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ELECTRICITY CASE: STATISTICAL ANALYSIS OF ELECTRIC POWER OUTAGES

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CREATE REPORT
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May 31 , 2005

Center for Risk and Economic Analysis of Terrorism Events
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Abstract

This report analyses electricity outages over the period January 1990-August 2004. A database was constructed using U.S. data from the DAWG database, which is maintained by the North American Electric Reliability Council (NERC). The data includes information about the date of the outage, geographical location, utilities affected, customers lost, duration of the outage in hours, and megawatts lost. Information found the DAWG database was also used to code the primary cause of the outage. Categories that included weather, equipment failure, human error, fires, and others were added to the database. In addition, information about the total number of customers served by the affected utilities, as well as total population and population density of the state affected in each incident, was also incorporated to the database. The resulting database included information about 400 incidents over this period.

The database was used to carry out two sets of analyses. The first is a set of analyses over time using three-, six-, or twelve-month averages for number of incidents, average outage duration, customers lost and megawatts lost. Negative binomial regression models, which account for overdispersion in the data, were used. For the number of incidents over time a seasonal analysis suggests there is a 9.3% annual increase in incident rate given season over this period. Given the year, summer is estimated to have 65-85% more incidents than the other seasons. The duration data suggest a more complicated trend; an analysis of duration per incident over time using a loess nonparametric regression "scatterplot smoother" suggests that between 1990-93 durations were getting shorter on average but this trend changed in the mid-1990s when average duration started to increase, and this increase became more pronounced after 2002. When looking at average customer losses by season there is weak evidence of an upward trend in the average customer loss per incident, with an estimated increase of a bit less than 10,000 customers per incident per year. Similar analyses of MW lost per incident over time showed no evidence of any time or seasonal patterns for this variable.

The second part of the report includes a number of event-level analyses. The data in these analyses are modeled in two parts. First, the different characteristics related to whether an incident has zero or nonzero customers lost are determined. Then, given that the number lost in nonzero, the characteristics that help to predict the customers lost are analyzed. Unlike the first set of models described, in this section a number of predictors such as primary cause of the outage (including variables such as weather, equipment failure, system protection, human error and others), total number of customers served by the affected utilities, and the population density of the states where the outages were used in the analyses to gain a better understanding of the three key variables: customers lost, megawatts lost and duration of electric outages. Logistic regression was used in these analyses. For logged customers lost, the only predictor showing much of a relationship was logged MW lost. The total number of customers served by the utility was found to be a marginally significant predictor of customers lost per incident. Customer losses are higher for natural weather related events, crime, unknown causes, and third party, and lower for capacity shortage, demand reduction, and equipment failure, holding all else in the model fixed.

The analyses for duration at the event level find that the two most common causes of outages, equipment failure and weather, are very different, with the former associated with shorter events and the latter associated with longer ones. When the primary cause of the events is included in the regression models, the time trend for the average duration per incident found in earlier analyses disappears. According to the data, weather related incidents are becoming more common in later years and equipment failures less common, and this change in the relative frequency of primary cause of the events accounts for much of the overall pattern of increasing average durations by season. Holding all else in the model constant, these analyses also suggest that winter events have an expected duration that is 2.25 times the duration of summer events, with autumn and spring in between.

Acknowledgements

This research was supported by the United States Department of Homeland Security through the Center for Risk and Economic Analysis of Terrorism Events (CREATE), grant number EMW-2004-GR-0112. However, any opinions, findings, and conclusions or recommendations in this document are those of the author (s) and do not necessarily reflect views of the U.S. Department of Homeland Security.

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Electricity Case: Statistical Analysis of Electric Power Outages

This report presents the detailed results of the statistical analysis of electric power outage data summarized in the Electricity Case – Main Report. It contributes to the sections on the evaluation of risks and consequences of electric power outages.

I. *Summary analyses over time*

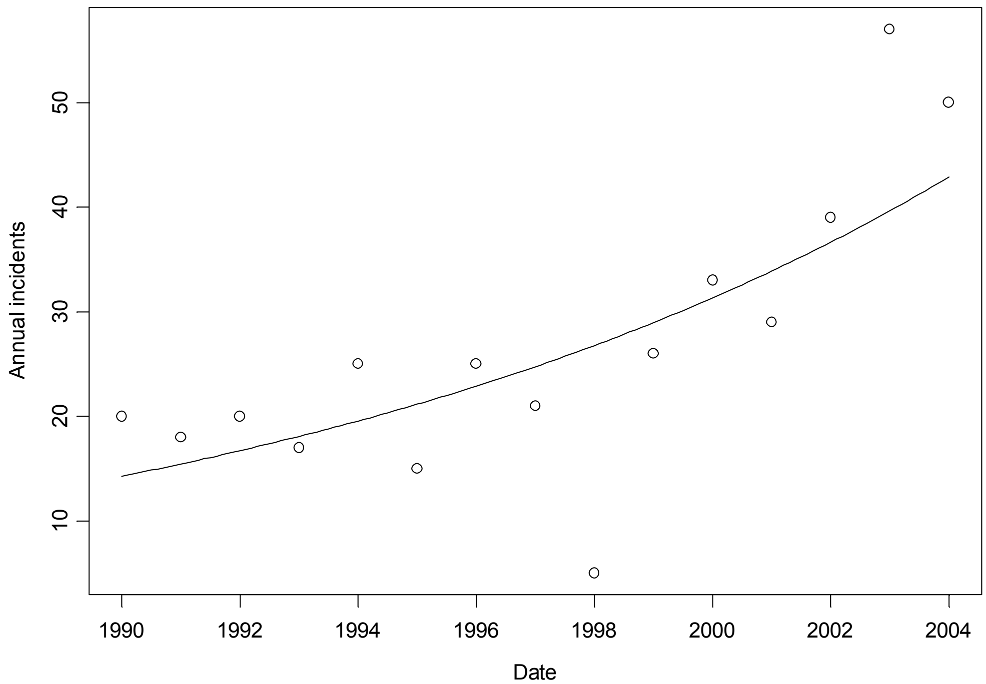
A. Analysis of the number of incidents over time

This report summarizes the analyses of incident counts over time. Such count data are typically analyzed using special count regression models based on the Poisson and negative binomial distributions; see Simonoff (2003, chapter 5), for extensive discussion of these models. The standard count regression model is based on the Poisson distribution. The Poisson distribution has the property that its mean equals its variance, which can account for the observed pattern in count data that variability increases with level.

Count regression models are generally fit as *loglinear* models; that is, it is the logarithm of the mean that is modeled as a linear function of predictors, or equivalently, the mean is modeled as an exponential function of the predictors. This implies, for example, a *proportional* relationship with a variable, rather than an *additive* one. Loglinear models are natural for count data because the true mean of the response cannot possibly be negative; a linear model on predictors can lead to estimated negative means, but a loglinear model cannot.

Annual data

We start with data measured at the annual level. The following is a plot of the annual incident figures for the U.S. data, along with the estimate of the time trend based on a Poisson regression model. Note that the estimated time trend is based only on years 1990 through 2003, since the 2004 data are incomplete (the data only run through August).



There are several noteworthy points here:

1. The fitted curve is consistent with an estimated annual increase in incidents of 8.2%. Note, by the way, that it is apparent from the plot that a loglinear model is more reasonable than a linear model here, as the increase in incidents is slower in the 1990s than in the 2000s.
2. The estimated increase is highly significantly different from zero, with a Wald statistic (the analogue of a t-statistic for Poisson regression models) of 5.8.

   Here is output from the model detailing the significance testing based on the Poisson model:

   ```
   Coefficients:
                        Value Std. Error       Wald
   (Intercept) -153.6724123 27.2931301 -5.630443
          Date    0.0785583  0.0136619  5.750174
   ```

   The significance of the time trend can be assessed by calculating a tail probability for the 5.75 based on a normal distribution; in this case it is zero to 8 digits. The estimated annual increase in incidents comes from exponentiating the slope coefficient in this model, as exp(.0786) = 1.082, implying an estimated 8.2% annual increase.
3. The year 1998 was obviously a very unusual one, with a very small number of incidents (5, where the model implies an estimate of 26.0).

4. There is evidence that the incident rate is increasing in recent years. The model implies an estimated 39.6 incidents in 2003, when there were, in fact, 57 (this is roughly 2 ¾ standard deviations above the expected number), and an estimated 42.9 in 2004, when there were 50 in only the first 8 months of the year. The 2003 number is apparently not because of the August 14, 2003 blackout, since that event only accounts for 8 incidents.

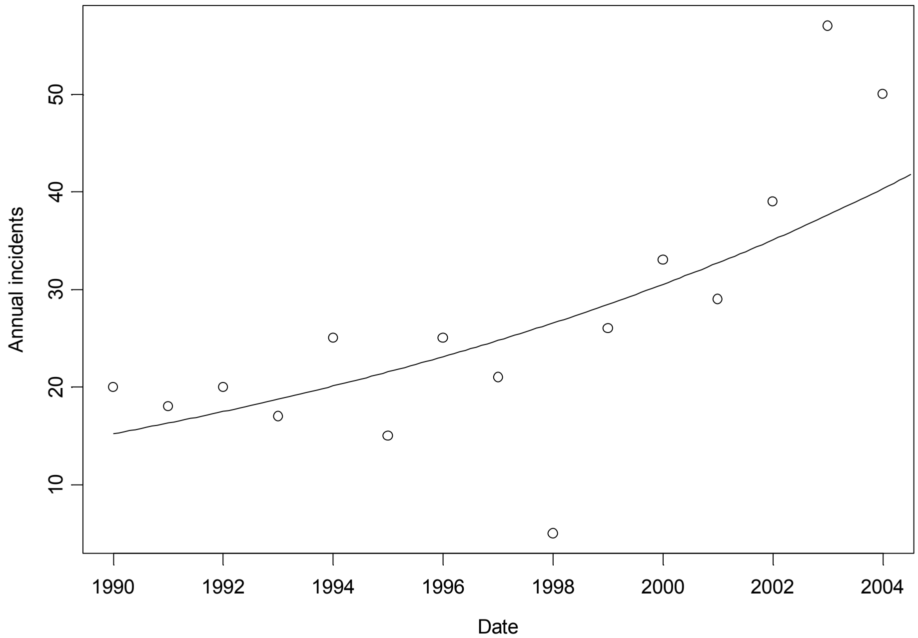
There is a flaw in this analysis, in that the Poisson regression model does not fit the data well, because of *overdispersion*. Overdispersion occurs when there is unmodeled heterogeneity in the data. The Poisson model treats each year as identical, other than the actual difference in year. This is unlikely to be true, as the chances are very good that there have been many changes to the structure of power generation over the years (new power plants come on line, old ones go off, new drains on power generation occur, political situations change, and so on). The Poisson model does not account for this possibility, and as a result the observed variability in the response is larger than that implied by the Poisson model (recall that the Poisson distribution has the property that the mean equals the variance). An important result of overdispersion is that the statistical significance of effects in the model are overstated.

Overdispersion has occurred here, as both the Pearson (X^2=34.1) and deviance (G^2=42.0, both on 12 degrees of freedom) goodness-of-fit statistics indicate that the Poisson model does not fit the data.

A way of addressing overdispersion is to fit a count regression model that allows for the variance being larger than the mean. The standard model of this type is the negative binomial regression model. Here is output for this model:

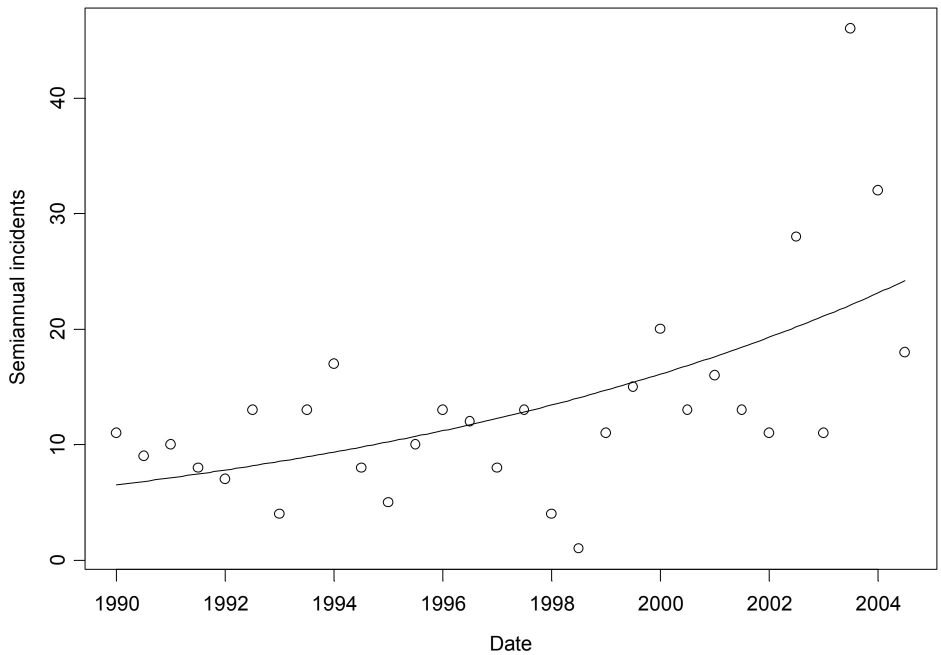
```
Coefficients:
                    Value  Std. Error      Wald
(Intercept) -135.76307835 47.91257415 -2.833558
       Date    0.06959082  0.02399384  2.900362
```

The Wald statistic for this model is smaller than in the Poisson model, but it is still highly significant (p=.002). The model fits the data well, as the deviance equals 15.3 on 12 degrees of freedom (p=.23, not rejecting the fit of the model). The estimated annual increase in incidents based on this model is slightly lower than before, implying a 7.2% annual increase in incidents. Here is a graphical representation of the estimated trend:



Semiannual data

One potential problem with the analysis on annual data is that there are only 14 data points. The following analysis is based on semiannual incident counts, resulting in roughly twice as many data points. Once again the last data point (corresponding to the second half of 2004) has been omitted, since it is incomplete.



This analysis reinforces and refines some of the earlier impressions.

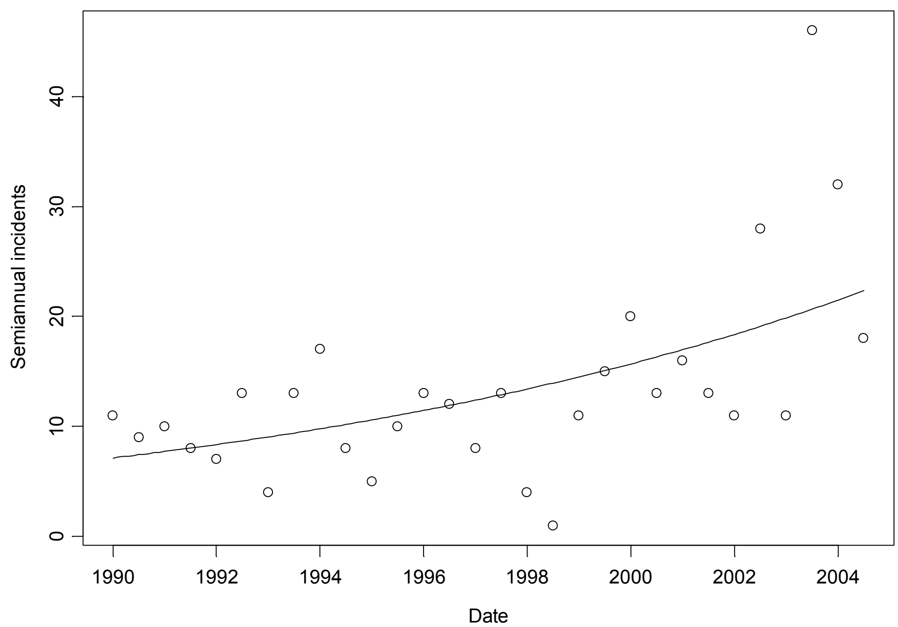
1. The implications regarding the increase in incidents are similar for these semiannual data to those for the annual data. The estimated rate of increase is 9.5% annually, similar to what was seen before.
2. The estimated increase is even more significantly different from zero, with a Wald statistic of 7.1. Here is output for the model:

```
Coefficients:
                    Value  Std. Error      Wald
(Intercept) -178.12611859 25.49168622 -6.987616
       Date    0.09045251  0.01275513  7.091459
```

3. We can see from the plot that it was the second half of 1998 that was so unusual, with only 1 incident (and 14.1 predicted by the model).
4. The first part of 2003 actually had fewer incidents than expected; it was the 46 incidents in the second half of 2003 (more than twice the expected number) that was so unusual. Again, only eight of these were from the August 14 blackout. The first half of 2004 was a bit above normal, but not overwhelmingly so, but the 18 incidents in the first two months of the second half of 2004 is noticeably high. Thus, in addition to the relatively stable annual increase in incidents, there is still (limited) evidence of an increasing rate recently.
5. There is evidence of overdispersion in these data as well, as the Pearson (X^2=87.2) and deviance (G^2=92.4, both on 27 degrees of freedom) indicate lack of fit. A negative binomial fit to these data is as follows:

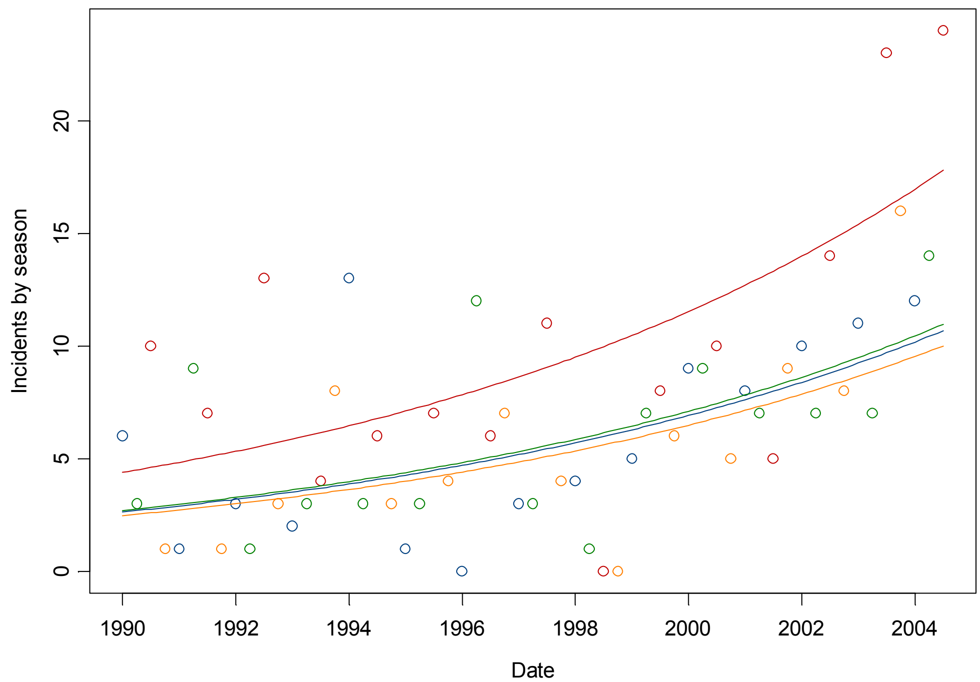
```
Coefficients:
                   Value  Std. Error      Wald
(Intercept) -154.57911519 44.34697394 -3.485674
       Date    0.07866603  0.02220172  3.543240
```

The time trend is highly statistically significant (p=.0004). The model fits the data well (the deviance is 30.4 on 27 degrees of freedom, p=.29), and it implies an estimated 8.2% annual increase in incidents. Here is a plot:



Seasonal data

Examining the data at a seasonal level allows for the inclusion of different levels for different seasons. Winter is defined as December through February, spring as March through May, summer as June through August, and autumn as September through November. In this plot, the winter points and line are in blue, the spring points and line are in green, the summer points and line are in red, and the autumn points and line are in orange. Note that all of the data points other than the first one are used, since the data go through August 2004 (that is, summer 2004), but the first data point only includes two months instead of three.



1. Taking the season into account, the estimated annual increase in incident rate is 10.1%. All of the estimates obtained thus far are within the estimated standard errors of each other, so from a statistical point of view, all are equally reasonable. That is, what is most reasonable is to say is that the estimated increase in incidents is roughly 7-10% annually.
2. This increase is highly statistically significantly different from zero (Wald statistic 7.7). Here is output; the tests for the seasons take Autumn as a baseline category.

```
Coefficients:
                    Value  Std. Error       Wald
 (Intercept) -191.08893534 25.12676351 -7.6049960
        Date    0.09647909  0.01257097  7.6747538
SeasonSpring    0.09125890  0.15677009  0.5821193
SeasonSummer    0.57571503  0.14186204  4.0582740
SeasonWinter    0.06511136  0.15980717  0.4074371
```

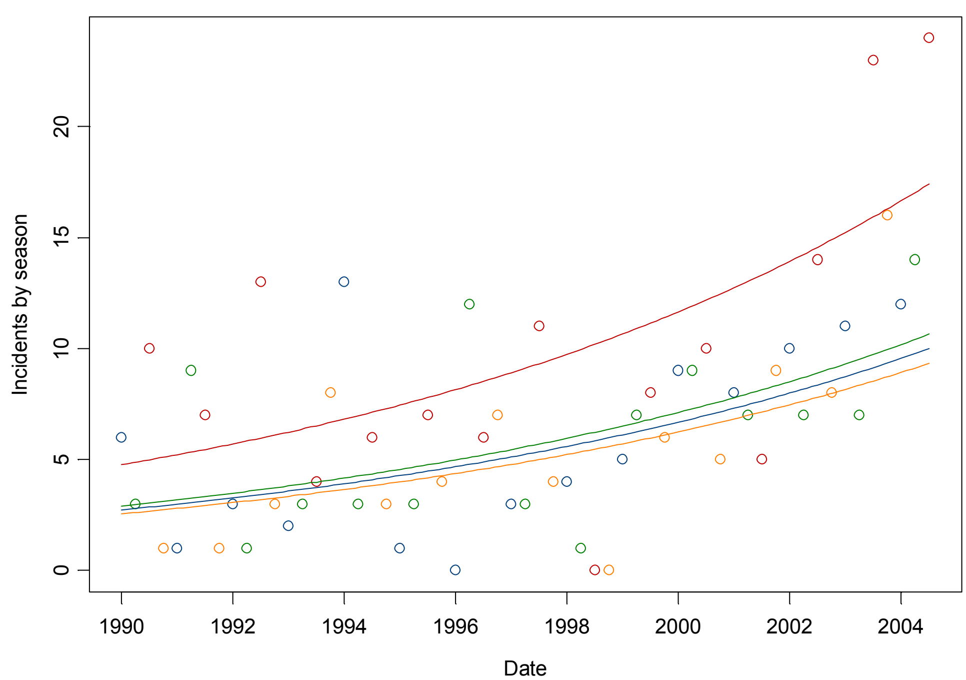
3. While the winter, spring, and autumn estimated rates are similar to each other (with autumn having a rate that is slightly lower), summer has a noticeably higher rate of incidents. This is presumably from weather effects: snow and ice in the winter, thunderstorms in parts of the US in spring, and most importantly thunderstorms and intense heat (with corresponding air conditioner use) in the summer (and the lack of all of these factors in the autumn; we might have expected evidence of a hurricane effect in autumn, but only Hurricane Floyd in 1999 and Hurricane Isabel in 2003 show up as noteworthy). The difference between the summer rate and that of the other seasons is highly statistically significant, but more importantly, corresponds to an important effect

in practical terms, since the estimated number of incidents is 60% to 80% higher in summer than in the other seasons, given the year.

4. The unusually high rates of the last two years noted earlier come from the summers of 2003 and 2004, which have incident counts that are unusually high. Note, however, that once season is taken into account, these observations are no longer alarmingly high, only being between 1 ½ and 2 standard deviations above the expected value.
5. There is evidence of overdispersion here, as the Pearson (X^2=127.1) and deviance (G^2=132.8, both on 53 degrees of freedom) tests indicate lack of fit. A negative binomial fit to these data is as follows:

```
Coefficients:
                    Value  Std. Error       Wald
 (Intercept) -176.83433714 38.06541369 -4.645538
        Date    0.08933316  0.01905175  4.688973
SeasonSpring    0.13104417  0.23103941  0.567194
SeasonSummer    0.62354889  0.22063885  2.826107
SeasonWinter    0.06813003  0.23598164  0.288709
```

The model fits the data adequately, but not as well as the earlier negative binomial models fit (the deviance is 68.4 on 53 degrees of freedom, p=.08). The model implies an estimated 9.3% annual increase in incidents given season, and an estimated 65-85% higher rate for summer than for the other seasons given year. Here is a plot summarizing the model; it is clearly broadly similar to the one based on the Poisson model:



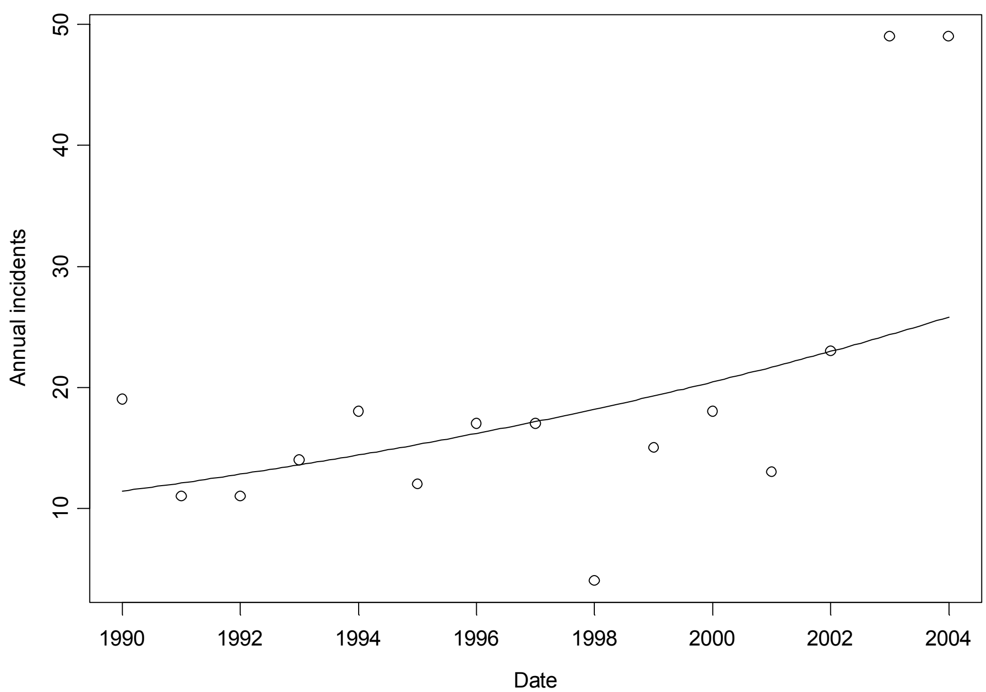
B. Analysis of the number of incidents that were associated with nonzero MW loss or nonzero customer loss over time

The earlier analyses included incidents where there was no effect on the customer base, either in terms of customers affected or power loss. It could be argued that it is incidents that affect customers that are most interesting, so this portion of the report focuses on those incidents. Overdispersion occurs in all of the models, so all analyses are based on the negative binomial model.

1. INCIDENTS WITH NONZERO MW LOST

Annual data

Here is a plot with the negative binomial fit superimposed.



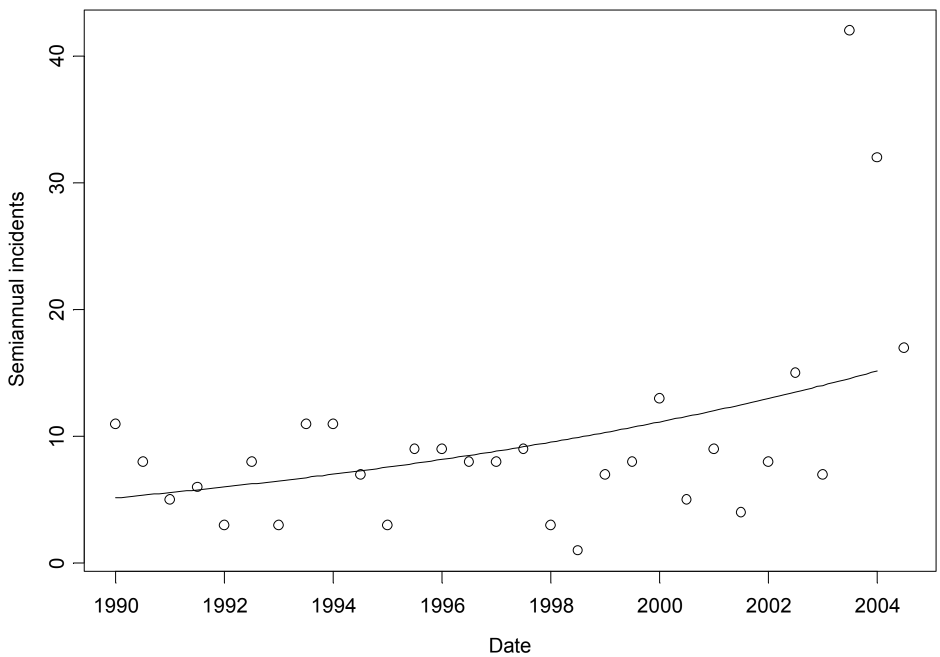
Here is output for this model:

```
Coefficients:
                  Value  Std. Error      Wald
(Intercept) -113.5721447 57.91502205 -1.961014
       Date    0.0582949  0.02900386  2.009901
```

The strength of the time trend is weaker than for the complete data, having a tail probability of .044. The estimated annual increase in incidents with nonzero MW is exp(.058295)-1=6.0%, so apparently the incidents with zero MW lost inflated the rate slightly (since this rate, with those incidents omitted, is smaller than the rate estimated based on all incidents). Note that 1998 is still unusually low, and 2003 and 2004 are unusually high.

Semiannual data

Here is a plot with the fitted model on the semiannual data.



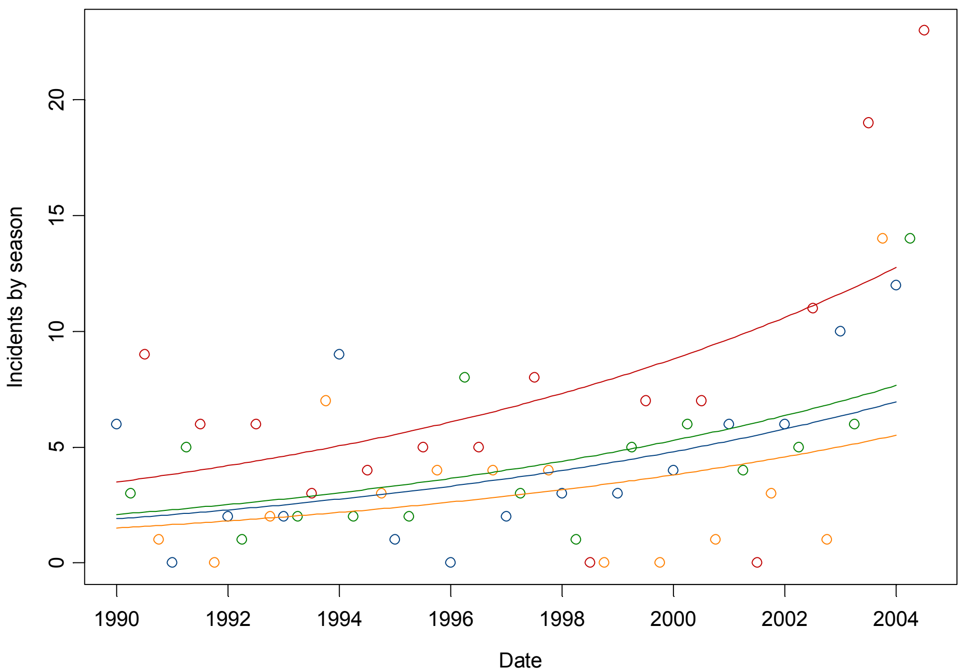
Here is output for the model:

```
Coefficients:
                    Value   Std. Error      Wald
(Intercept) -151.48640808 54.82831060 -2.762923
       Date    0.07694855  0.02744971  2.803256
```

The estimated annual increase in incidents with nonzero MW loss is 8.0%, and is highly significant (p=.005). Note that while the second half of 2003 and of 2004 (only two months) are still high, now the first half of 2003 is also very high (this is because all of the incidents in the first half of 2003 were nonzero MW loss incidents).

Seasonal data

Here is a plot by season.



The fit to these data is as follows:

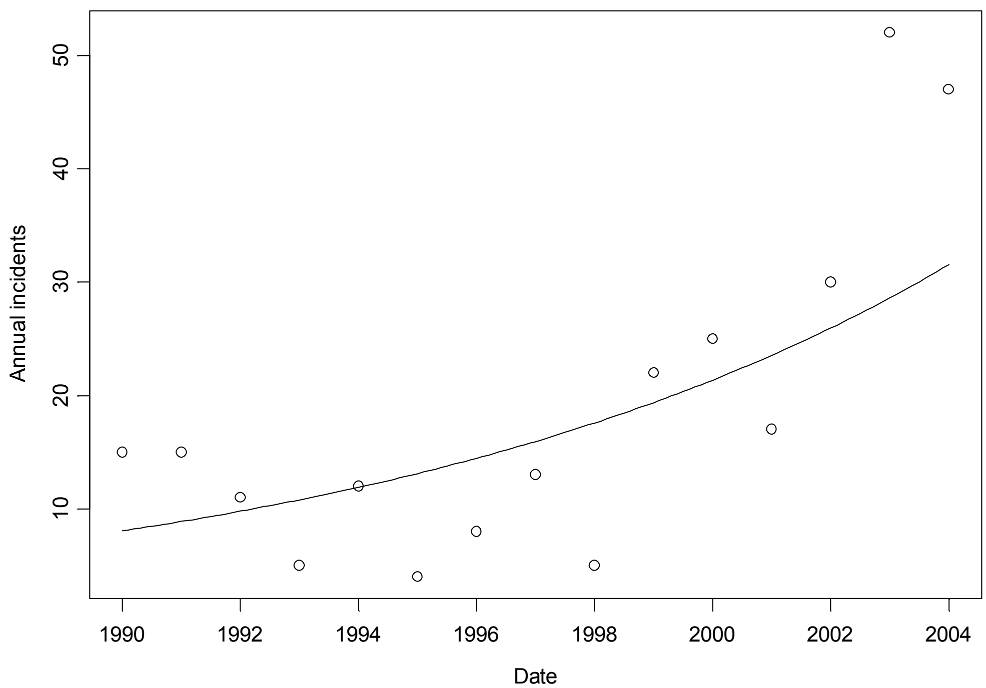
```
Coefficients:
                     Value   Std. Error       Wald
 (Intercept) -183.80666893 47.40955640 -3.876996
        Date    0.09257176  0.02372817  3.901344
SeasonSpring    0.32906080  0.29114767  1.130220
SeasonSummer    0.83965494  0.27956975  3.003383
SeasonWinter    0.23304525  0.29788955  0.782321
```

The model implies an estimated 9.7% annual increase in incident rate given season, which is highly statistically significant ($p<.0001$), and an estimated 65-130% higher rate for summer than for the other seasons. The summer effect is stronger than before, which is easy to understand: while more than 90% of the summer incidents had nonzero MW loss, roughly ¼ of the incidents in the autumn had zero MW loss. That is, nonzero MW incidents are more likely in the summer, thereby strengthening the “summer effect” here. In terms of the time trend, we see a similar pattern to before, of a 6-10% annual increase in incidents from the analyses based on the three different time aggregations.

2. INCIDENTS WITH NONZERO CUSTOMERS LOST

Annual data

Here is a plot with the negative binomial fit superimposed.



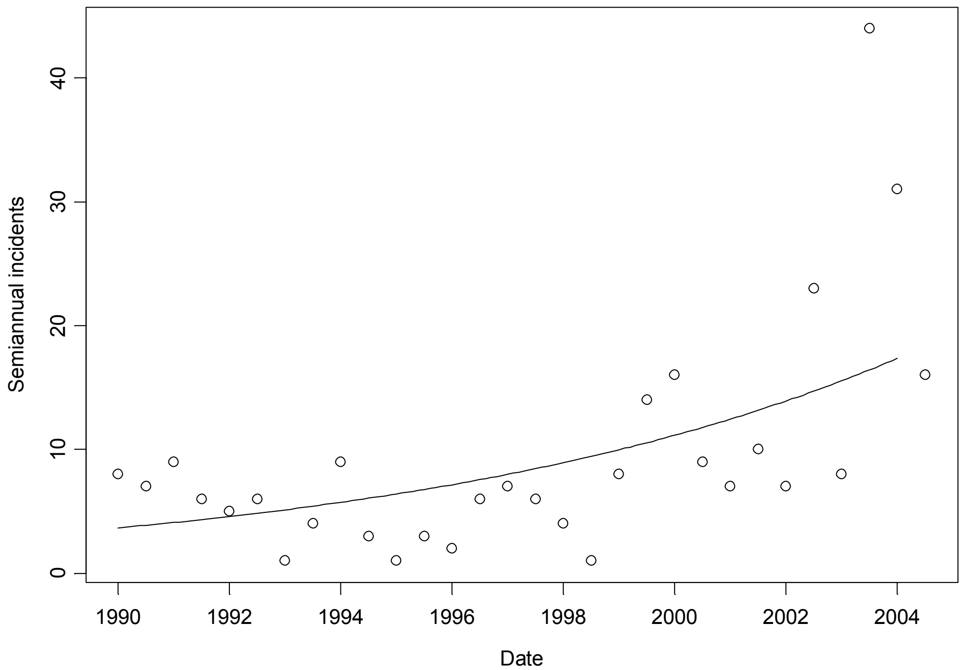
Here is output for this model:

```
Coefficients:
                   Value  Std. Error      Wald
(Intercept) -191.83850183 69.27401101 -2.769271
       Date    0.09745008  0.03469084  2.809101
```

The strength of the time trend is stronger than for the analysis based only on nonzero MW incidents, having a tail probability of .005. The estimated annual increase in incidents with nonzero customer loss is exp(.09745)-1=10.2%, so apparently the incidents with zero customers lost deflated the rate earlier (the rate is higher once the zero customer loss events are omitted). This makes sense: the rate of incidents that had no customer loss was more than 35% from 1990-1997, but has been only 7.5% since then. Note that 1998 is not unusually low now, but 2003 and 2004 are still unusually high.

Semiannual data

Here is a plot with the fitted model on the semiannual data.



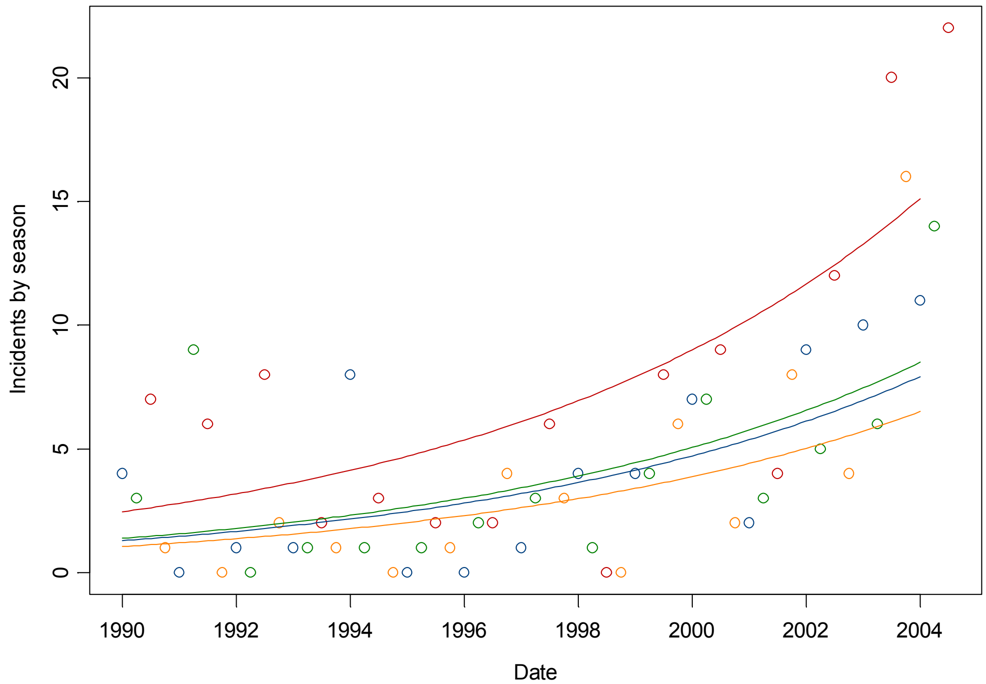
Here is output for the model:

```
Coefficients:
                   Value  Std. Error       Wald
(Intercept) -219.3758662 59.57344642 -3.682444
       Date    0.1108936  0.02982306  3.718385
```

The estimated annual increase in incidents with nonzero MW loss is 11.7%, and is highly statistically significant (p=.0002). The second half of 2003 and first half of 2004 are unusually high.

Seasonal data

Here is a plot of the seasonal data.



The fit to these data is as follows:

```
Coefficients:
                    Value   Std. Error        Wald
 (Intercept) -257.7296583 50.12320622 -5.1419228
        Date    0.1295428  0.02508268  5.1646296
SeasonSpring    0.2660959  0.30367008  0.8762666
SeasonSummer    0.8417521  0.28977870  2.9048102
SeasonWinter    0.1965276  0.30967757  0.6346199
```

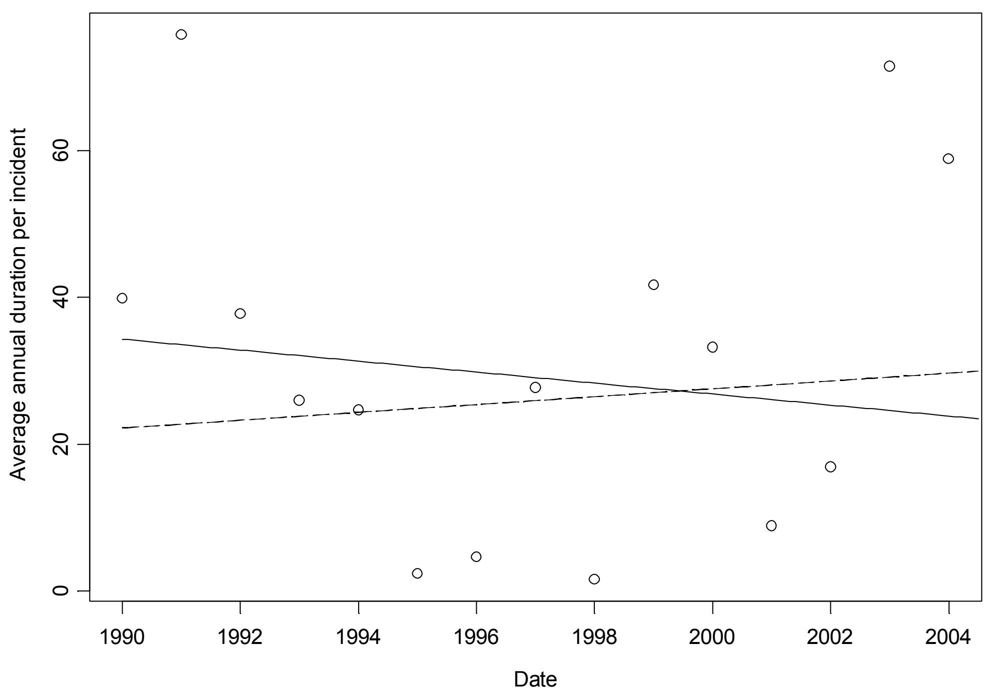
The model implies an estimated 13.8% annual increase in incident rate (p zero to six digits), and an estimated 75-135% higher rate for summer than for the other seasons. The summer effect is similar to that for the nonzero MW loss data, but the pattern is a little more complicated: both summer and winter have lower rates of incidents with zero customer loss compared to spring and autumn, so the estimated relative chances of incidents in those seasons compared to spring and autumn are now higher. Overall, while removing the zero MW loss incidents has relatively little effect on the estimated annual increase in incident rate, removing the zero customer loss incidents has a stronger effect on the estimated annual increase of rates, increasing it to 12-14%.

C. Analysis of duration over time

We now discuss the pattern of average duration of incidents over time. The response variable, whether measured annually, semiannually, or seasonally, is the average duration per incident over that time period. Note that zero-loss events are included, since they seem to be directly relevant to an analysis of duration. Obviously, events with missing duration are not included, which raises the issue of nonresponse bias. If the incidents for which duration is missing are different from those in which it was reported, that can bias the results in ways that are impossible to ascertain.

Annual data

We start with analyses based on a linear model for durations. Here is a plot of the average duration versus time, with two lines superimposed.



It is apparent that there is little evidence of any time trend in average duration. There is one early outlier, corresponding to 1991, although it is not that different from the values for 2003 and 2004. The solid line is the fitted time trend of average duration based on all of the data other than

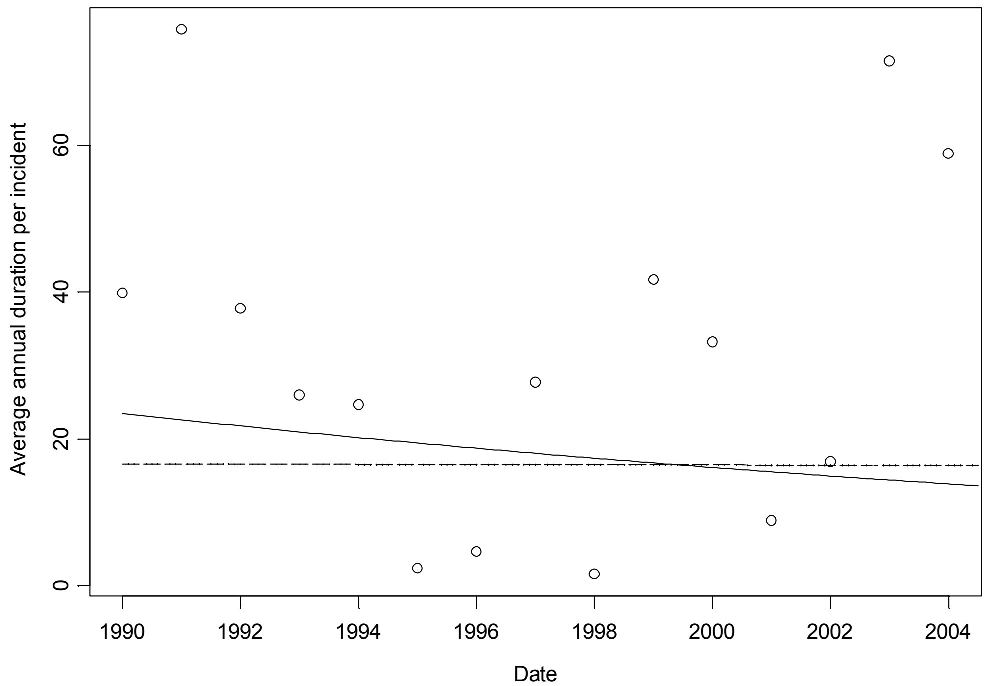
2004 (since those data were incomplete), which has a negative slope that is far from statistically significant:

```
Coefficients:
                 Value Std. Error    t value   Pr(>|t|)
(Intercept)  1521.9638  3165.4638     0.4808     0.6393
       Date    -0.7476     1.5855    -0.4715     0.6457

Residual standard error: 23.91 on 12 degrees of freedom
Multiple R-Squared: 0.01819
```

The dashed line in the plot gives the estimated time trend omitting 1991. The slope has shifted to be positive, but there is still no evidence of any trend:

```
Coefficients:
                 Value Std. Error    t value   Pr(>|t|)
(Intercept) -1039.5609  2933.9925    -0.3543     0.7298
       Date     0.5335     1.4693     0.3631     0.7234

Residual standard error: 20.51 on 11 degrees of freedom
Multiple R-Squared: 0.01185
```

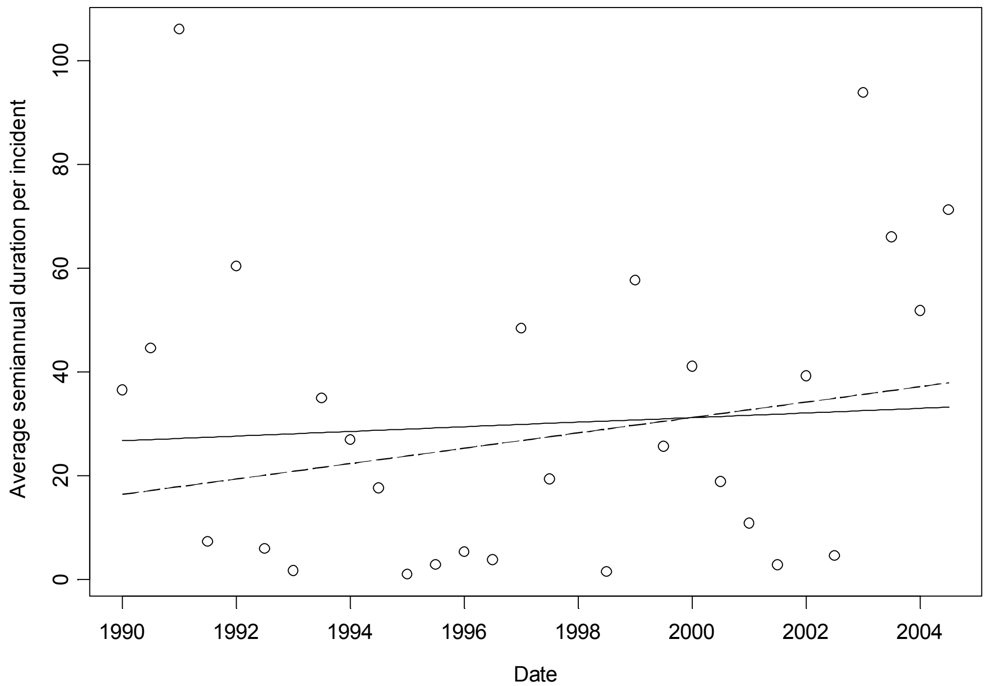
It is possible that multiplicative growth or decay of average duration might be sensible, which would imply the use of a model where logged duration is the response variable. In fact, the results are effectively the same:




```
Full data set

Coefficients:
                Value Std. Error   t value  Pr(>|t|)
(Intercept)   77.8956  165.8329     0.4697    0.6470
       Date   -0.0376    0.0831    -0.4522    0.6592

Residual standard error: 1.253 on 12 degrees of freedom
Multiple R-Squared: 0.01675

Data set omitting 1991

Coefficients:
                Value Std. Error   t value  Pr(>|t|)
(Intercept)    4.3909  177.7861     0.0247    0.9807
       Date   -0.0008    0.0890    -0.0089    0.9930

Residual standard error: 1.243 on 11 degrees of freedom
Multiple R-Squared: 7.267e-006
```

Semiannual data

Here is a plot of the semiannual data, with linear trend lines superimposed.



The results are similar to those for the annual data. The estimated time trend is slightly positive when the 1991 time period is included, and slightly negative when it is not included, but in neither case is it close to statistical significance. Note that the value for the second half of 2004 is not included in either model, since the data are incomplete for that time period.

Here is computer output for the two models:

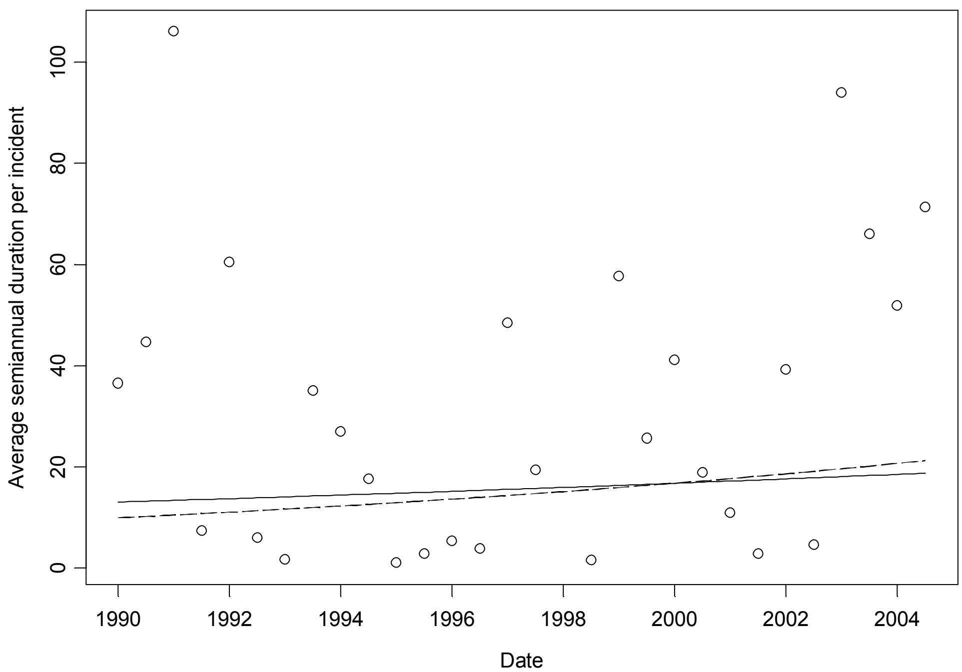
Full data set

```
Coefficients:
                  Value Std. Error    t value   Pr(>|t|)
(Intercept)  -857.6518  2569.1990    -0.3338     0.7412
       Date     0.4445     1.2865     0.3455     0.7325

Residual standard error: 28.95 on 26 degrees of freedom
Multiple R-Squared: 0.004569
```

Data set omitting first half of 1991

```
Coefficients:
                  Value Std. Error    t value   Pr(>|t|)
(Intercept) -2933.8052  2246.1745    -1.3061     0.2034
       Date     1.4825     1.1247     1.3182     0.1994

Residual standard error: 24.37 on 25 degrees of freedom
Multiple R-Squared: 0.06499
```

Models for logged duration also find no evidence of any effect:



Full data set

```
Coefficients:
                 Value Std. Error   t value  Pr(>|t|)
(Intercept)  -47.1819  122.4689    -0.3853    0.7032
       Date    0.0250    0.0613     0.4077    0.6869

Residual standard error: 1.38 on 26 degrees of freedom
Multiple R-Squared: 0.006351
```

Data set omitting first half of 1991

```
Coefficients:
                Value Std. Error   t value  Pr(>|t|)
(Intercept) -101.6895  123.2912    -0.8248    0.4173
       Date    0.0523    0.0617     0.8465    0.4053

Residual standard error: 1.338 on 25 degrees of freedom
Multiple R-Squared: 0.02786
```

Seasonal data

Here is a plot based on all of the data other than the first data point, fitting a linear time trend.

There is a slight upward slope, but it is not statistically significant. There is also no evidence of a season effect; the spring line is marginally higher than the other lines, but this is not close to significance.

```
Coefficients:
                Value Std. Error    t value   Pr(>|t|)
(Intercept) -1924.2276  2748.3347    -0.7001     0.4874
```

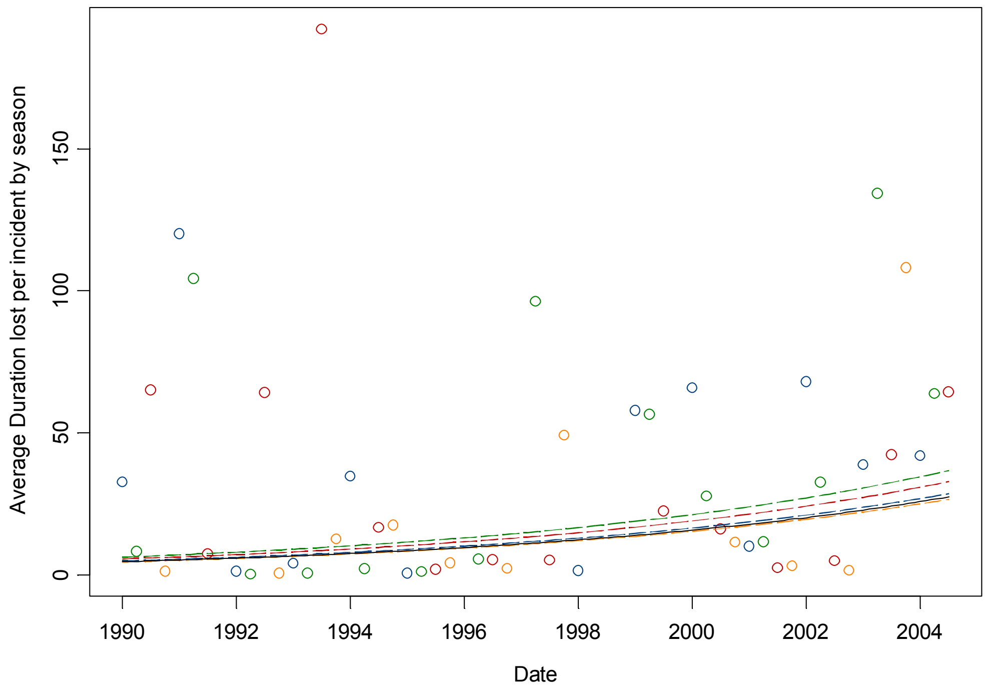
```
      Date     0.9798     1.3759     0.7121     0.4800
   Season1     9.9299     8.6390     1.1494     0.2563
   Season2     2.4131     4.7839     0.5044     0.6164
   Season3     1.2941     3.5458     0.3650     0.7168

Residual standard error: 42.88 on 46 degrees of freedom
Multiple R-Squared: 0.04353
F-statistic: 0.5233 on 4 and 46 degrees of freedom, the p-value i
s 0.719


Anova Table

Response: Duration
              Sum Sq Df   F value    Pr(>F)
(Intercept)   901.21  1 0.4902004 0.4873640
       Date   932.31  1 0.5071208 0.4799843
     Season  2921.74  3 0.5297475 0.6641179
  Residuals 84568.48 46
```

The summer 1993 point is unusual, so here is a summary omitting that data point.

There is now (very) weak evidence of an upward slope, but no season effect. This is presumably coming from the last six seasons, wherein four had average durations of more than 60 hours.

```
Coefficients:
                 Value Std. Error    t value   Pr(>|t|)
(Intercept) -3338.4889  2295.7900    -1.4542     0.1528
       Date     1.6863     1.1493     1.4672     0.1493
    Season1    10.0033     7.1542     1.3982     0.1689
    Season2    -1.7791     4.0609    -0.4381     0.6634
    Season3     2.2743     2.9438     0.7726     0.4438

Residual standard error: 35.51 on 45 degrees of freedom
Multiple R-Squared: 0.09675
F-statistic: 1.205 on 4 and 45 degrees of freedom, the p-value is
 0.3218


Anova Table

Response: Duration
              Sum Sq Df  F value    Pr(>F)
(Intercept)  2666.13  1 2.114636 0.1528365
       Date  2714.16  1 2.152735 0.1492709
     Season  3466.54  3 0.916493 0.4405690
  Residuals 56735.87 45
```

The increasing trend in the last few data points suggests that a model for logged duration based on seasonal data might be appropriate, since in such a model while the proportional increase in duration is constant over time, the absolute level increases more quickly as time goes on (assuming that the slope is positive).



The time trend is statistically significant, but there is no season effect. For this reason, the solid black line (the estimated time trend not including a season effect) is added to the plot.

```
Coefficients:
                Value Std. Error   t value  Pr(>|t|)
(Intercept) -240.7477  108.7498   -2.2138    0.0318
       Date    0.1217    0.0544    2.2360    0.0302
    Season1    0.3244    0.3418    0.9490    0.3476
    Season2    0.2108    0.1893    1.1134    0.2713
    Season3    0.0727    0.1403    0.5178    0.6071

Residual standard error: 1.697 on 46 degrees of freedom
Multiple R-Squared: 0.1365
F-statistic: 1.818 on 4 and 46 degrees of freedom, the p-value
is
 0.1416
```

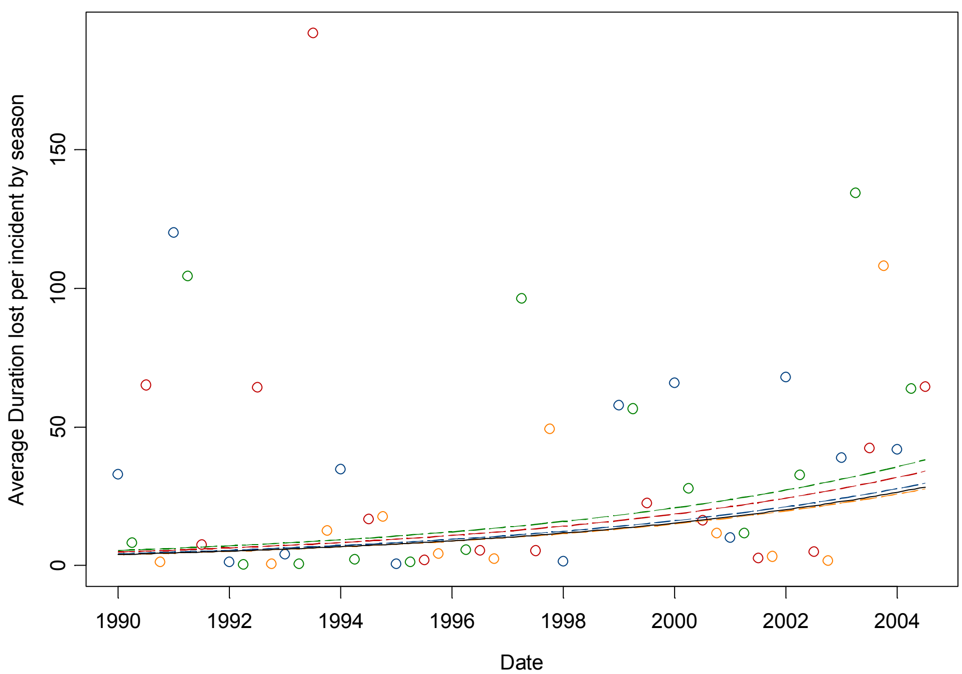
Anova Table

```
Response: log(Duration)
               Sum Sq Df  F value    Pr(>F)
(Intercept)   14.1070  1 4.900800 0.0318417
       Date   14.3918  1 4.999730 0.0302440
     Season    6.3232  3 0.732224 0.5381081
  Residuals 132.4118 46
```

Omitting season effect

```
Coefficients:
                 Value Std. Error   t value  Pr(>|t|)
(Intercept) -242.3461  107.7683    -2.2488    0.0291
       Date    0.1226    0.0540     2.2714    0.0275

Residual standard error: 1.683 on 49 degrees of freedom
Multiple R-Squared: 0.09526
```

This corresponds to an estimated annual increase in duration of 13.0% (exp(.1226)=1.1304). The summer of 1993 is unusual, so here is the analysis with that point omitted:




```
Coefficients:
                 Value Std. Error   t value  Pr(>|t|)
```

```
(Intercept) -267.0844  106.7902    -2.5010    0.0161
       Date    0.1349    0.0535     2.5232    0.0152
    Season1    0.3258    0.3328     0.9789    0.3328
    Season2    0.1327    0.1889     0.7025    0.4860
    Season3    0.0909    0.1369     0.6639    0.5102

Residual standard error: 1.652 on 45 degrees of freedom
Multiple R-Squared: 0.1549
F-statistic: 2.062 on 4 and 45 degrees of freedom, the p-value
is
 0.1016

Anova Table

Response: log(Duration)
              Sum Sq Df  F value    Pr(>F)
(Intercept)  17.0639  1 6.255098 0.0160914
       Date  17.3681  1 6.366600 0.0152306
     Season   4.7354  3 0.578614 0.6320780
  Residuals 122.7598 45
```

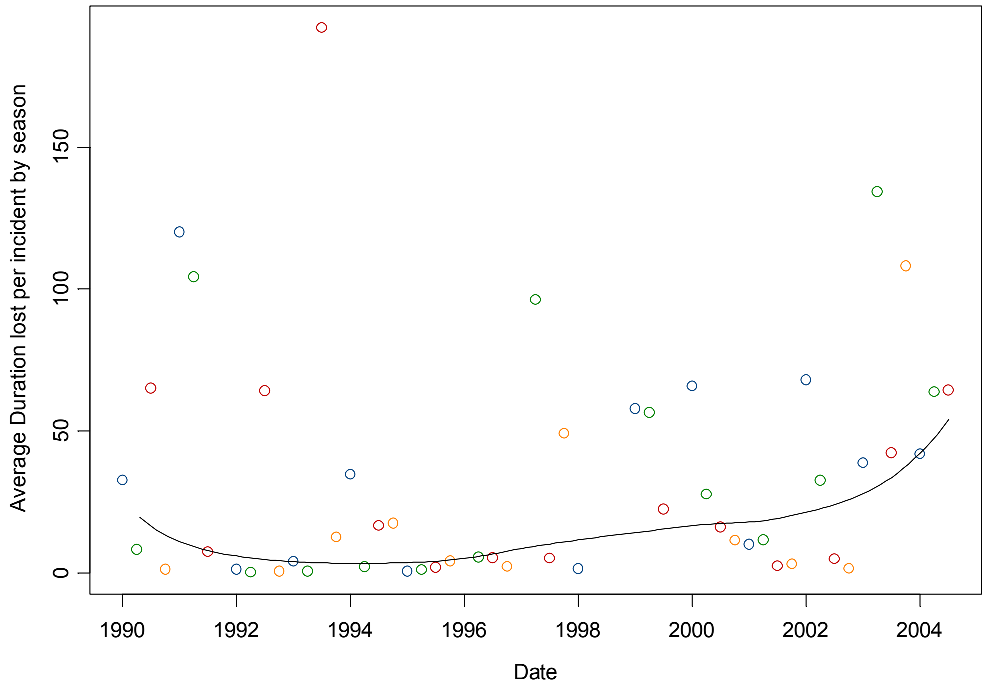
Omitting season effect

```
Coefficients:
                Value Std. Error   t value  Pr(>|t|)
(Intercept) -269.7994  105.2309    -2.5639    0.0135
       Date    0.1363    0.0527     2.5866    0.0128

Residual standard error: 1.63 on 48 degrees of freedom
Multiple R-Squared: 0.1223
```

This model implies an estimated annual increase in duration of 14.6%. We also can note that the observed average durations in the last 7 seasons (winter 2003 through summer 2004) are all higher than what is implied by the model. That is, what the multiplicative model is picking up, which the linear model cannot pick up, is an increase in durations in the last few years. This is supported when noting that the average duration up through autumn 2002 was 27.2 hours, while the average duration after that was 65.5 hours. Further, the corresponding medians are 3.6 hours and 25.8 hours.

A more precise representation of this pattern comes from the following plot, which is a *loess* nonparametric curve for the durations. This is a nonparametric regression “scatterplot smoother,” which puts a smooth curve through the points, thereby avoiding the linear or loglinear assumptions made in the parametric statistical models. Details on nonparametric regression can be found in Simonoff (1996, chapter 5).

The loess curve implies that average durations dropped in the first few years of the 1990s. After a period of relatively flat durations, the average duration first started to increase in the mid 1990s, and then increased more rapidly after 2002.



It is possible to get estimates of the local annual rates of change of duration from this curve. These estimates have subtle statistical properties, so they should only be considered guidelines, but they do give a feel for what is going on. Here are the estimated annual changes in duration:

```
1991 -0.46325898
1992 -0.32701169
1993 -0.16128099
1994  0.09265965
1995  0.39943522
1996  0.68879830
1997  0.34206888
1998  0.22424034
1999  0.17072734
2000  0.07342993
2001  0.19359276
2002  0.30423857
2003  0.51101651
```

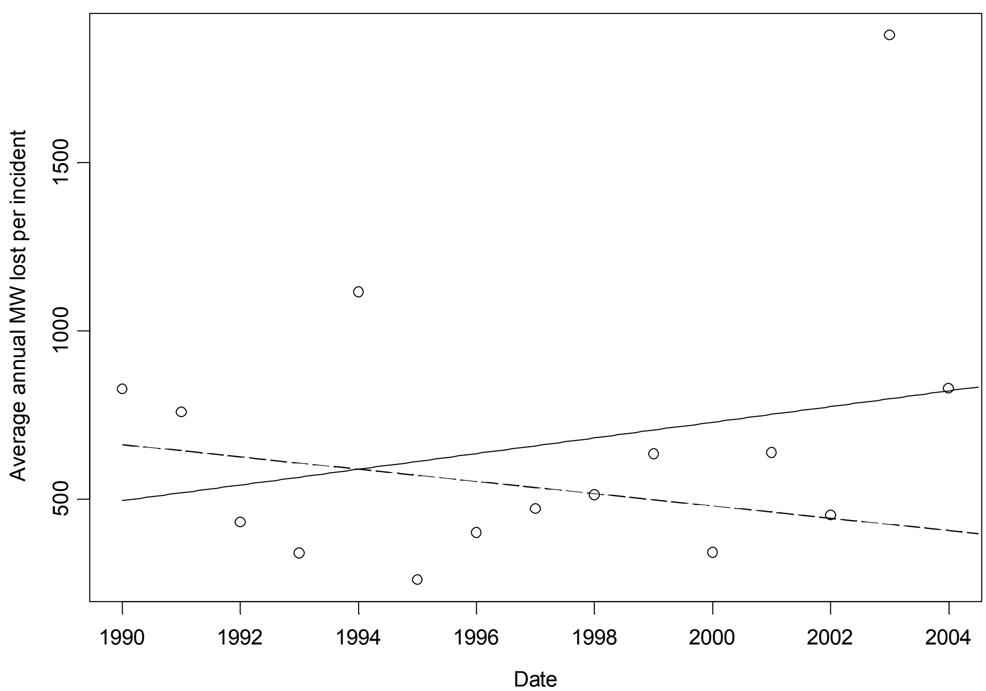
Up until 1993, durations were getting shorter on average (an estimated 46% shorter from 1991 to 1992, 33% shorter from 1992 to 1993, and so on). This changed in 1995, and for a few years the average duration went up 35-70% annually (note that this was at a time when durations were lower, so the absolute increase wasn't that large). This was followed by a period (1998-2001) of fairly stable growth of 10-20% annually. Finally, from 2002 on, average durations have started increasing again at a high 30-50% rate. Thus, the constant estimate of 14.6% annually obtained from the regression model actually seems to mask some very different periods in average duration change.

D. Analysis of MW loss over time

We now examine average MW loss over time.

Annual data

Here is a plot of the average MW losses versus time, with two lines superimposed.



It is apparent that there is little evidence of any time trend in average MW loss. There is one very obvious outlier, corresponding to 2003. This comes from the August 14, 2003 blackout; four of the seven incidents associated with that blackout had large MW loss values, ranging from 7000 to 23000 MW. The solid line is the fitted time trend of average MW loss based on all of the data other than 2004 (since those data were incomplete); while it has a positive slope, it is far from statistically significant:

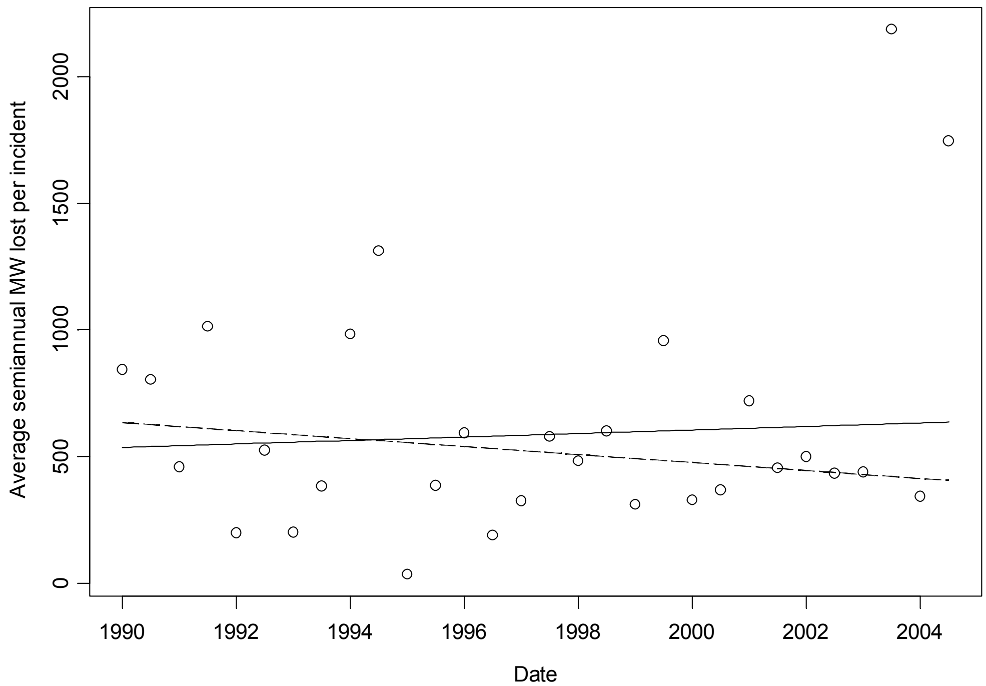
```
Coefficients:
                  Value  Std. Error     t value    Pr(>|t|)
(Intercept) -45865.1122  56524.0160     -0.8114      0.4329
       Date     23.2969     28.3115      0.8229      0.4266

Residual standard error: 427 on 12 degrees of freedom
Multiple R-Squared: 0.05341
```

The dashed line in the plot gives the estimated time trend omitting 2003. The slope has shifted to be negative, but there is still no evidence of any real trend:

```
Coefficients:
                  Value  Std. Error     t value    Pr(>|t|)
(Intercept)  36925.3025  35110.5655      1.0517      0.3155
       Date    -18.2229     17.5904     -1.0360      0.3225

Residual standard error: 237.3 on 11 degrees of freedom
Multiple R-Squared: 0.08889
```

Semiannual data

Here is a plot of the semiannual data, with trend lines superimposed.



The results are similar to those for the annual data. The estimated time trend is slightly positive when the August 2003 blackout time period is included, and slightly negative when it is not included, but in neither case is it close to statistical significance. Note that the unusually high value for the second half of 2004 is not included in either model, since the data are incomplete for that time period.

Here is computer output for the two models:

Full data set

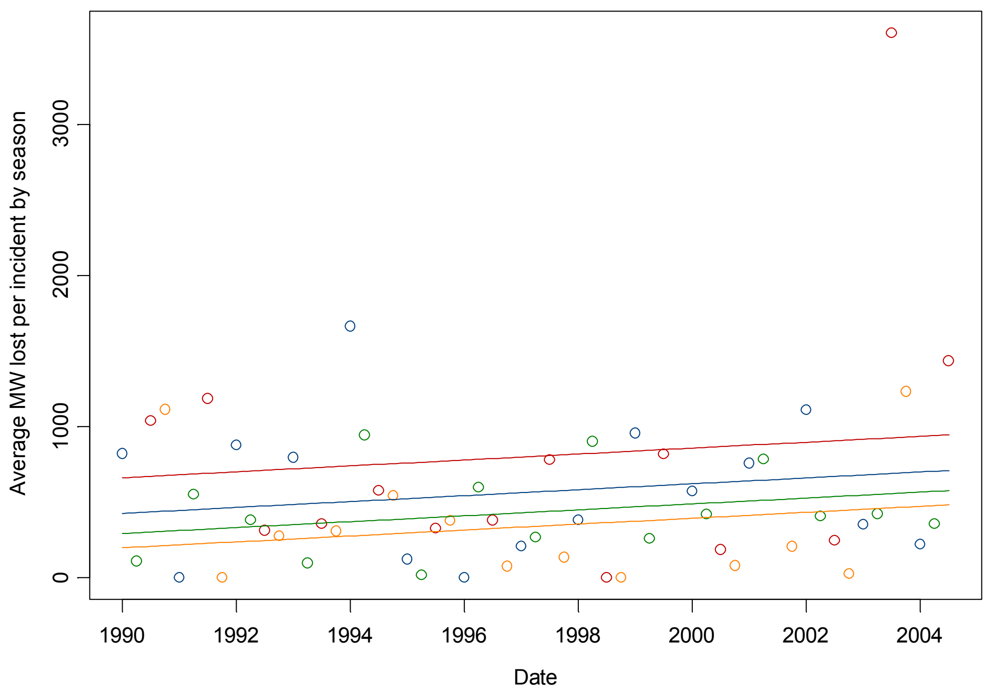
```
Coefficients:
                 Value  Std. Error     t value    Pr(>|t|)
(Intercept) -13163.5432  37887.7200     -0.3474      0.7310
       Date      6.8844     18.9723      0.3629      0.7195

Residual standard error: 427.4 on 27 degrees of freedom
Multiple R-Squared: 0.004853
```

Data set omitting second half of 2003

```
Coefficients:
                  Value  Std. Error     t value    Pr(>|t|)
(Intercept)  31910.7556  26878.7923      1.1872      0.2459
       Date    -15.7170     13.4611     -1.1676      0.2536

Residual standard error: 289.9 on 26 degrees of freedom
Multiple R-Squared: 0.04982
```

Seasonal data

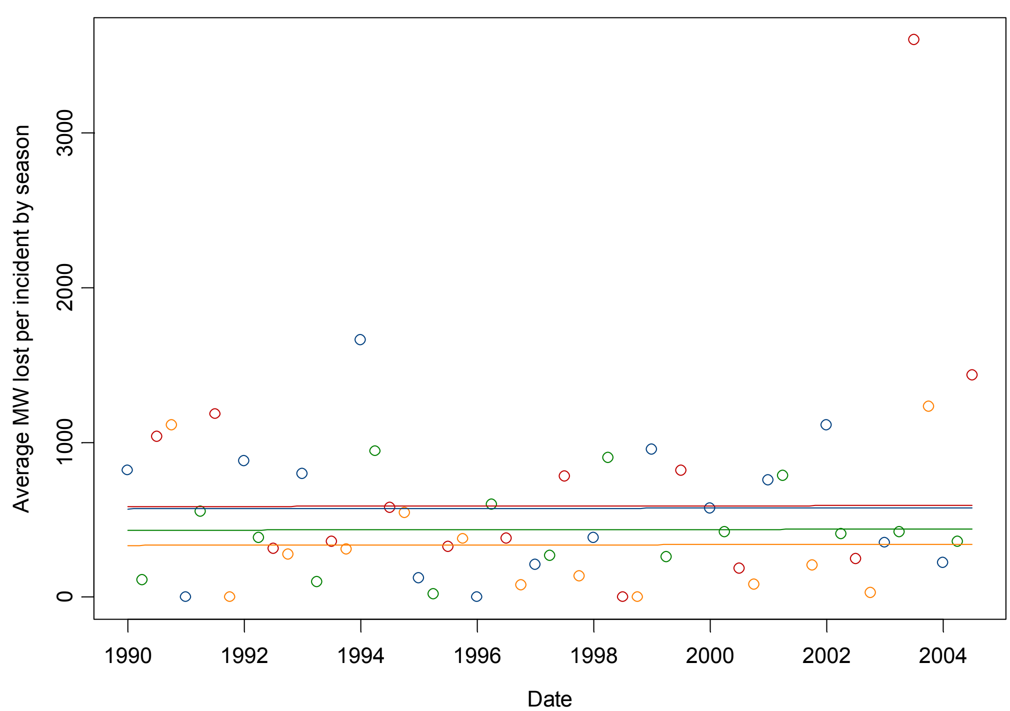
Here is a plot based on all of the data (other than the first data point, which was not based on a full three months of a season).



There is a slight upward slope, but it is not statistically significant. There is also no evidence of a season effect; the summer line is marginally significantly higher than the autumn line, but this difference is not close to significance if all of the pairwise comparisons between seasons that can be made are taken into account.

```
Coefficients:
                   Value  Std. Error    t value    Pr(>|t|)
 (Intercept) -38753.1741  35931.9860    -1.0785      0.2859
        Date     19.5735     17.9923     1.0879      0.2818
SeasonSpring     94.4690    214.6689     0.4401      0.6617
SeasonSummer    463.6138    218.1893     2.1248      0.0385
SeasonWinter    227.6008    218.3162     1.0425      0.3021

Residual standard error: 566.4 on 51 degrees of freedom
Multiple R-Squared: 0.1122
F-statistic: 1.612 on 4 and 51 degrees of freedom, the p-value is
 0.1855


Anova Table

Response: MW
               Sum Sq Df  F value    Pr(>F)
(Intercept)    373211  1 1.163194 0.2858788
       Date    379723  1 1.183491 0.2817609
     Season   1670190  3 1.735172 0.1714707
  Residuals 16363347 51
```

The summer 2003 point is highly unusual, so a summary omitting that data point follows.



There is even less evidence of any effect, as summer is no different from winter, and the slope is virtually flat.

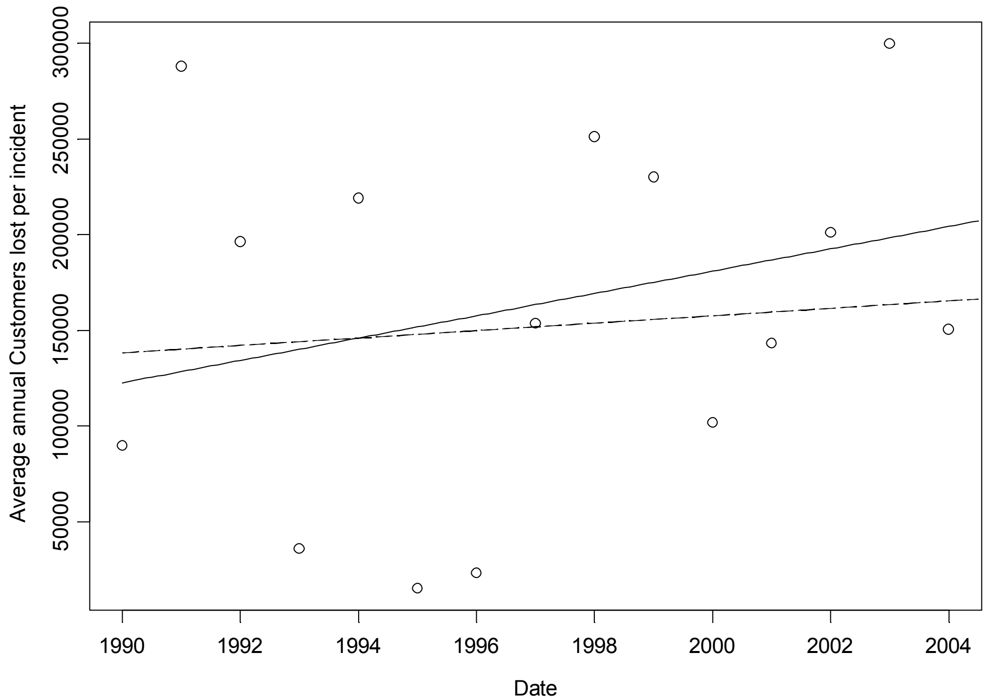
```
Coefficients:
                  Value  Std. Error     t value    Pr(>|t|)
 (Intercept)  -605.6489  26420.4151     -0.0229      0.9818
        Date     0.4717     13.2295      0.0357      0.9717
SeasonSpring    98.1424    154.4194      0.6356      0.5280
SeasonSummer   251.4646    159.8761      1.5729      0.1221
SeasonWinter   236.0497    157.0468      1.5031      0.1391

Residual standard error: 407.5 on 50 degrees of freedom
Multiple R-Squared: 0.06423
F-statistic: 0.858 on 4 and 50 degrees of freedom, the p-value is
 0.4956


Anova Table

Response: MW
             Sum Sq Df  F value    Pr(>F)
(Intercept)      87  1 0.000525 0.9818025
       Date     211  1 0.001271 0.9717019
     Season  569579  3 1.143589 0.3406192
  Residuals 8301043 50
```

Thus, there is no evidence of any time or seasonal patterns in average MW loss per incident.

E. Analysis of customer loss over time

Annual data

Here is a plot of the average customer losses versus time, with two lines superimposed.



It is apparent that there is little evidence of any time trend in average customer loss. I've also included the trend omitting 2003, although that year doesn't really show up as outlying with respect to customer loss; in any event, that only make the time trend less significant. Here is computer output:

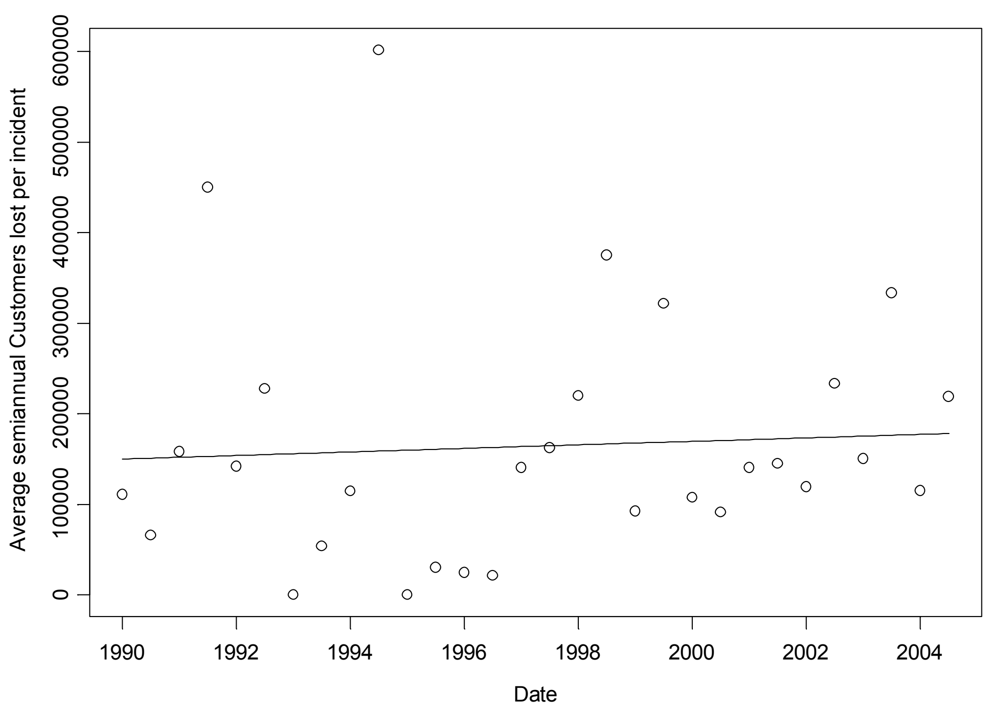
```
Full data set

Coefficients:
                     Value     Std. Error        t value
(Intercept) -11476942.2686  12761932.1574        -0.8993
       Date      5828.8956      6392.1393         0.9119

                  Pr(>|t|)
(Intercept)         0.3862
       Date         0.3798

Residual standard error: 96410 on 12 degrees of freedom
Multiple R-Squared: 0.0648
```

Data set omitting 2003

```
Coefficients:
                      Value      Std. Error          t value
(Intercept)  -3715474.8515  13947861.8743          -0.2664
       Date      1936.4846      6987.8945           0.2771

                   Pr(>|t|)
(Intercept)         0.7949
       Date         0.7868

Residual standard error: 94270 on 11 degrees of freedom
Multiple R-Squared: 0.006933
```

Semiannual data

Here is a plot of the semiannual data, with a trend line superimposed.

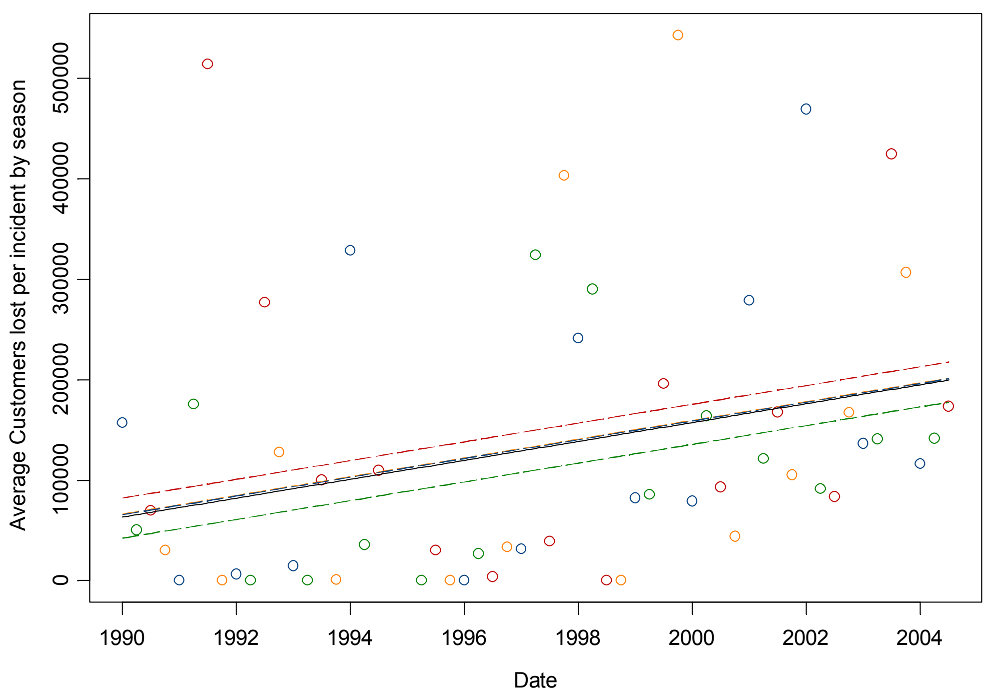


The results are similar to those for the annual data, in that there is a slight positive slope, but not close to statistical significance.

```
Coefficients:
                     Value      Std. Error         t value
(Intercept)  -3718770.1426  12534458.3895         -0.2967
       Date      1944.1571      6276.6304          0.3097

                  Pr(>|t|)
(Intercept)         0.7690
       Date         0.7591

Residual standard error: 141400 on 27 degrees of freedom
Multiple R-Squared: 0.003541
```

Seasonal data

Here is a plot of the data.



The season lines are dashed in this picture. There is now an upward slope, and it is marginally statistically significant. There is no evidence of a season effect.

```
Coefficients:
                    Value     Std. Error         t value
 (Intercept) -18523917.4668  8871954.6887        -2.0879
        Date      9341.6306     4441.6147         2.1032
```

```
SeasonSpring    -23850.1368     53271.1703        -0.4477
SeasonSummer     16092.9496     53264.9384         0.3021
SeasonWinter      -554.0199     55144.9920        -0.0100

                  Pr(>|t|)
 (Intercept)        0.0418
        Date        0.0404
SeasonSpring        0.6563
SeasonSummer        0.7638
SeasonWinter        0.9920

Residual standard error: 140600 on 51 degrees of freedom
Multiple R-Squared: 0.09129
F-statistic: 1.281 on 4 and 51 degrees of freedom, the p-value is
 0.2897


Anova Table

Response: Customers
                  Sum Sq Df  F value    Pr(>F)
(Intercept)   86134360122  1 4.359403 0.0418184
       Date   87400317840  1 4.423475 0.0404010
     Season   12141569101  3 0.204835 0.8925836
  Residuals 1007672863895 51
```

These results suggest simplifying the model by removing the season factor, and this single line is the black line in the figure. Here is output for this model:

```
Coefficients:
                     Value     Std. Error        t value
(Intercept) -18692704.1744   8667796.2290        -2.1566
       Date      9425.0265      4339.3901         2.1720

                 Pr(>|t|)
(Intercept)        0.0355
       Date        0.0343

Residual standard error: 137400 on 54 degrees of freedom
Multiple R-Squared: 0.08034
```

Thus, when looking at average customer losses season by season, there is weak evidence of an upward trend in the average customer loss per incident, with an estimated increase of a bit less than 10,000 customers per incident per year. The effect is weak, accounting for only 8% in the variability of average customer losses. Looking at the plot, it seems that this effect is being driven by the lack of points in the lower right corner; that is, the lack of very low customer loss events in the past 5 years, compared to pre-1999. This coincides with the pattern noted in sections I. A and I. B when comparing the trend of the number of incidents over time to the number of incidents with nonzero customer loss over time. In those analyses, it was apparent that the number of zero customer loss incidents has dropped significantly since 1999, which could account for the increase in average customer loss seen here.

II. Event-level analyses

A. Analysis of customer loss at the event level

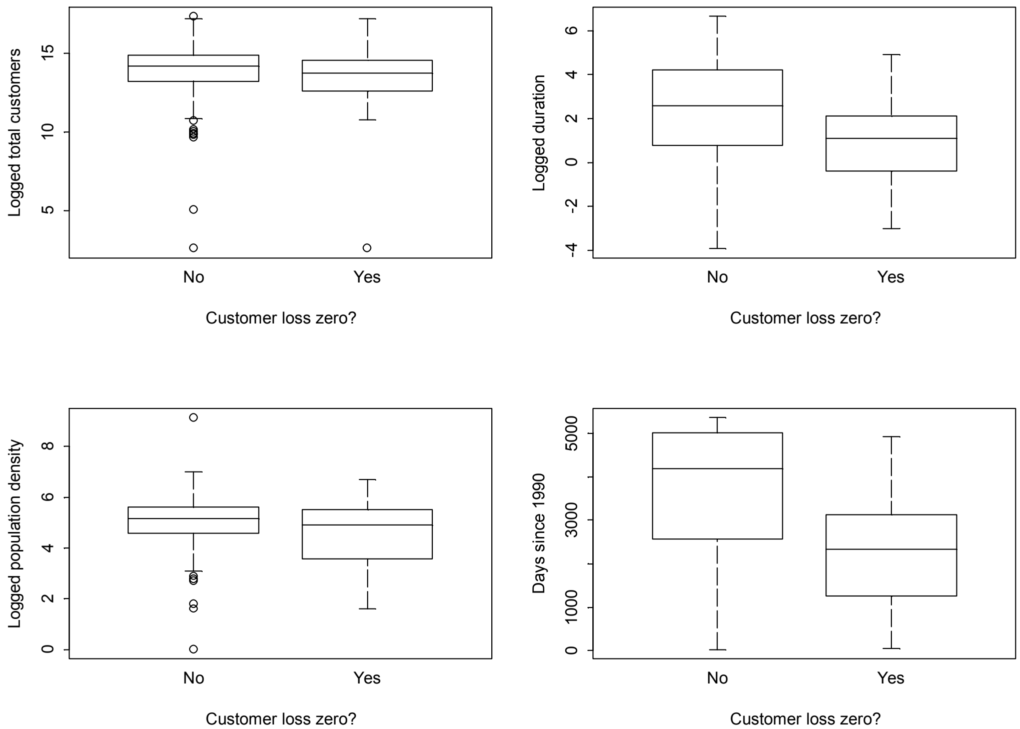
In this section customer loss is reanalyzed, but now at the event level. There are two important distinctions between these analyses and those of section I. E. First, the earlier analyses were based on average customer losses over three- six- or twelve-month time periods, and as such there is far lower variability in the responses than for the event-by-event customer losses. Second, the present analyses can account for characteristics unique to the particular event through regression modeling, while the earlier analyses ignored those characteristics.

These data are modeled in two parts. First, we try to understand what characteristics are related to whether an incident has zero or nonzero customers lost. Then, given that the number lost is nonzero, we attempt to determine what characteristics help to predict the actual number lost.

1. WHY DOES AN INCIDENT HAVE ZERO OR NONZERO CUSTOMERS LOST?

This analysis is based on a logistic regression. In a logistic regression, the response variable is binary (in this case, whether or not the event had zero customer loss), and a binomial distribution is used to represent its random character. The probability of an event having zero customer loss, p, is related to predictors through the odds, $p/(1-p)$; specifically, the logarithm of the odds is modeled as a linear function of the predictors. Further details on the model can be found in Simonoff (2003, chapter 9).

Side-by-side boxplots for each predictor that separate the two groups (zero and nonzero customer loss) can be useful to see which variables are associated with one group or the other. Here are four such boxplots:



There is apparently little difference in the distribution of logged total customers of the utility for incidents with nonzero customer loss (the left box in each plot) versus for incidents with zero customer loss (the right box in each plot), as can be seen in the upper left plot. As might be expected, shorter incidents are associated with zero customer loss (upper right plot). Incidents in more densely populated states are more likely to have nonzero customer loss (bottom left plot). Finally, as noted in the earlier time trend analyses of incident rates and customer loss, there is a strong pattern where incidents earlier in time are more likely to have zero customer loss (bottom right plot).

The other potential predictors are season and cause. The following table summarizes the marginal relationship with season:

	Winter	Spring	Summer	Autumn
Nonzero loss	62	60	111	48
Zero loss	10	21	20	13

Zero loss incidents are more common in the spring (26.3%) and autumn (21.3%), and less common in the summer (15.3%) and winter (13.9%). These are not, however, very strong effects. The following table summarizes the relationship with cause of the incident:

	C	Crime	D	E	F	H	N	O	S	T	U	W
Nonzero loss	6	2	1	63	7	10	2	3	4	2	7	173
Zero loss	1	6	3	26	4	7	1	2	0	3	1	8

Weather-related incidents (W) are very likely to have nonzero customer loss. Capacity shortage (C), system protection (S), and unknown causes (U) are also strongly associated with nonzero customer loss, but this is based on far fewer incidents. Equipment failure (E) is noticeably less related to nonzero customer loss (while also having a large number of incidents). More atypical causes that are less associated with nonzero customer loss include fire (F), human error (H), natural disaster (N), and operational error (O), and crime, demand reduction (D), and third party (T) cause have zero customer loss rates more than 50% (although again, based on few incidents).

Here is the output from a logistic regression modeling the probability that an incident has zero customer loss.

```
Coefficients:
                           Value    Std. Error         Wald
        (Intercept)  -9.8993803080 7.922356e+002 -0.012495501
Log.total.customers  -0.1049879954 8.960303e-002 -1.171701352
       Log.duration  -0.2169415033 1.356431e-001 -1.599354795
    Log.pop.density  -0.5184093874 2.385999e-001 -2.172713762
    Days.since.1990  -0.0003543886 1.499079e-004 -2.364042847
       SeasonSpring  -0.0449659583 8.266169e-001 -0.054397579
       SeasonSummer  -0.7088575436 7.925076e-001 -0.894448900
       SeasonWinter   0.1577912155 8.342260e-001  0.189146846
 Primary.CauseCrime  16.2205548218 7.922350e+002  0.020474424
     Primary.CauseD  16.0934851626 7.922353e+002  0.020314021
     Primary.CauseE  13.6924499579 7.922338e+002  0.017283344
     Primary.CauseF  13.6490611501 7.922345e+002  0.017228562
     Primary.CauseH  13.5840448738 7.922342e+002  0.017146501
     Primary.CauseN  14.1107838269 7.922354e+002  0.017811352
     Primary.CauseO  13.8845960756 7.922351e+002  0.017525853
     Primary.CauseS  -1.6487955012 1.186869e+003 -0.001389198
     Primary.CauseT  17.1955933431 7.922346e+002  0.021705177
     Primary.CauseU   0.3021950694 1.092641e+003  0.000276573
     Primary.CauseW  12.6509256410 7.922339e+002  0.015968675
```

This output is a little strange, in that the standard errors for the effects related to cause are much too high, resulting in very low Wald statistics. The problem is that the model is overspecified, and separation has occurred, making the logistic regression fit unstable. The model needs to be simplified to fix this. From the Wald statistic, and recalling the earlier boxplots, it seems clear that logged total customers is not helping here, so that variable has been removed from the model below. This also has the advantage of bringing back into the model 29 incidents for which we did not have total customer data.

Here is the output from the simplified model:

```
Coefficients:
```

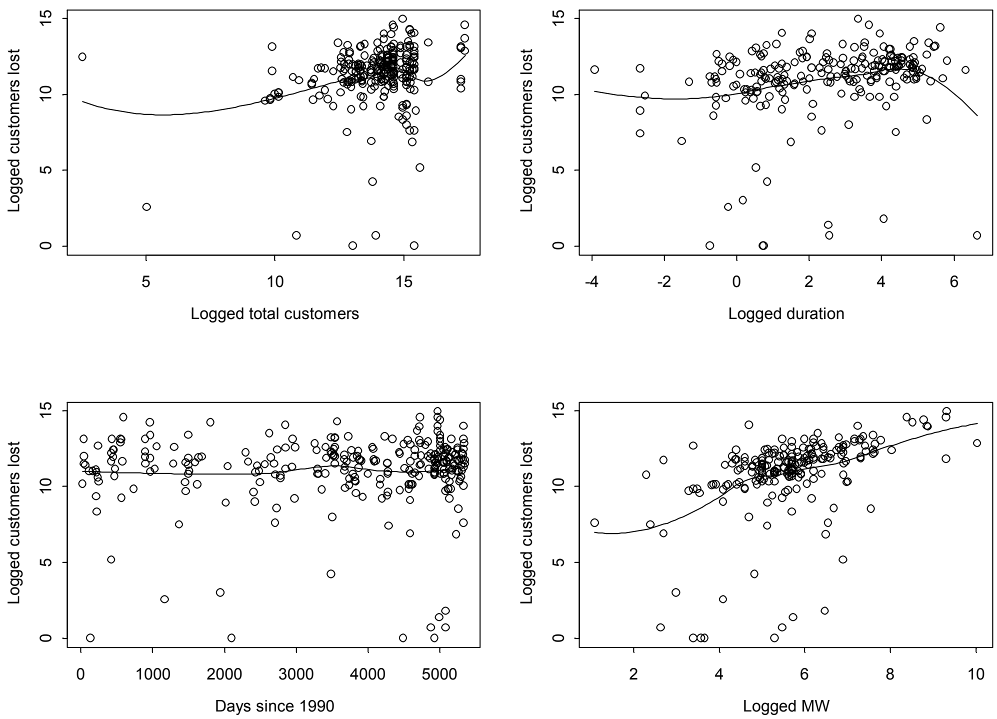
```
                          Value    Std. Error        Wald
       (Intercept)   3.2908954993 1.706303e+000  1.92866973
      Log.duration  -0.3068145491 1.244615e-001 -2.46513591
   Log.pop.density  -0.6073834125 1.945081e-001 -3.12266465
   Days.since.1990  -0.0003271641 1.291495e-004 -2.53322034
      SeasonSpring   0.1511873868 6.982464e-001  0.21652441
      SeasonSummer  -0.6695254150 6.961581e-001 -0.96174332
      SeasonWinter   0.2130934059 7.700996e-001  0.27670889
Primary.CauseCrime   2.6911800897 1.684306e+000  1.59779734
    Primary.CauseD   2.7720269862 1.708543e+000  1.62245062
    Primary.CauseE  -0.2664512138 1.194480e+000 -0.22306882
    Primary.CauseF  -0.1170414575 1.441739e+000 -0.08118077
    Primary.CauseH  -0.5060062221 1.380445e+000 -0.36655308
    Primary.CauseN   0.4467313019 1.973418e+000  0.22637437
    Primary.CauseO  -1.1496985596 1.773590e+000 -0.64823260
    Primary.CauseS -13.9244551234 3.204103e+002 -0.04345821
    Primary.CauseT   3.0384818062 1.672036e+000  1.81723427
    Primary.CauseU   0.1401502460 1.695997e+000  0.08263589
    Primary.CauseW  -1.7355275486 1.257502e+000 -1.38013937


Tests for terms with more than 1 degree of freedom

Term           Chi-Square  DF       P
Season             2.5385   3  0.468
Primary.Cause     28.5179  11  0.003
```

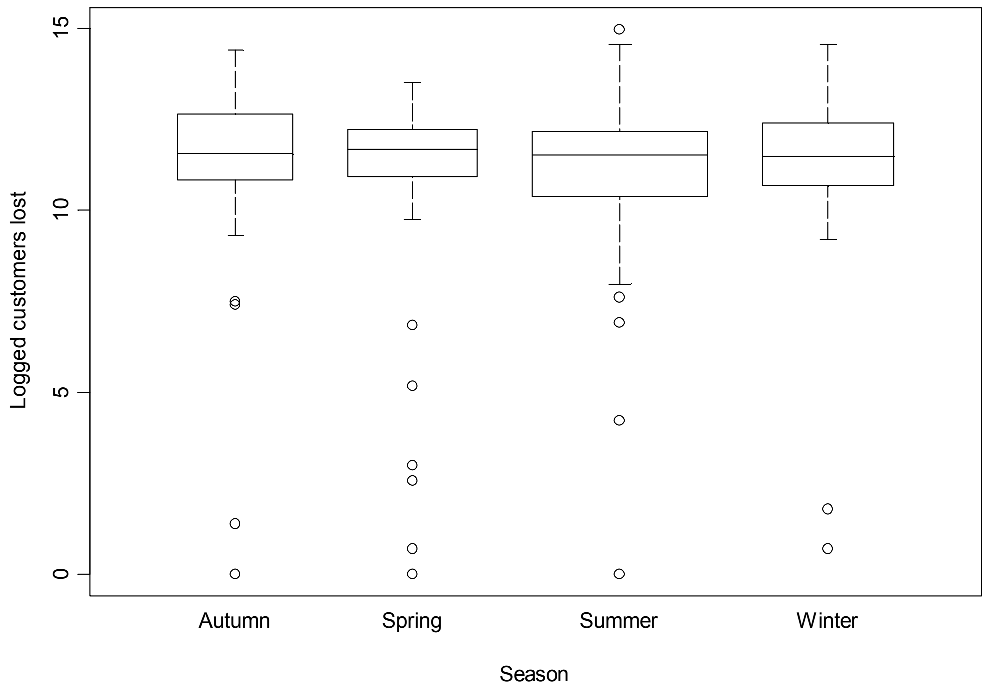
We see that logged duration, logged population density, a time trend (days since 1990), and cause are significant predictors, but season is not. The coefficients have the following interpretations. A 1% increase in the duration of an incident is associated with an estimated 0.3% decrease in the odds that an incident will have zero customer loss, holding all else in the model fixed. A 1% increase in the state population density is associated with an estimated 0.6% decrease in the odds that an incident will have zero customer loss, holding all else in the model fixed. Since
exp(365 X -.0003271641)=.887, each additional year later is associated with an estimated 11.3% decrease in the odds that an incident has zero customer loss, holding all else in the model fixed (that is, the estimated annual decrease in the odds of an event having zero customer loss is 11.3%, holding all else in the model fixed). Finally, given the other predictors, crime, demand reduction, and third party cause are strongly associated with zero customer loss, while operational error, system protection, and weather are strongly associated with nonzero loss.

2. Given that more than zero customers are lost, what factors are related to the amount lost?

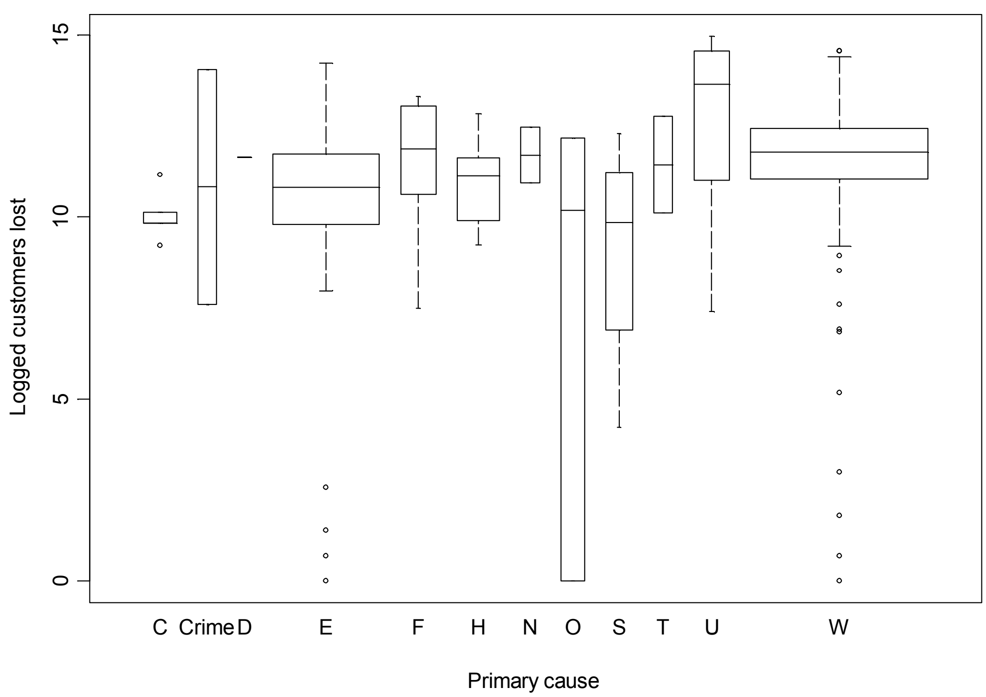
We now examine regression modeling for the (logged) number of customers lost, given that that number is nonzero.

First, here are some pictures of the observed relationships, with loess curves superimposed on the plots.





15
10
5
0
Logged customers lost
Autumn
Spring
Summer
Winter
Season



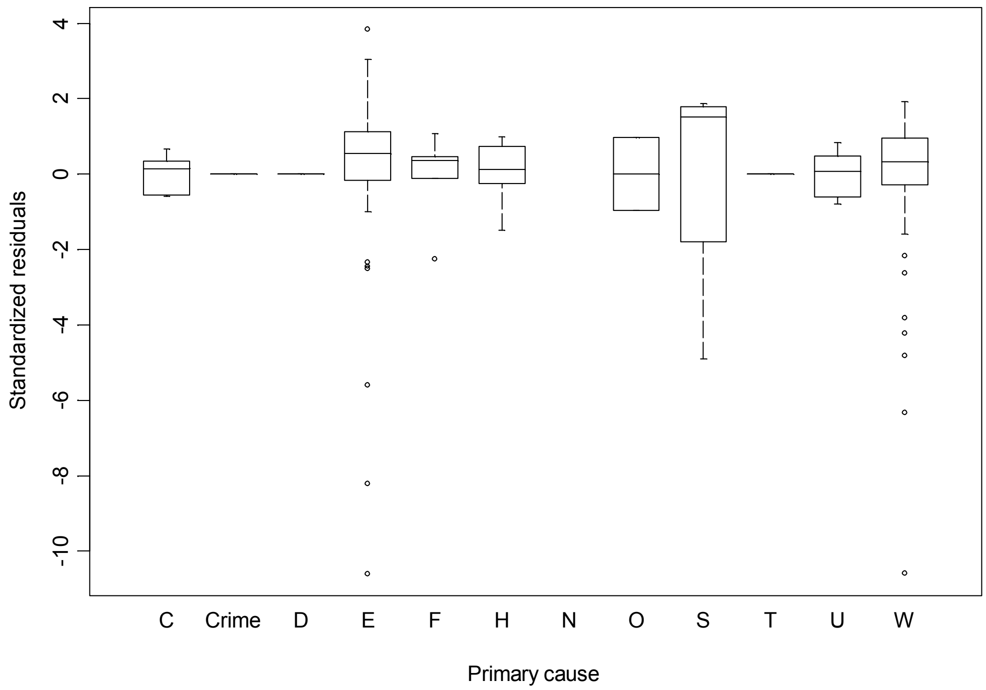
15
10
5
0
Logged customers lost
C
Crime
D
E
F
H
N
O
S
T
U
W
Primary cause

The only potential predictor showing much of a relationship with logged customers lost is logged MW loss. There is little evident seasonal effect. There is a primary cause effect, however, with fire, natural disaster, weather, and especially unknown causes having generally higher customer losses, and capacity shortage, operational error, and system protection having smaller losses. Note that these boxplots have been constructed so that the width of the box is proportional to the square root of the sample size for that group, so the wider the box, the more information there is for that group. It is evident that most incidents are either weather-related, or due to equipment failure.

A least squares regression implies that only logged MW is a significant predictor, but there is extreme nonconstant variance related to primary cause.

```
                   Df Sum of Sq  Mean Sq  F Value     Pr(F)
           Log.MW   1   67.7417 67.74171 17.05755 0.0000591
     Log.duration   1    3.1032  3.10323  0.78140 0.3780820
  Log.pop.density   1    0.0025  0.00249  0.00063 0.9800483
Log.total.customers 1    5.1732  5.17319  1.30262 0.2554946
    Primary.Cause  10   24.4770  2.44770  0.61634 0.7983204
           Season   3    4.8571  1.61902  0.40767 0.7477002
   Days.since.1990  1    2.4502  2.45015  0.61696 0.4333798
        Residuals 155  615.5610  3.97136
```

Here are side-by-side boxplots of the residuals separated by cause, which illustrates the nonconstant variance. Note that there is much higher variability in the residuals from the regression model for some causes than for others. This invalidates the inferences from the ordinary least squares model.



Weighted least squares (WLS) is used to correct for the nonconstant variance. In a WLS analysis, the events from causes with less variability, such as capacity shortage and fire, are weighted higher, while those from causes with more variability, such as equipment failure and system protection, are weighted lower. Here is output for the WLS model.

	Df	Sum of Sq	Mean Sq	F Value	Pr(F)
Log.MW	1	33.4173	33.41728	32.49694	0.0000001
Log.duration	1	0.2267	0.22668	0.22044	0.6393648
Log.pop.density	1	0.0177	0.01770	0.01722	0.8957766
Log.total.customers	1	3.9135	3.91349	3.80571	0.0528816
Primary.Cause	10	15.5513	1.55513	1.51230	0.1396358
Season	3	1.0843	0.36143	0.35148	0.7881295
Days.since.1990	1	2.8564	2.85637	2.77771	0.0976045
Residuals	155	159.3898	1.02832		

The (logged) MW effect is by far the strongest effect. The total number of customers served by the utility is also a (marginally) significant predictor of the customers lost. There is weak evidence of a time trend (p=.098), and weaker evidence of an effect related to cause (p=.14).

Here is output for the model:

```
Coefficients:
```

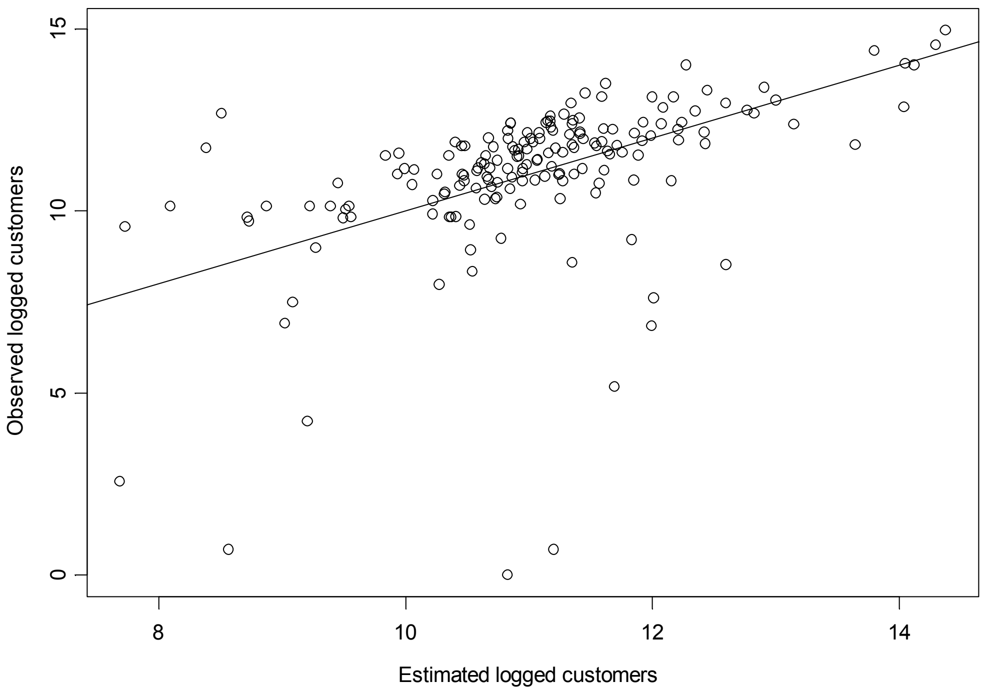
```
                       Value Std. Error t value Pr(>|t|)
          (Intercept)  4.1896  1.3327     3.1438  0.0020
               Log.MW  0.6572  0.1153     5.7006  0.0000
         Log.duration  0.0337  0.0718     0.4695  0.6394
      Log.pop.density -0.0195  0.1487    -0.1312  0.8958
  Log.total.customers  0.1820  0.0933     1.9508  0.0529
   Primary.CauseCrime  3.6575  1.1364     3.2184  0.0016
       Primary.CauseD  1.0868  1.1074     0.9814  0.3279
       Primary.CauseE  0.1542  0.4947     0.3117  0.7557
       Primary.CauseF  0.7506  0.5600     1.3404  0.1821
       Primary.CauseH  0.6864  0.5019     1.3676  0.1734
       Primary.CauseO  0.3431  1.0876     0.3155  0.7528
       Primary.CauseS -0.6940  1.7278    -0.4017  0.6885
       Primary.CauseT  1.4763  1.1351     1.3006  0.1953
       Primary.CauseU  1.0386  0.6317     1.6442  0.1022
       Primary.CauseW  0.4433  0.3795     1.1683  0.2445
         SeasonSpring -0.3259  0.4581    -0.7114  0.4779
         SeasonSummer -0.3630  0.3964    -0.9159  0.3612
         SeasonWinter -0.1314  0.4226    -0.3110  0.7562
      Days.since.1990  0.0001  0.0001     1.6666  0.0976

Residual standard error: 1.014 on 155 degrees of freedom
Multiple R-Squared: 0.479
F-statistic: 7.917 on 18 and 155 degrees of freedom, the p-value
is 1.787e-014
162 observations deleted due to missing values
```

The model implies that a 1% increase in MW lost is associated with a 0.66% increase in customers lost, holding all else in the model fixed; a 1% increase in total customers is associated with a 0.18% increase in customers lost, holding all else in the model fixed; and (marginally) each additional year is associated with an expected increase in customers lost of exp(.0365)=1.037, or a 3.7% annual increase in customers lost, holding all else in the model fixed. The (weak) primary cause effect is summarized by the adjusted means:

```
Primary.Cause
        C  Crime      D      E      F      H      O      S
   10.717 14.374 11.803 10.871 11.467 11.403 11.060 10.022
se  0.328  1.081  1.091  0.387  0.438  0.361  1.021  1.689

        T      U      W
   12.193 11.755 11.160
se  1.058  0.482  0.211
```

The adjusted means represent the estimated logged customers lost when all numerical predictors are at their mean values, and any other categorical predictors are accounted for. Given there is nonzero customer loss, customer losses are higher for crime, third party, demand reduction, and unknown causes, and lower for system protection, capacity shortage, equipment failure, and operational error, holding all else in the model fixed. Differences between adjusted means correspond to estimates of the multiplicative relative effect of the two causes. So, for example, an event related to crime is estimated to have exp(14.374-10.717) = exp(3.657)=38.7 times the customer loss of an event related to capacity shortage, holding all else in the model fixed.

There is a problem with this model, in that roughly 7-10 incidents had customer losses that were very unusually low. These show up at the bottom of the following plot. This is a plot of the observed (logged) customer losses versus the estimated (logged) losses, which would follow the line on the plot if the predictions were perfect:



The low incidents correspond to outages on March 4, 1991 (176 customers lost), March 18, 1993 (13 customers lost), July 23, 1999 (68 customers lost), May 15, 2003 (2 customers lost), July 2, 2003 (1 customer lost), and December 5, 2003 (2 customers lost). These incidents are poorly modeled with the information available.

If these incidents are omitted, the resultant inferences don't change materially, but are sharpened considerably:

	Df	Sum of Sq	Mean Sq	F Value	Pr(F)
Log.MW	1	28.26771	28.26771	61.98163	0.0000000
Log.duration	1	0.71290	0.71290	1.56314	0.2131658

```
    Log.pop.density   1   0.00016  0.00016  0.00035 0.9850837
Log.total.customers   1   2.79064  2.79064  6.11893 0.0144969
      Primary.Cause  10  16.46791  1.64679  3.61086 0.0002541
             Season   3   2.28335  0.76112  1.66887 0.1761861
    Days.since.1990   1   2.04398  2.04398  4.48175 0.0359196
          Residuals 149  67.95384  0.45607
```

Logged MW, logged total customers, cause, and a time trend are all strongly statistically significant.

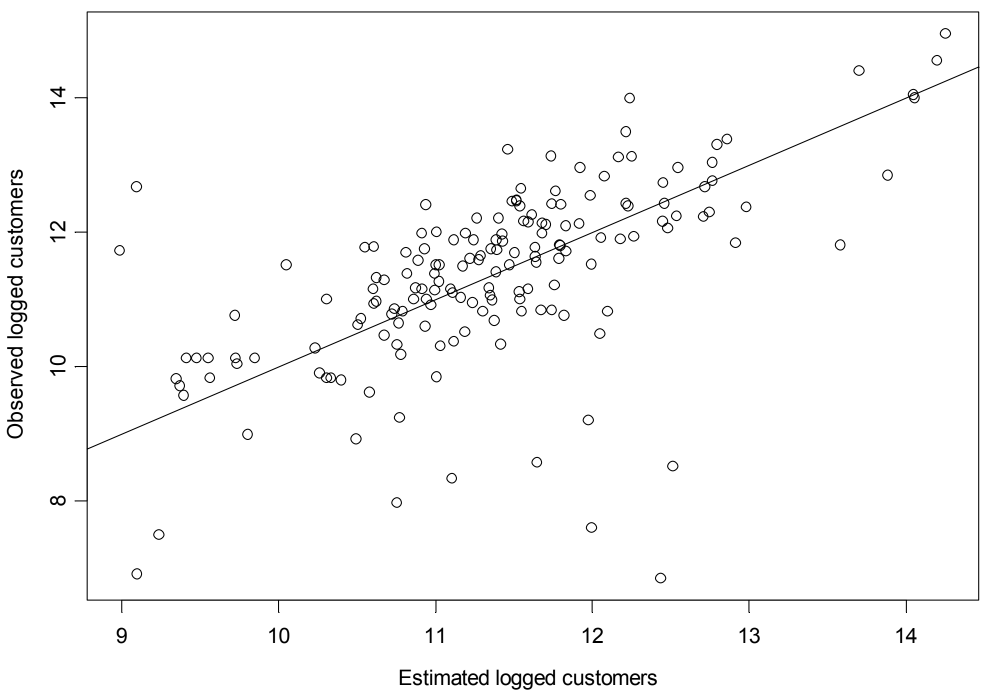
```
Coefficients:
                      Value Std. Error t value Pr(>|t|)
        (Intercept)  4.3597  0.9190     4.7439  0.0000
             Log.MW  0.6094  0.0774     7.8728  0.0000
       Log.duration  0.0611  0.0488     1.2503  0.2132
    Log.pop.density -0.0019  0.0998    -0.0187  0.9851
Log.total.customers  0.1622  0.0656     2.4736  0.0145
 Primary.CauseCrime  3.9378  0.7585     5.1915  0.0000
     Primary.CauseD  0.7722  0.7393     1.0445  0.2979
     Primary.CauseE  0.7895  0.3372     2.3415  0.0205
     Primary.CauseF  0.9240  0.3750     2.4642  0.0149
     Primary.CauseH  0.9103  0.3383     2.6908  0.0079
     Primary.CauseO  0.3595  0.7276     0.4941  0.6220
     Primary.CauseS  1.1428  1.3232     0.8637  0.3892
     Primary.CauseT  1.7655  0.7568     2.3329  0.0210
     Primary.CauseU  1.3134  0.4221     3.1117  0.0022
     Primary.CauseW  0.7239  0.2539     2.8515  0.0050
       SeasonSpring  0.2397  0.3096     0.7744  0.4399
       SeasonSummer -0.2825  0.2647    -1.0674  0.2875
       SeasonWinter  0.0290  0.2823     0.1028  0.9183
    Days.since.1990  0.0001  0.0001     2.1170  0.0359

Residual standard error: 0.6753 on 149 degrees of freedom
Multiple R-Squared: 0.6629
F-statistic: 16.28 on 18 and 149 degrees of freedom, the p-value
is 0
162 observations deleted due to missing values
```

A 1% increase in MW is associated with an estimated 0.61% increase in customers lost, holding all else in the model fixed; a 1% increase in total customers is associated with an estimated 0.16% increase in customers lost, holding all else in the model fixed (that is, as utilities get bigger, they suffer much less than proportional losses of customers in their incidents, holding all else fixed); each passing year is associated with an estimated 3.7% increase in customers lost given all else in the model is held fixed. The pattern related to causes is as follows:

```
Primary.Cause
       C  Crime      D      E      F      H      O      S
  10.657 14.595 11.430 11.447 11.581 11.568 11.017 11.800
```

```
se  0.219  0.721  0.728  0.265  0.293  0.243  0.682  1.299

        T      U      W
   12.423 11.971 11.381
se  0.705  0.321  0.142
```

We see that given there is nonzero customer loss, customer losses are higher for crime, third party, and unknown causes, and lower for capacity shortage and operational error, holding all else in the model fixed. Predictions based on the model follow the observed values reasonably well, although there are still more unusually low values than unusually high values:



It is not clear that logged MW should be used as a predictor of logged customers lost, since one could argue that both are results of the inherent severity of the incident. This can be explored by refitting the regression models without the logged MW predictor. We start with an ordinary least squares model, but not surprisingly, this exhibits nonconstant variance. The weighted least squares model is as follows:

```
                 Df Sum of Sq  Mean Sq  F Value     Pr(F)
    Log.duration  1    1.5852 1.585234 1.538035 0.2164727
 Log.pop.density  1    1.1451 1.145137 1.111041 0.2932230
```

```
Log.total.customers   1    6.2401 6.240108 6.054314 0.0147849
      Primary.Cause  11   54.6587 4.968974 4.821027 0.0000016
             Season   3    0.4849 0.161617 0.156805 0.9251973
    Days.since.1990   1    0.4341 0.434131 0.421205 0.5171368
          Residuals 186  191.7080 1.030688
```

The only significant terms are those for logged total customers and primary cause. Here is a summary of the model:

```
Coefficients:
                      Value Std. Error t value Pr(>|t|)
        (Intercept)  5.7295  1.4848     3.8586  0.0002
       Log.duration  0.0894  0.0721     1.2402  0.2165
    Log.pop.density  0.1475  0.1399     1.0541  0.2932
Log.total.customers  0.2343  0.0952     2.4606  0.0148
 Primary.CauseCrime  3.6588  1.1444     3.1970  0.0016
     Primary.CauseD  1.3423  1.1239     1.1943  0.2339
     Primary.CauseE  0.6946  0.4811     1.4439  0.1505
     Primary.CauseF  1.4748  0.8339     1.7687  0.0786
     Primary.CauseH  1.2778  0.5416     2.3592  0.0194
     Primary.CauseN  5.3388  1.5278     3.4945  0.0006
     Primary.CauseO  1.6409  1.0981     1.4943  0.1368
     Primary.CauseS -0.1313  1.8096    -0.0726  0.9422
     Primary.CauseT  3.2755  1.0816     3.0285  0.0028
     Primary.CauseU  3.2880  0.6495     5.0622  0.0000
     Primary.CauseW  1.4214  0.3548     4.0056  0.0001
       SeasonSpring -0.2523  0.4379    -0.5762  0.5652
       SeasonSummer -0.2459  0.3932    -0.6254  0.5325
       SeasonWinter -0.2514  0.4172    -0.6027  0.5475
    Days.since.1990  0.0001  0.0001     0.6490  0.5171

Residual standard error: 1.015 on 186 degrees of freedom
Multiple R-Squared: 0.2663
F-statistic: 3.75 on 18 and 186 degrees of freedom, the p-value
is 2.06e-006
```

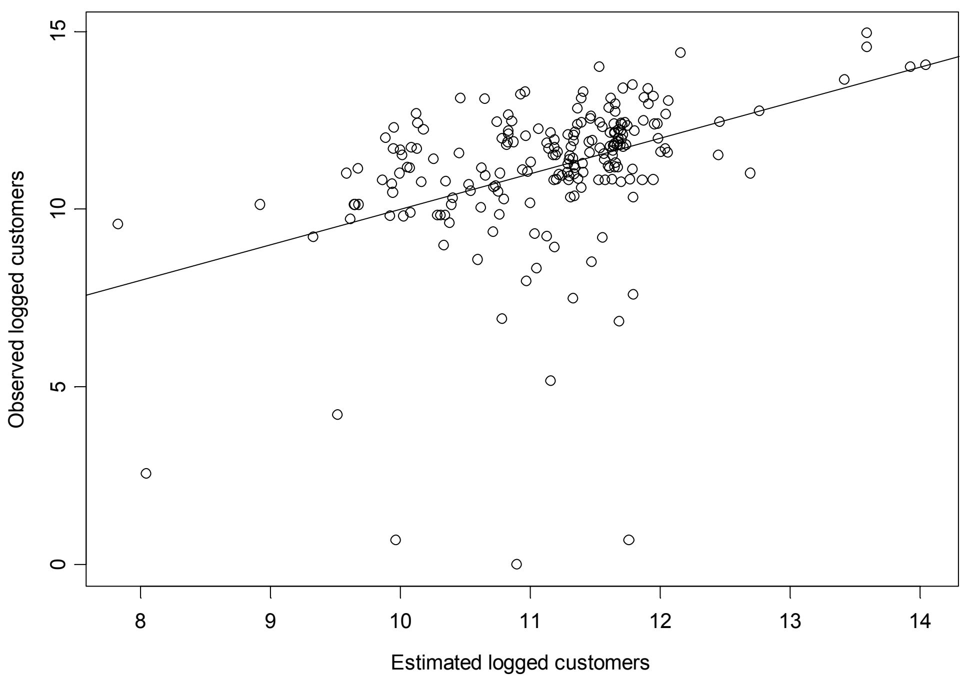
A 1% increase in total customers is associated with a 0.23% estimated increase in customers lost, holding all else in the model fixed. The primary cause effect is summarized by the adjusted means:

```
Primary.Cause
       C  Crime      D      E      F      H      N      O
```

```
    9.932 13.590 11.274 10.626 11.406 11.209 15.270 11.572
se  0.320  1.073  1.076  0.365  0.768  0.420  1.498  1.049

        S      T      U      W
    9.800 13.207 13.220 11.353
se  1.783  1.042  0.586  0.185
```

Customer losses are higher for natural disaster, crime, unknown causes, and third party, and lower for system protection, capacity shortage, and equipment failure, holding all else in the model fixed. This might be viewed as a more intuitive result than that in the earlier model, since the largest customer losses are coming from causes that are clearly beyond the control of the utility, while the smallest losses are coming from causes that are internal to the utility.

The unusually small customer losses still show up as distinct:



If these incidents are omitted, logged duration now comes in as a significant predictor.

```
                Df  Sum of Sq  Mean Sq  F Value     Pr(F)
Log.duration     1    2.56276 2.562762 5.232056 0.0233378
```

```
    Log.pop.density   1   0.77118 0.771181 1.574418 0.2111933
Log.total.customers   1   3.08369 3.083692 6.295570 0.0129871
      Primary.Cause  11  50.31277 4.573888 9.337910 0.0000000
             Season   3   2.10399 0.701330 1.431813 0.2350431
    Days.since.1990   1   0.45808 0.458078 0.935199 0.3348132
          Residuals 180  88.16747 0.489819


Coefficients:
                      Value Std. Error t value Pr(>|t|)
        (Intercept)  6.4084  1.0787     5.9409  0.0000
       Log.duration  0.1163  0.0508     2.2874  0.0233
    Log.pop.density  0.1218  0.0970     1.2548  0.2112
Log.total.customers  0.1768  0.0705     2.5091  0.0130
 Primary.CauseCrime  3.9623  0.7907     5.0113  0.0000
     Primary.CauseD  1.0758  0.7762     1.3860  0.1675
     Primary.CauseE  1.2282  0.3371     3.6429  0.0004
     Primary.CauseF  1.5693  0.5756     2.7262  0.0070
     Primary.CauseH  1.4230  0.3764     3.7803  0.0002
     Primary.CauseN  4.7145  1.0940     4.3093  0.0000
     Primary.CauseO  1.5332  0.7595     2.0189  0.0450
     Primary.CauseS  1.5843  1.4367     1.1027  0.2716
     Primary.CauseT  3.3238  0.7458     4.4568  0.0000
     Primary.CauseU  3.3640  0.4484     7.5030  0.0000
     Primary.CauseW  1.5631  0.2450     6.3804  0.0000
       SeasonSpring  0.2893  0.3055     0.9467  0.3451
       SeasonSummer -0.1906  0.2720    -0.7007  0.4844
       SeasonWinter -0.1058  0.2883    -0.3672  0.7139
    Days.since.1990  0.0001  0.0001     0.9671  0.3348

Residual standard error: 0.6999 on 180 degrees of freedom
Multiple R-Squared: 0.4231
F-statistic: 7.335 on 18 and 180 degrees of freedom, the p-value
is 5.751e-014
```

A 1% increase in duration is associated with an estimated 0.12% increase in customers lost, holding all else in the model fixed; a 1% increase in customers is associated with an estimated 0.18% increase in customers lost, holding all else in the model fixed. The primary cause effect is summarized below:

```
Primary.Cause
        C  Crime      D      E      F      H      N      O
    9.960 13.923 11.036 11.189 11.530 11.383 14.675 11.494
se  0.221  0.741  0.742  0.258  0.530  0.293  1.075  0.725
```

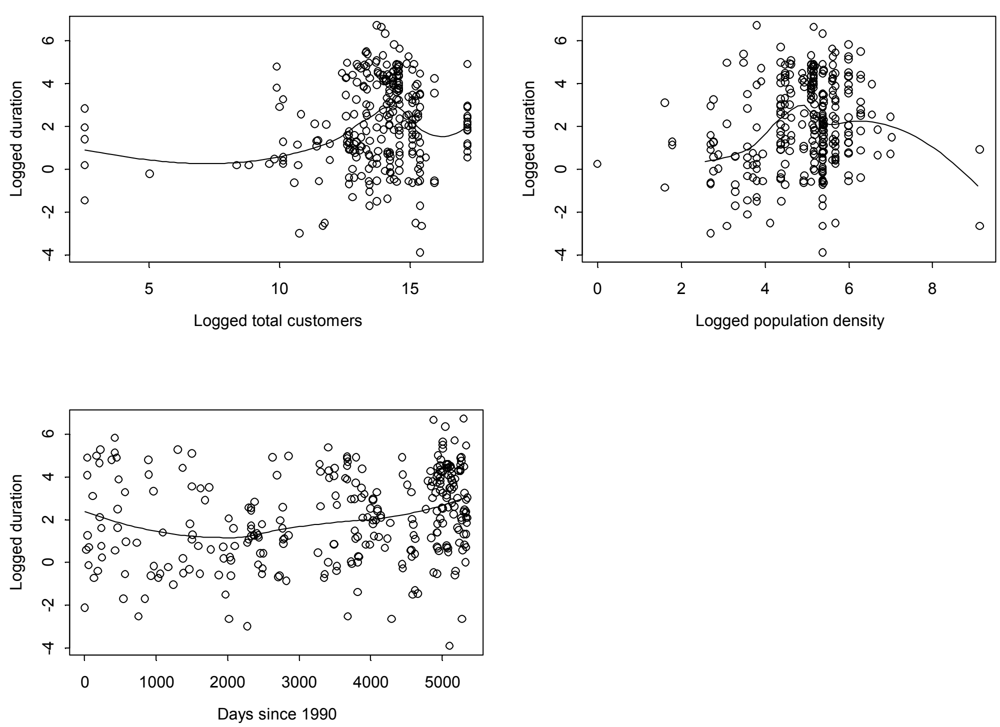
	S	T	U	W
	11.545	13.284	13.324	11.524
se	1.421	0.718	0.405	0.128

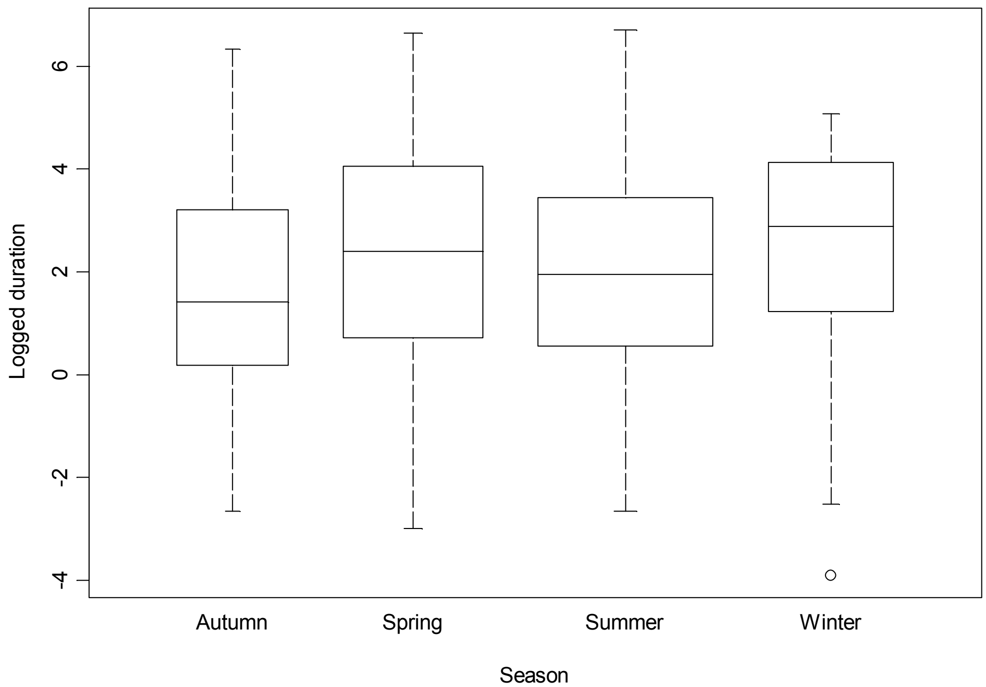
Customer losses are higher for natural disaster, crime, unknown causes, and third party, and lower for capacity shortage, demand reduction, and equipment failure, holding all else in the model fixed. Although demand reduction has replaced system protection as being associated with low customer losses when the smallest losses are omitted, the pattern still remains: the largest customer losses are coming from causes that are clearly beyond the control of the utility, while the smallest losses are coming from causes that are internal to the utility.

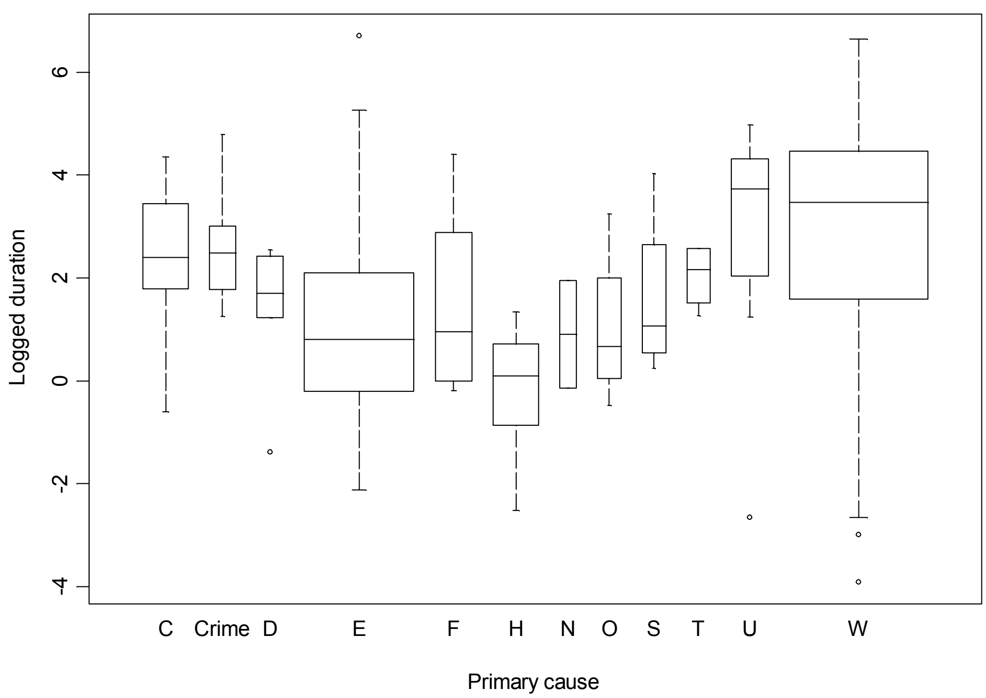
B. Analysis of duration at the event level

This section examines regression modeling for the (logged) duration of each incident. As was noted earlier, this allows for event-level characteristics to be used as predictors, but is based on a response variable that is much more variable than in the three-, six-, and twelve-month average analyses summarized earlier.

First, here are plots of the observed relationships.




Logged duration
6
4
2
0
-2
-4
Autumn
Spring
Summer
Winter
Season

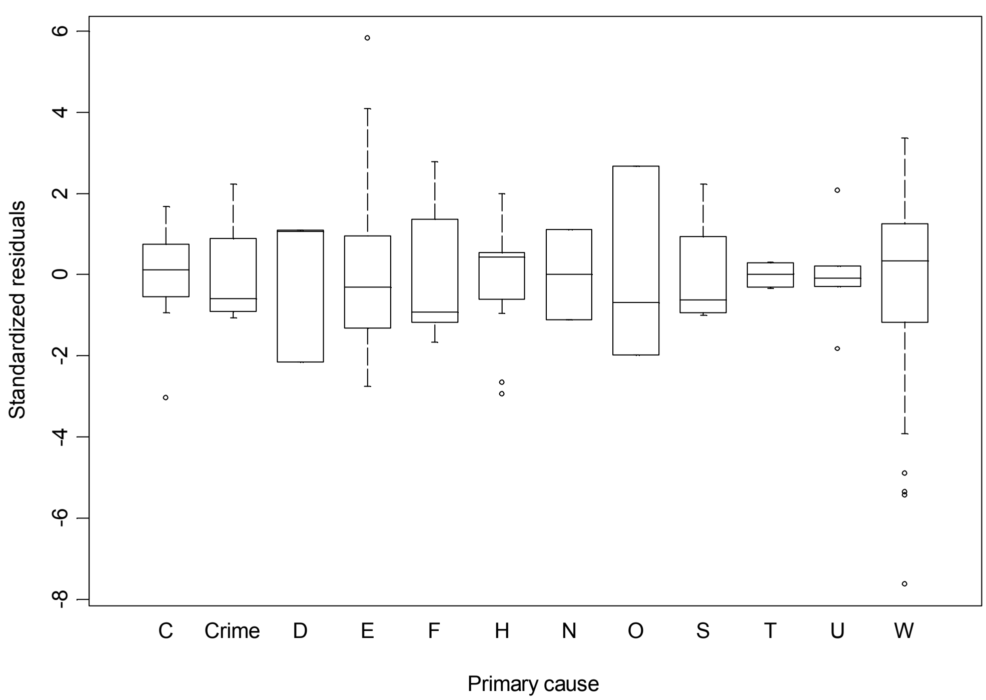

Logged duration
6
4
2
0
-2
-4
C
Crime
D
E
F
H
N
O
S
T
U
W
Primary cause

We see that there is little evidence of a relationship between logged duration and logged total customers. There is evidence of a positive relationship with logged population density (ignoring the two rare events at the very high population density level). There is weak evidence of the time trend on duration (note that since this plot is in the logged scale, trends upwards will be less apparent than in the original scale). There is some evidence of a season effect, with winter and spring events longer and autumn and summer events shorter. There is a clear relationship with primary cause. Note in particular that the two most common causes, equipment failure and weather are very different, with the former associated with shorter events and the latter associated with longer ones.

A least squares regression implies that logged population density, primary cause, and season are significant predictors, but there is extreme nonconstant variance related to primary cause.

	Df	Sum of Sq	Mean Sq	F Value	Pr(F)
Log.pop.density	1	15.7092	15.70916	5.043797	0.0255918
Log.total.customers	1	0.1415	0.14149	0.045427	0.8313946
Primary.Cause	11	202.8429	18.44027	5.920681	0.0000000
Season	3	24.3224	8.10748	2.603098	0.0525254
Days.since.1990	1	2.2344	2.23440	0.717407	0.3978090
Residuals	249	775.5232	3.11455		

Here are side-by-side boxplots of the residuals separated by cause, which illustrates the nonconstant variance.



Weighted least squares (WLS) is used to correct for the nonconstant variance. In this analysis, events from causes with less variability, such as capacity shortage, human error, third party, and unknown, are weighted higher, while those from causes with more variability, such as demand reduction, equipment failure, operational error, and weather, are weighted lower. Here is output for the WLS model.

```
                     Df Sum of Sq  Mean Sq  F Value     Pr(F)
    Log.pop.density   1   11.8728 11.87284 11.64325 0.0007518
Log.total.customers   1    0.0243  0.02433  0.02386 0.8773556
      Primary.Cause  11   82.2162  7.47420  7.32967 0.0000000
             Season   3    7.6400  2.54667  2.49743 0.0602774
    Days.since.1990   1    0.0233  0.02328  0.02283 0.8800299
          Residuals 249  253.9101  1.01972
```

The inferential results are relatively unchanged.

Here is output for the model:

```
Coefficients:
                      Value Std. Error t value Pr(>|t|)
        (Intercept)  0.3099  0.9051     0.3424  0.7323
    Log.pop.density  0.3324  0.0974     3.4122  0.0008
Log.total.customers  0.0078  0.0504     0.1545  0.8774
 Primary.CauseCrime  0.0212  0.8518     0.0249  0.9801
     Primary.CauseD -1.1692  1.1500    -1.0167  0.3103
     Primary.CauseE -0.6795  0.4078    -1.6662  0.0969
     Primary.CauseF -0.2449  0.6356    -0.3854  0.7003
     Primary.CauseH -2.2477  0.5341    -4.2085  0.0000
     Primary.CauseN -1.6121  1.2369    -1.3033  0.1937
     Primary.CauseO -0.5587  1.4469    -0.3861  0.6998
     Primary.CauseS  0.2674  0.8710     0.3070  0.7591
     Primary.CauseT  0.4361  0.4262     1.0232  0.3072
     Primary.CauseU  1.7313  0.6414     2.6993  0.0074
     Primary.CauseW  0.9379  0.3760     2.4945  0.0133
       SeasonSpring  0.0507  0.3721     0.1362  0.8918
       SeasonSummer -0.3310  0.3323    -0.9959  0.3203
       SeasonWinter  0.4791  0.3673     1.3043  0.1933
    Days.since.1990  0.0000  0.0001     0.1511  0.8800

Residual standard error: 1.01 on 249 degrees of freedom
Multiple R-Squared: 0.3218
F-statistic: 6.949 on 17 and 249 degrees of freedom, the p-value
is 1.111e-013
133 observations deleted due to missing values
```

The model implies that a 1% increase in population density is associated with a 0.33% increase in duration, holding all else in the model fixed. The primary cause and season effects are summarized by the adjusted means:

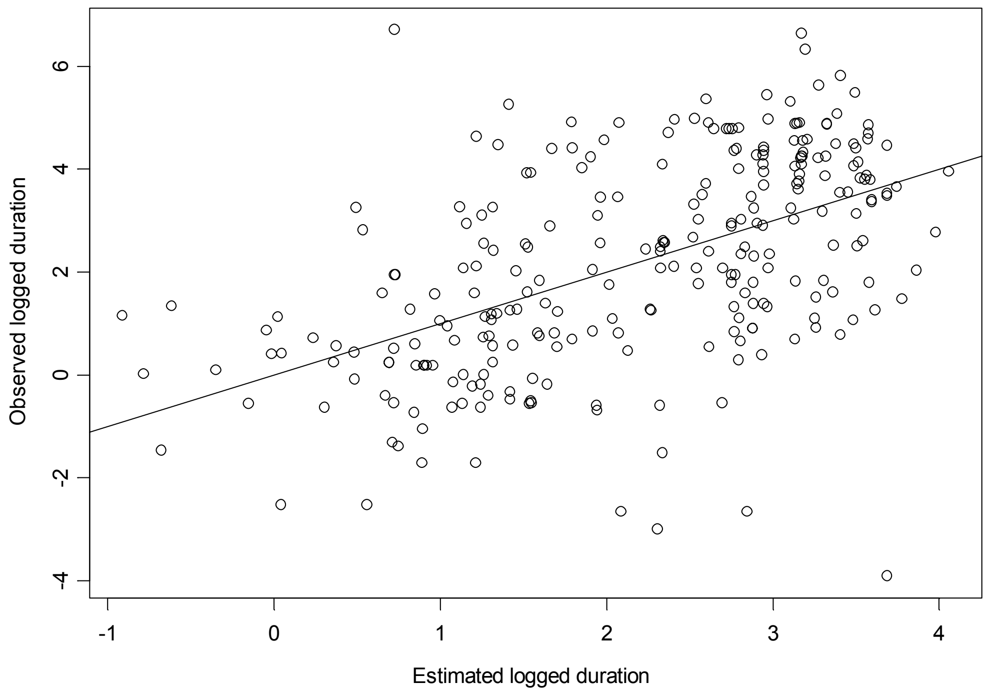
```
Primary.Cause
          C    Crime        D        E        F        H        N
    2.1383  2.1595  0.9691  1.4588  1.8934 -0.1094  0.5262
se  0.3410  0.7777  1.1014  0.2056  0.5381  0.3960  1.1786

          O        S        T        U        W
    1.5796  2.4057  2.5744  3.8696  3.0762
se  1.4105  0.7945  0.2536  0.5452  0.1789
```

```
 Season
   Autumn Spring Summer Winter
   1.8288 1.8794 1.4978 2.3078
se 0.3478 0.3106 0.2460 0.2919
```

The season effect is noting that, holding all else in the model fixed, winter events have expected duration that is 2.25 times the duration of summer events, with autumn and spring in between. Presumably this has something to do with issues like the difficulty in traveling to downed power lines in snow and ice.

The adjusted means for primary cause show that, holding all else fixed, incidents caused by human error, natural disaster, demand reduction, and equipment failure tend to be shorter, while those caused by system protection, third party, weather, and unknown causes tend to be longer. Considering that more than ¾ of the events are caused by equipment failure or weather, the contrast between the two is particularly important (events caused by weather are expected to last more than five times longer than those caused by equipment failure, holding all else in the model fixed).

The plot below shows that there isn't any evidence of any systematic problem with the predictions from this model, although two incidents are particularly poorly predicted (one high, the other low). These correspond to a weather-related event on December 22, 2003 of .02 hours, and an equipment-related event on July 6, 2004 of 822.0 hours:



If these incidents are omitted, the inferences remain the same, but are stronger than before:

	Df	Sum of Sq	Mean Sq	F Value	Pr(F)
Log.pop.density	1	13.5121	13.51212	14.85111	0.0001484
Log.total.customers	1	0.0074	0.00745	0.00819	0.9279762
Primary.Cause	11	90.5572	8.23247	9.04827	0.0000000
Season	3	11.2945	3.76483	4.13790	0.0069308
Days.since.1990	1	0.0036	0.00364	0.00400	0.9496319
Residuals	247	224.7303	0.90984		

Here is a summary of the model:

Coefficients:

	Value	Std. Error	t value	Pr(>|t|)
(Intercept)	0.2569	0.8564	0.3000	0.7644
Log.pop.density	0.3557	0.0923	3.8537	0.0001
Log.total.customers	0.0043	0.0477	0.0905	0.9280
Primary.CauseCrime	-0.0280	0.8048	-0.0348	0.9723
Primary.CauseD	-1.1358	1.0865	-1.0454	0.2969
Primary.CauseE	-0.7180	0.3863	-1.8585	0.0643
Primary.CauseF	-0.1610	0.6006	-0.2681	0.7888

```
      Primary.CauseH -2.2390  0.5048    -4.4355  0.0000
      Primary.CauseN -1.7305  1.1688    -1.4806  0.1400
      Primary.CauseO -0.5046  1.3668    -0.3692  0.7123
      Primary.CauseS  0.3997  0.8231     0.4855  0.6277
      Primary.CauseT  0.5454  0.4031     1.3532  0.1772
      Primary.CauseU  1.8346  0.6061     3.0268  0.0027
      Primary.CauseW  1.0477  0.3561     2.9424  0.0036
        SeasonSpring  0.0403  0.3515     0.1148  0.9087
        SeasonSummer -0.4000  0.3144    -1.2724  0.2044
        SeasonWinter  0.5937  0.3480     1.7062  0.0892
     Days.since.1990  0.0000  0.0001    -0.0632  0.9496

Residual standard error: 0.9539 on 247 degrees of freedom
Multiple R-Squared: 0.3705
F-statistic: 8.55 on 17 and 247 degrees of freedom, the p-value
is 0
133 observations deleted due to missing values
```

A 1% increase in population density is associated with an estimated 0.36% increase in customers lost, holding all else in the model fixed. The patterns related to causes and seasons are as follows:

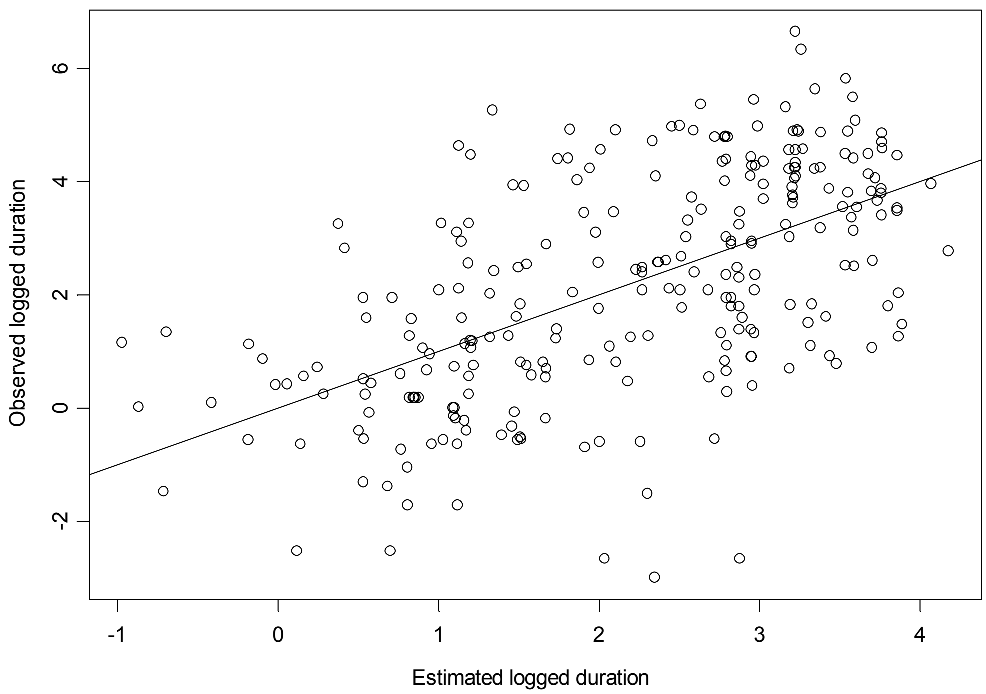
```
Primary.Cause
         C   Crime       D       E       F       H       N
    2.1135  2.0854  0.9776  1.3954  1.9524 -0.1255  0.3829
se  0.3225  0.7346  1.0403  0.1952  0.5084  0.3739  1.1135



         O       S       T       U       W
    1.6088  2.5131  2.6589  3.9481  3.1611
se  1.3324  0.7508  0.2401  0.5152  0.1699


 Season
   Autumn Spring Summer Winter
   1.8308 1.8711 1.4308 2.4245
se 0.3285 0.2933 0.2327 0.2767
```

The season effect implies that, holding all else in the model fixed, winter events have expected duration that is 2.7 times the duration of summer events, with autumn and spring events in the middle.

The adjusted means for primary cause show that, holding all else fixed, incidents caused by human error, natural disaster, demand reduction, and equipment failure tend to be shorter, while those caused by system protection, third party, weather, and unknown causes tend to be longer.

In particular, events caused by weather are expected to last almost six times longer than those caused by equipment failure, holding all else fixed.

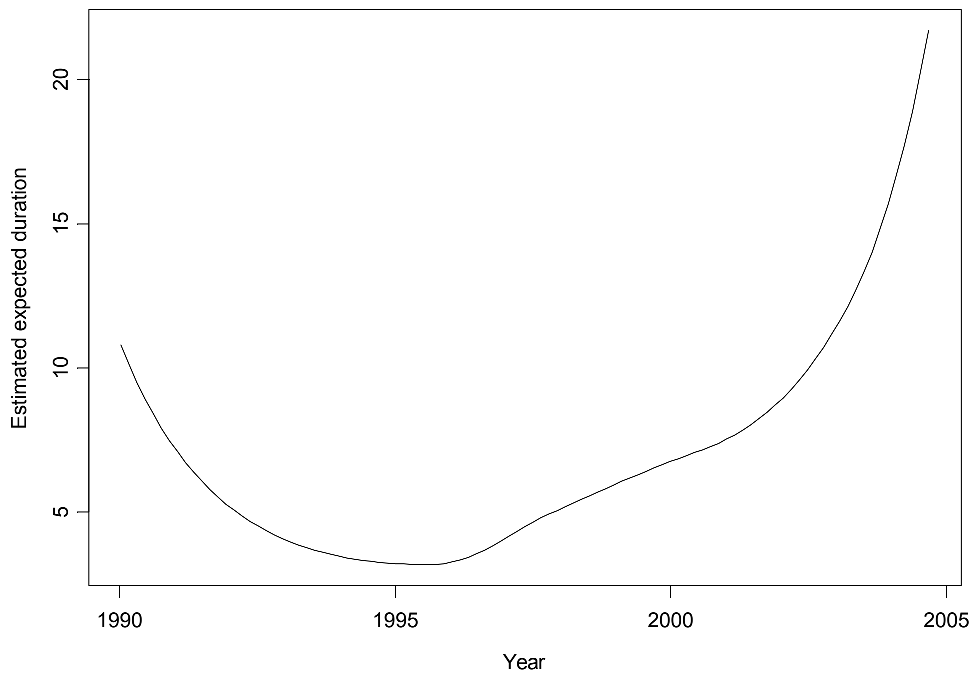
The model tracks the observed logged durations reasonably well.



The absence of a time trend in this model, given the earlier evidence for one in the season-level analysis, is worth comment. An analysis just on the time trend (Days since 1990) does yield statistical significance, as the following output shows:

```
Coefficients:
                 Value Std. Error t value Pr(>|t|)
    (Intercept) 1.1828 0.2461     4.8067  0.0000
Days.since.1990 0.0003 0.0001     3.7625  0.0002

Residual standard error: 1.191 on 299 degrees of freedom
Multiple R-Squared: 0.0452
F-statistic: 14.16 on 1 and 299 degrees of freedom, the p-value
is 0.0002024
99 observations deleted due to missing values
```

This model implies an estimated 11.6% annual increase in duration (exp(365*.0003)=1.116), which is not that different from the 14.6% found from the seasonal data (it is smaller because of the increased noise in the incident-level data). This reinforces the impression that the overall duration time trend, ignoring specific information about the individual events, is real. Here is a loess curve for the estimated duration using these incident-level data:



This U-shaped pattern is broadly similar to the one evident in the season-level data. The estimated annual changes in duration based on this curve are as follows:

```
1991 -0.28198311
1992 -0.21725013
1993 -0.14403860
1994 -0.07117135
1995  0.01160909
1996  0.25814792
1997  0.24967458
1998  0.16656962
1999  0.13245628
2000  0.11124667
2001  0.18375624
2002  0.28224436
2003  0.40632285
```

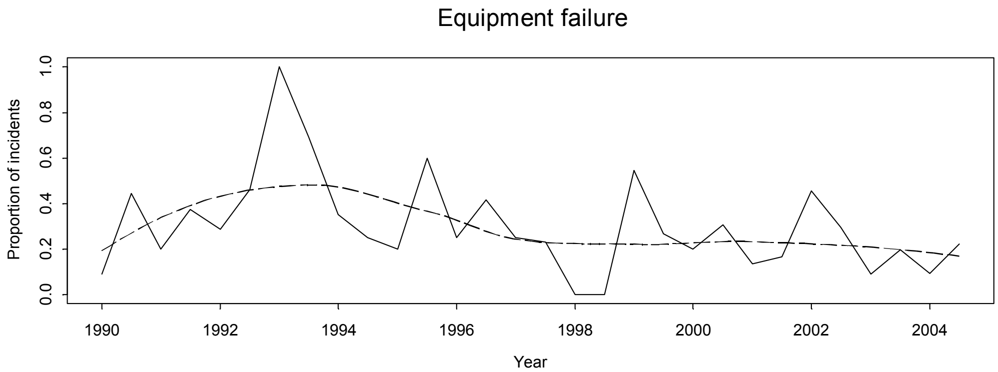
These can be compared to the season-level numbers from Section I. C., and they are very similar (a bit smaller, which reflects the additional noise in the event-level data). Up until 1994, durations were getting shorter. This turned around in 1995, and for a few years the average duration went up 15-25% annually. This was followed by a long period (1998-2001) of fairly stable growth of 10-20%. Finally, from 2002 on, average durations have started increasing again at a high 30-40% rate. Thus, the constant estimate of 11.6% annually obtained from the regression model actually seems to mask some very different periods in average duration change.

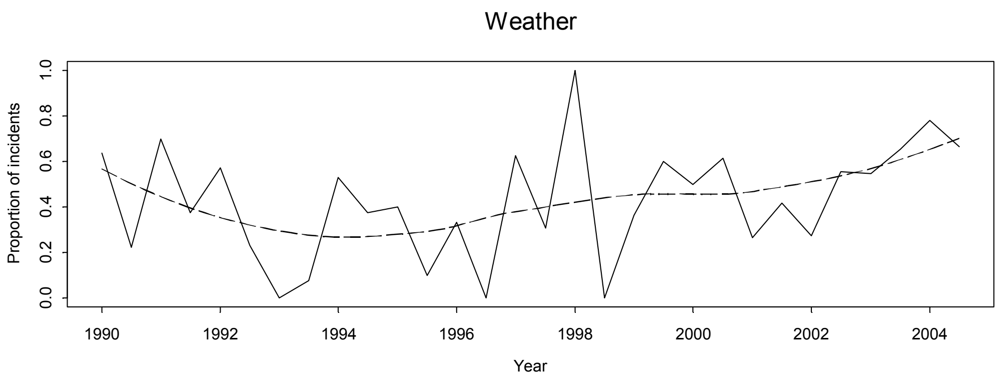
There is another factor at play here that leads to the time trend disappearing in the regression model. The models in this section take into account the other potential predictors. Note the results of a model that adds season and logged population density to the time trend:

```
                     Df Sum of Sq  Mean Sq  F Value     Pr(F)
    Days.since.1990   1    7.1460  7.14605 5.527602 0.0194659
             Season   3    2.1804  0.72681 0.562200 0.6404119
    Log.pop.density   1   10.1482 10.14815 7.849787 0.0054649
Log.total.customers   1    3.5317  3.53168 2.731823 0.0995739
          Residuals 260  336.1263  1.29279
```

The time variable is still highly significant, even with these other predictors. However, when primary cause is added, its significance disappears (as in the table earlier in this section), which shows that it is the primary cause effect that is driving the apparent time trend effect. (Note also that including primary cause allows a seasonal effect to show up, and the logged customers effect to disappear.)

Recall that more than ¾ of the incidents are either equipment failure- or weather-related, and that incidents caused by equipment failure tend to be shorter, while weather-related ones tend to be longer. In fact, weather-related incidents are becoming more common, while equipment failure-related ones are becoming less common, and this accounts for much of the overall pattern of increasing average durations by season. The following plots show the changing proportions of incidents from these two causes at the semiannual level; it is clear that since the mid 1990s, relatively speaking equipment failures are going down and weather incidents are going up, while before that the opposite pattern was occurring. This corresponds exactly to the drop in durations up to 1995, and the increase since then noted earlier. Thus, it would seem that further study of why equipment failures are becoming less common (relatively speaking) and weather-related events are becoming more common is warranted.


Equipment failure
Proportion of incidents
0.0
0.2
0.4
0.6
0.8
1.0
1990
1992
1994
1996
1998
2000
2002
2004
Year


Weather
Proportion of incidents
0.0
0.2
0.4
0.6
0.8
1.0
1990
1992
1994
1996
1998
2000
2002
2004
Year

References

1. Simonoff, J.S. (1996), *Smoothing Methods in Statistics*, Springer-Verlag, New York.
2. Simonoff, J.S. (2003), *Analyzing Categorical Data*, Springer-Verlag, New York.