 607,458,435 | 3,228,848   | 3,133,757   | 3,035,448   |  |  |  |
| 4             | 38 | 3,204,500   | 3,334,387   | 3,228,848   | 655,671,475 | 3,331,716   | 3,226,262   |  |  |  |
| 4             | 39 | 3,110,126   | 3,235,699   | 3,133,757   | 3,331,716   | 630,546,122 | 3,131,247   |  |  |  |
| 4             | 40 | 3,012,558   | 3,133,757   | 3,035,448   | 3,226,262   | 3,131,247   | 606,969,439 |  |  |  |
| 5             | 37 | 3,319,123   | 3,454,230   | 3,344,343   | 3,557,965   | 3,451,463   | 3,341,664   |  |  |  |
| 5             | 38 | 3,228,371   | 3,359,226   | 3,252,901   | 3,459,481   | 3,356,535   | 3,250,295   |  |  |  |
| 5             | 39 | 3,133,294   | 3,259,802   | 3,157,102   | 3,356,535   | 3,257,191   | 3,154,573   |  |  |  |
| 5             | 40 | 3,034,999   | 3,157,102   | 3,058,060   | 3,250,295   | 3,154,573   | 3,055,610   |  |  |  |
| 6             | 36 | 3,458,533   | 3,599,973   | 3,484,812   | 3,708,826   | 3,597,089   | 3,482,020   |  |  |  |
| 6             | 37 | 3,372,008   | 3,509,268   | 3,397,630   | 3,614,656   | 3,506,457   | 3,394,908   |  |  |  |
| 6             | 38 | 3,279,810   | 3,412,750   | 3,304,731   | 3,514,602   | 3,410,016   | 3,302,084   |  |  |  |
| 6             | 39 | 3,183,218   | 3,311,742   | 3,207,405   | 3,410,016   | 3,309,089   | 3,204,836   |  |  |  |
| 6             | 40 | 3,083,357   | 3,207,405   | 3,106,785   | 3,302,084   | 3,204,836   | 3,104,296   |  |  |  |
| 7             | 35 | 3,546,852   | 3,692,652   | 3,573,802   | 3,805,149   | 3,689,694   | 3,570,939   |  |  |  |
| 7             | 36 | 3,467,254   | 3,609,050   | 3,493,599   | 3,718,178   | 3,606,160   | 3,490,801   |  |  |  |
| 7             | 37 | 3,380,511   | 3,518,116   | 3,406,197   | 3,623,770   | 3,515,299   | 3,403,469   |  |  |  |
| 7             | 38 | 3,288,080   | 3,421,355   | 3,313,064   | 3,523,465   | 3,418,615   | 3,310,410   |  |  |  |
| 7             | 39 | 3,191,245   | 3,320,093   | 3,215,493   | 3,418,615   | 3,317,433   | 3,212,917   |  |  |  |
| 7             | 40 | 3,091,132   | 3,215,493   | 3,114,619   | 3,310,410   | 3,212,917   | 3,112,124   |  |  |  |
| 8             | 34 | 3,663,703   | 3,815,168   | 3,691,541   | 3,932,367   | 3,812,112   | 3,688,584   |  |  |  |
| 8             | 35 | 3,591,998   | 3,739,655   | 3,619,291   | 3,853,584   | 3,736,659   | 3,616,392   |  |  |  |
| 8             | 36 | 3,511,387   | 3,654,989   | 3,538,068   | 3,765,505   | 3,652,061   | 3,535,234   |  |  |  |
| 8             | 37 | 3,423,540   | 3,562,897   | 3,449,553   | 3,669,896   | 3,560,044   | 3,446,790   |  |  |  |
| 8             | 38 | 3,329,933   | 3,464,905   | 3,355,235   | 3,568,314   | 3,462,129   | 3,352,547   |  |  |  |
| 8             | 39 | 3,231,865   | 3,362,353   | 3,256,422   | 3,462,129   | 3,359,660   | 3,253,813   |  |  |  |
| 8             | 40 | 3,130,478   | 3,256,422   | 3,154,264   | 3,352,547   | 3,253,813   | 3,151,737   |  |  |  |
| 9             | 33 | 3,778,996   | 3,936,224   | 3,807,710   | 4,058,262   | 3,933,071   | 3,804,660   |  |  |  |
| 9             | 34 | 3,717,196   | 3,870,872   | 3,745,440   | 3,989,782   | 3,867,772   | 3,742,440   |  |  |  |
| 9             | 35 | 3,644,444   | 3,794,256   | 3,672,136   | 3,909,849   | 3,791,217   | 3,669,194   |  |  |  |
| 9             | 36 | 3,562,656   | 3,708,354   | 3,589,726   | 3,820,484   | 3,705,384   | 3,586,851   |  |  |  |
| 9             | 37 | 3,473,527   | 3,614,918   | 3,499,919   | 3,723,479   | 3,612,023   | 3,497,116   |  |  |  |
| 9             | 38 | 3,378,553   | 3,515,495   | 3,404,224   | 3,620,414   | 3,512,679   | 3,401,497   |  |  |  |
| 9             | 39 | 3,279,053   | 3,411,446   | 3,303,968   | 3,512,679   | 3,408,713   | 3,301,321   |  |  |  |
| 9             | 40 | 3,176,185   | 3,303,968   | 3,200,318   | 3,401,497   | 3,301,321   | 3,197,755   |  |  |  |
| 10            | 32 | 3,861,688   | 4,023,507   | 3,891,031   | 4,149,543   | 4,020,284   | 3,887,914   |  |  |  |
| 10            | 33 | 3,812,564   | 3,971,189   | 3,841,533   | 4,094,311   | 3,968,008   | 3,838,456   |  |  |  |

| Exhibit 4 |     |             |             |             |             |             |             |
|-----------|-----|-------------|-------------|-------------|-------------|-------------|-------------|
| aqtr      |     | 2           | 3           | 3           | 4           | 4           | 4           |
| aqtr      | age | 40          | 39          | 40          | 38          | 39          | 40          |
| 2         | 40  | 557,010,999 | 3,076,909   | 3,007,116   | 3,181,310   | 3,115,232   | 3,044,109   |
| 3         | 39  | 3,076,909   | 583,099,003 | 3,141,809   | 3,324,615   | 3,255,594   | 3,181,296   |
| 3         | 40  | 3,007,116   | 3,141,809   | 561,346,864 | 3,249,349   | 3,183,066   | 3,111,471   |
| 4         | 38  | 3,181,310   | 3,324,615   | 3,249,349   | 605,880,842 | 3,367,957   | 3,291,128   |
| 4         | 39  | 3,115,232   | 3,255,594   | 3,183,066   | 3,367,957   | 582,719,205 | 3,225,207   |
| 4         | 40  | 3,044,109   | 3,181,296   | 3,111,471   | 3,291,128   | 3,225,207   | 560,981,739 |
| 5         | 37  | 3,309,854   | 3,459,950   | 3,381,707   | 3,580,453   | 3,506,202   | 3,426,258   |
| 5         | 38  | 3,248,025   | 3,395,306   | 3,319,801   | 3,513,545   | 3,442,061   | 3,364,808   |
| 5         | 39  | 3,180,038   | 3,324,227   | 3,251,437   | 3,439,980   | 3,371,218   | 3,296,648   |
| 5         | 40  | 3,106,968   | 3,247,836   | 3,177,730   | 3,360,919   | 3,294,831   | 3,222,924   |
| 6         | 36  | 3,465,072   | 3,623,357   | 3,541,518   | 3,750,844   | 3,673,110   | 3,589,404   |
| 6         | 37  | 3,408,292   | 3,563,915   | 3,484,814   | 3,689,234   | 3,614,287   | 3,533,269   |
| 6         | 38  | 3,344,022   | 3,496,650   | 3,420,281   | 3,619,536   | 3,547,345   | 3,469,022   |
| 6         | 39  | 3,273,491   | 3,422,845   | 3,349,190   | 3,543,076   | 3,473,604   | 3,397,971   |
| 6         | 40  | 3,197,796   | 3,343,649   | 3,272,681   | 3,461,044   | 3,394,244   | 3,321,287   |
| 7         | 35  | 3,571,152   | 3,735,590   | 3,651,328   | 3,868,496   | 3,788,379   | 3,702,096   |
| 7         | 36  | 3,521,668   | 3,683,685   | 3,602,101   | 3,814,585   | 3,737,218   | 3,653,557   |
| 7         | 37  | 3,463,277   | 3,622,482   | 3,543,587   | 3,751,066   | 3,676,435   | 3,595,423   |
| 7         | 38  | 3,397,363   | 3,553,427   | 3,477,220   | 3,679,434   | 3,607,512   | 3,529,163   |
| 7         | 39  | 3,325,166   | 3,477,814   | 3,404,282   | 3,601,029   | 3,531,782   | 3,456,095   |
| 7         | 40  | 3,247,795   | 3,396,803   | 3,325,924   | 3,517,048   | 3,450,436   | 3,377,400   |
| 8         | 34  | 3,708,164   | 3,880,415   | 3,793,016   | 4,020,164   | 3,936,970   | 3,847,360   |
| 8         | 35  | 3,667,175   | 3,837,284   | 3,752,499   | 3,975,213   | 3,894,734   | 3,807,677   |
| 8         | 36  | 3,615,573   | 3,783,079   | 3,700,941   | 3,918,824   | 3,841,063   | 3,756,609   |
| 8         | 37  | 3,554,928   | 3,719,439   | 3,639,966   | 3,852,693   | 3,777,639   | 3,695,822   |
| 8         | 38  | 3,486,652   | 3,647,838   | 3,571,034   | 3,778,341   | 3,705,975   | 3,626,814   |
| 8         | 39  | 3,412,007   | 3,569,596   | 3,495,454   | 3,697,135   | 3,627,427   | 3,550,925   |
| 8         | 40  | 3,332,125   | 3,485,894   | 3,414,395   | 3,610,295   | 3,543,208   | 3,469,358   |
| 9         | 33  | 3,846,268   | 4,026,672   | 3,936,130   | 4,173,643   | 4,087,347   | 3,994,380   |
| 9         | 34  | 3,815,764   | 3,994,377   | 3,906,352   | 4,139,764   | 4,056,121   | 3,965,605   |
| 9         | 35  | 3,772,676   | 3,948,954   | 3,863,507   | 4,092,331   | 4,011,365   | 3,923,380   |
| 9         | 36  | 3,718,786   | 3,892,266   | 3,809,438   | 4,033,270   | 3,954,991   | 3,869,594   |
| 9         | 37  | 3,655,700   | 3,825,989   | 3,745,804   | 3,964,313   | 3,888,716   | 3,805,947   |
| 9         | 38  | 3,584,857   | 3,751,625   | 3,674,094   | 3,887,013   | 3,814,085   | 3,733,966   |
| 9         | 39  | 3,507,548   | 3,670,523   | 3,595,643   | 3,802,764   | 3,732,479   | 3,655,021   |
| 9         | 40  | 3,424,928   | 3,583,889   | 3,511,646   | 3,712,812   | 3,645,138   | 3,570,336   |