

# An Introduction to the Analysis of Rare Events

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## ABSTRACT

Analyzing rare events like disease incidents, natural disasters, or component failures requires specialized statistical techniques since common methods like linear regression (`PROC REG`) are inappropriate. In this paper, we'll first explain what it means to use a statistical model, then explain why the most common one (linear regression) is inappropriate for rare events. Then we'll introduce the most basic statistical model for rare events: Poisson regression (using `PROC GENMOD` or `PROC COUNTREG`).

**KEYWORDS:** SAS, Poisson regression, `PROC COUNTREG`.

The graphical output in this paper is from SAS 9.3 TS1M0. All data sets and SAS code used in this paper are downloadable from [www.stakana.com/RareEvents](http://www.stakana.com/RareEvents).

## INTRODUCTION: STATISTICAL MODELING WITH LINEAR REGRESSION

Suppose we have a data set of two variables of  $n$  observations, written as  $X_i$  and  $Y_i$  for the  $i^{\text{th}}$  observation. Our objective is to use (known)  $X_i$  to get an estimate of (unknown)  $Y_i$ . That is, while we know both  $X_i$  and  $Y_i$  in our data set of past events, to predict future events with our model, we will know  $X_i$  only.

As a simple example, let's look at Figure 1 on page 2, generated from `PROC GPLOT`:

```
SYMBOL1 HEIGHT=3 COLOR=blue;

PROC GPLOT DATA=home.fuel;
  PLOT fuel*dlic=1 / ...;
RUN;
```

This data set, taken from Weisberg (2005, pp. 15-17, 52-64), shows the percentage of the adult population with a driver's license (hereafter referred to as driver population percentage) and per capita fuel consumption for each of the 50 states and the District of Columbia, with all data from 2001. We want to look at the effect of the driver population percentage on per capita fuel consumption – meaning that we'd like to estimate the state per capita fuel consumption  $Y$ , given the state population percentage  $X$ .<sup>1</sup> We can do this using a *statistical model*.

When we create a statistical model, we really mean that we're going to fit a *trend line* to the data. Meaning, we want to fit a line (or certain types of curves, as described on page 4) that best describes the general trend of the data. Most of the time, the data don't fit a linear trend exactly, but we can use a variety of statistical algorithms to find the line that fits the data better than any other lines according to some criteria. Mathematically, we fit the equation

$$Y_i = \underbrace{\beta_0 + \beta_1 X_i}_{\text{linear trend}} + \underbrace{\varepsilon_i}_{\text{error term}}$$

where  $\beta_0$  and  $\beta_1$  are unknown quantities (called *parameters*) that we will need to estimate to make our model. The error term  $\varepsilon_i$  is simply the difference between our linear trend line  $\beta_0 + \beta_1 X_i$  and the data point  $Y_i$ . This term necessary in the equation above, since there will always be some remainder term after the linear trend.

When we *fit a model*, we mean that we have estimates for  $\beta_0$  and  $\beta_1$ , denoted  $\hat{\beta}_0$  and  $\hat{\beta}_1$  (the hat  $\hat{\cdot}$  designates the estimate of something), which means that if we have  $X_i$ , we can estimate the data point  $Y_i$  by

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_i. \quad (1)$$

<sup>1</sup>As described in Weisberg (2005, pp. 52-64), there are actually many other variables that have an effect on per capita fuel consumption. Here, we're looking at just one of them.

# Fuel Consumption vs Driver Population Percentage

Scatterplot

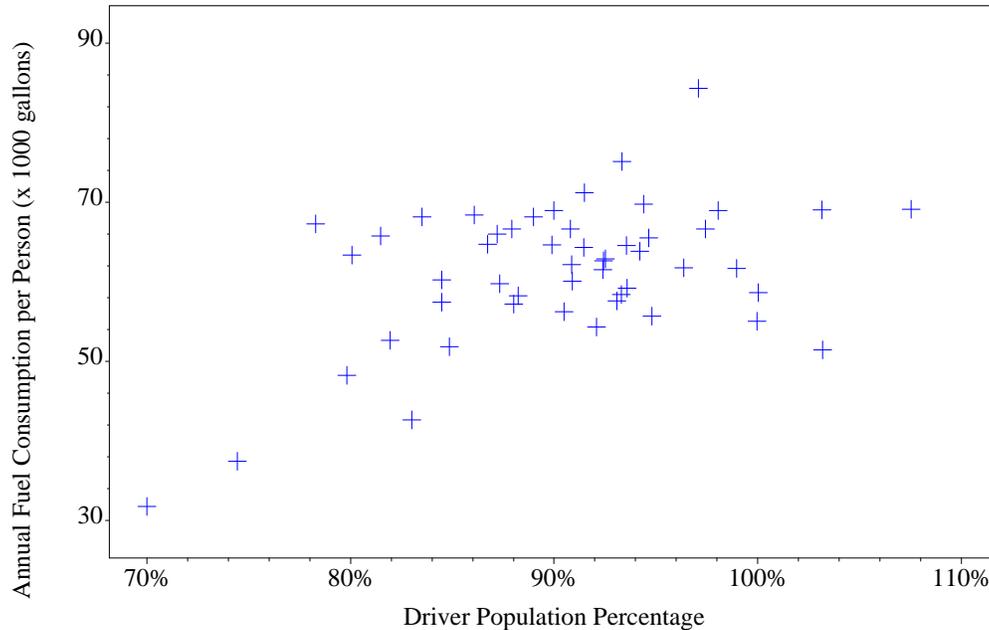


Figure 1: Scatterplot of population percentage with a driver's license and per capita fuel consumption for each of the 50 states and the District of Columbia, from 2001. Data set is described in Weisberg (2005, pp. 15-17, 52-64) and ultimately from US DoT (2001). Note that data points with a driver population percentage over 100% are perfectly legit, as many driver license holders are residents of another state and thus not counted in the population.

As mentioned above, this was our objective: To estimate (unknown)  $Y_i$  from (known)  $X_i$ . That's what linear regression does.

As an example, suppose we want to find a line that best fits the data shown in Figure 1 – meaning we want to find estimates for  $\beta_0$  and  $\beta_1$  in equation (1) on page 1. We can do this in SAS via `PROC REG` or a number of other procedures, but to make a simple graph, there's a trick we can do:

```
SYMBOL1 COLOR=blue ...;
SYMBOL2 LINE=1 COLOR=red INTERPOL=r1 ...;

PROC GPLOT DATA=home.fuel;
  ...
  PLOT fuel*dlic=1
       fuel*dlic=2 / ... OVERLAY;
RUN;
```

The `INTERPOL=r1` option tells SAS to include a regression line in the output (`r1` = “regression linear”), which we see in Figure 2(a) on page 3. Doing this gives the equation of the regression line in the log output:

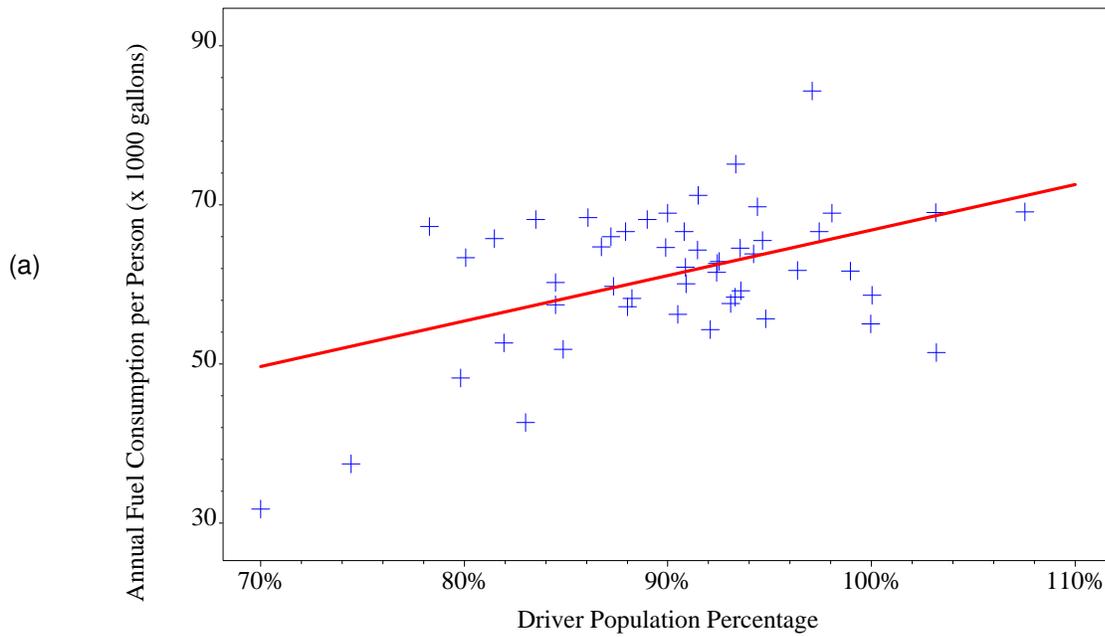
```
NOTE: Regression equation : fuel = 9.617975 + 57.20502*dlic.
```

So that in our equation (1) on page 1, given the driver population percentage  $DLIC_i$ , our estimate of the per capita fuel consumption  $FUEL_i$  is

$$\widehat{FUEL}_i = \widehat{\beta}_0 + \widehat{\beta}_1 \cdot DLIC_i = 9.617975 + 57.20502 \cdot DLIC_i.$$

## Fuel Consumption vs Driver Population Percentage

Linear Regression Line



## Fuel Consumption vs Driver Population Percentage

Linear Regression Line + 95% Prediction Bounds

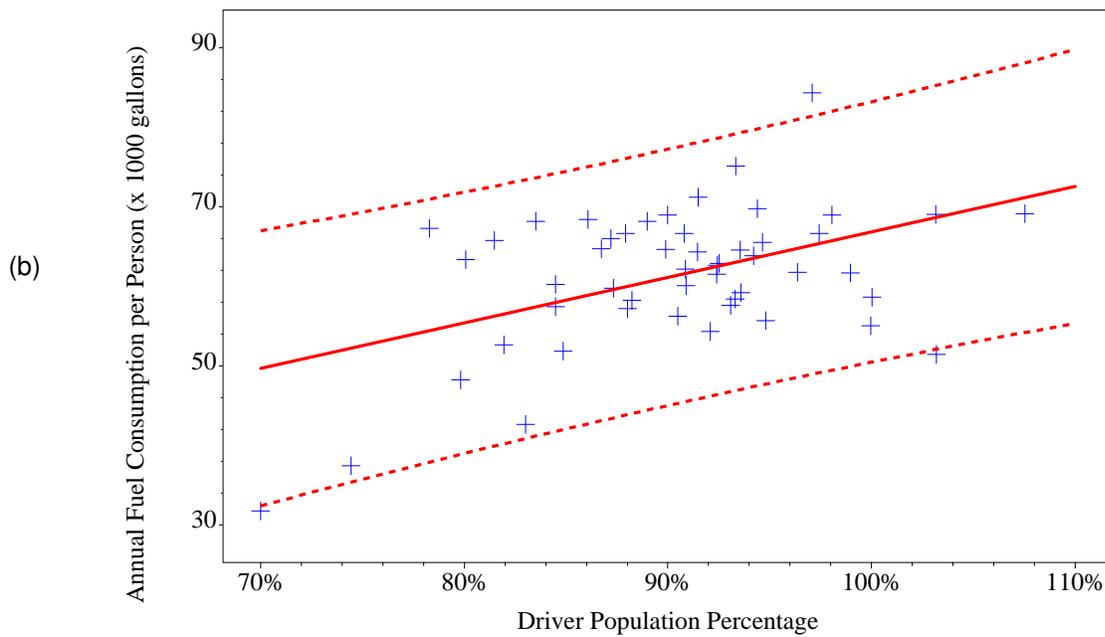


Figure 2: Fuel scatterplot (a) with a linear regression line only and (b) with 95% prediction bounds. Note that data points with a driver population percentage over 100% are perfectly legit, as many driver license holders are residents of another state and thus not counted in the population.

In addition to giving us estimates of  $\beta_0$ ,  $\beta_1$  and this  $Y_i$  (equal to  $\hat{\beta}_0 + \hat{\beta}_1 X_i$ ), linear regression gives us much more output. For example, it gives us estimates of how accurate each of those estimates are by giving us *prediction intervals* of the output  $Y_i$ . A 95% *prediction interval* of the dependent variable  $Y_i$  tells us that we are 95% sure that the predicted model of  $Y_i$  (given  $X_i$  is within this interval. This definition is analogous for any percentage. To show this graphically in SAS, we can follow a similar trick as above:

```

SYMBOL1 COLOR=blue ...;
SYMBOL3 COLOR=red INTERPOL=rlcli ...;

PROC GPLOT DATA=home.fuel;
  ...
  PLOT fuel*dlic=1
       fuel*dlic=3 / ... OVERLAY;
RUN;

```

The `INTERPOL=rlcli` option tells SAS to include a regression line in the output with prediction intervals (`rlcli` = “regression linear with confidence limits for the individual observations”), which we see in Figure 2(b) on page 3. There are 95% *prediction bounds*, where roughly 95% of the data fall between the two dotted lines. Indeed, of the 51 data points shown, you can see that all but three data points are within those bounds, thus  $\frac{48}{51} = 94.12\%$  of the data are within those bounds, as expected.

Linear regression need not fit a straight line. Indeed, the word “linear” simply means that the equation follows a linear form. However, you can also have a *quadratic* or *cubic* trend, meaning a linear equation with powers of  $X_i$  up to 2 or 3:

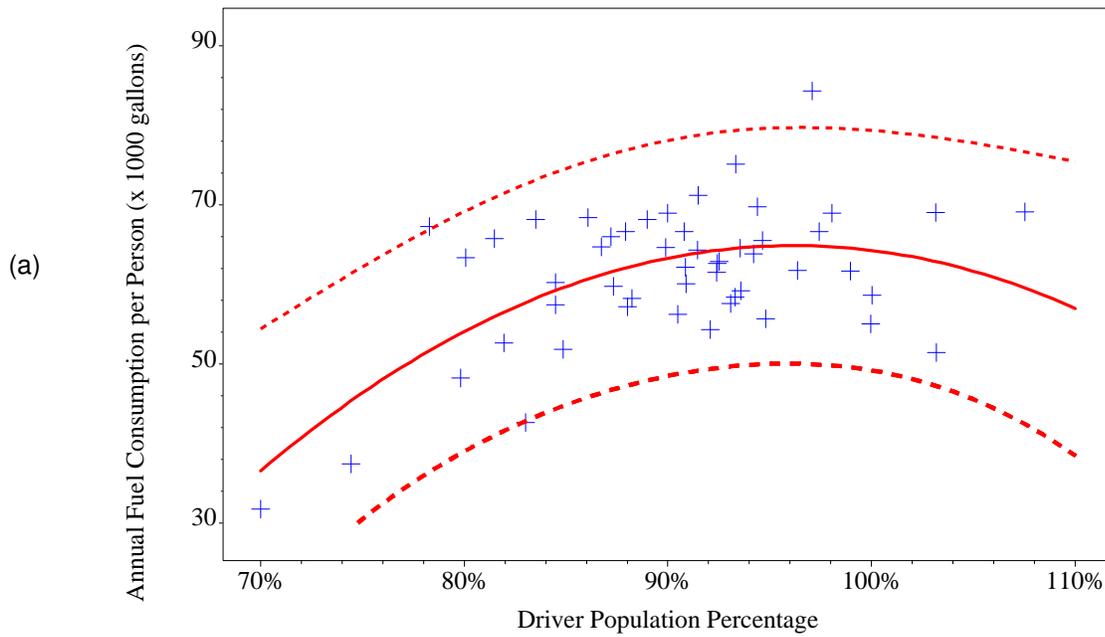
$$\begin{aligned} \text{Quadratic trend: } & Y_i = \beta_0 + \beta_1 X_i + \beta_2 X_i^2 + \varepsilon_i \\ \text{Cubic trend: } & Y_i = \beta_0 + \beta_1 X_i + \beta_2 X_i^2 + \beta_3 X_i^3 + \varepsilon_i \end{aligned}$$

This can be graphed in SAS via the `INTERPOL=rqli` or `INTERPOL=rccli` options in the `SYMBOL` statements (or without `cli` for the line only). As before, SAS gives you the equation of the line in the log output. The results are shown in Figure 3(a)-(b) on page 5. As before, we have roughly 95% of the data within these bounds (in each case, only two data points =  $\frac{2}{51} = 3.92\%$  are left out).

The choice of whether to use a linear, quadratic or cubic regression line depends on the context. The added flexibility gives a better fit, but it’s more difficult to interpret the results. That is, for a linear regression line, for a one-unit change in  $X$ ,  $Y$  increases by  $\beta_1$ . But this doesn’t hold for a quadratic or cubic fit. Furthermore, you need more data to give you statistically valid results, since you’re now estimating one or two more parameters from the same data set. Lastly, these problems become worse when we model  $Y$  on more variables than just  $X$ . As such, it’s typical to just use linear regression, even if a quadratic or cubic model fits the data better.

## Fuel Consumption vs Driver Population Percentage

Quadratic Regression Line + 95% Prediction Bounds



## Fuel Consumption vs Driver Population Percentage

Cubic Regression Line + 95% Prediction Bounds

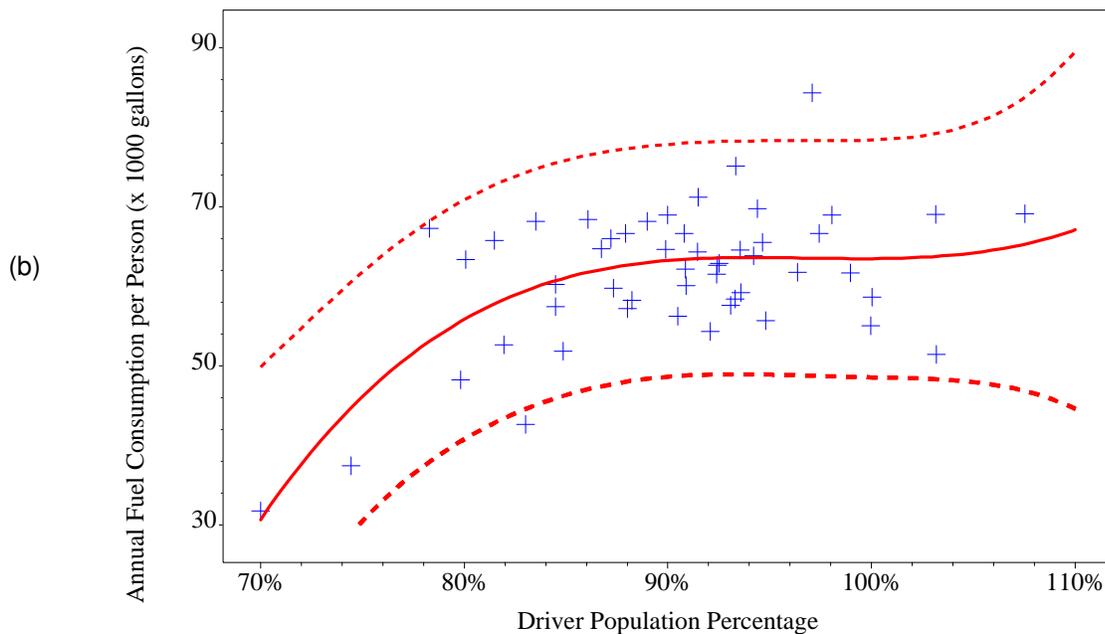


Figure 3: Fuel scatterplot with a (a) quadratic and (b) cubic regression line, each with 95% prediction bounds. Note that data points with a driver population percentage over 100% are perfectly legit, as many driver license holders are residents of another state and thus not counted in the population.

## LINEAR REGRESSION WITH RARE EVENTS

The term *rare events* simply refers to events that don't happen very frequently, but there's no rule of thumb as to what it means to be "rare." Any disease incidence is generally considered a rare event (van Belle (2008)). Therefore, if an event happens about as rarely as a given disease (such as earthquakes or component failures), we can consider it a rare event.

For rare events, we look at counts of how many events happened within a given time period. If the events in question really are rare, we would expect most of the observations to be in the single digits, but clearly this depends on the time period in question. For example, the number of earthquakes in various regions of the West Coast in the past ten years would be in the single digits, but the same quantity over the past million years would most definitely not be! As such, we can devise our own rule of thumb for what constitutes as rare: If the number of events within a certain time period is often in the single digits.

As with linear regression, when we model rare events, we want to find a linear relationship between a rare event  $Y_i$  and another variable  $X_i$ , which may or may not be rare. That is, it's the dependent variable  $Y_i$  that needs to be rare. As an example, Figure 4(a) on page 7 shows a scatterplot of the number of worker's compensation claims per firm for one year before and after an inspection for the Oregon Occupational Safety and Health Division (OSHA). Given the number of pre-inspection claims  $X$ , what is our best estimate of the number of post-inspection claims  $Y$ ?

As we can see from that figure, just showing a scatterplot gives us problems because there are data points stacked on top of each other. There are 49 data points shown, but the data set has 1293 points. For a better view of the data, Figure 4(b) on page 7 shows a *bubble plot*, which has a bubble for each coordinate with a radius proportional to how many data points are shown there. We make this in SAS via the following code:

```
PROC FREQ DATA=home.claims NOPRINT;
  TABLES post_claims*pre_claims / out=stats1 ( KEEP=post_claims pre_claims count );
RUN;

PROC GPLOT DATA=stats1;
  BUBBLE post_claims*pre_claims=count / ... BSIZE=10;
RUN;
```

PROC FREQ is needed to calculate the counts (*count*) for the bubbles. The *BSIZE* option above gives a scaling factor for the bubbles (the default is *bsize=5*), which we use here to make the smaller bubbles more visible. If a bubble plot is difficult to interpret, we can make box plots with the mean shown, as in Figure 5(a). After sorting the data by *pre\_claims*, we could do this via

```
PROC BOXPLOT DATA=claims_sorted;
  PLOT post_claims*pre_claims;
RUN;
QUIT;
```

but to have the same axes as the previous plots and to get a better-looking plot overall, it's better to do

```
SYMBOL6 COLOR=blue INTERPOL=boxt00 ...;
SYMBOL7 COLOR=red VALUE=diamondfilled ...;

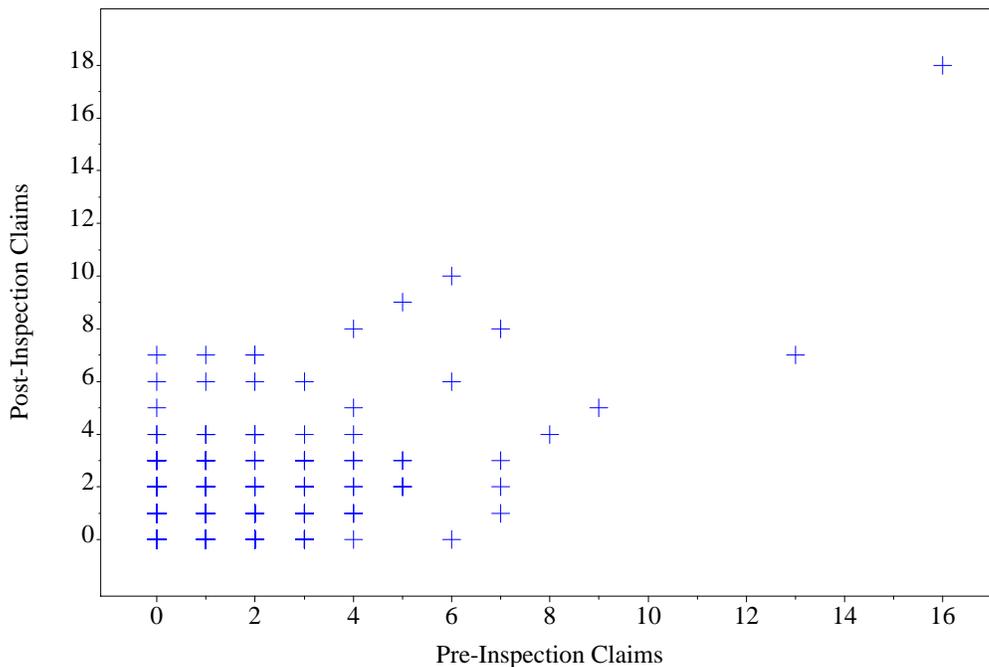
PROC GPLOT DATA=home.claims;
  PLOT post_claims*pre_claims=6
      m_post_claims*pre_claims=7 / HAXIS=axis3 VAXIS=axis4 OVERLAY;
RUN;
QUIT;
```

The *INTERPOL=boxt00* option in the *SYMBOL* statement tells SAS to make a box plot with tops and bottoms on the whiskers showing the minimum and maximum values. More details about this approach are given in Spruell (2006), Adams (2008) and Zhang et al. (2009). Note that this data set includes the mean post-claim values (*m\_post\_claims*) by pre-claim values, calculated elsewhere in the code.

## Pre- vs Post-Inspection Claims

Scatterplot

(a)



## Pre- vs Post-Inspection Claims

Bubble Plot

(b)

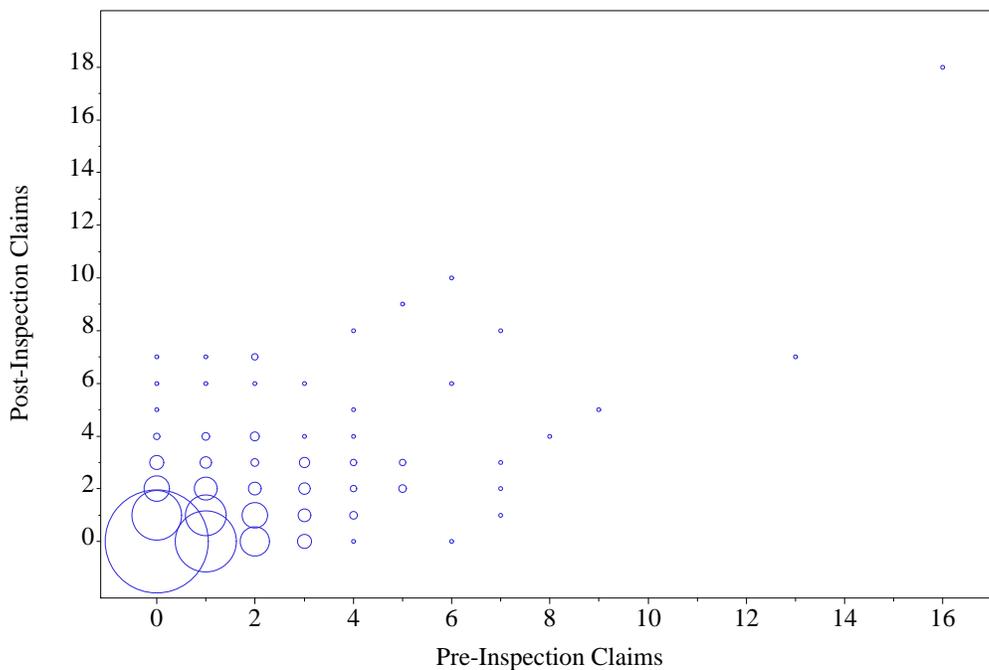
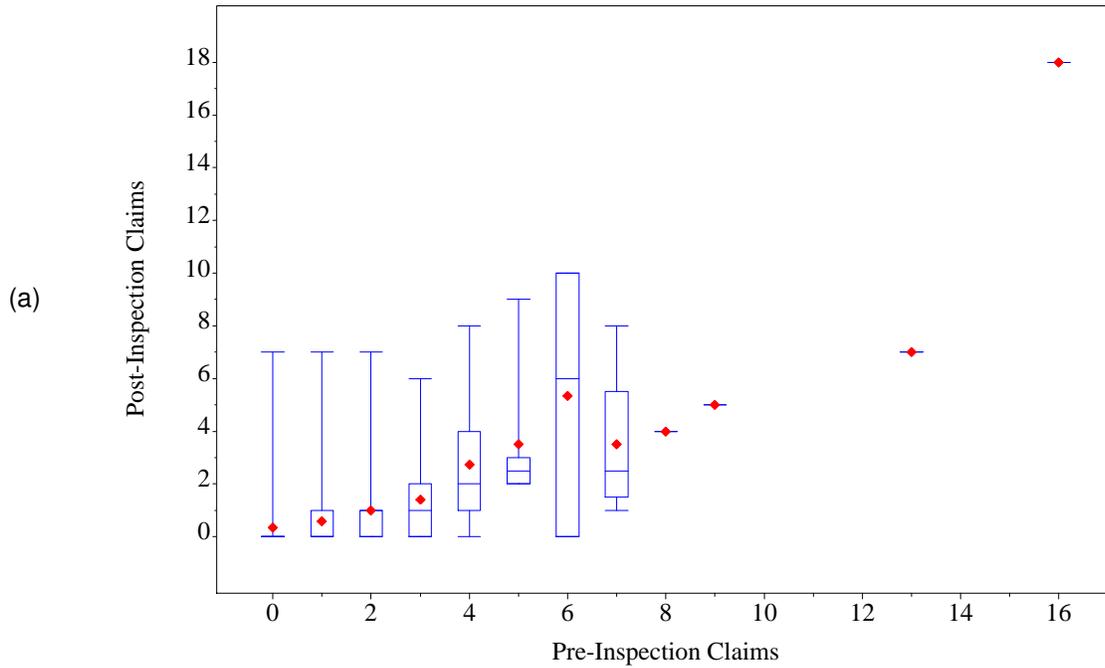


Figure 4: (a) A scatterplot and (b) a bubble plot of the number of the number of worker's compensation claims for one year before and after an inspection by the Oregon Occupational Safety and Health Division (OSHA), for individual firms.

# Pre- vs Post-Inspection Claims

Box Plots



# Pre-Inspection Claims

Histogram

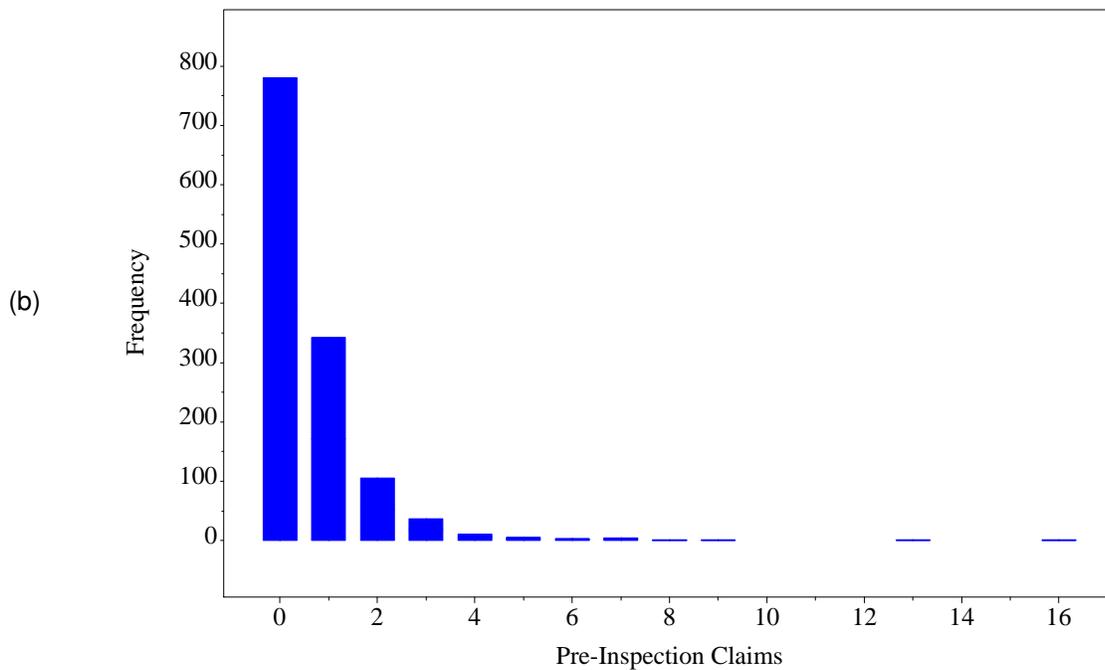


Figure 5: (a) A box plot of the number of pre- and post-Oregon OSHA inspection claims by individual firm, with the red diamond indicating the mean, and (b) a histogram of the number of pre-inspection claims.

While this box plot shows the distribution of the data, it doesn't show how many data points are in each category. We can do this with a simple histogram, which we're making with PROC GHPLOT to keep the horizontal axis consistent:

```
SYMBOL9 COLOR=blue INTERPOL=boxf00 CV=blue ...;

PROC GHPLOT DATA=stats2;
  PLOT count*pre_claims=9 / HAXIS=axis3 VAXIS=axis6;
RUN;
QUIT;
```

Again, we make use of the INTERPOL option in the SYMBOL statement to make our graphs. In this case, the INTERPOL=boxf00 tells us to make a box plot, but filled with the CV color (blue). There are no whiskers because we read the data set stats2 (in the downloadable code), which creates a data set showing only the final tallies and the value 0 for each value of pre\_claims for which there are data.

The main thing to see in the box plots and histograms is that the data are highly *skewed*, or lopsided. Certainly we can see from the histogram in Figure 5(b) on page 8 that the pre-claim claims are highly skewed, with by far the most data (number of firms) with 0 claims. This would tell us that having a pre-inspection claim is a rare event, but as mentioned before, what we really care about in the analysis of rare events is the outcome variable, which in this case is the number of post-inspection claims. These are shown to be highly skewed in the box plots in a number of ways:

- The standard definition of skewness, as explained in e.g., Derby (2009, p. 6), is that the distribution is left-skewed (or left-tailed) if the mean is less than the median, and right-skewed (right-tailed) is the mean is more than the median. In Figure 5(a), with the mean and median represented by the red diamond and blue center line of the box, we clearly see this is the case for 3, 4, 5 and 7 pre-inspection claims.
- At first glance, it's difficult to see what's happening for 0, 1 or 2 pre-inspection claims because we don't see a complete box and whiskers plot. We get a better picture when we combine this with the bubble plot of Figure 4(b) on page 7:
  - For 0 pre-inspection claims ( $X = 0$ ), the data are so concentrated at 0 post-inspection claims ( $Y = 0$ ) that the minimum, 25<sup>th</sup> percentile, median and 75<sup>th</sup> percentile are all at  $Y = 0$ . This is why we don't see a box at all.
  - For 1 pre-inspection claim ( $X = 1$ ), the minimum, 25<sup>th</sup> percentile and median are all at  $Y = 0$ , so we just see the top half of the box. The data are still highly right skewed (mean > median).
  - For 2 pre-inspection claims ( $X = 2$ ), the minimum, 25<sup>th</sup> percentile and median are again all at  $Y = 0$ , so we once again just see the top half of the box. Once again, the mean > the median so the data are again right-skewed.
- With 6 pre-inspection claims, we only have three data points. It's a little left-skewed (mean less than the median), but with so few data points, it hardly matters.
- There is no real distribution to speak of for 8, 9, 13 and 16 pre-inspection claims, since each of those categories has one data point.

There is one subtle but important additional point from the box plots: *The data get less skewed for larger values of X.*

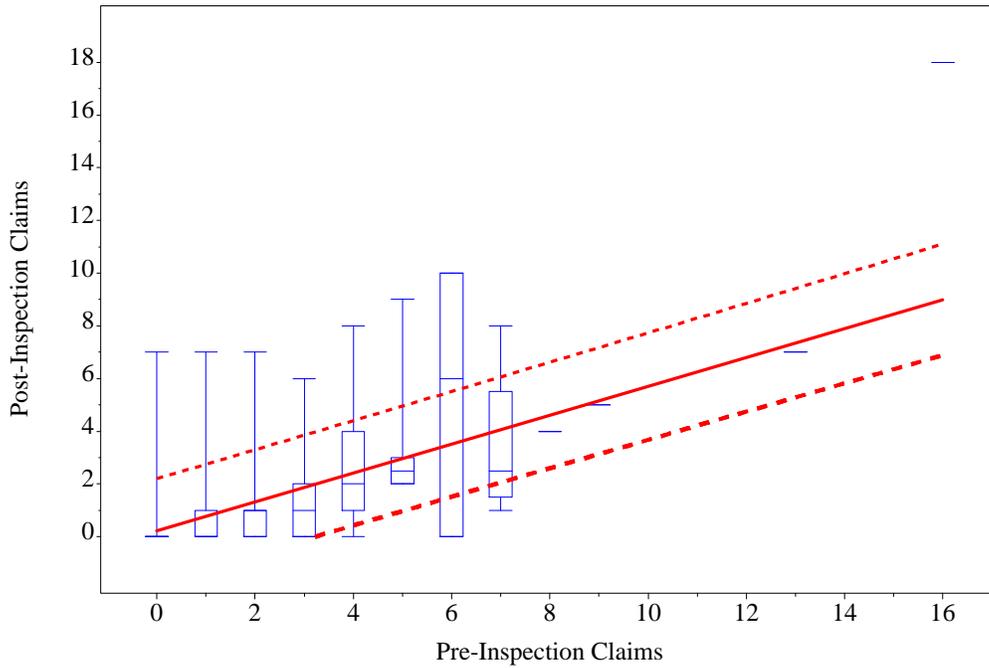
Now that we have a good visualization of the data, how should we model it? That is, what is a trend line that fits the data well? Unfortunately, linear regression doesn't help us very much. Figure 6(a) on page 10 shows a linear fit, whereas Figures 6(b) and 7(a) (page 11) show a quadratic and cubic fit. At first glance, this might look good. The lines go through the boxes, right? The real thing to look for are the 95% prediction bounds. There are two main points to notice:

- The median (the horizontal line in the center of the box) is usually below the linear regression line. This tells us that more than 50% of the data is below the line for these categories.
- As noted before, the prediction bounds are symmetric around the regression line – meaning, they are the same distance above it as they are below it. But the data are *not* symmetric around the median values. **This is a fundamental mismatch between linear regression and rare events.**

### Pre- vs Post-Inspection Claims

Linear Regression Line + 95% Prediction Bounds

(a)



### Pre- vs Post-Inspection Claims

Quadratic Linear Regression Line + 95% Prediction Bounds

(b)

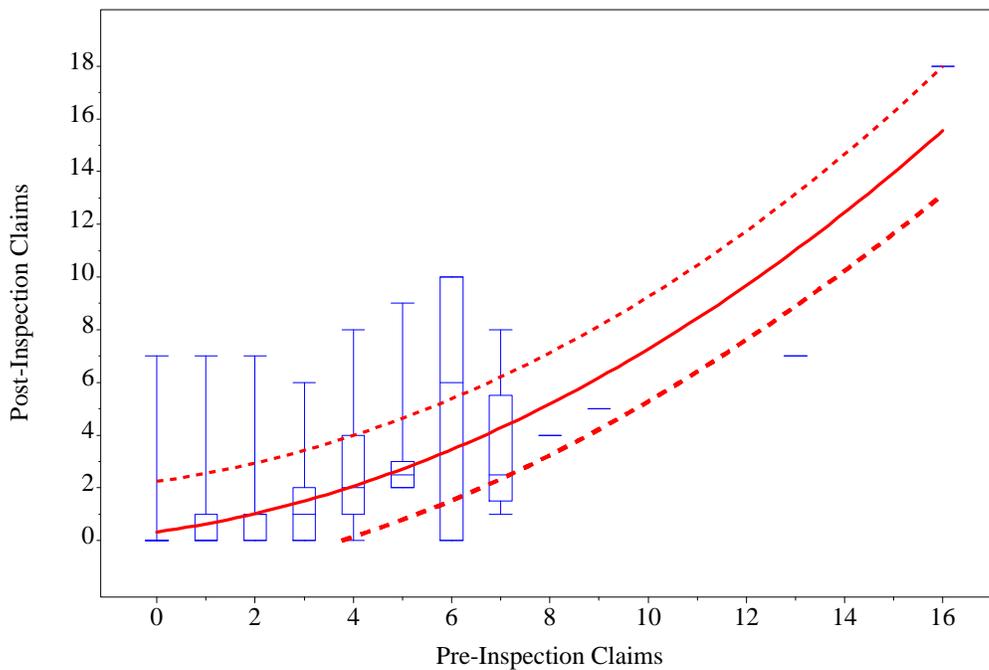
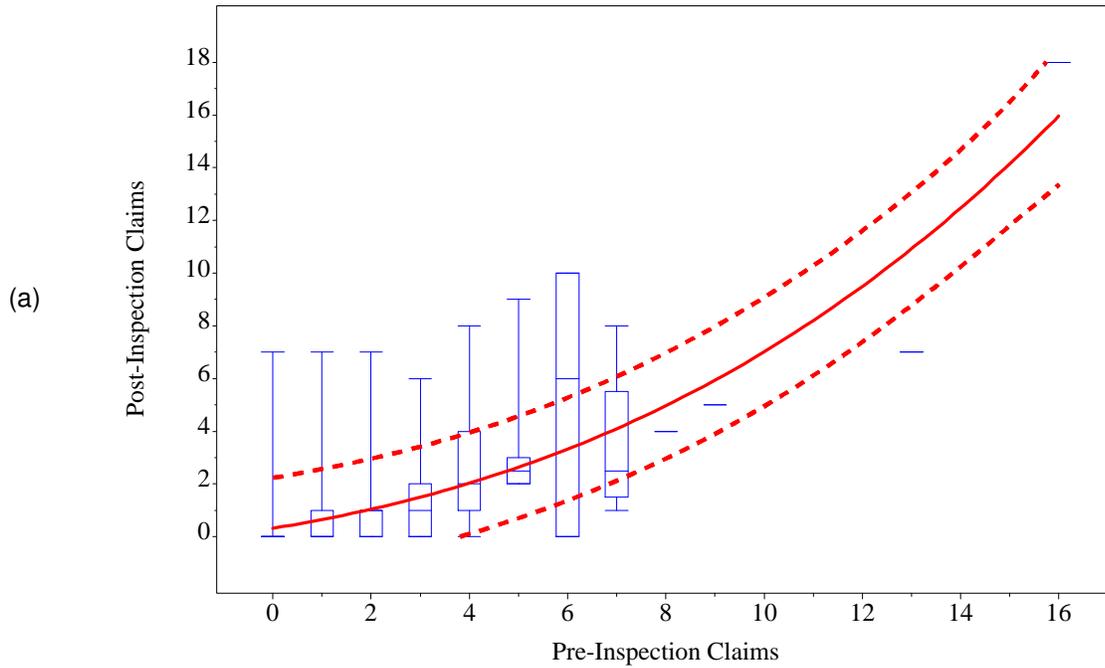


Figure 6: A box plot of the number of pre- and post-Oregon OSHA inspection claims by individual firm, with the (a) linear and (b) quadratic regression lines and their 95% prediction bounds.

## Pre- vs Post-Inspection Claims

Cubic Linear Regression Line + 95% Prediction Bounds



## Pre- vs Post-Inspection Claims

Connecting the Means

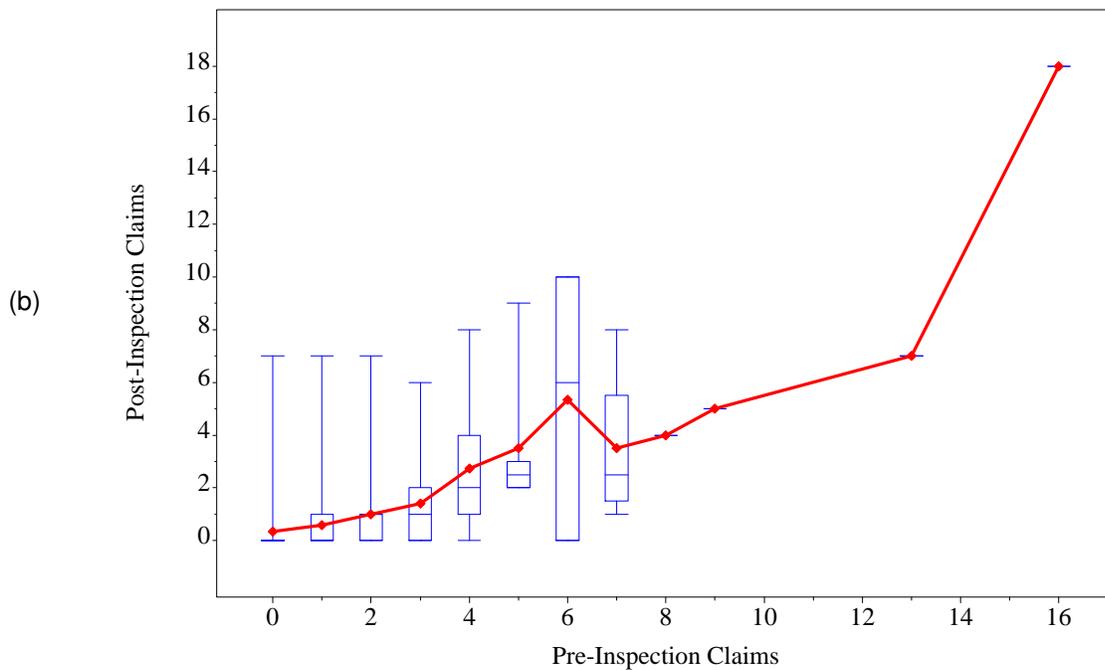


Figure 7: A box plot of the number of pre- and post-Oregon OSHA inspection claims by individual firm, with (a) the cubic regression line and 95% prediction bounds and (b) just connecting the means.

This is important because we can get erroneous results. In statistical terms, we would say that the data violate a fundamental assumption about the linear regression model. You can see the erroneous results by looking at the data outside the 95% prediction bounds. We should have just 5% of our data outside of those bounds. However, visually you can see that there is actually a lot of data outside of those bounds. So not only is the trend line biased (more over the median lines than below them), but the intervals are off as well. That is, **we have a wrong trend line and a false level of accuracy**. If we didn't look at any of these graphs, it would look like we have really accurate models. **This is completely false.**

If linear regression doesn't work, what are we to do? We would like a smooth trend line with some intervals. One simple method could be to connect the mean lines (Figure 7(b) on page 11), but this isn't smooth, it's not a model, and it doesn't give us any intervals.

## POISSON REGRESSION

The solution is actually very easy: We go through a similar process to linear regression, but instead of assuming a symmetric, continuous distribution (the normal distribution), we assume a skewed, discrete distribution (the Poisson distribution). All we are really doing is applying a theoretical distribution that better fits the data better.

Recall that for linear regression, we fit the model

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i \quad (2)$$

which really means

$$Y_i \text{ follows a symmetric (normal) distribution with mean } E[Y_i] = \beta_0 + \beta_1 X_i.$$

since in equation (2), we assume that the mean of the error term  $\varepsilon_i$  is zero. However, for rare events, this doesn't work because the effect is highly nonlinear, as shown by connecting the mean values in Figure 6(b) on page 10. A solution to this is to change the above somewhat to

$$Y_i \text{ follows a right-skewed distribution with mean } E[Y_i] = \exp(\beta_0 + \beta_1 X_i).$$

There are two parts to this:

- $Y_i$  follows a right-skewed distribution. However, to fit our data situation, we'd like a distribution which becomes less skewed for larger values of  $E[Y_i]$ .
- The expected value is  $\exp(\beta_0 + \beta_1 X_i) = e^{\beta_0 + \beta_1 X_i}$  rather than  $\beta_0 + \beta_1 X_i$  itself.<sup>2</sup> This is just a way to make a curve that starts out small but rapidly increases, as shown in Figure 8 on page 13. The increase can then be scaled by the parameters  $\beta_0$  and  $\beta_1$ .

It turns out that the *Poisson distribution* is a skewed distribution which fits our needs rather well. An introduction to this distribution is shown in Lavery (2010). This approach might seem complicated, but mathematically, it makes the estimation technique quite easy. We'll see later that using a regression with the Poisson distribution (called *Poisson regression*) gives a better fit for our data, for both of the reasons above.

## FITTING THE MODEL

Poisson regression is easily implemented in SAS with either PROC GENMOD or PROC COUNTREG:

- PROC GENMOD is part of the SAS/STAT package and is more generalized, so it provides more output.
- PROC COUNTREG is part of the SAS/ETS package and is more specialized, so it provides less output.

Both approaches will be shown below.

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<sup>2</sup>The number  $e$  is equal to 2.71828....

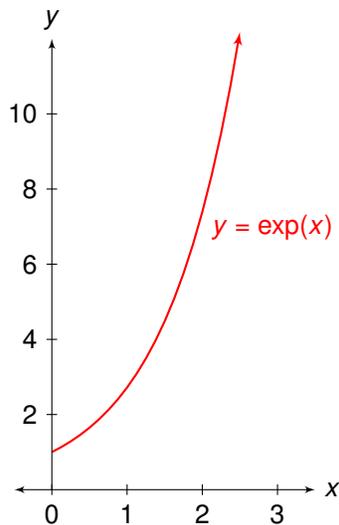


Figure 8: The function  $y = \exp(x) = e^x$ . The number  $e$  is equal to 2.71828....

For PROC GENMOD, we code it in SAS as such:

```
PROC GENMOD DATA=home.claims;
  MODEL post_claims = pre_claims / DIST=poisson;
RUN;
```

The output is shown in Figure 9 on page 14. Some explanation of what certain parts of the output mean, borrowing heavily from UCLA (2011):

❶ Criterion:

- Deviance: Also called the log likelihood ratio statistic, this is a measure of the goodness of fit, as explained in Dobson (2002, pp. 76-80). The smaller this number is, the better the fit.
- Scaled Deviance: This is the deviance divided by some number – but it's the same as the deviance since we didn't specify `scale=dscale` in the MODEL statement.
- Pearson Chi-Square: As explained in Dobson (2002, p. 125), this is the squared difference between the observed and predicted values divided by the variance of the predicted value summed over all observations in the model. It follows a chi-square distribution if certain assumptions hold. The smaller this number is, the better the fit.
- Scaled Pearson X2: This is the Pearson Chi-Square statistic divided by some number – but it's the same as the Pearson Chi-Square since we didn't specify `scale=dscale` in the MODEL statement.
- Log Likelihood: This is a measure similar to the log likelihood of the model.
- Full Log Likelihood: This is the log likelihood of the model. The difference between this and the log likelihood mentioned above is explained in the SAS documentation for PROC GENMOD.
- AIC: This is the Akaike information criterion, which (as explained in Dobson (2002, p. 208)) is a function of the log-likelihood function adjusted for the number of covariates. The smaller this number is, the better the fit.
- AICC: This is the corrected Akaike information criterion, which is the AIC corrected for finite sample spaces.
- BIC: This is the Bayesian information criterion. Again, the smaller this number is, the better the fit.

❷ DF: The degrees of freedom for the deviance and Chi-square measures.

❸ Value: The value of the measure in question.

❹ Value/DF: The value divided by the degrees of freedom. This is often of interest more than the value itself.

❺ Parameter: The variable in question.

The GENMOD Procedure

Model Information

Data Set HOME.CLAIMS  
 Distribution Poisson  
 Link Function Log  
 Dependent Variable post\_claims Post-Inspection  
 Claims

Number of Observations Read 1310  
 Number of Observations Used 1293  
 Missing Values 17

Criteria For Assessing Goodness Of Fit

Criterion ①	DF ②	Value ③	Value/DF ④
Deviance	1291	1623.3440	1.2574
Scaled Deviance	1291	1623.3440	1.2574
Pearson Chi-Square	1291	2070.2270	1.6036
Scaled Pearson X2	1291	2070.2270	1.6036
Log Likelihood		-972.7283	
Full Log Likelihood		-1309.5635	
AIC (smaller is better)		2623.1270	
AICC (smaller is better)		2623.1363	
BIC (smaller is better)		2623.4564	

Algorithm converged.

Analysis Of Maximum Likelihood Parameter Estimates

Parameter ⑤	DF	Estimate ⑥	Standard Error ⑦	Wald 95% Confidence Limits ⑧		Wald Chi-Square ⑨	Pr > ChiSq ⑩
Intercept	1	-0.8425	0.0415	-0.9238	-0.7611	412.14	<.0001
pre_claims	1	0.2686	0.0098	0.2493	0.2878	749.10	<.0001
Scale	0	1.0000	0.0000	1.0000	1.0000		

NOTE: The scale parameter was held fixed.

Figure 9: Output of a Poisson regression using PROC GENMOD.

- ⑥ Estimate: The estimate of the coefficient of the variable in question.
- ⑦ Standard Error: The standard error of the estimate.
- ⑧ Wald 95% Confidence Limits: 95% confidence limits for the estimate. For an estimate to be considered statistically significant, we do not want these limits to include zero.
- ⑨ Wald Chi-Square: The Wald Chi-square statistic for the hypothesis test that the parameter is equal to zero.
- ⑩ Pr > ChiSq: The  $p$ -value of the Wald Chi-square statistic.

Before we interpret these results, let's fit the model with PROC COUNTREG:

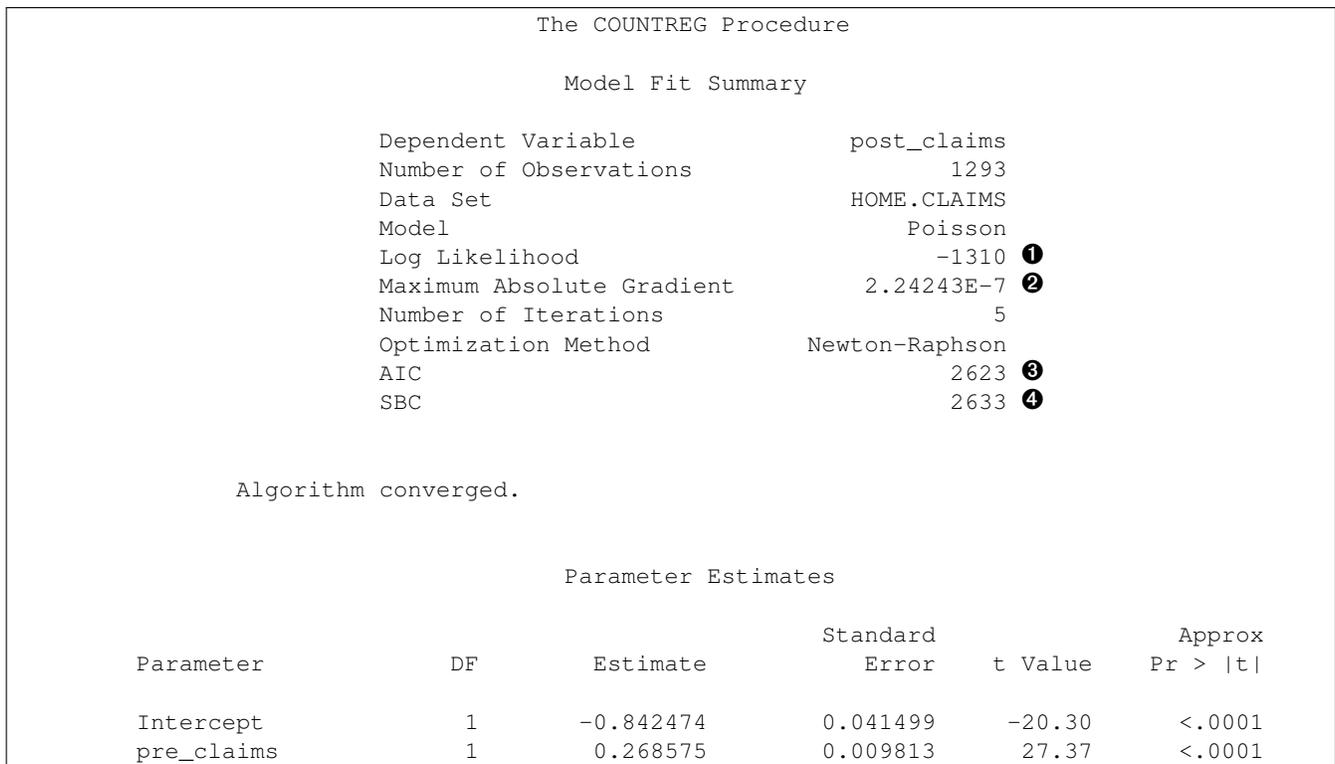


Figure 10: Output of a Poisson regression using PROC COUNTREG.

```

PROC COUNTREG DATA data=home.claims;
  MODEL post_claims = pre_claims / DIST=poisson;
RUN;

```

This gives us the results in Figure 10, which definitely looks different from the PROC GENMOD output we've had before. A few notes:

- ❶ Log Likelihood: This is equal to Full Log Likelihood in our PROC GENMOD output.
- ❷ Maximum Absolute Gradient: This, plus the next two lines (Number of Iterations and Optimization Method), just give specifics about the method used to get the log likelihood value in ❶.
- ❸ AIC: This is the Akaike information criterion, equal to AIC in the PROC GENMOD output.
- ❹ SBC: This is the Bayesian information criterion, equal to BIC in the PROC GENMOD output. It's odd that SAS doesn't just call it BIC.

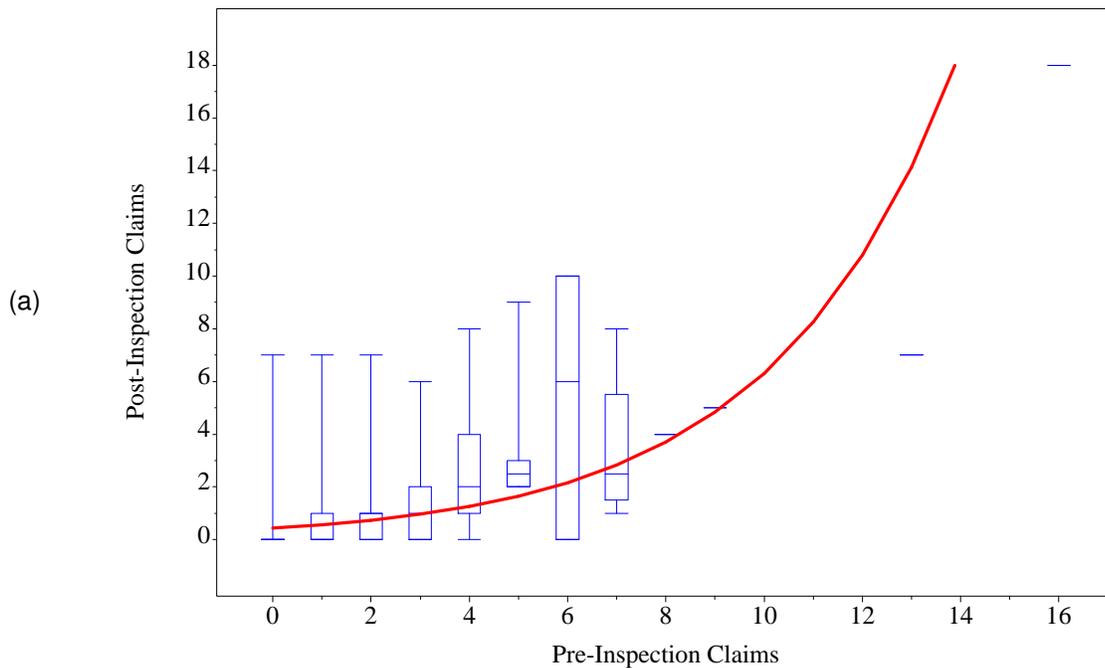
The graphical output is shown in Figure 11(a) on page 16. Here we see that it is a much better fit than the normal regression line. In fact, we can compare the two in Figure 11(b). Sadly, SAS doesn't yet implement prediction intervals for Poisson regression, but this might be implemented sometime in the future.

## INTERPRETING THE RESULTS

Looking at the results of Figures 9 (page 14) and 10, we look at the goodness of fit statistics (deviance, Pearson Chi-square, AIC, AICC and/or BIC), the estimated values of the parameters, and the  $p$ -values of those estimates. The goodness of fit statistics are only important when comparing them to the same statistics from other models, which we won't cover in this paper. For estimated values we hope to have the sign (i.e., positive or negative) that makes sense logically. And we hope that all estimates have a  $p$ -value less than the rule-of-thumb value of 0.05.

## Pre- vs Post-Inspection Claims

Poisson Regression Line



## Pre- vs Post-Inspection Claims

Poisson (solid) and Cubic Linear Regression (dashed) Lines

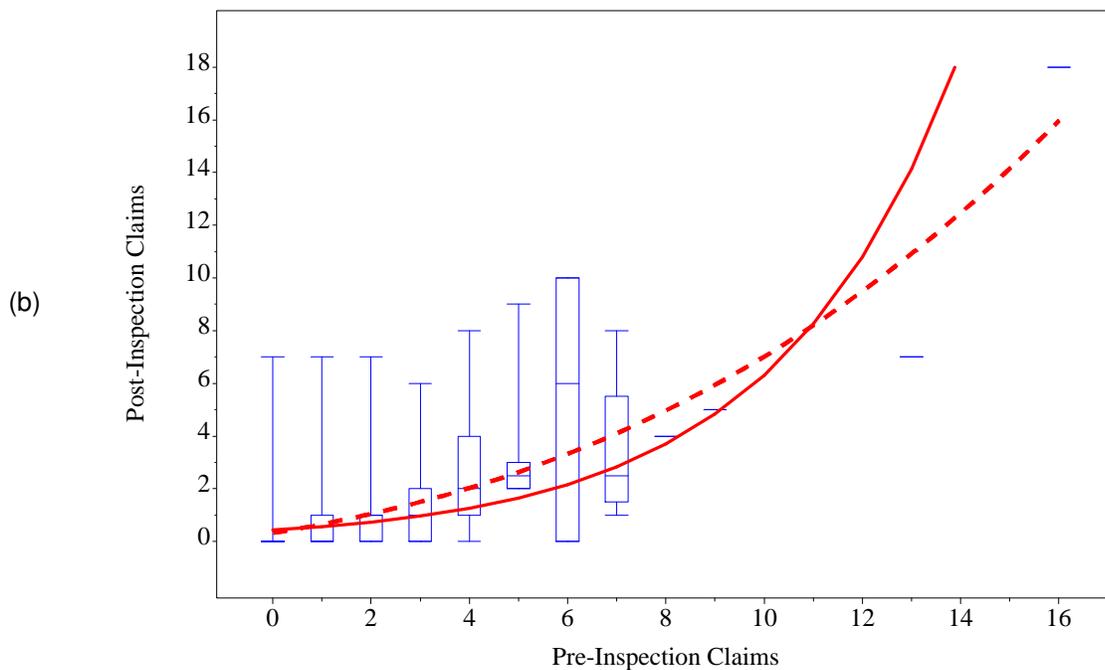


Figure 11: Fitted values from (a) Poisson regression and (b) compared to cubic regression.

Our fitted model is thus

$$E[Y_i] = \exp(-0.842474 + 0.268575X_i)$$

where for firm  $i$ ,  $X_i$  is the number of pre-inspection claims and  $Y_i$  follows a Poisson distribution (with the mean and variance equal to  $E[Y_i]$  above).

As an interpretation, we can say that

- A firm that has no pre-inspection claims has an expected of  $E[Y_i] = \exp(-0.842474) \approx 0.43$  post-inspection claims. We get this by setting  $X_i = 0$  in the above equation.
- For every pre-inspection claim that a firm has, that firm's expected number of post-inspection claims will rise by  $\exp(0.268575) - 1 \approx 1.308099 - 1 = 30.81\%$ . We get this by setting

$$\begin{aligned} E[Y_i|X_i + 1] &= \exp(-0.842474 + 0.268575(X_i + 1)) \\ &= \exp(-0.842474 + 0.268575X_i + 0.268575) \\ &= \exp(-0.842474 + 0.268575X_i) \cdot \exp(0.268575) \\ &= E[Y_i|X_i] \cdot 1.3081. \end{aligned}$$

## GETTING PREDICTED COUNTS

*Predicted counts* means that if we have an input value  $X$ , what is the estimated value of  $Y = \exp(\beta_0 + \beta_1 X)$ ? This is the point of the model fit, and we have all the results we need from Figures 9 (page 14) and 10 (page 15) to figure these out. We can always run a `DATA` step to add a column of predicted counts to an input data set. However, SAS can do this automatically with an `OUTPUT OUT=` option:

```
PROC GENMOD DATA=home.claims;
  MODEL post_claims = pre_claims / DIST=poisson;
  OUTPUT OUT=home.claims_pred PRED=predicted;
RUN;

PROC COUNTREG DATA=home.claims;
  MODEL post_claims = pre_claims / DIST=poisson;
  OUTPUT OUT=home.claims_pred PRED=predicted;
RUN;
```

Note that for `PROC COUNTREG`, you only get predicted values for unknown values of  $Y$ , whereas you get it for all values of  $Y$  with `PROC GENMOD`.

The `OUTPUT OUT=` statement doesn't work for `PROC COUNTREG` before 9.22. In that case, use the `%PROBOUNDS` macro as given in SAS Institute (2011). Sadly, prediction bounds are not (yet) available from either `PROC COUNTREG` or `PROC GENMOD`.

We can graph the predicted values against the box plots as we did with the regression output, only using this new variable:

```
SYMBOL10 COLOR=blue INTERPOL=boxt00 ...;
SYMBOL11 COLOR=red INTERPOL=join MODE=include ...;

PROC GPLOT DATA=home.claims_pred;
  PLOT post_claims*pre_claims=10
       predicted*pre_claims=11 / HAXIS=axis3 VAXIS=axis4 OVERLAY;
RUN;
```

The result is shown in Figure 11(a) on page 16. There are a couple things to notice here, especially when compared with the cubic regression fit in Figure 11(b):

- First of all, this is a smooth line, as opposed to the bumpy line that would result from connecting the mean points as in Figure 7(b) on page 11. This is one goal of a statistical model.

- As opposed to the cubic regression fit, or any of the regression fits of Figures 6(a) (page 10), 6(b) or 7(a) (page 11), the Poisson regression line comes very close to most of the median values. This is better than hitting the mean values, since the median is robust against outliers, and we are dealing with skewed distributions.
- The Poisson regression fit even comes close to the singular values at  $X = 8$  and  $X = 9$ .

Overall, **we see visual evidence that the Poisson regression fit is a better fit of the data than the linear, quadratic, or cubic regression fits.**

## BEYOND POISSON REGRESSION

This paper is merely an introduction to Poisson regression. Indeed, we didn't even cover using multiple regressors. While Poisson regression solves many problems, it still has some limitations:

- The theoretical distribution assumes that the mean is equal to the variance, which is often not the case.
- Often there can be many more zero values than the model can handle.

These two problems can be solved by using the *negative binomial regression* and *zero-inflated Poisson/negative binomial regression*. But those topics are beyond the scope of this paper.

Lastly, note that the analysis done in this paper does *not* isolate the effect of inspections, and doesn't show that inspections have any effect at all. To do that, we need to have a control group of firms without inspections, then incorporate a Poisson regression with a variable indicating whether the firm in question had an inspection. Again, this is outside the scope of this paper.

## CONCLUSIONS

When we model a process  $Y$  with linear regression, we're really fitting a trend line to the data, which can also be a curve if we incorporate squared or cube versions of the independent variable  $X$ . One important aspect of linear regression is to give us 95% prediction bounds, between which roughly 95% of the data should be. For linear regression, these prediction bounds are symmetric, reflecting the fact that the data points are assumed to be symmetrically distributed around that regression line.

For rare events, this symmetry doesn't match the distribution of the data. In this situation, the data distribution is typically skewed, or lopsided, concentrated on a low value. Furthermore, the distribution of the independent variable  $Y$  typically becomes less skewed for a range of values of the independent variable  $X$ . Lastly, the trend line typically rapidly increases for larger values of the independent variable  $X$ . This behavior violates the underlying assumptions of the linear regression model, which can give erroneous results such as a biased estimate of the trend or prediction bounds which are too narrow (giving a false measure of accuracy).

Poisson regression solves this skewed distribution problem in two ways:

- It uses the Poisson regression to model the skewed distribution of the data.
- Rather than use a linear model of the data, it uses an exponential function, with the linear model in the exponent. This effectively models a rapid increase in the trend line which is typical of rare events.

The Poisson regression coefficients give us an estimate of the baseline estimate of the dependent variable  $Y$  (i.e., when the independent variable  $X = 0$ ) and of a percentage expected increase in  $Y$  for a one-unit increase in  $X$ .

SAS implements Poisson regression with `PROC GENMOD` or `PROC COUNTREG`, although without the prediction intervals at this time. We can effectively use `PROC GRAPH` to see both the data and the fitted trend line on the same set of axes.

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