# Insurance Risk Analytics

**First Model** : Construct a GLM using only the first **order terms** (linear terms) of the potential predictor variables by assuming **Poisson distribution and log link function**. Please do the following:

1. Assess the significance of each predictor by looking at the global test (i.e. Type 3 test). Use the testing results to perform variable selection.

Full model with all predictors:

| Analysis Of Maximum Likelihood Parameter Estimates | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Parameter | | DF | Estimate | Standard Error | Wald 95% Confidence Limits | | Wald Chi-Square | Pr > ChiSq |
| Intercept | | 1 | -0.6724 | 0.9737 | -2.5809 | 1.2361 | 0.48 | 0.4898 |
| ppc | A | 1 | -0.4668 | 0.2307 | -0.9189 | -0.0147 | 4.09 | 0.0430 |
| ppc | B | 1 | -0.4377 | 0.2000 | -0.8297 | -0.0458 | 4.79 | 0.0286 |
| ppc | C | 1 | -0.2229 | 0.1729 | -0.5617 | 0.1160 | 1.66 | 0.1974 |
| cons_typ | fire_re | 1 | -0.4581 | 0.2403 | -0.9291 | 0.0130 | 3.63 | 0.0567 |
| cons_typ | frame | 1 | 0.0696 | 0.1201 | -0.1659 | 0.3050 | 0.34 | 0.5624 |
| height | | 1 | 0.0302 | 0.0492 | -0.0661 | 0.1266 | 0.38 | 0.5385 |
| sqf | | 1 | 0.0005 | 0.0002 | 0.0001 | 0.0008 | 7.72 | 0.0054 |
| Scale | | 0 | 1.0000 | 0.0000 | 1.0000 | 1.0000 | | |

There are three variables insignificant at the 10% significance level: ppc level C, construction type frame, and height. We can first remove height since it has a high p-value and is a single continuous variable, while the other two are dummy variables of other factor variables.

| Analysis Of Maximum Likelihood Parameter Estimates | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Parameter | | DF | Estimate | Standard Error | Wald 95% Confidence Limits | | Wald Chi-Square | Pr > ChiSq |
| Intercept | | 1 | -0.0951 | 0.2561 | -0.5971 | 0.4068 | 0.14 | 0.7102 |
| ppc | A | 1 | -0.4626 | 0.2289 | -0.9311 | -0.0340 | 4.45 | 0.0350 |
| ppc | B | 1 | -0.4516 | 0.1985 | -0.8407 | -0.0625 | 5.17 | 0.0229 |
| ppc | C | 1 | -0.2282 | 0.1725 | -0.5663 | 0.1099 | 1.75 | 0.1858 |
| cons_typ | fire_re | 1 | -0.4764 | 0.2385 | -0.9436 | -0.0089 | 3.99 | 0.0458 |
| cons_typ | frame | 1 | 0.0762 | 0.1197 | -0.1584 | 0.3107 | 0.41 | 0.5245 |
| sqf | | 1 | 0.0006 | 0.0001 | 0.0004 | 0.0007 | 57.27 | <.0001 |
| Scale | | 0 | 1.0000 | 0.0000 | 1.0000 | 1.0000 | | |

After removing height, ppc level C and construction type frame are still insignificant. But some levels of the categorical variables are significant, so it's ok keep all the levels of the two categorical variable in the model.

2. With all significant variables in the type3 test, further look at the needs of collapsing levels for the categorical variables. Perform contrast tests for the between-level comparisons to determine the needs of reducing levels. Follow the contrast test results to reduce the levels of any categorical variables in the model if needed and refit model.

**Contrast Estimate Results**

| Label | Mean Estimate | Mean Confidence Limits | | L'Beta Estimate | Standard Error | Alpha | L'Beta Confidence Limits | | Chi-Square | Pr > ChiSq |
|---|---|---|---|---|---|---|---|---|---|---|
| ppc A vs.B | 0.9695 | 0.6804 | 1.3816 | -0.0309 | 0.1807 | 0.05 | -0.3851 | 0.3233 | 0.03 | 0.8641 |
| Exp(ppc A vs.B) | | | | 0.9695 | 0.1752 | 0.05 | 0.6804 | 1.3816 | | |
| ppc B vs.C | 0.7998 | 0.6329 | 1.0107 | -0.2234 | 0.1194 | 0.05 | -0.4574 | 0.0106 | 3.50 | 0.0613 |
| Exp(ppc B vs.C) | | | | 0.7998 | 0.0955 | 0.05 | 0.6329 | 1.0107 | | |
| ppc C vs.D | 0.7959 | 0.5676 | 1.1161 | -0.2282 | 0.1725 | 0.05 | -0.5663 | 0.1099 | 1.75 | 0.1858 |
| Exp(ppc C vs.D) | | | | 0.7959 | 0.1373 | 0.05 | 0.5676 | 1.1161 | | |
| cons_typ fire_re vs.frame | 0.5755 | 0.3718 | 0.8907 | -0.5525 | 0.2228 | 0.05 | -0.9893 | -0.1158 | 6.15 | 0.0132 |
| Exp(cons_typ fire_re vs.frame) | | | | 0.5755 | 0.1282 | 0.05 | 0.3718 | 0.8907 | | |

**Contrast Estimate Results**

| Label | Mean Estimate | Mean Confidence Limits | | L'Beta Estimate | Standard Error | Alpha | L'Beta Confidence Limits | | Chi-Square | Pr > ChiSq |
|---|---|---|---|---|---|---|---|---|---|---|
| ppc AB vs.CD | 0.7825 | 0.6400 | 0.9566 | -0.2453 | 0.1025 | 0.05 | -0.4463 | -0.0443 | 5.72 | 0.0167 |
| Exp(ppc AB vs.CD) | | | | 0.7825 | 0.0802 | 0.05 | 0.6400 | 0.9566 | | |
| cons_typ ao vs.fire_re | 1.6796 | 1.0911 | 2.5855 | 0.5185 | 0.2201 | 0.05 | 0.0872 | 0.9499 | 5.55 | 0.0185 |
| Exp(cons_typ ao vs.fire_re) | | | | 1.6796 | 0.3697 | 0.05 | 1.0911 | 2.5855 | | |

The p value for ppc A vs. B, and ppc C vs. D are larger than 0.1, indicating that they're not significantly different. Since ppc is ordinal variable, it makes sense to combine level A and B, level C and D. On the other hand, the p value for contrast of cons_type fire and cons_type frame is smaller than 0.1, indicating that these two levels are significantly different. Furthermore, since frame is insignificant in the previous test, we can collapse frame and masonry together as base level.

**Analysis Of Maximum Likelihood Parameter Estimates**

| Parameter | | DF | Estimate | Standard Error | Wald 95% Confidence Limits | | Wald Chi-Square | Pr > ChiSq |
|---|---|---|---|---|---|---|---|---|
| Intercept | | 1 | -0.2090 | 0.2009 | -0.6028 | 0.1849 | 1.08 | 0.2983 |
| ppc_new | AB | 1 | -0.2453 | 0.1025 | -0.4463 | -0.0443 | 5.72 | 0.0167 |
| cons_new | fire_re | 1 | -0.5185 | 0.2201 | -0.9499 | -0.0872 | 5.55 | 0.0185 |
| sqf | | 1 | 0.0005 | 0.0001 | 0.0004 | 0.0007 | 61.37 | <.0001 |
| Scale | | 0 | 1.0000 | 0.0000 | 1.0000 | 1.0000 | | |

Now, we have three variables remaining in the model and all are significant.

The final model is: E(claims) = -0.209 -0.2453*ppc_new - 0.5185*cons_new + 0.0005* sqf

if ppc =A or B, then ppc_new =1, otherwise ppc_new = 0;

if construction type is fire_re, then cons_new =1, otherwise cons_new =0.

3. Please write a small paragraph to summarize and explain the model results to the Chief Actuary including interpreting all parameter estimates of the model.
   The expected value of claim of a house is linearly related to its public protection class, construction type and the square footage of the house.
   If the house has a Public Protection Class level A or B, its expected claim will be 0.2453 less than level C or D when other conditions are the same; If the construction type is Fire Resistant, the house's expected claim will be - 0.5185 less than masonry and frame when other conditions are the same; one unit increase of the square footage of the house will increase claims by 0.0005.

4. Now, the Chief Actuary wants to know for a particular house with Level B in Public Protection Class, Masonry Construction Type, 25 ft tall, and 2850 sqf, what is the expected loss frequency based on this first model?

   E(claims) = -0.209 -0.2453*ppc_new - 0.5185*cons_new + 0.0005* sqf
   if ppc =A or B, then ppc_new =1, otherwise ppc_new = 0;
   if construction type is fire_re, then cons_new =1, otherwise cons_new =0.

   In the above case, ppc level = B, construction type = Masonry, then ppc_new = 1, cons_new = 0.
   y = - 0.209 -0.2453 + 0.0005* 2850
   = 0.9707

   If the exposure for this particular house is 1, then:
   The expected loss frequency = Expected claims / Exposure = 0.9707

5. Assess the goodness of fit for the model by looking at:
   a. Overdispersion from specific statistics or residual analysis, and propose 2 different ways to correct overdispersion if it exists

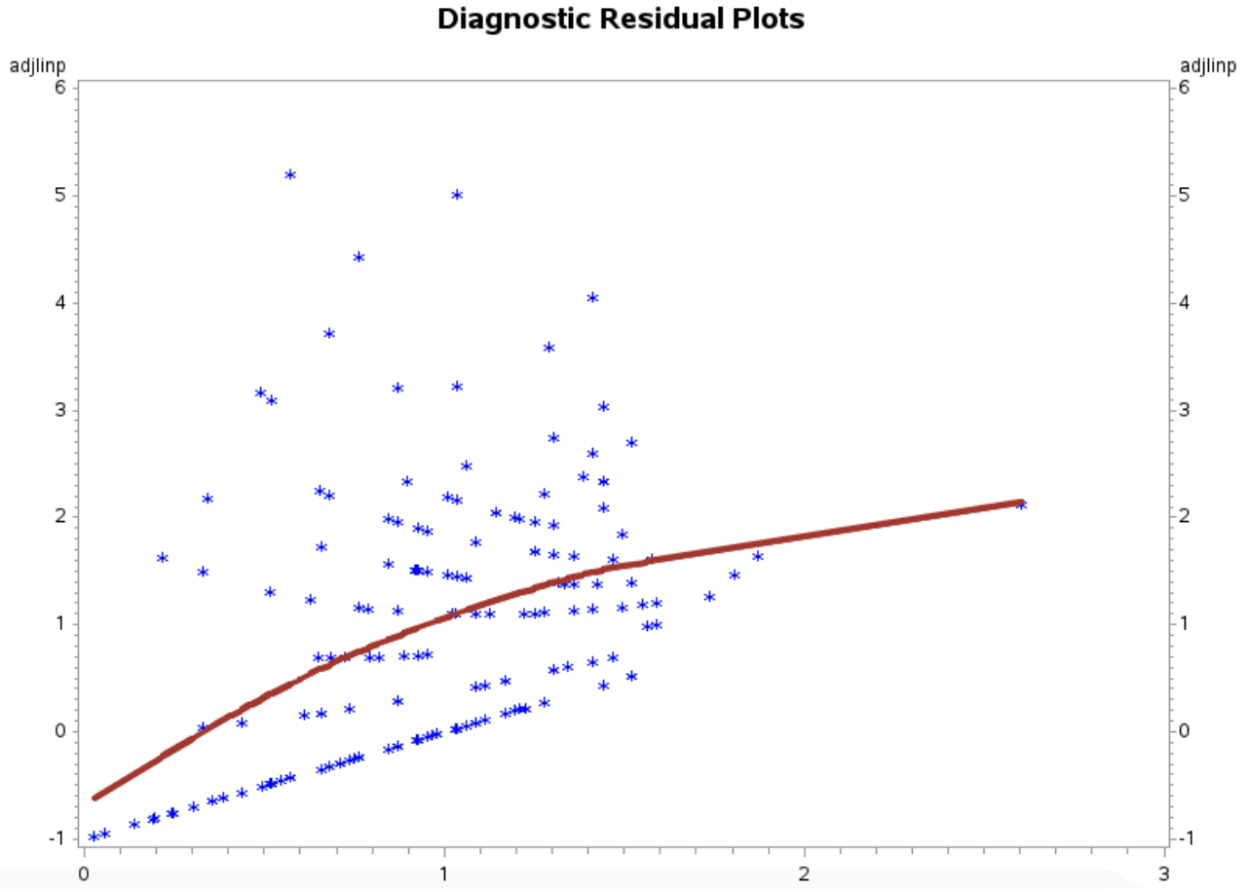
| Criteria For Assessing Goodness Of Fit | | | |
|---|---|---|---|
| **Criterion** | **DF** | **Value** | **Value/DF** |
| **Deviance** | 169 | 543.0998 | 3.2136 |
| **Scaled Deviance** | 169 | 543.0998 | 3.2136 |
| **Pearson Chi-Square** | 169 | 526.0316 | 3.1126 |
| **Scaled Pearson X2** | 169 | 526.0316 | 3.1126 |
| **Log Likelihood** | | 71.6769 | |
| **Full Log Likelihood** | | -447.9070 | |
| **AIC (smaller is better)** | | 903.8141 | |
| **AICC (smaller is better)** | | 904.0522 | |
| **BIC (smaller is better)** | | 916.4272 | |

   b. Since the scale of the first model is 1, the scaled deviance is the same with deviance (543.0998), and the scaled Pearson X2 is the same with Pearson Chi-Square (526.0316). The DF is 169 (number of observation = 173, number of parameters = 4). Pearson Chi-

Square Value/DF = 3.1126, which is far larger than 1, indicating that there is a problem of over-dispersion.

There are two ways to address over-dispersion: 1) to run the same model as a negative binomial regression, or by estimate the scale parameter = (Pearson Chi / D.F.) 2) to correct the standard errors of the estimates by removing outliers etc.

c. Linearity Assumption




From the residual plot above, we can see that the assumption of linearity is not well satisfied.

d. Identifying outliers

We can use Cook's D statistics to identify outliers. If the value Di >= 4/(n-p-1), then observation i is considered as a model outlier. In our case, 4/(n-p-) = 4/(173-4-1) = 0.0238.

For each observation, Cook's D statistics. $D_i = r_i^2 h_i/(p(1-h_i))$, where p is the number of parameters in the model, r is the standardized Pearson Residual, h = Hessian weight * variance of the linear predictor.

Thus, the outliers identified by Cook's D statistics are listed as above.

**Potential Influential Observations**

| Obs | claims | Pred | ppc_new | cons_new | sqf | CookD | Stresdev |
|---|---|---|---|---|---|---|---|
| 3 | 9 | 2.8152508 | CD | ao | 2300 | 0.0403045 | 2.9410694 |
| 13 | 11 | 4.2237024 | CD | ao | 3050 | 0.0377311 | 2.7583004 |
| 15 | 14 | 2.8152508 | CD | ao | 2300 | 0.1318139 | 4.7756725 |
| 22 | 3 | 1.676165 | CD | fire_re | 2300 | 0.023969 | 0.9572842 |
| 33 | 0 | 1.4251031 | CD | fire_re | 2000 | 0.0275188 | -1.748016 |
| 34 | 8 | 2.3935726 | CD | ao | 2000 | 0.0484219 | 2.8655336 |
| 45 | 9 | 3.6824428 | AB | ao | 3250 | 0.0793404 | 2.380591 |
| 56 | 15 | 4.1110071 | CD | ao | 3000 | 0.0940618 | 4.1560936 |
| 67 | 10 | 4.5806653 | CD | ao | 3200 | 0.0277841 | 2.2039848 |
| 71 | 7 | 2.8868903 | AB | ao | 2800 | 0.0344953 | 2.0664153 |
| 77 | 3 | 1.2424788 | AB | fire_re | 2200 | 0.0440457 | 1.3754511 |
| 117 | 12 | 3.6329839 | AB | ao | 3225 | 0.1922641 | 3.5215628 |
| 121 | 6 | 1.6808488 | AB | ao | 1800 | 0.0430397 | 2.5947135 |
| 126 | 0 | 1.676165 | CD | fire_re | 2300 | 0.0384251 | -1.906769 |
| 131 | 3 | 1.387079 | CD | fire_re | 1950 | 0.035278 | 1.2252474 |
| 134 | 10 | 2.1440474 | AB | ao | 2250 | 0.1154397 | 3.9146049 |
| 139 | 6 | 1.6314422 | CD | fire_re | 2250 | 0.2601534 | 2.7307187 |
| 141 | 7 | 13.512378 | CD | ao | 5200 | 0.9201355 | -2.541894 |
| 146 | 8 | 1.9769657 | AB | ao | 2100 | 0.0710824 | 3.2368949 |
| 149 | 10 | 1.7742664 | AB | ao | 1900 | 0.1465648 | 4.2903481 |
| 160 | 4 | 2.509927 | AB | fire_re | 3500 | 0.0469409 | 0.9395594 |
| 173 | 0 | 1.4251031 | CD | fire_re | 2000 | 0.0275188 | -1.748016 |

**Second Model**: With the model you have in Step 1 (i.e. your first model), try **Negative Binomial distribution and log link function** and see if you have get a better fit for modeling the dispersion.

1. Assess the significance of each predictor by looking at the global test (i.e. Type 3 test). Use the testing results to perform variable selection. (drop one insignificant variable at a time if you have multiple of them.)

| Analysis Of Maximum Likelihood Parameter Estimates | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Parameter | | DF | Estimate | Standard Error | Wald 95% Confidence Limits | | Wald Chi-Square | Pr > ChiSq |
| Intercept | | 1 | -0.6450 | 0.4743 | -1.5746 | 0.2846 | 1.85 | 0.1738 |
| ppc_new | AB | 1 | -0.2633 | 0.1933 | -0.6422 | 0.1155 | 1.86 | 0.1731 |
| cons_new | fire_re | 1 | -0.5401 | 0.3560 | -1.2380 | 0.1577 | 2.30 | 0.1293 |
| sqf | | 1 | 0.0007 | 0.0002 | 0.0004 | 0.0011 | 16.12 | <.0001 |
| Dispersion | | 1 | 1.0212 | 0.1873 | 0.7128 | 1.4630 | | |

| Contrast Estimate Results | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Label | Mean Estimate | Mean Confidence Limits | | L'Beta Estimate | Standard Error | Alpha | L'Beta Confidence Limits | | Chi-Square | Pr > ChiSq |
| ppc AB vs.CD | 0.7685 | 0.5261 | 1.1224 | -0.2633 | 0.1933 | 0.05 | -0.6422 | 0.1155 | 1.86 | 0.1731 |
| Exp(ppc AB vs.CD) | | | | 0.7685 | 0.1485 | 0.05 | 0.5261 | 1.1224 | | |
| cons_typ ao vs.fire_re | 0.5827 | 0.2900 | 1.1708 | -0.5401 | 0.3560 | 0.05 | -1.2380 | 0.1577 | 2.30 | 0.1293 |
| Exp(cons_typ ao vs.fire_re) | | | | 0.5827 | 0.2075 | 0.05 | 0.2900 | 1.1708 | | |

If we run the first model using negative binomial distribution and log link function, we see that only 1 independent variable sqf is significant. Both ppc_new and cons_new are insignificant under 10% S.L. The contrast test shows the same p-value result for two categorical variables we have because there are only 2 levels for each.

We first drop ppc_new with the highest p-value. As we can see from the result below, cons_new is still insignificant under 10% S.L.

| Analysis Of Maximum Likelihood Parameter Estimates | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Parameter | | DF | Estimate | Standard Error | Wald 95% Confidence Limits | | Wald Chi-Square | Pr > ChiSq |
| Intercept | | 1 | -0.8583 | 0.4534 | -1.7471 | 0.0304 | 3.58 | 0.0584 |
| sqf | | 1 | 0.0008 | 0.0002 | 0.0004 | 0.0011 | 18.64 | <.0001 |
| cons_new | fire_re | 1 | -0.5180 | 0.3593 | -1.2223 | 0.1862 | 2.08 | 0.1494 |
| Dispersion | | 1 | 1.0421 | 0.1897 | 0.7294 | 1.4890 | | |

The final model only contains sqf which has a p value less than 0.0001.

| Analysis Of Maximum Likelihood Parameter Estimates | | | | | | | |
|---|---|---|---|---|---|---|---|
| Parameter | DF | Estimate | Standard Error | Wald 95% Confidence Limits | | Wald Chi-Square | Pr > ChiSq |
| Intercept | 1 | -0.9684 | 0.4513 | -1.8528 | -0.0839 | 4.60 | 0.0319 |
| sqf | 1 | 0.0008 | 0.0002 | 0.0004 | 0.0011 | 20.01 | <.0001 |
| Dispersion | 1 | 1.0637 | 0.1923 | 0.7463 | 1.5161 | | |

**Note:** The negative binomial dispersion parameter was estimated by maximum likelihood.

| LR Statistics For Type 3 Analysis | | | |
|---|---|---|---|
| Source | DF | Chi-Square | Pr > ChiSq |
| sqf | 1 | 20.29 | <.0001 |

2. compare the differences between Model 1 and 2

   Model 1: E(claims) = - 0.209 - 0.2453*ppc_new - 0.5185*cons_new + 0.0005* sqf
   if ppc =A or B, then ppc_new =1, otherwise ppc_new = 0;
   if construction type is fire_re, then cons_new =1, otherwise cons_new =0.

   Model 2: E(claims) = - 0.9684 + 0.0008* sqf

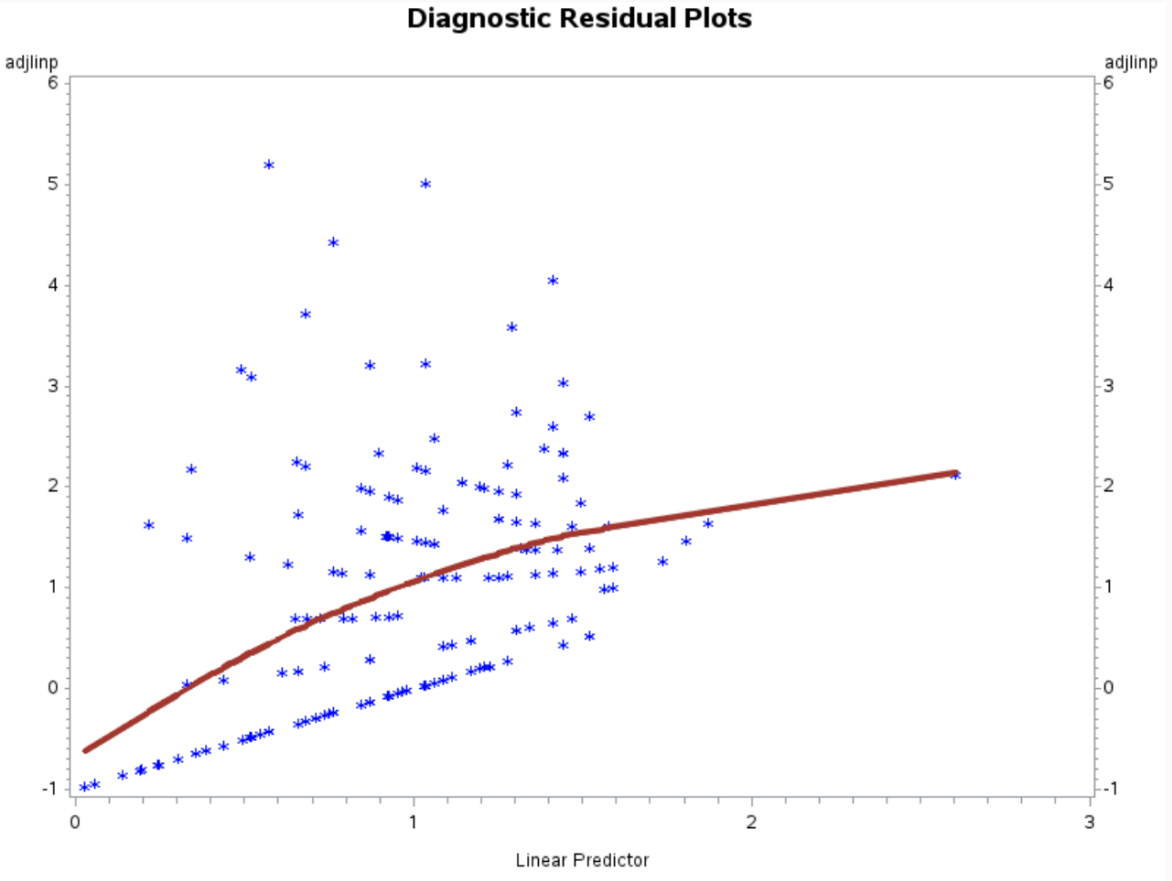
   The first model consists 3 significant independent variables while the second model only contains 1 significant independent variable. It is because the first model is a regular Poisson model, assuming variable's mean equal to its variance. It fails to address the problem of over-dispersion and leads to over-estimation of the significance of the predictors, making those insignificant variables significant aka. Type I Error. The second model uses a negative binomial model which successfully addresses the over-dispersion problem.

3. Assess the goodness of fit for the model by looking at:
   a. Overdispersion

| Criteria For Assessing Goodness Of Fit | | | |
|---|---|---|---|
| **Criterion** | **DF** | **Value** | **Value/DF** |
| **Deviance** | 171 | 195.4597 | 1.1430 |
| **Scaled Deviance** | 171 | 195.4597 | 1.1430 |
| **Pearson Chi-Square** | 171 | 152.3088 | 0.8907 |
| **Scaled Pearson X2** | 171 | 152.3088 | 0.8907 |
| **Log Likelihood** | | 148.4597 | |
| **Full Log Likelihood** | | -371.1243 | |
| **AIC (smaller is better)** | | 748.2485 | |
| **AICC (smaller is better)** | | 748.3905 | |
| **BIC (smaller is better)** | | 757.7084 | |

The Deviance Value/DF = 1.1430 and the Pearson Chi Value/DF = 0.8907, which are both close to 1, indicating that the over-dispersion issue is addressed.

b. Linearity Assumption




From the residual plot above, we see that the assumption of linearity is still not satisfied.

c. Identifying outliers

The outlier criteria for Cook's D statistic is 4/(n-p-1) = 4/170 = 0.0235. Observations with a higher CookD is listed as below:

**Potential Influential Observations**

| Obs | claims | Pred | sqf | CookD | Stresdev |
|---|---|---|---|---|---|
| 3 | 9 | 2.8152508 | 2300 | 0.0806089 | 2.9410694 |
| 8 | 0 | 1.0563759 | 1900 | 0.0310926 | -1.493504 |
| 13 | 11 | 4.2237024 | 3050 | 0.0754622 | 2.7583004 |
| 14 | 0 | 1.0281901 | 1850 | 0.0294054 | -1.472396 |
| 15 | 14 | 2.8152508 | 2300 | 0.2636279 | 4.7756725 |
| 16 | 8 | 4.0013188 | 2950 | 0.0246651 | 1.7678733 |
| 22 | 3 | 1.676165 | 2300 | 0.0479379 | 0.9572842 |
| 29 | 0 | 2.5908959 | 2600 | 0.0253191 | -2.298078 |
| 33 | 0 | 1.4251031 | 2000 | 0.0550375 | -1.748016 |
| 34 | 8 | 2.3935726 | 2000 | 0.0968438 | 2.8655336 |
| 45 | 9 | 3.6824428 | 3250 | 0.1586808 | 2.380591 |
| 51 | 5 | 1.9769657 | 2100 | 0.0358136 | 1.8116334 |
| 56 | 15 | 4.1110071 | 3000 | 0.1881235 | 4.1560936 |
| 61 | 0 | 2.5217665 | 2550 | 0.0237114 | -2.26642 |
| 62 | 5 | 1.9242171 | 2050 | 0.0378736 | 1.8571982 |
| 67 | 10 | 4.5806653 | 3200 | 0.0555682 | 2.2039848 |
| 71 | 7 | 2.8868903 | 2800 | 0.0689905 | 2.0664153 |
| 74 | 6 | 2.7401354 | 2250 | 0.0237829 | 1.7088771 |
| 76 | 0 | 1.1478513 | 1600 | 0.036541 | -1.559995 |
| 77 | 3 | 1.2424788 | 2200 | 0.0880914 | 1.3754511 |
| 81 | 0 | 1.2765389 | 2250 | 0.0467586 | -1.6517 |
| 82 | 0 | 3.0473367 | 2900 | 0.0400583 | -2.50018 |
| 87 | 0 | 4.2237024 | 3050 | 0.0293178 | -2.926276 |
| 88 | 0 | 2.8098633 | 2750 | 0.0314323 | -2.396406 |
| 90 | 0 | 1.2116461 | 1700 | 0.040341 | -1.604725 |
| 94 | 0 | 4.5806653 | 3200 | 0.0397001 | -3.052453 |
| 117 | 12 | 3.6329839 | 3225 | 0.3845282 | 3.5215628 |
| 120 | 6 | 2.4544817 | 2500 | 0.0464927 | 1.9235205 |
| 121 | 6 | 1.6808488 | 1800 | 0.0860793 | 2.5947135 |
| 126 | 0 | 1.676165 | 2300 | 0.0768502 | -1.906769 |
| 128 | 4 | 1.4098913 | 1475 | 0.0394365 | 1.7926542 |
| 131 | 3 | 1.387079 | 1950 | 0.0705559 | 1.2252474 |
| 134 | 10 | 2.1440474 | 2250 | 0.2308794 | 3.9146049 |
| 138 | 5 | 2.3252499 | 2400 | 0.0263071 | 1.5314683 |
| 139 | 6 | 1.6314422 | 2250 | 0.5203067 | 2.7307187 |
| 141 | 7 | 13.512378 | 5200 | 1.840271 | -2.541894 |
| 146 | 8 | 1.9769657 | 2100 | 0.1421648 | 3.2368949 |
| 149 | 10 | 1.7742664 | 1900 | 0.2931296 | 4.2903481 |
| 150 | 9 | 4.1110071 | 3000 | 0.0379233 | 2.0932624 |
| 157 | 0 | 4.5806653 | 3200 | 0.0397001 | -3.052453 |
| 160 | 4 | 2.509927 | 3500 | 0.0938817 | 0.9395594 |
| 172 | 0 | 2.6261679 | 2625 | 0.0261962 | -2.314111 |
| 173 | 0 | 1.4251031 | 2000 | 0.0550375 | -1.748016 |

**Third Model** : Test high order terms (i.e. quadratic terms etc.) for any continuous variables in your Second Model and assess the variable significances and goodness of the model.

| Criteria For Assessing Goodness Of Fit | | | |
|---|---|---|---|
| Criterion | DF | Value | Value/DF |
| Deviance | 170 | 195.9132 | 1.1524 |
| Scaled Deviance | 170 | 195.9132 | 1.1524 |
| Pearson Chi-Square | 170 | 156.6727 | 0.9216 |
| Scaled Pearson X2 | 170 | 156.6727 | 0.9216 |
| Log Likelihood | | 150.1493 | |
| Full Log Likelihood | | -369.4346 | |
| AIC (smaller is better) | | 746.8693 | |
| AICC (smaller is better) | | 747.1074 | |
| BIC (smaller is better) | | 759.4824 | |

| Analysis Of Maximum Likelihood Parameter Estimates | | | | | | | |
|---|---|---|---|---|---|---|---|
| Parameter | DF | Estimate | Standard Error | Wald 95% Confidence Limits | | Wald Chi-Square | Pr > ChiSq |
| Intercept | 1 | -2.8940 | 1.0809 | -5.0126 | -0.7755 | 7.17 | 0.0074 |
| sqf | 1 | 0.0023 | 0.0008 | 0.0008 | 0.0038 | 8.84 | 0.0029 |
| sqf*sqf | 1 | -0.0000 | 0.0000 | -0.0000 | -0.0000 | 4.28 | 0.0385 |
| Dispersion | 1 | 1.0244 | 0.1881 | 0.7147 | 1.4682 | | |

Both sqf and sqf^2 are significant in the model. But the estimate of sqf * sqf is very close to 0, we should consider divide sqf*sqf by 1000 to see the relationship more clearly.

The goodness of fit indicates that this model is better than the second one. 1) the Value/DF is closer to 1; 2) The AIC, AICC is smaller than those of the second model (748.25, 748.39), although BIC is smaller in the second model. The linearity plot also looks better.