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Electricity Case: Statistical Analysis of Electric Power Outages

CREATE Report

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New York University-Wagner Graduate School, Institute for Civil Infrastructure Systems**

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HOMELAND SECURITY CENTER

**Center for Risk and Economic Analysis of Terrorism Events
University of Southern California
Los Angeles, CA**

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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 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 9.7% annual increase in incident rate given season (that is, “holding season constant”) 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 more 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 is 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 occurred were used in the analyses to gain a better understanding of the three key outcome 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 were higher for events caused by natural disaster, crime, unknown causes, and third party, and lower for incidents resulting from 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.

The event-level models can be used to construct predictions for outage outcomes based on different scenarios. We look at scenarios for New York, Chicago, San Francisco, and Seattle. Using the characteristics of the utilities in these four cities, the estimated expected duration and estimated expected customer loss (given nonzero loss) of an incident, separated by season and cause, can be determined for each city. We also construct 50% prediction intervals for duration and for customer loss (given that the loss is nonzero) for any cause and season for the four cities.

Acknowledgements

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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*

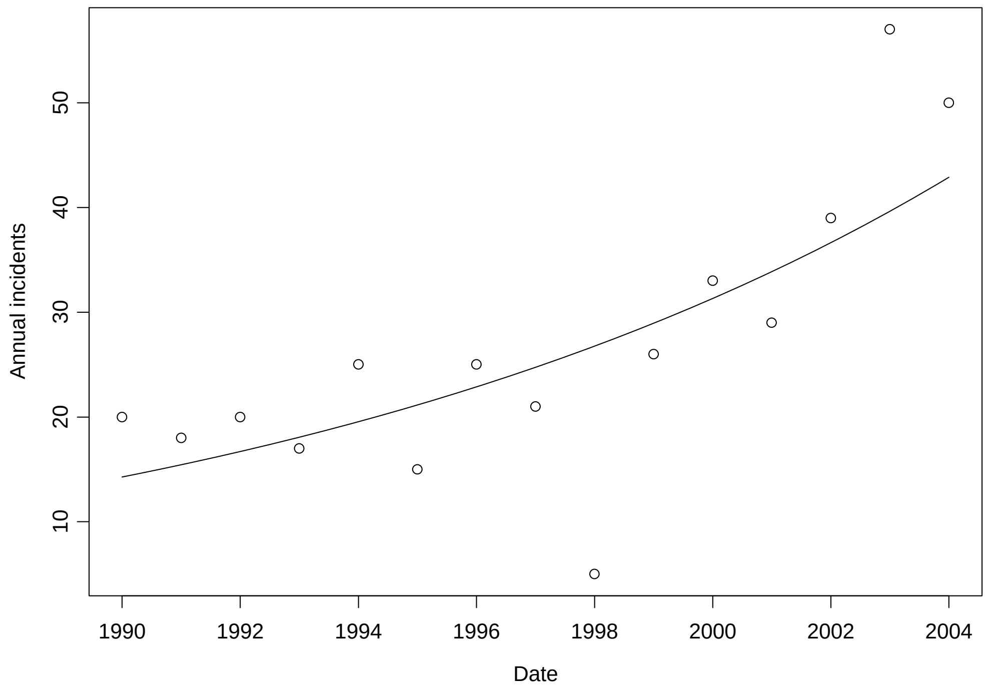
A. Analysis of the number of incidents over time

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 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.

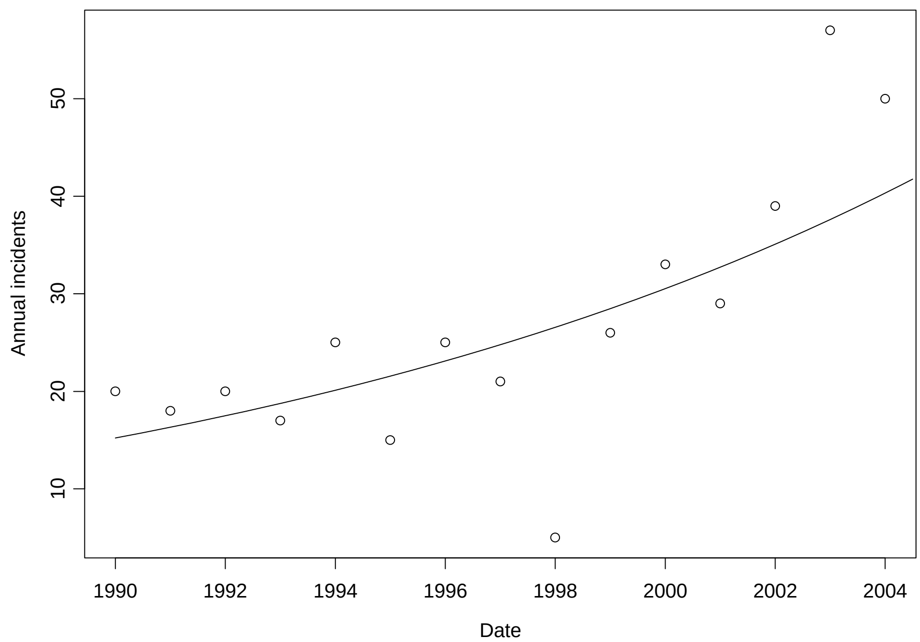
There is a flaw in this analysis, in that the Poisson regression model does not fit the data well, because of *overdispersion*. Overdispersion occurs when there is unmodeled heterogeneity in the data. The Poisson model treats each year as identical, other than the actual difference in year. This is unlikely 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:

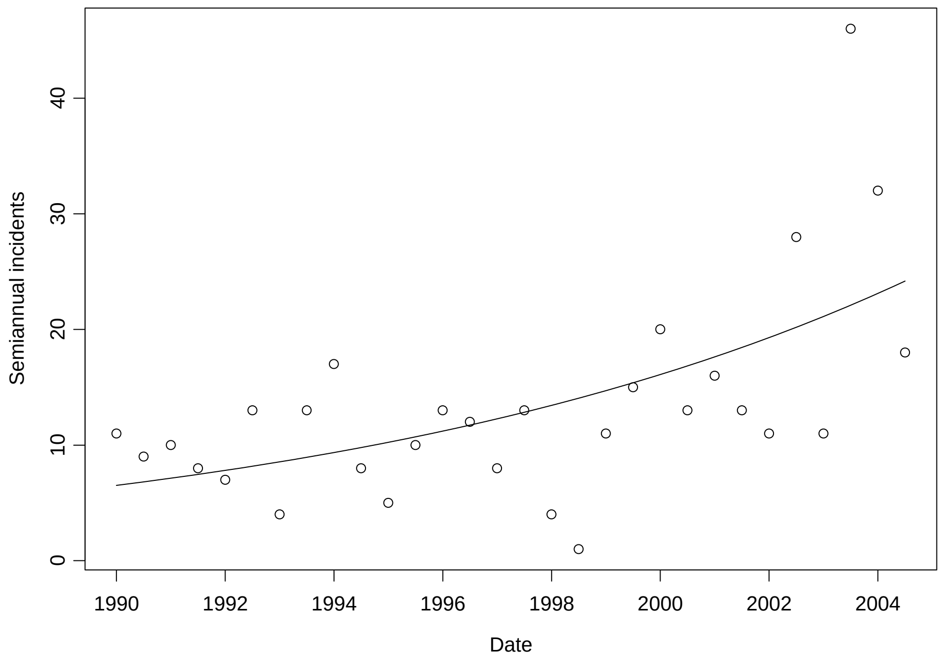
```
Coefficients:
                    Value  Std. Error      Wald
(Intercept) -135.76307835 47.91257415 -2.833558
       Date    0.06959082  0.02399384  2.900362
```

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 Poisson and negative binomial modeling of 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.

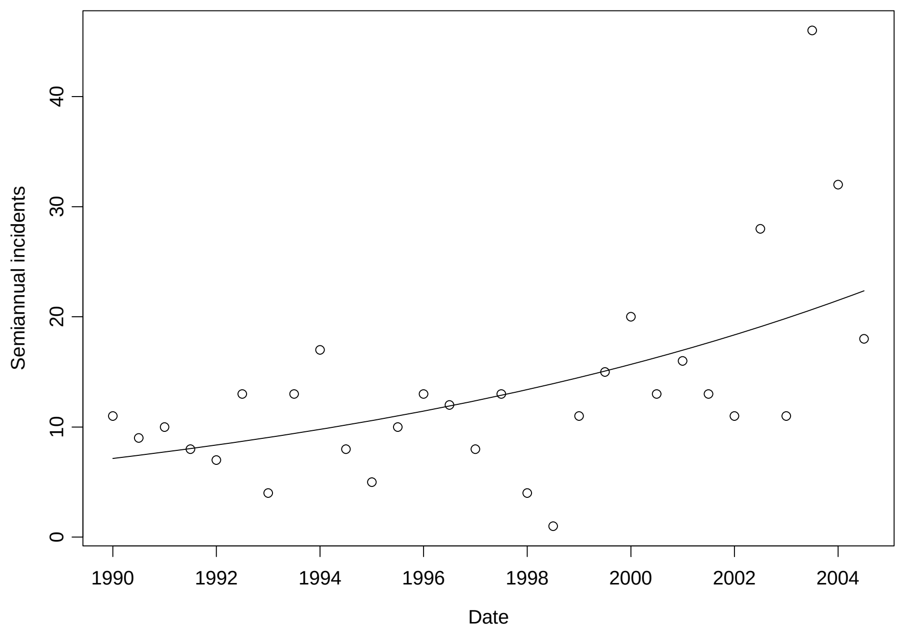
1. The implications regarding the increase in incidents are similar for these semiannual data to those for the annual data. The estimated rate of increase is 9.5% annually, similar to what was seen before.
2. The estimated increase is even more significantly different from zero, with a Wald statistic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

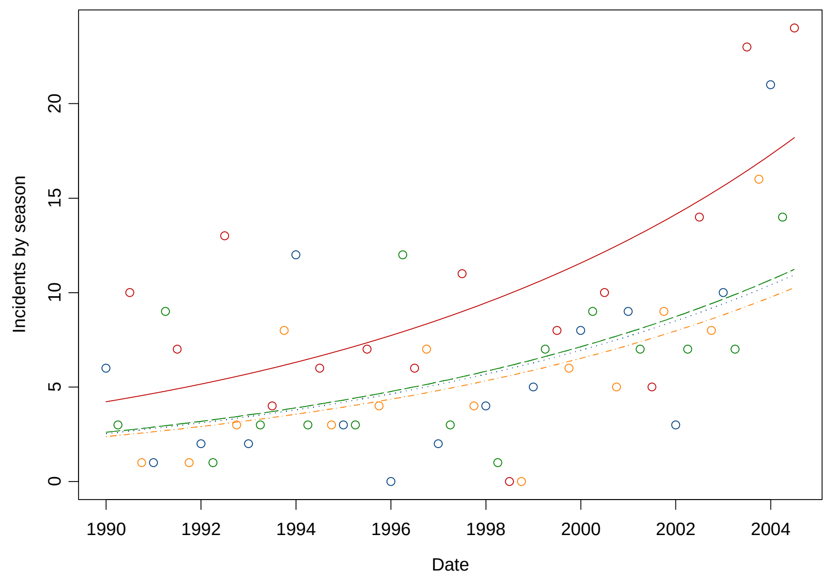
```
Coefficients:
                    Value  Std. Error      Wald
(Intercept) -154.57911519 44.34697394 -3.485674
       Date    0.07866603  0.02220172  3.543240
```

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 (dotted line), the spring points and line are in green (dashed line), the summer points and line are in red (solid line), and the autumn points and line are in orange (dotted-and-dashed line). 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. Once again analyses are based on Poisson and negative binomial regression models.



1. Taking the season into account, the estimated annual increase in incident rate is 10.6%. 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 8.0). Here is output; the tests for the seasons take Autumn as a baseline category.

```
Coefficients:
                    Value  Std. Error       Wald
 (Intercept) -199.65377545 25.23546760 -7.9116337
        Date    0.10076407  0.01262495  7.9813418
SeasonSpring    0.09030258  0.15677222  0.5760114
SeasonSummer    0.57368747  0.14186760  4.0438230
SeasonWinter    0.06404012  0.15980743  0.4007330
```

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 (and statistically significantly) 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=137.2) and deviance (G^2=141.4, both on 53 degrees of freedom) tests indicate lack of fit. A negative binomial fit to these data is as follows:

```
                    Value  Std. Error        Wald
 (Intercept) -182.85082327 39.64193987 -4.6125599
        Date    0.09234319  0.01984104  4.6541509
SeasonSpring    0.13493740  0.23978936  0.5627331
SeasonSummer    0.62850560  0.22970540  2.7361377
SeasonWinter    0.05084357  0.24537984  0.2072035
```

The model fits the data adequately, but not as well as the earlier negative binomial models fit (the deviance is 66.5 on 53 degrees of freedom, p=.10). The model implies an estimated 9.7% 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:

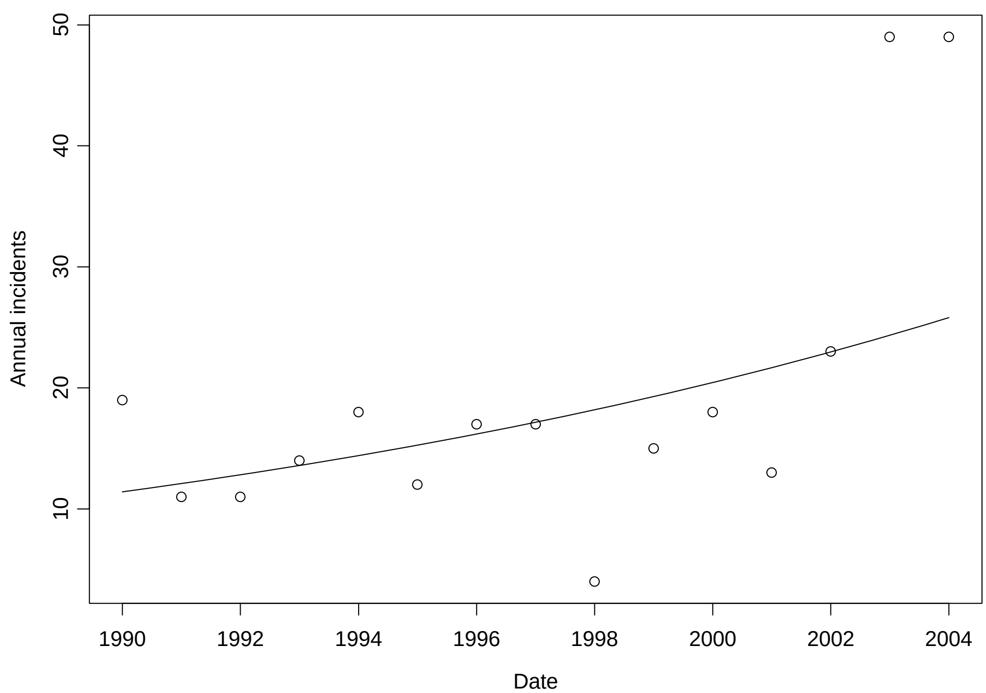
B. Analysis of the number of incidents that were associated with nonzero MW loss or nonzero customer loss over time

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 alone, excluding events with zero customers lost. 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.



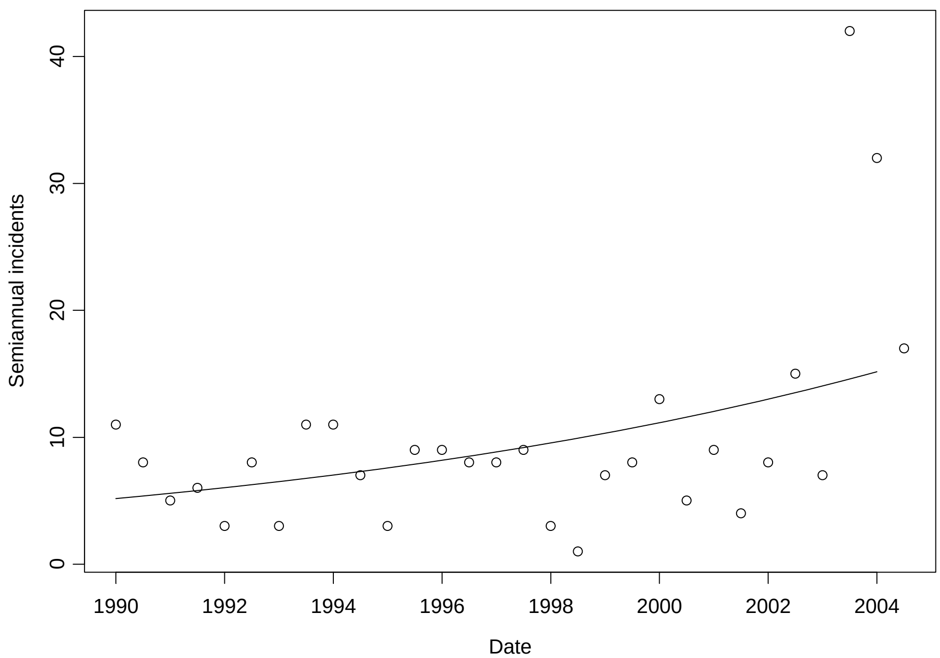
Here is output for this model:

```
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.



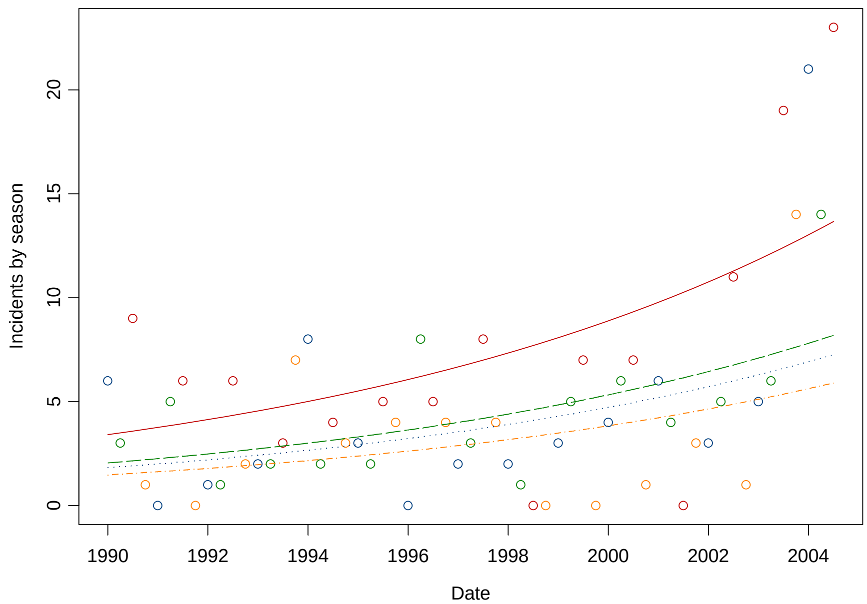
Here is output for the model:

```
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:

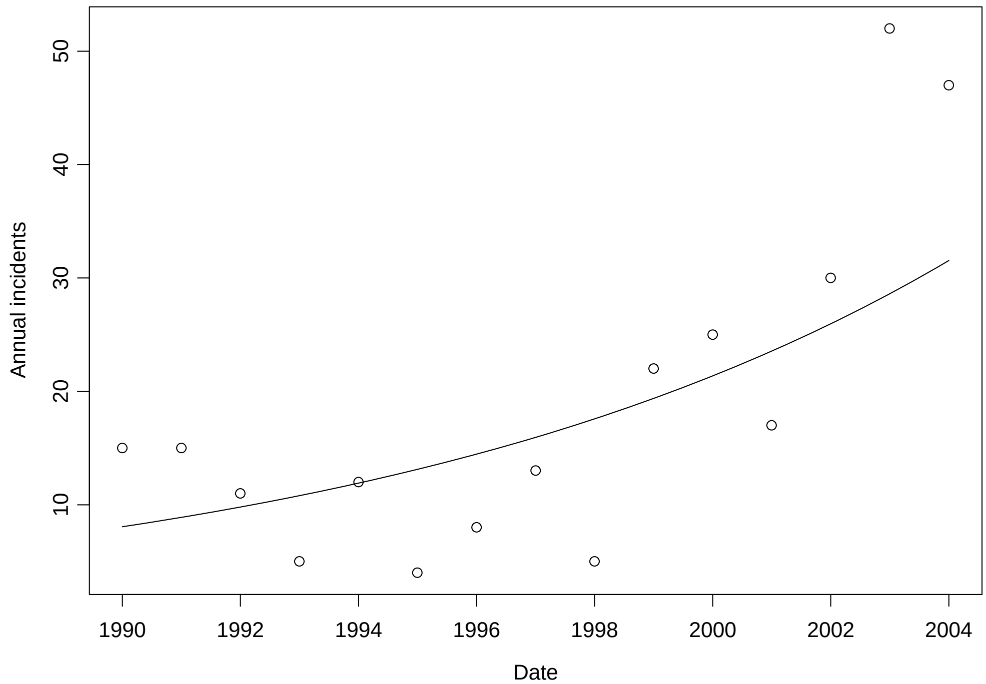
```
Coefficients:
                    Value  Std. Error       Wald
 (Intercept) -189.77487351 49.48534232 -3.8349714
        Date    0.09555951  0.02476742  3.8582754
SeasonSpring    0.32805162  0.30244169  1.0846772
SeasonSummer    0.84044230  0.29118948  2.8862385
SeasonWinter    0.20764577  0.31001341  0.6697961
```

The model implies an estimated 10.0% 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.



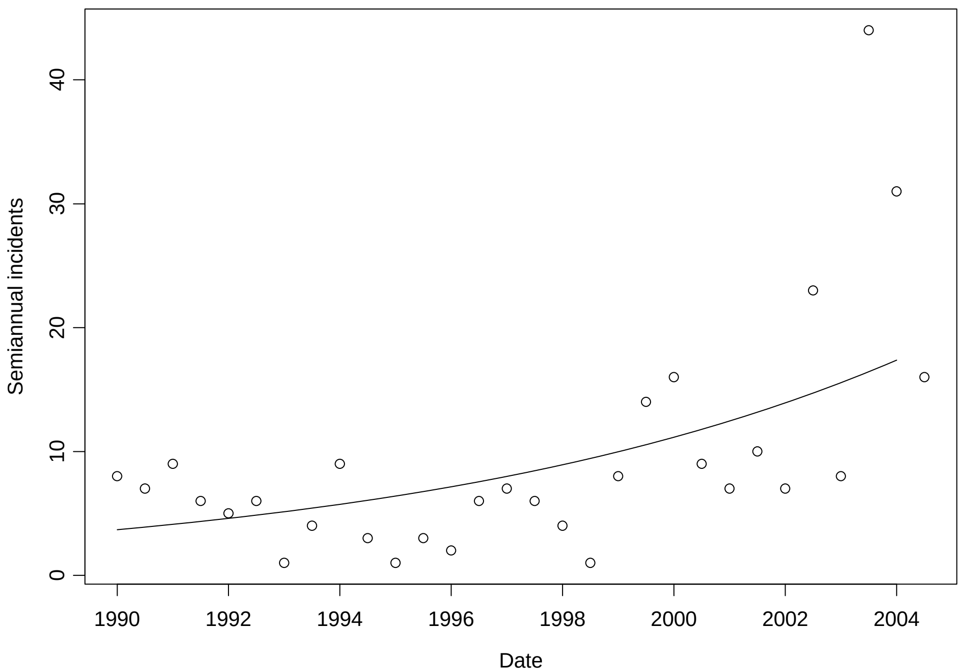
Here is output for this model:

```
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.



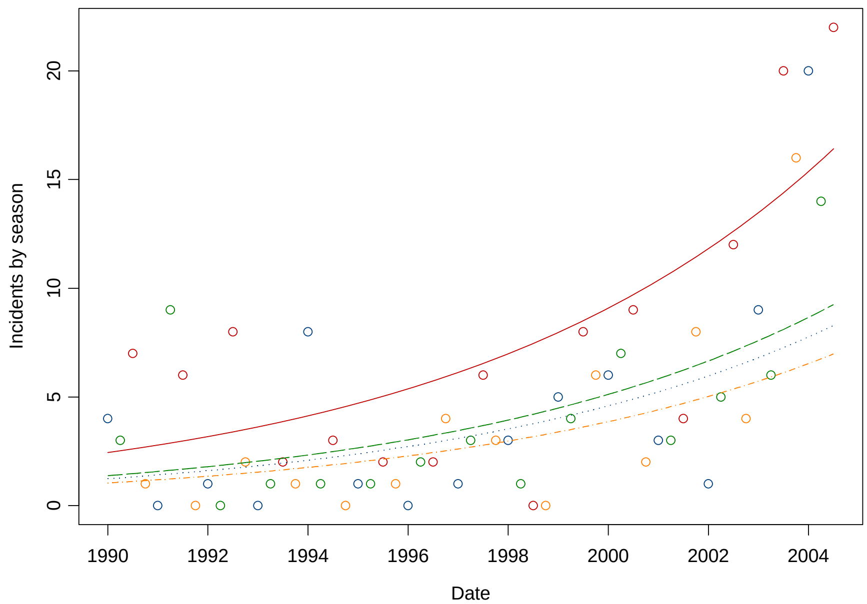
Here is output for the model:

```
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) -261.5615113 52.93962548 -4.9407511
        Date    0.1314558  0.02649295  4.9619145
SeasonSpring    0.2818310  0.31959945  0.8818255
SeasonSummer    0.8567975  0.30630300  2.7972219
SeasonWinter    0.1727073  0.32699348  0.5281674
```

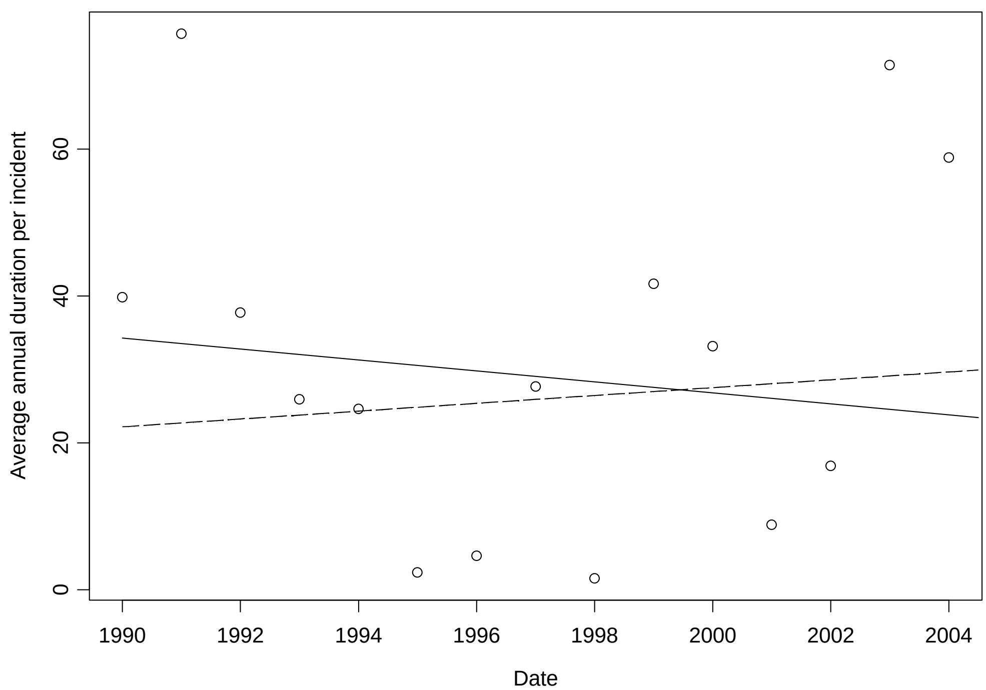
The model implies an estimated 14.0% annual increase in incident rate (p zero to six digits), and an estimated 75-135% higher rate for summer than for the other seasons. The summer effect is similar to that for the nonzero MW loss data, but the pattern is a little more complicated: both summer and winter 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.



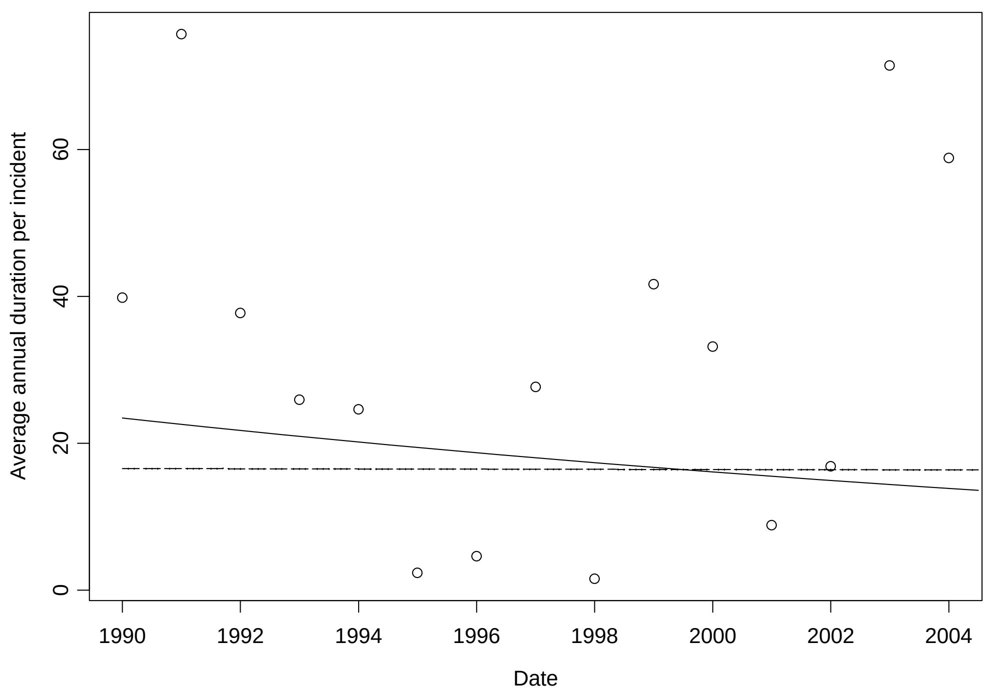
It is apparent that there is little evidence of any time trend in average duration. There is one early outlier, corresponding to 1991, although it is not that different from the values for 2003 and 2004. The solid line is the fitted time trend of average duration based on all of the data other than 2004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

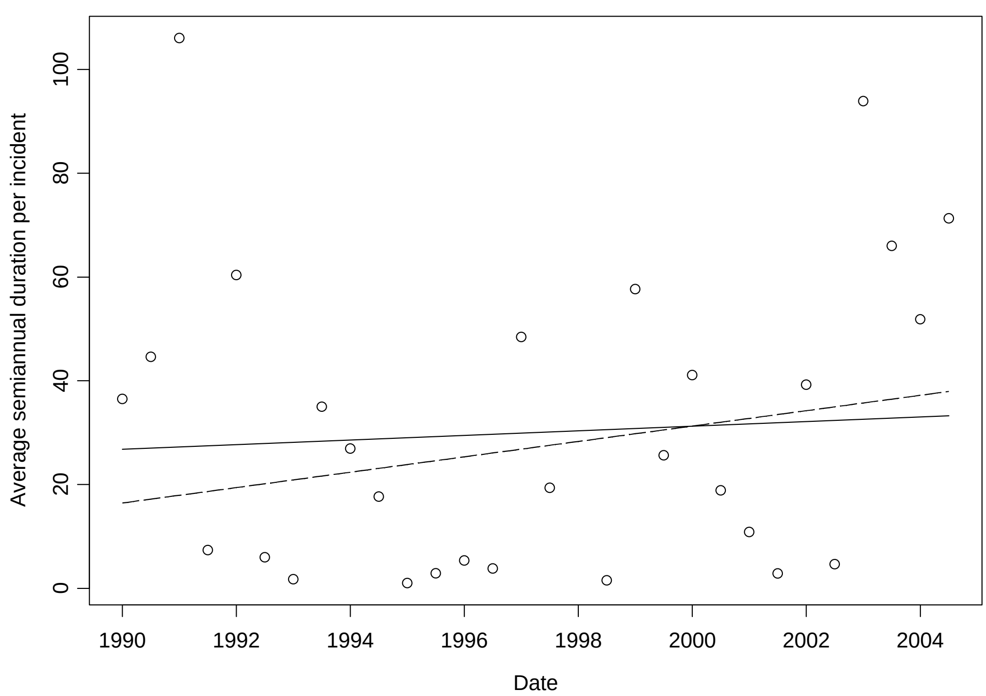
```
Coefficients:
                Value Std. Error   t value  Pr(>|t|)
(Intercept)   77.8956  165.8329     0.4697    0.6470
       Date   -0.0376    0.0831    -0.4522    0.6592

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:

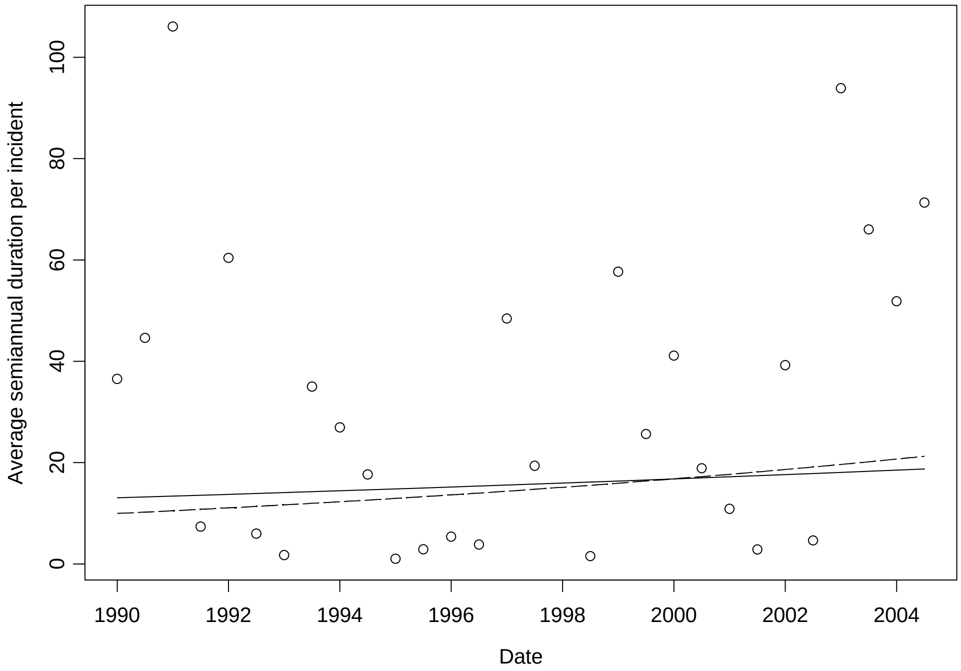
Full data set

```
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

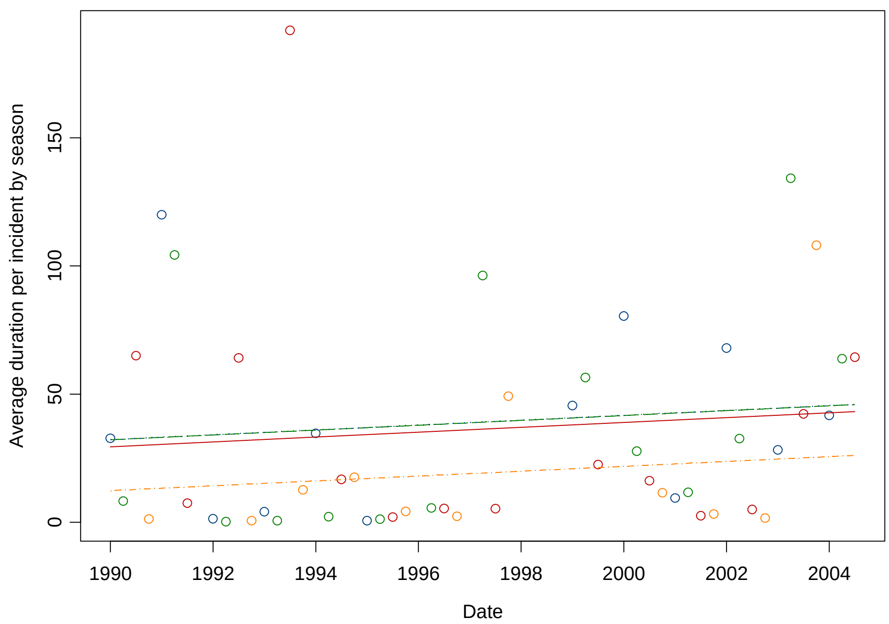
```
Coefficients:
                Value Std. Error   t value  Pr(>|t|)
(Intercept)  -47.1819  122.4689    -0.3853    0.7032
       Date    0.0250    0.0613     0.4077    0.6869

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.

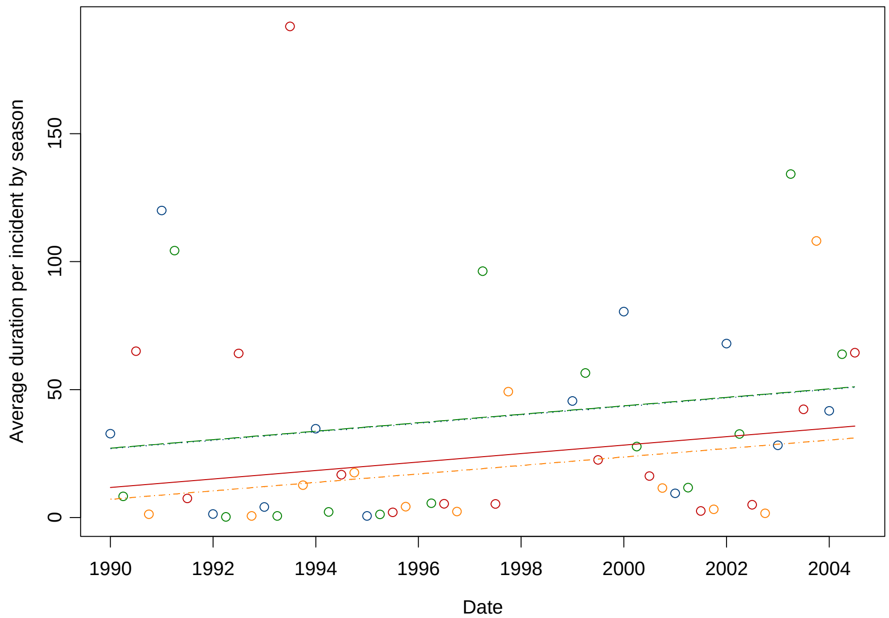


There is a slight upward slope, but it is not statistically significant. There is also no evidence of a season effect; the autumn line is marginally lower than the other lines, but this is not close to significance.

```
Coefficients:
                 Value Std. Error    t value   Pr(>|t|)
 (Intercept) -1875.0749  2771.2612    -0.6766     0.5021
        Date     0.9484     1.3874     0.6836     0.4978
SeasonSpring    19.8532    17.4212     1.1396     0.2605
SeasonSummer    17.1705    17.4189     0.9857     0.3295
SeasonWinter    19.9349    18.4376     1.0812     0.2854

Residual standard error: 43.23 on 45 degrees of freedom
Multiple R-Squared: 0.04553
F-statistic: 0.5366 on 4 and 45 degrees of freedom, the p-value is
0.7095

Anova Table

Response: Duration
              Sum Sq Df   F value    Pr(>F)
(Intercept)   855.66  1 0.4578069 0.5021140
       Date   873.34  1 0.4672694 0.4977509
```

```
     Season   3135.53   3 0.5592066 0.6447021
  Residuals 84106.52 45
```

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

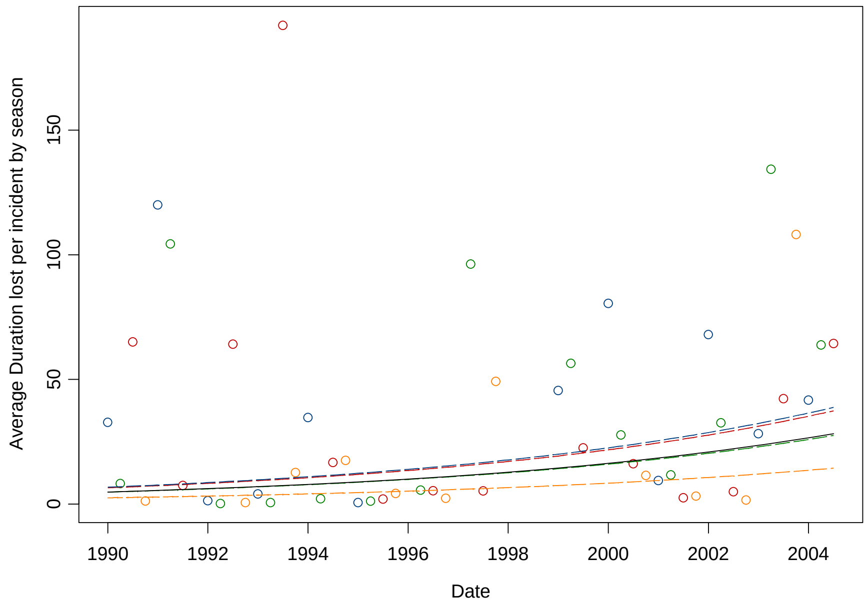


There is now (very) weak evidence of an upward slope, but no season effect. This is presumably coming from the last six seasons, wherein four had average durations of more than 60 hours.

```
Coefficients:
                 Value Std. Error    t value   Pr(>|t|)
 (Intercept) -3285.2832  2313.1906    -1.4202     0.1626
        Date     1.6544     1.1581     1.4286     0.1602
SeasonSpring    19.9999    14.4166     1.3873     0.1723
SeasonSummer     4.6768    14.6619     0.3190     0.7513
SeasonWinter    19.7584    15.2577     1.2950     0.2021

Residual standard error: 35.78 on 44 degrees of freedom
Multiple R-Squared: 0.1011
F-statistic: 1.237 on 4 and 44 degrees of freedom, the p-value is
 0.3091

Anova Table

Response: Duration
              Sum Sq Df  F value    Pr(>F)
              Sum Sq Df  F value    Pr(>F)
(Intercept)  2581.72  1 2.017079 0.1625856
       Date  2612.13  1 2.040840 0.1601858
```

```
    Season  3820.00  3 0.994847 0.4041244
Residuals 56316.96 44
```

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.

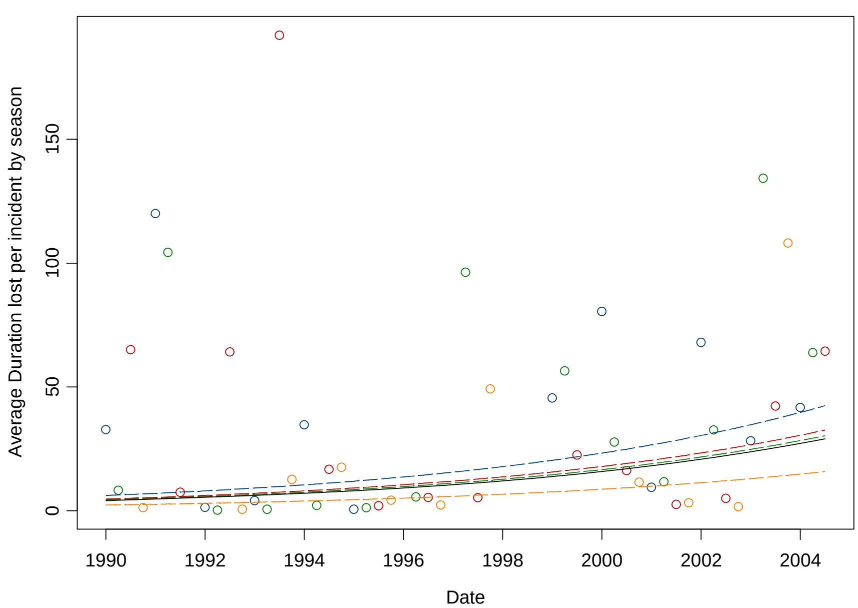
```
Coefficients:
                Value Std. Error   t value  Pr(>|t|)
 (Intercept) -239.2458  107.6682   -2.2221    0.0314
        Date    0.1207    0.0539    2.2389    0.0302
SeasonSpring    0.6486    0.6768    0.9583    0.3430
SeasonSummer    0.9567    0.6768    1.4137    0.1643
SeasonWinter    0.9926    0.7163    1.3856    0.1727

Residual standard error: 1.68 on 45 degrees of freedom
Multiple R-Squared: 0.1458
F-statistic: 1.92 on 4 and 45 degrees of freedom, the p-value is
0.1235
```

```
Anova Table

Response: log(Duration)

             Sum Sq Df  F value    Pr(>F)
(Intercept)  13.9300  1 4.937573 0.031350
       Date  14.1414  1 5.012505 0.030155
     Season   7.2384  3 0.855231 0.471228
  Residuals 126.9551 45
```

Omitting season effect

```
Coefficients:
                Value Std. Error   t value  Pr(>|t|)
(Intercept) -240.8782  107.1072    -2.2489    0.0291
       Date    0.1218    0.0536     2.2721    0.0276

Residual standard error: 1.672 on 48 degrees of freedom
Multiple R-Squared: 0.0971
F-statistic: 5.162 on 1 and 48 degrees of freedom, the p-value
is 0.0276
```

This corresponds to an estimated annual increase in duration of 13.0% (exp(.1218)=1.1295). The summer of 1993 is unusual, so here is the analysis with that point omitted:



```
Coefficients:
                 Value Std. Error   t value  Pr(>|t|)
 (Intercept) -265.4906  105.5836    -2.5145    0.0157
        Date    0.1338    0.0529     2.5316    0.0150
SeasonSpring    0.6513    0.6580     0.9898    0.3277
SeasonSummer    0.7242    0.6692     1.0822    0.2851
SeasonWinter    0.9893    0.6964     1.4205    0.1625

Residual standard error: 1.633 on 44 degrees of freedom
Multiple R-Squared: 0.1662
F-statistic: 2.193 on 4 and 44 degrees of freedom, the p-value
is 0.08532

Anova Table

Response: log(Duration)
              Sum Sq Df  F value    Pr(>F)
(Intercept)  16.8602  1 6.322745 0.0156500
       Date  17.0907  1 6.409193 0.0150001
     Season   5.8621  3 0.732782 0.5380322
  Residuals 117.3300 44
```

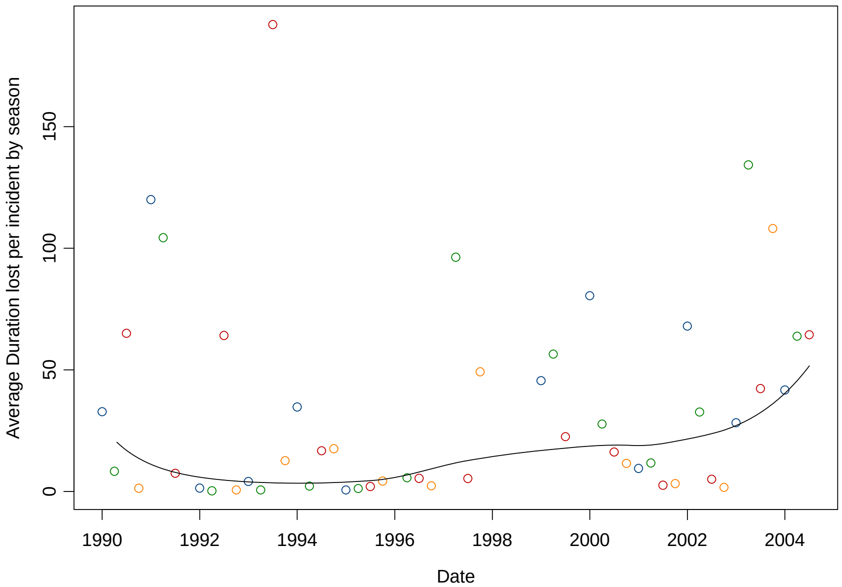
Omitting season effect

```
Coefficients:
                Value Std. Error   t value  Pr(>|t|)
(Intercept) -267.9718  104.5487    -2.5631    0.0136
       Date    0.1354    0.0523     2.5863    0.0129

Residual standard error: 1.619 on 47 degrees of freedom
Multiple R-Squared: 0.1246
```

This model implies an estimated annual increase in duration of 14.5%. 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 28.4 hours, while the average duration after that was 69.0 hours. Further, the corresponding medians are 10.4 hours and 63.8 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 -0.47688186
1992 -0.32825299
1993 -0.14540827
1994  0.14093464
1995  0.50430449
1996  0.84530415
1997  0.35273835
1998  0.17398574
1999  0.11282195
2000  0.00913204
2001  0.13988508
2002  0.26066940
2003  0.48978316
```

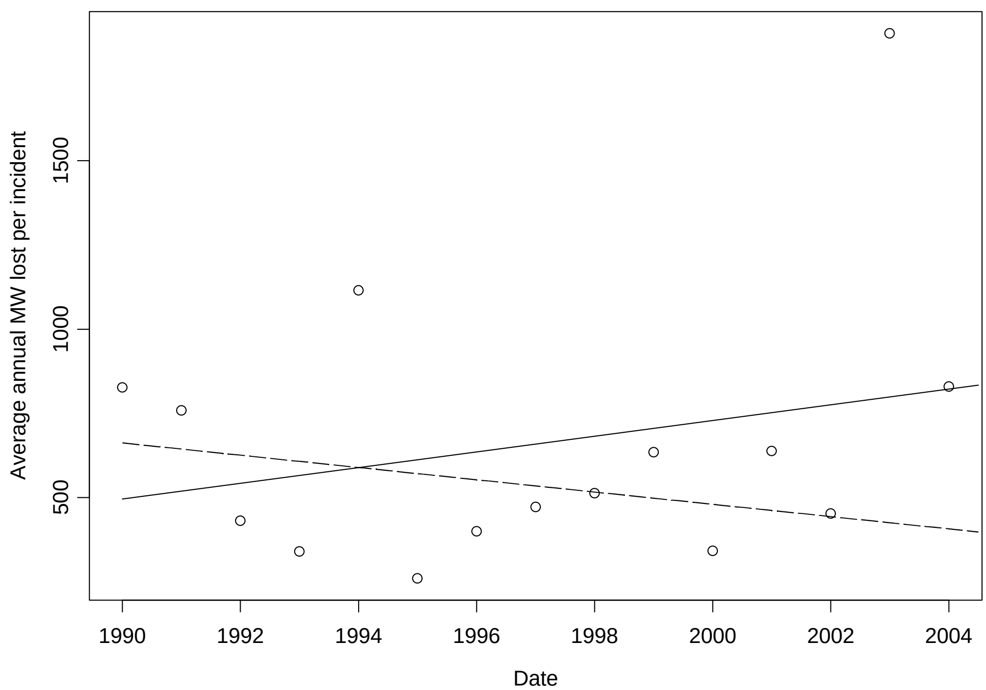
Up until 1993, durations were getting shorter on average (an estimated 48% shorter from 1991 to 1992, 33% shorter from 1992 to 1993, and so on). This changed in 1994, and for a few years the average duration went up 35-85% annually (note that this was at a time when durations were lower, so the absolute increase wasn't that large). This was followed by a period (1998-2001) of fairly stable growth of 10-20% annually (with growth in 2000 less than that). Finally, from 2002 on, average durations have started increasing again at a high 25-50% 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
```

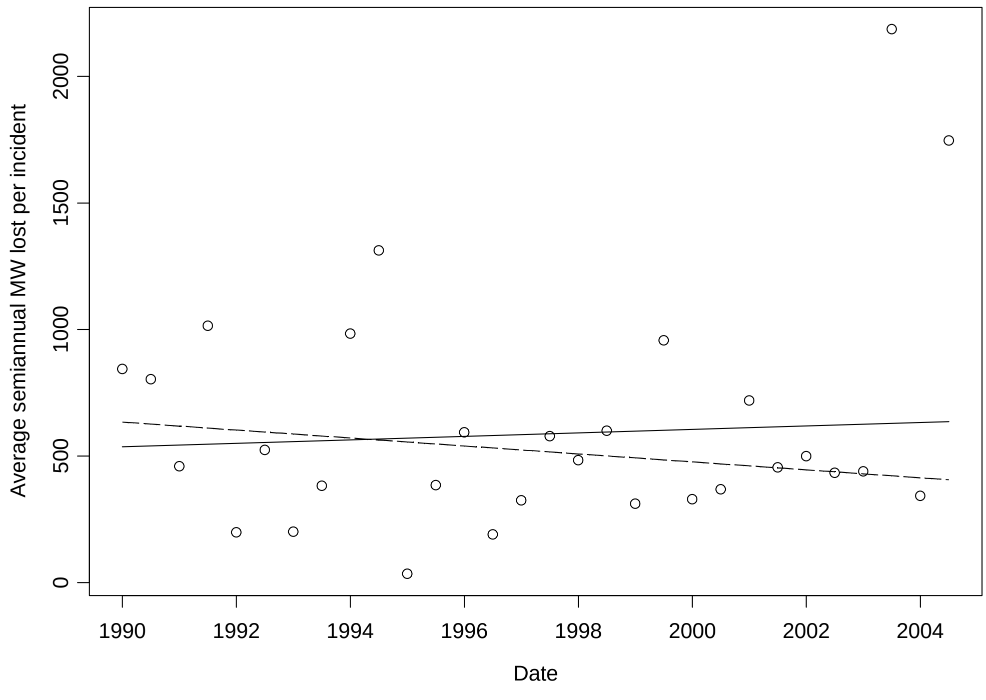
```
       Date     23.2969     28.3115      0.8229      0.4266

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
```

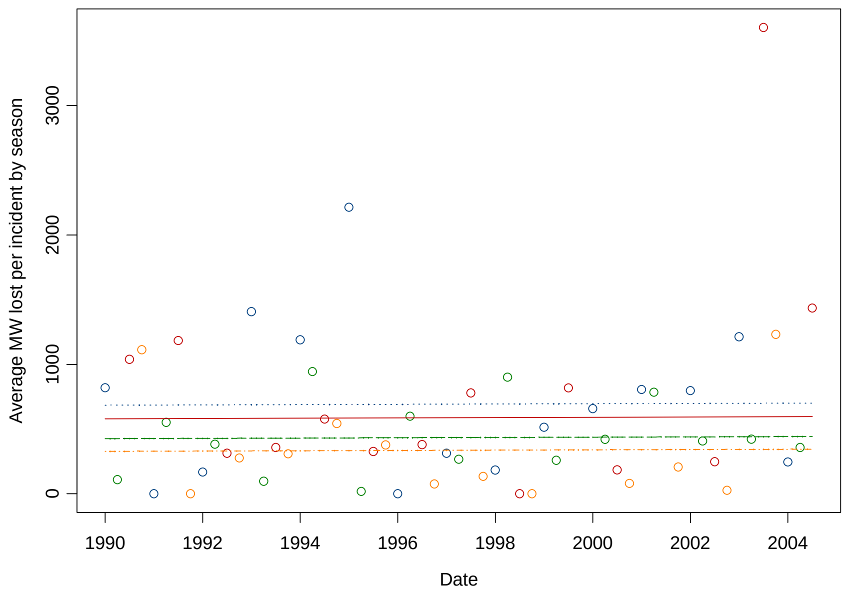
Seasonal data

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) -40041.5623  38282.5274     -1.0459      0.3005
        Date     20.2187     19.1693      1.0547      0.2965
SeasonSpring     94.3449    228.7118      0.4125      0.6817
SeasonSummer    463.5128    232.4624      1.9939      0.0515
SeasonWinter    348.0473    232.5976      1.4963      0.1407

Residual standard error: 603.5 on 51 degrees of freedom
Multiple R-Squared: 0.1129
F-statistic: 1.622 on 4 and 51 degrees of freedom, the p-value is
 0.183


Anova Table

Response: MW
              Sum Sq Df  F value    Pr(>F)
(Intercept)   398439  1 1.094009 0.3005168
       Date   405167  1 1.112483 0.2965141
     Season  1921266  3 1.758432 0.1668606
  Residuals 18574233 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.

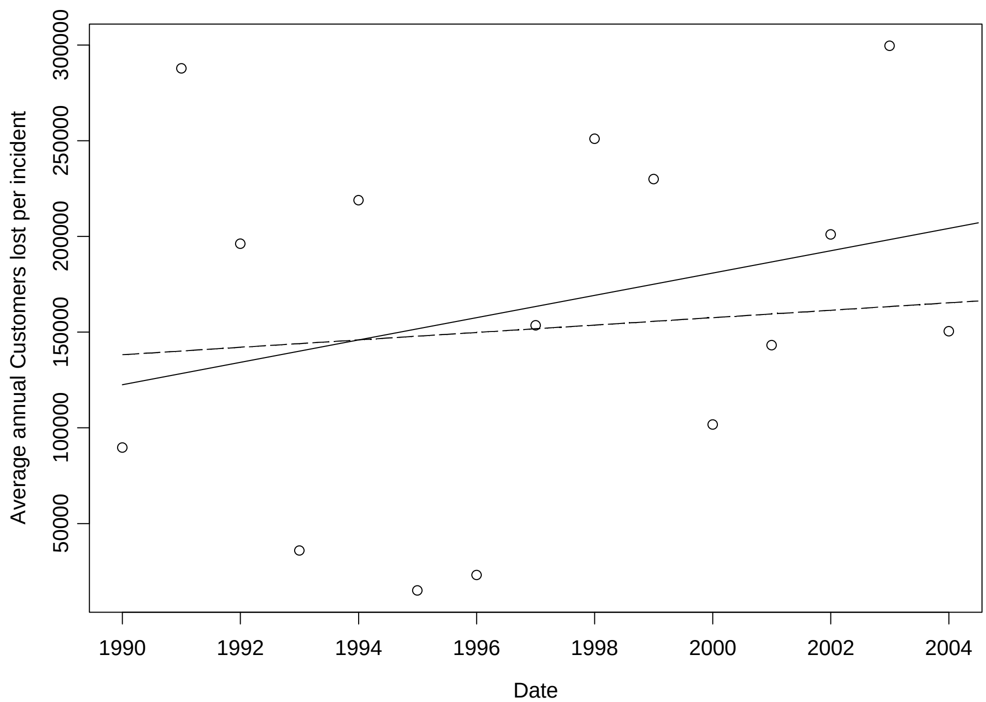
```
Coefficients:
                   Value  Std. Error     t value    Pr(>|t|)
 (Intercept)  -1951.8292  29765.8421     -0.0656      0.9480
        Date      1.1457     14.9047      0.0769      0.9390
SeasonSpring     98.0128    173.9725      0.5634      0.5757
SeasonSummer    251.6850    180.1201      1.3973      0.1685
SeasonWinter    356.4834    176.9325      2.0148      0.0493

Residual standard error: 459 on 50 degrees of freedom
Multiple R-Squared: 0.08881
F-statistic: 1.218 on 4 and 50 degrees of freedom, the p-value is
 0.3149


Anova Table

Response: MW
              Sum Sq Df  F value    Pr(>F)
(Intercept)      906  1 0.004300 0.9479794
       Date     1245  1 0.005909 0.9390329
     Season  1024037  3 1.619850 0.1965117
  Residuals 10536339 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
```

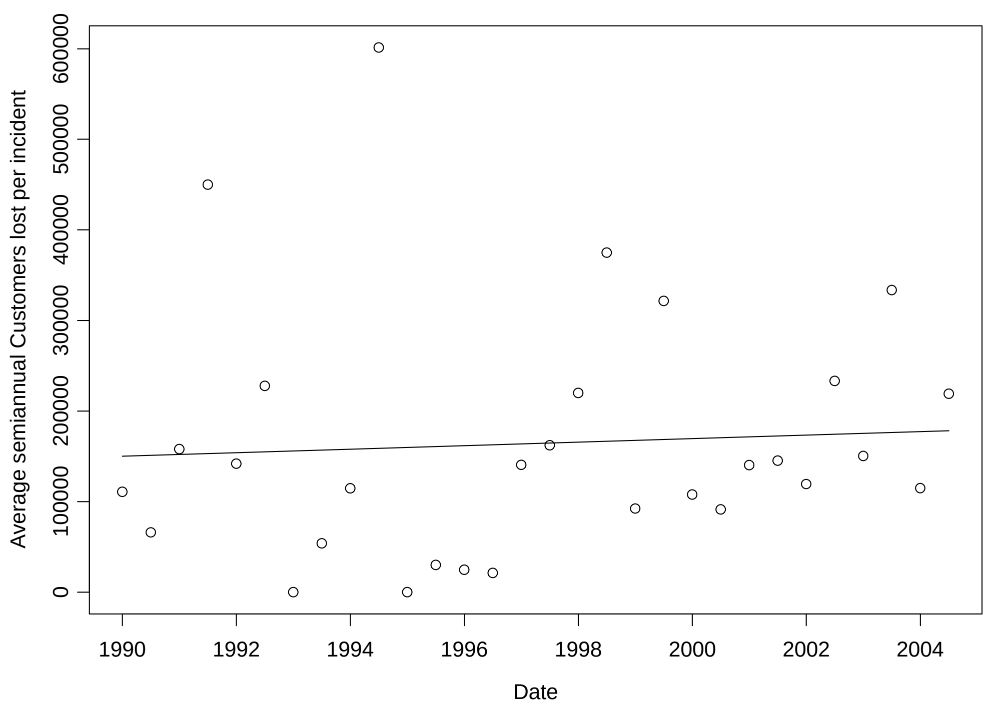
```
       Date         0.3798

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.

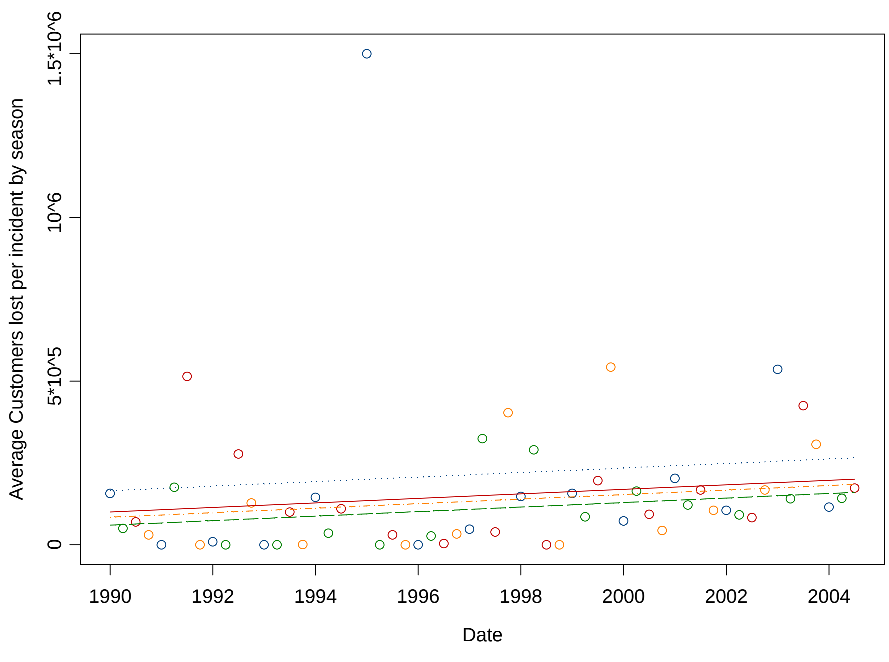


The results are similar to those for the annual data, in that there is a slight positive slope, but not close to statistical significance.

```
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

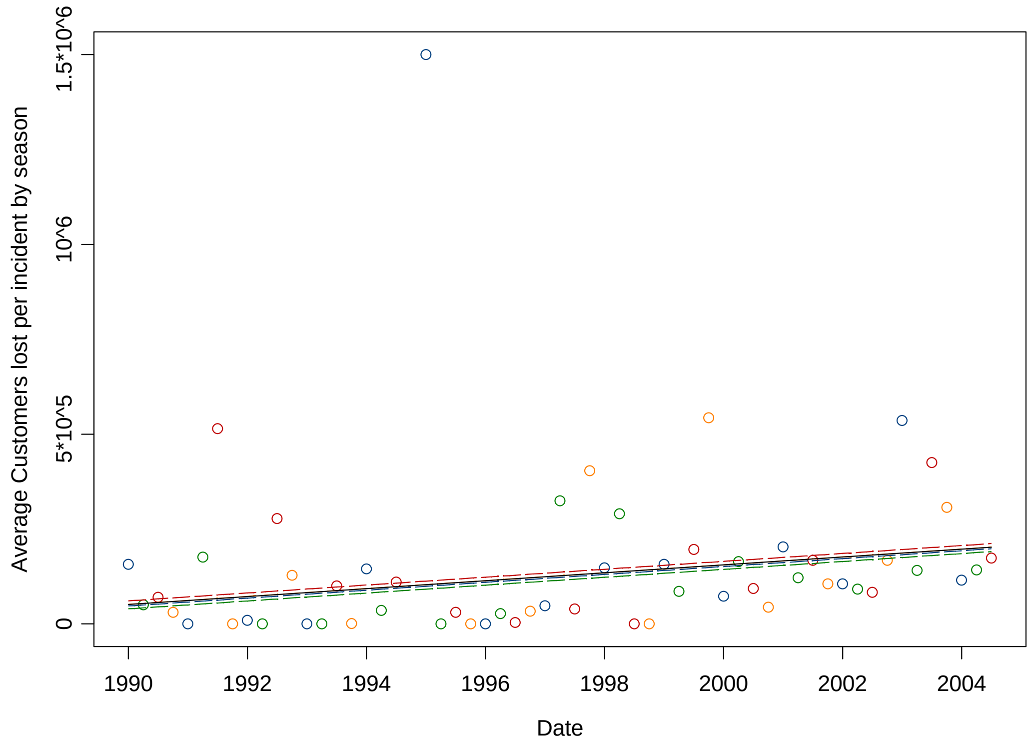
Here is a plot of the data.



It is apparent that there is no evidence of either a time or season effect.

```
Coefficients:
                     Value     Std. Error        t value
 (Intercept) -13669781.7516  14595904.6082        -0.9365
        Date      6911.4549      7307.2262         0.9458
SeasonSpring    -24317.4782     87934.2329        -0.2765
SeasonSummer     16233.1520     87924.0146         0.1846
SeasonWinter     81139.2433     89370.0144         0.9079

                   Pr(>|t|)
 (Intercept)         0.3533
        Date         0.3486
SeasonSpring         0.7832
SeasonSummer         0.8542
SeasonWinter         0.3681

Residual standard error: 232000 on 52 degrees of freedom
Multiple R-Squared: 0.04681
F-statistic: 0.6385 on 4 and 52 degrees of freedom, the p-value is
0.6374


Anova Table

Response: Customers
                   Sum Sq Df   F value    Pr(>F)
(Intercept)   47221822505  1 0.8771243 0.3533200
       Date   48163215547  1 0.8946102 0.3486056
     Season   86900927084  3 0.5380486 0.6583191
  Residuals 2799528926494 52
```

Winter 1995 is evidently unusual (there was only one incident where customer loss was recorded, and it was 1.5 million customers). Omitting that point from the model fitting now highlights a time effect. The season lines are dashed in the following picture. There is now an upward slope, and it is statistically significant. There is no evidence of a season effect.




```
Coefficients:
                      Value      Std. Error        t value
(Intercept) -20658490.3354   8688786.2747        -2.3776
       Date     10406.8580      4349.8834         2.3924
    Season1    -11822.6427     26085.4891        -0.4532
    Season2      9284.7123     14697.3116         0.6317
    Season3     -4304.7448     10903.2789        -0.3948

                   Pr(>|t|)
(Intercept)          0.0212
       Date          0.0205
    Season1          0.6523
    Season2          0.5304
    Season3          0.6946

Residual standard error: 137700 on 51 degrees of freedom
Multiple R-Squared: 0.1137
F-statistic: 1.636 on 4 and 51 degrees of freedom, the p-value
is 0.1795
```

```
Anova Table

Response: Customers
                  Sum Sq Df  F value    Pr(>F)
(Intercept) 107127706057  1 5.652999 0.0212125
       Date 108469312202  1 5.723794 0.0204587
     Season  14856817016  3 0.261325 0.8529158
  Residuals 966480393522 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) -20710107.4567   8502707.6973         -2.4357
       Date     10432.8078      4256.7412          2.4509

                 Pr(>|t|)
(Intercept)        0.0182
       Date        0.0175

Residual standard error: 134800 on 54 degrees of freedom
Multiple R-Squared: 0.1001
```

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 more than 10,000 customers per incident per year. The effect is weak, accounting for only 10% 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

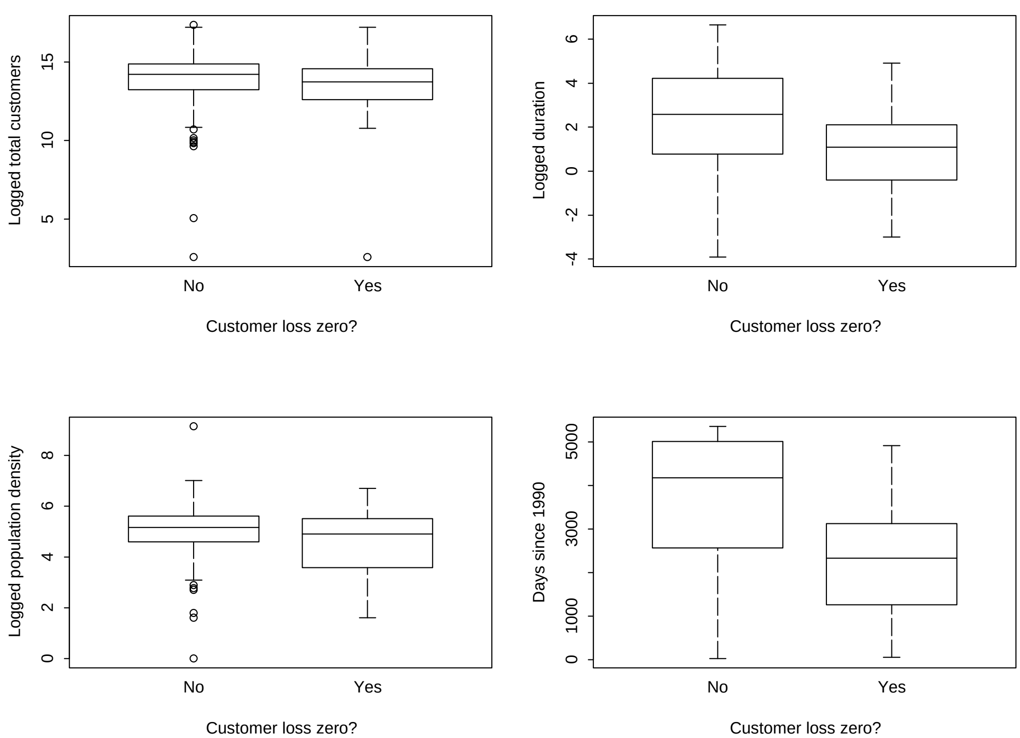
In this section customer loss is reanalyzed, but now at the event level. There are two important distinctions between these analyses and those of section I. E. First, the earlier analyses were based on average customer losses over three- six- or twelve-month time periods, and as such there is far lower 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 affected 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 cause of the incident is also a potentially important predictor of the seriousness of the event. The following table gives the catalogued causes for the incidents, along with the codes used for them in the output and figures to follow.

Cause	*Code*
Capacity shortage	C
Crime	Crime
Demand reduction	D
Equipment failure	E
Fire	F
Human error	H
Operational error	O
Natural disaster	N
System protection	S
Third party	T
Unknown	U
Weather	W

Table 1. Causes of incidents with codes.

The following table summarizes the relationship between the occurrence of zero or nonzero customer loss and 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). Crime, demand reduction (D), and third party (T) causes 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
```

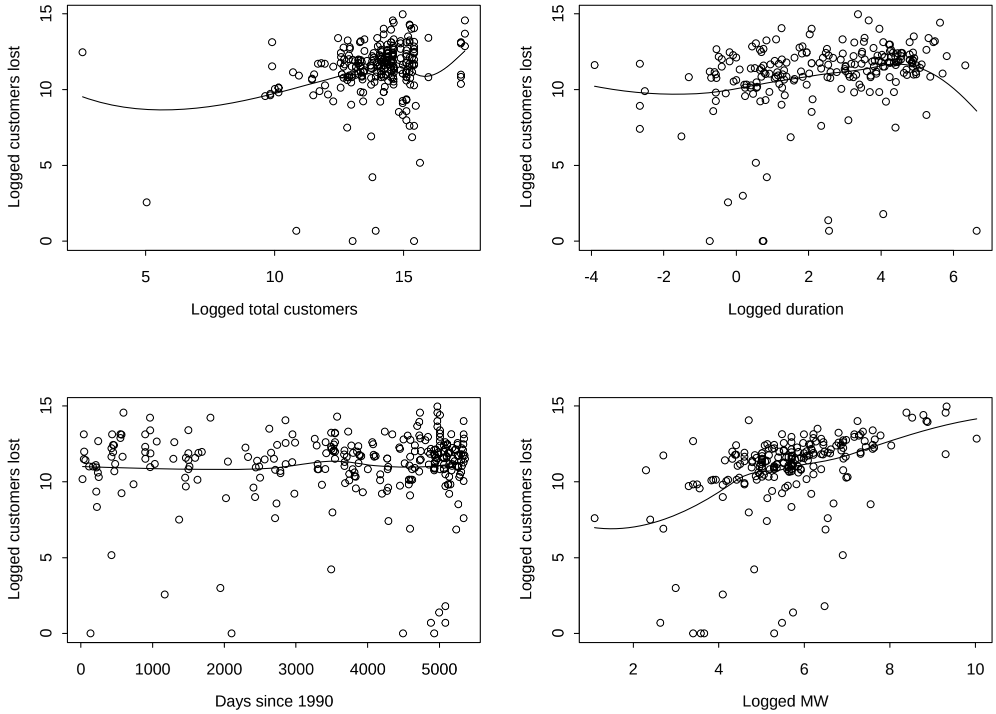
```
Tests for terms with more than 1 degree of freedom

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

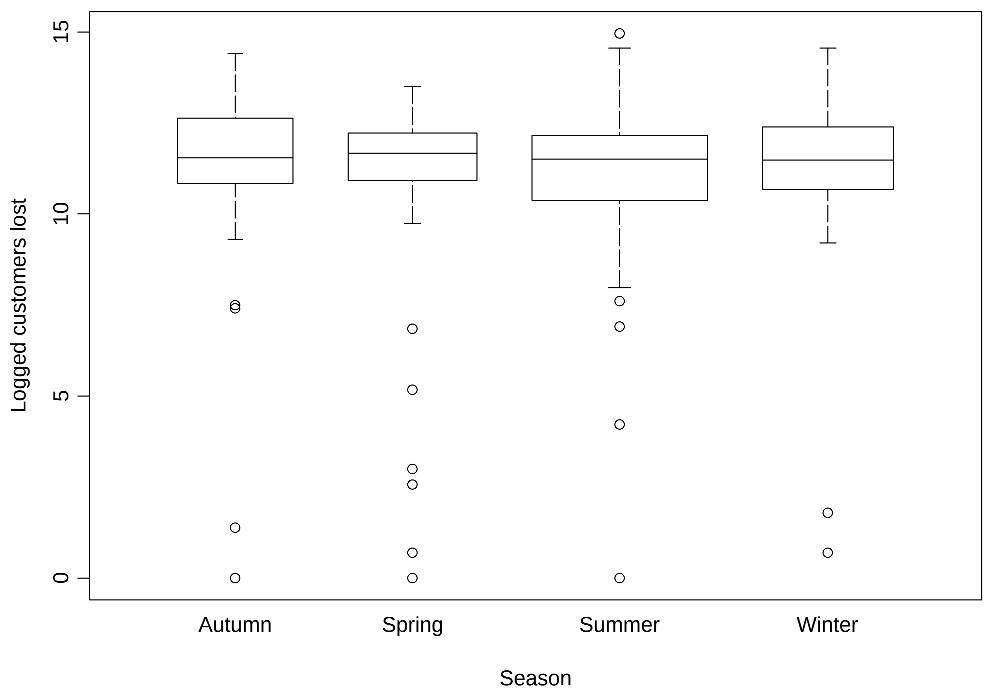
We see that logged duration, logged population density, a time trend (days since 1990), and cause are significant predictors, but season is not. The coefficients have the following interpretations. A 1% increase in the duration of an incident is associated with an estimated 0.3% decrease in the odds 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.

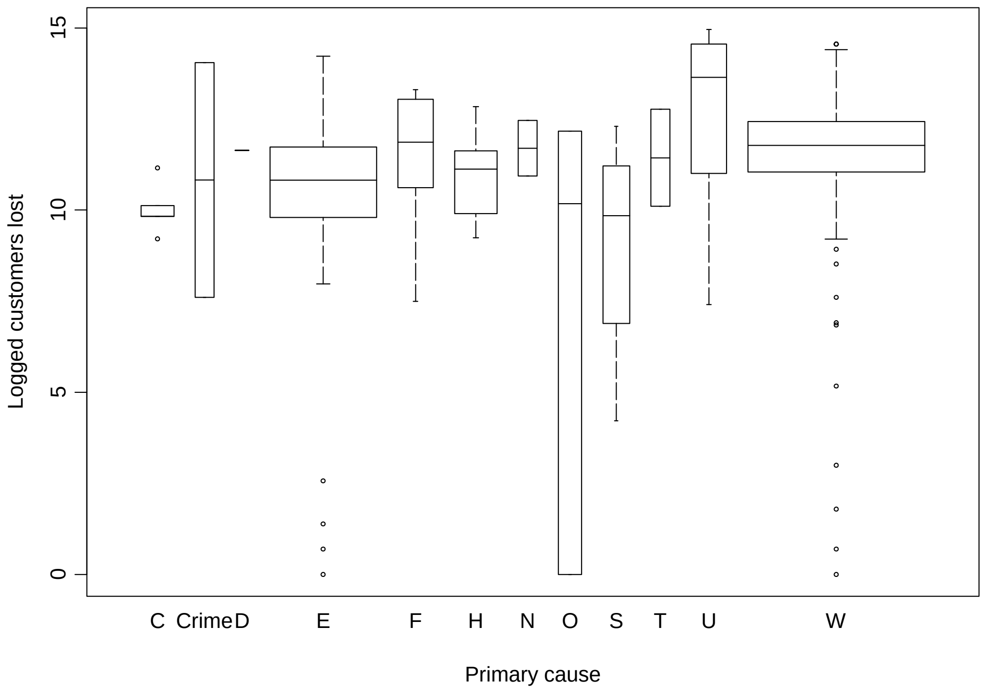
2. Given that more than zero customers are lost, what factors are related to the amount lost?

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.


Logged customers lost
Logged total customers
Logged duration
Days since 1990
Logged MW


Logged customers lost
Autumn
Spring
Summer
Winter
Season

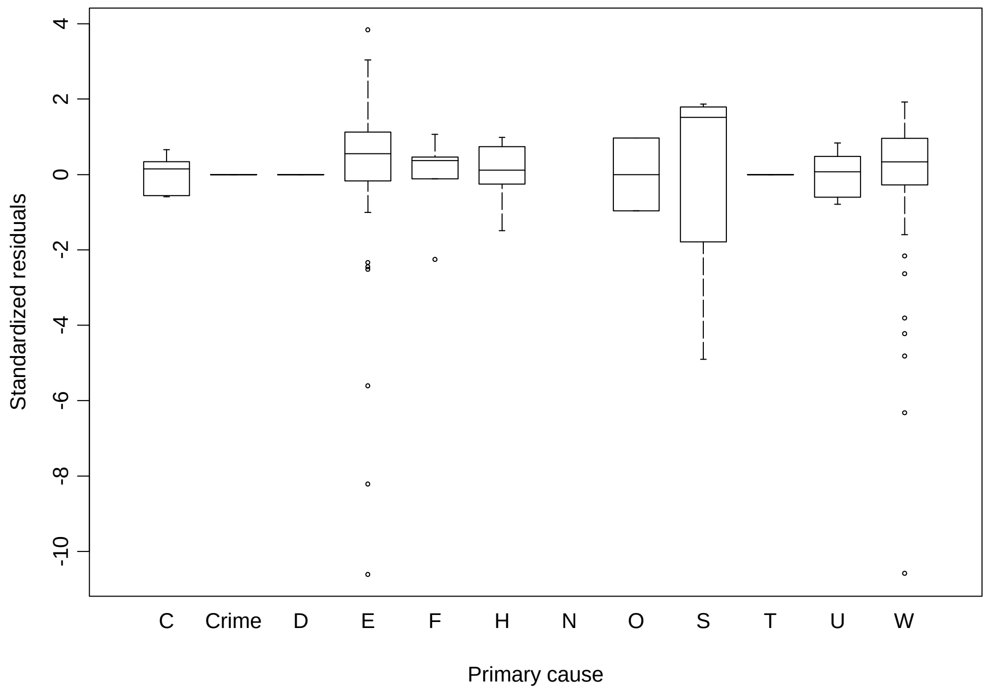


The only potential predictor showing much of a relationship with logged customers lost is logged MW loss. There is little evident seasonal effect. There is a primary cause effect, however, with fire, natural disaster, weather, and especially unknown causes having generally higher customer losses, and 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:

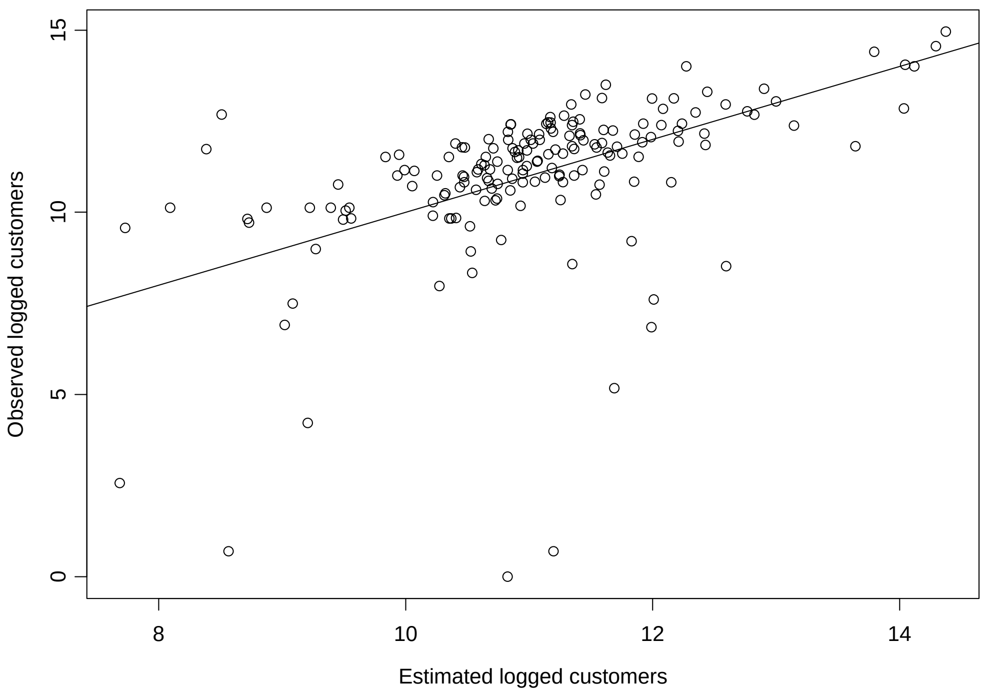
```
Coefficients:
                       Value Std. Error t value Pr(>|t|)
        (Intercept)  4.1896  1.3327     3.1438  0.0020
             Log.MW  0.6572  0.1153     5.7006  0.0000
       Log.duration  0.0337  0.0718     0.4695  0.6394
    Log.pop.density -0.0195  0.1487    -0.1312  0.8958
Log.total.customers  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(0.047)=1.048, or a 4.8% annual increase in customers lost, holding all else in the model fixed (the coefficient for Days since 1990 is actually 0.00013, and (365)(.00013)=.047). 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
```

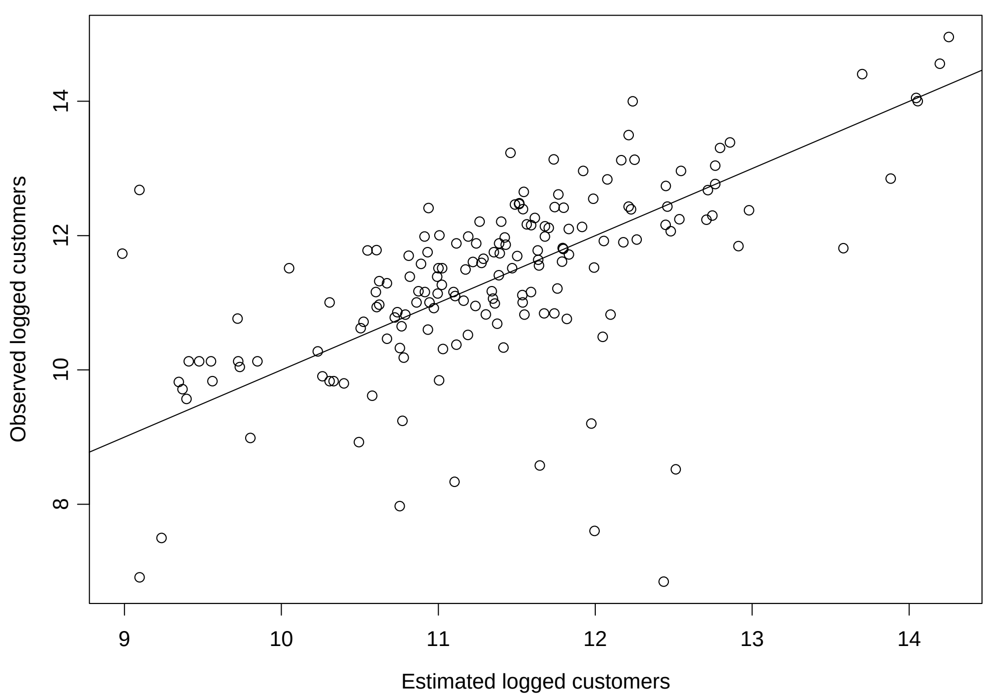
Logged MW, logged total customers, cause, and a time trend are all strongly statistically significant.

```
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 4.2% 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

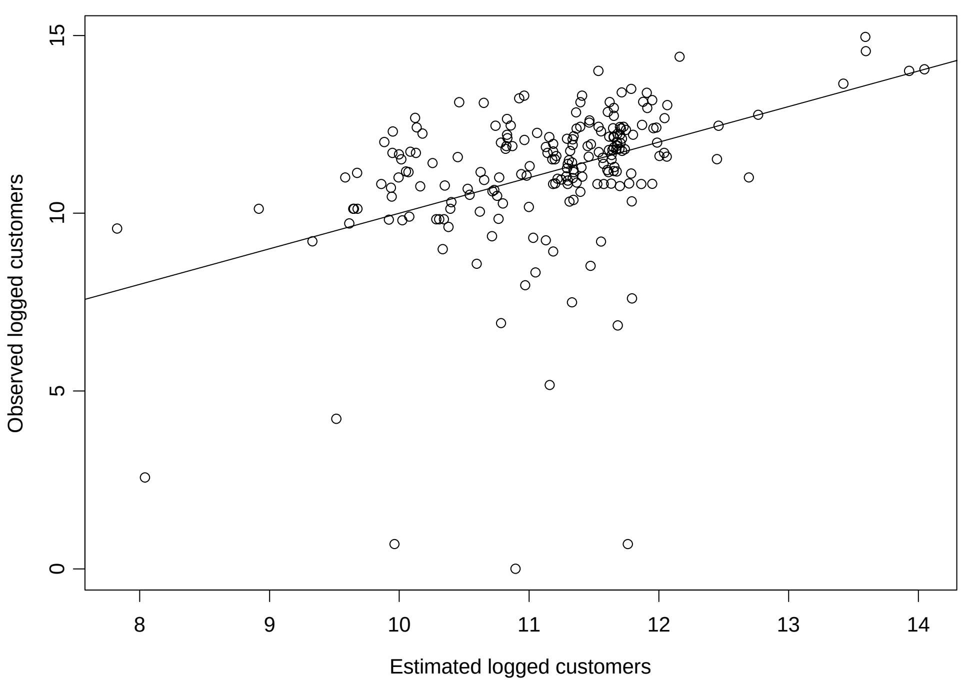
```
Residual standard error: 1.015 on 186 degrees of freedom
Multiple R-Squared: 0.2663
F-statistic: 3.75 on 18 and 186 degrees of freedom, the p-value
is 2.06e-006
```

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:

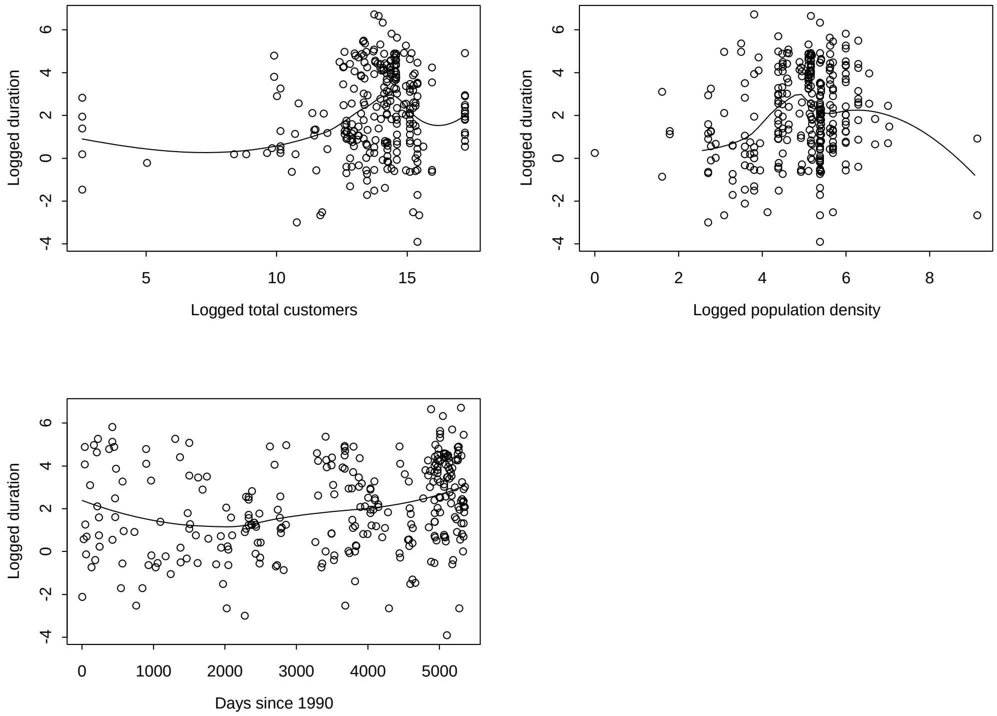
```
Primary.Cause
        C  Crime      D      E      F      H      N      O
    9.960 13.923 11.036 11.189 11.530 11.383 14.675 11.494
se  0.221  0.741  0.742  0.258  0.530  0.293  1.075  0.725


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

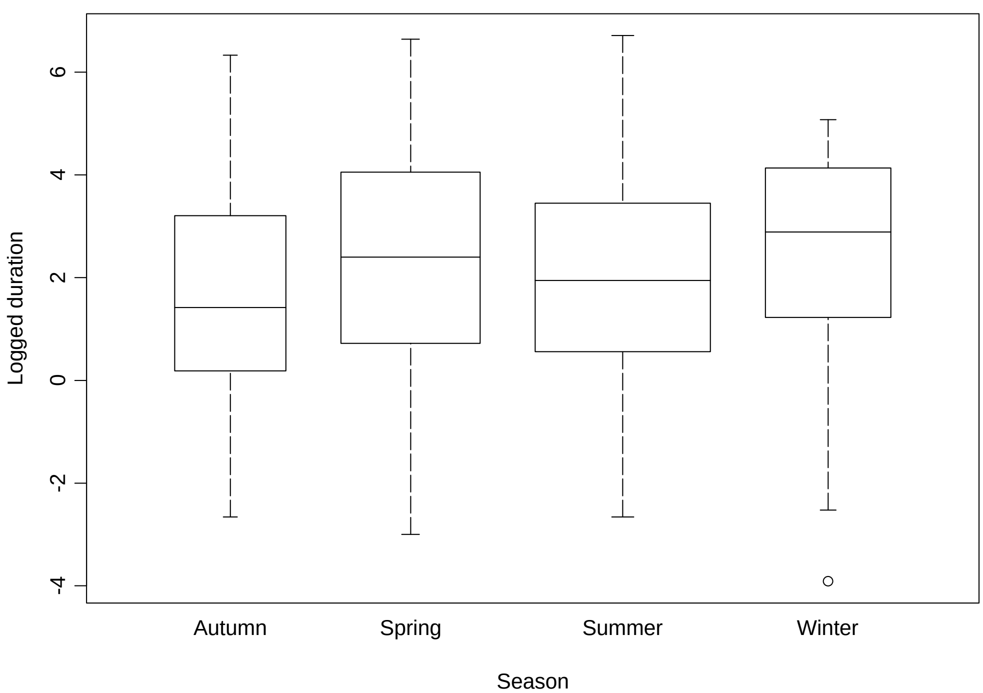
Customer losses are higher for natural disaster, crime, unknown causes, and third party, and lower for capacity shortage, demand reduction, and equipment failure, holding all else in the model fixed. Although demand reduction has replaced system protection as being associated with low customer losses 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.

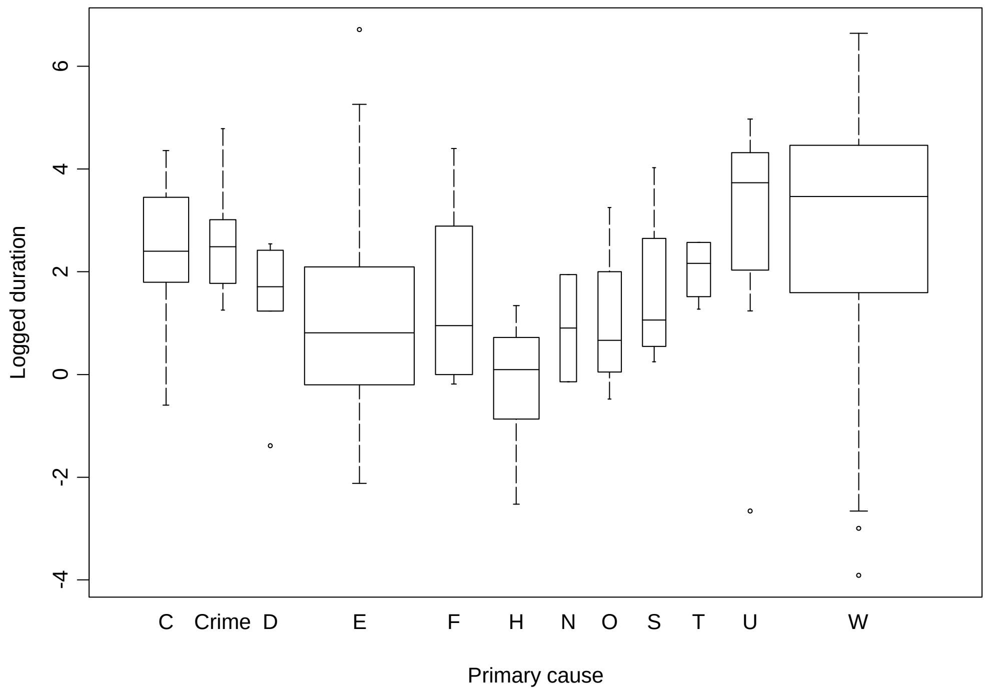
B. Analysis of duration at the event level

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
Logged total customers
Logged population density
Days since 1990
-4
-2
0
2
4
6
5
10
15
0
2
4
6
8
1000
2000
3000
4000
5000


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

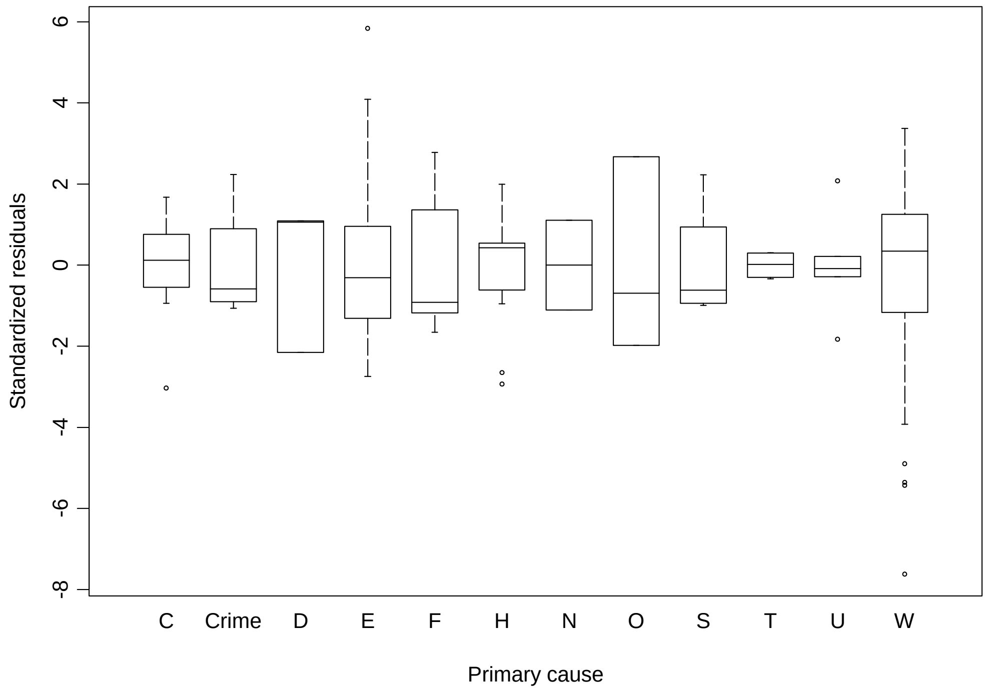


We see that there is little evidence of a relationship between logged duration and logged total customers. There is evidence of a positive relationship with logged population density (ignoring the two rare events at the very high population density level). There is weak evidence of the time trend on 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
```

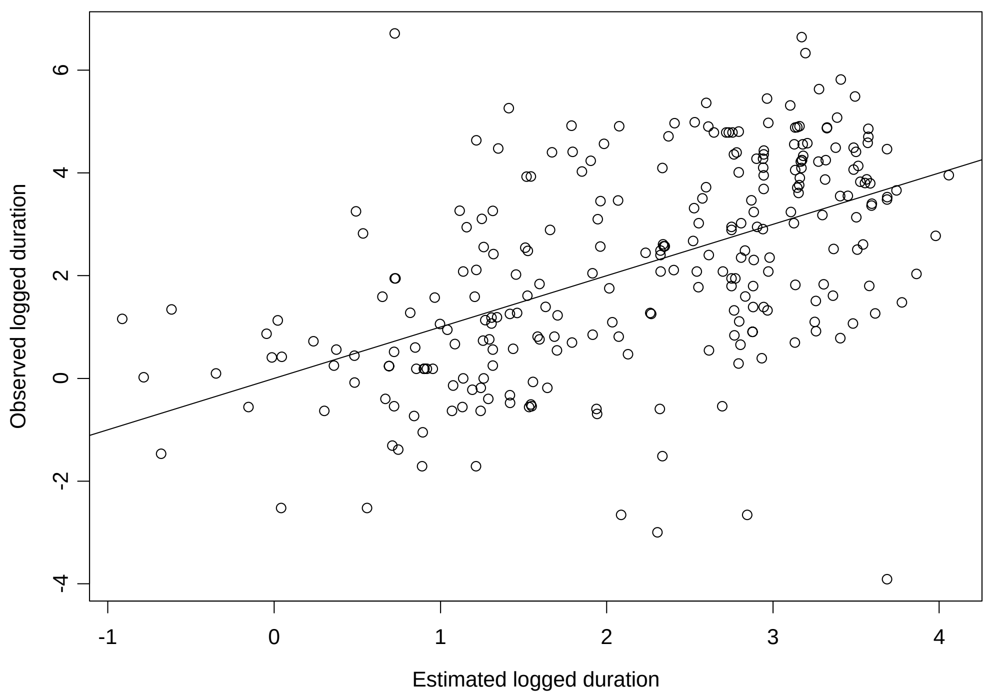
The model implies that a 1% increase in population density is associated with a 0.33% increase in duration, holding all else in the model fixed. The primary cause and season effects are summarized by the adjusted means:

```
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:

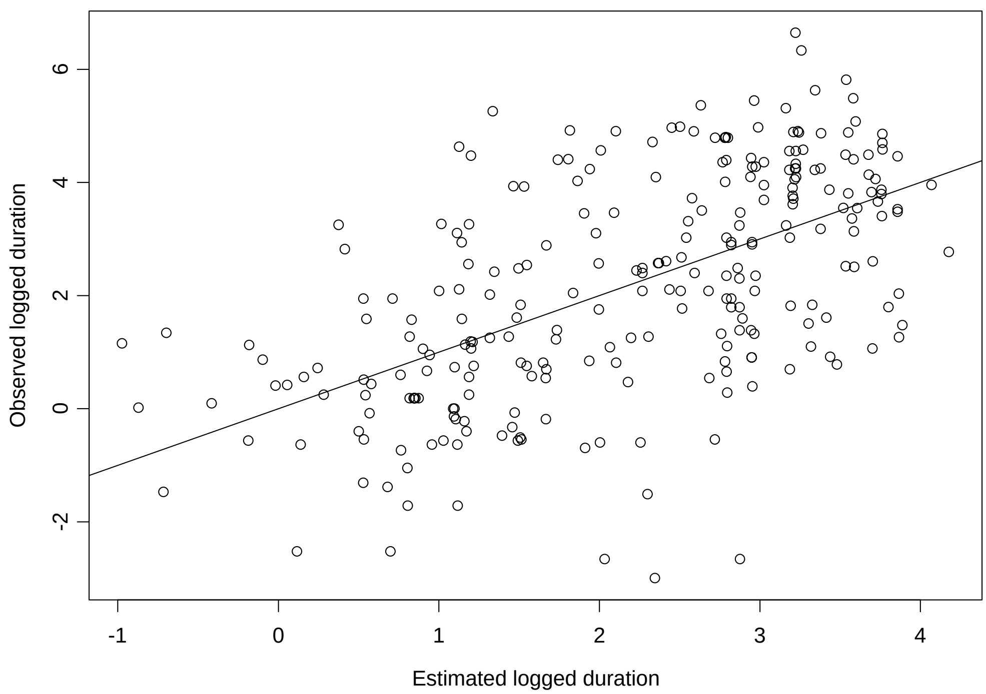
```
Primary.Cause
         C   Crime       D       E       F       H       N
    2.1135  2.0854  0.9776  1.3954  1.9524 -0.1255  0.3829
se  0.3225  0.7346  1.0403  0.1952  0.5084  0.3739  1.1135



         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.

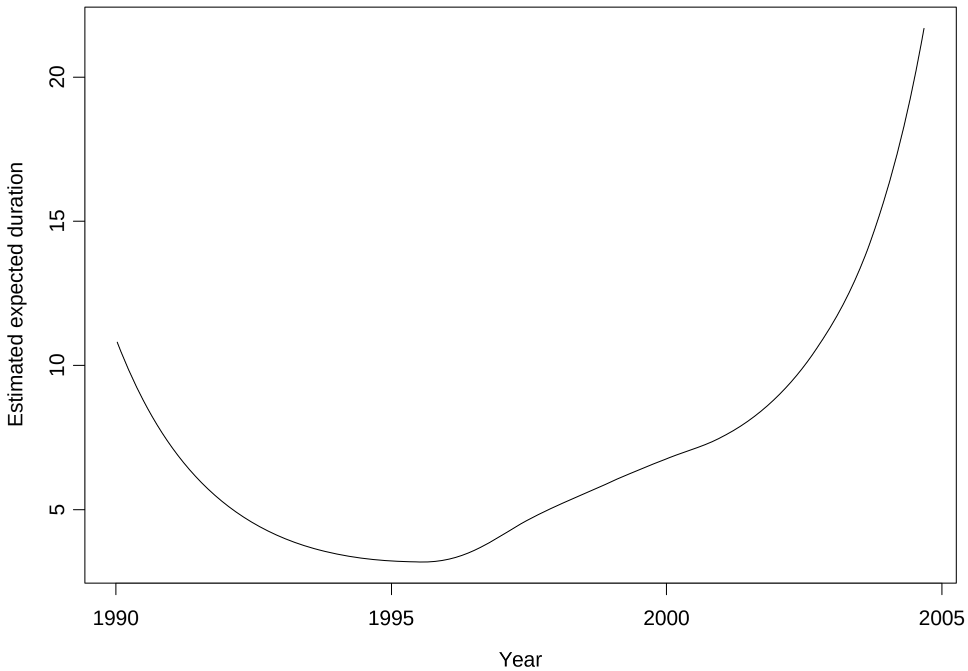
The model tracks the observed logged durations reasonably well.



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

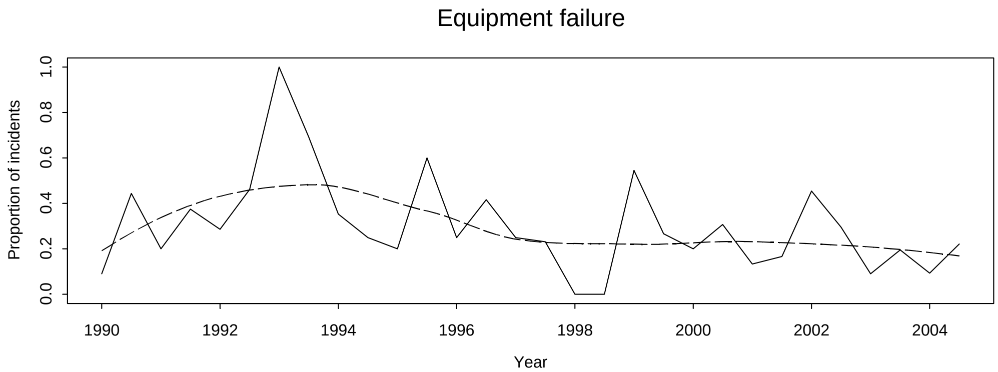
These can be compared to the season-level numbers from Section I. C., and they are very similar (a bit smaller, which reflects the additional noise in the event-level data). Up until 1994, durations were getting shorter. This turned around in 1995, and for a few years the average duration went up 15-25% 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.

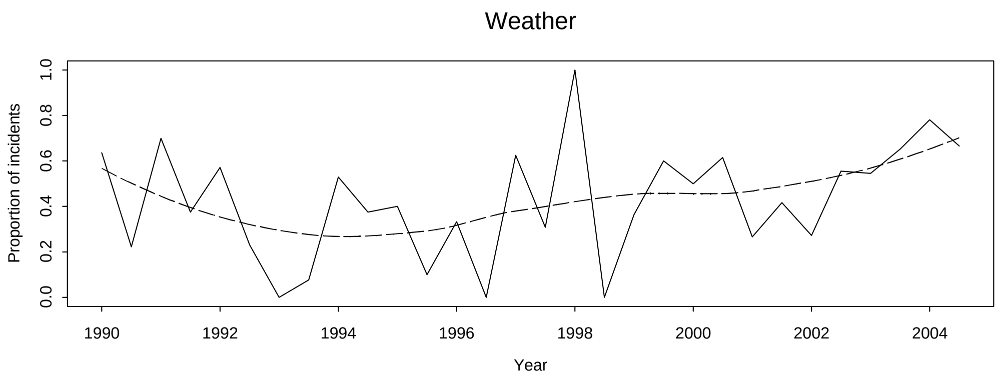
There is another factor at play here that leads to the time trend disappearing in the regression model. The models in this section take into account the other potential predictors. Note the results of a model that adds season and logged population density to the time trend:

	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.





C. Using the models for scenario prediction

These models provide useful information about the factors related to the seriousness of a power outage, but they also can be used to construct predictions for outage outcomes based on different scenarios. By examining predicted duration and customer loss under different conditions, it is possible to map out possible outage outcomes in the event of a terrorist attack (for which there is virtually no data).

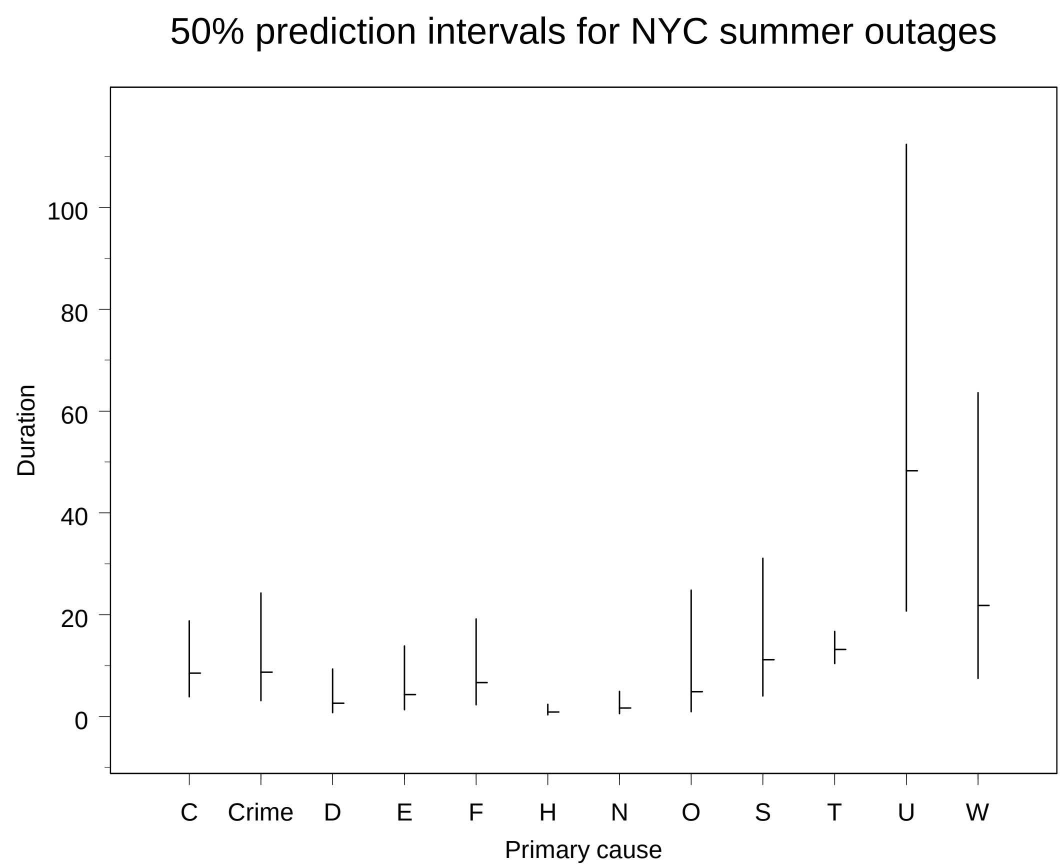
We look at scenarios for four different cities: New York, Chicago, San Francisco, and Seattle. Using the characteristics of the utilities in these four cities, the estimated duration of an incident, separated by season and cause, can be determined for each city using the weighted least squares model described on pages 53-54. Since (logged) duration is an important predictor for customer loss, these estimated durations can then be used as inputs to the logistic regression model discussed on pages 38-39 to estimate the probability that there is zero customer loss. Finally, the estimated (logged) duration value, along with the characteristics of the utility, are used to estimate the number of customers lost, given there is nonzero customer loss, using the weighted least squares model of pages 42-43. The estimated values for the four cities are given in the Appendix, along with overall estimated customer losses for several scenarios.

In addition to estimated expected values, we can construct 50% prediction intervals for duration and for customer loss (given that the loss is nonzero) for any cause and season for the four cities. These intervals give the central range within which there is 50% chance of the duration or customer loss falling in an individual incident.

It is important to note that these predictions and prediction intervals are based on using city-specific values as inputs to models based on national data, rather than models tailored to each specific city. Thus, these results are best viewed as scenarios for cities with the general demographic characteristics of New York, Chicago, and so on, rather than as scenarios based on characteristics unique to each city.

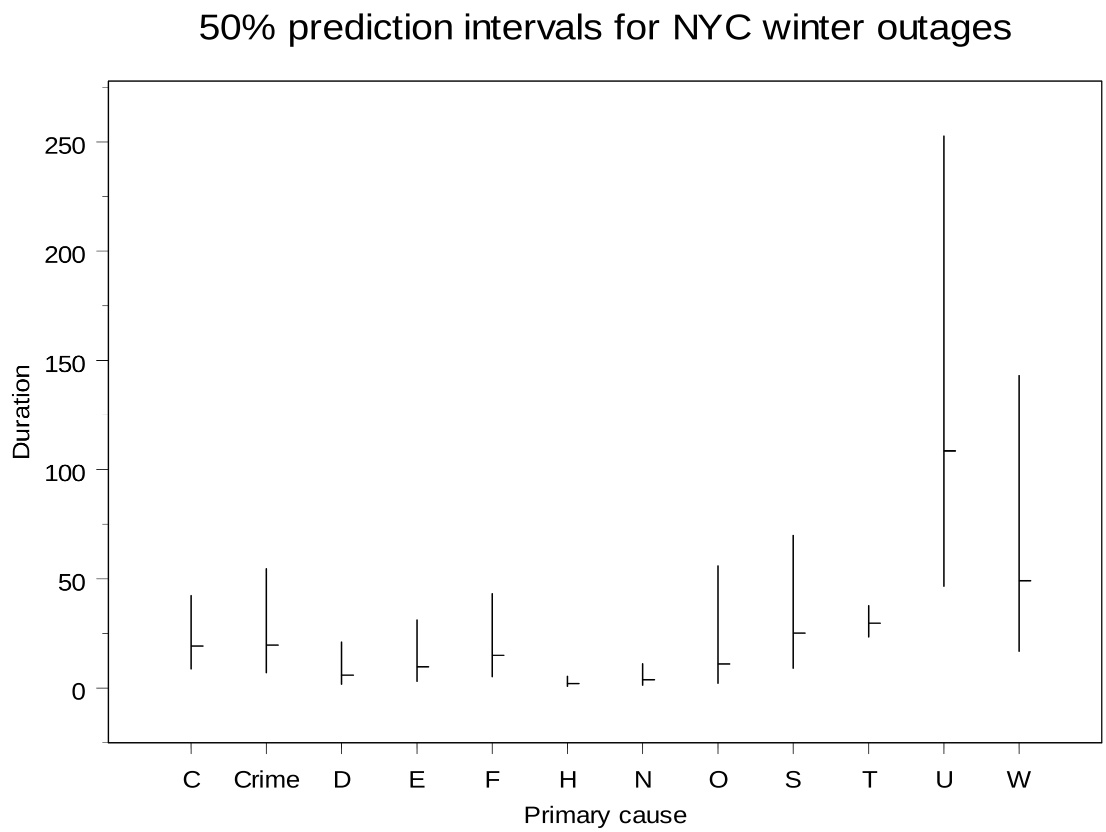
1. Duration of an incident

First, consider intervals for duration. The following figure gives 50% prediction intervals for duration of an incident in New York City during the summer.



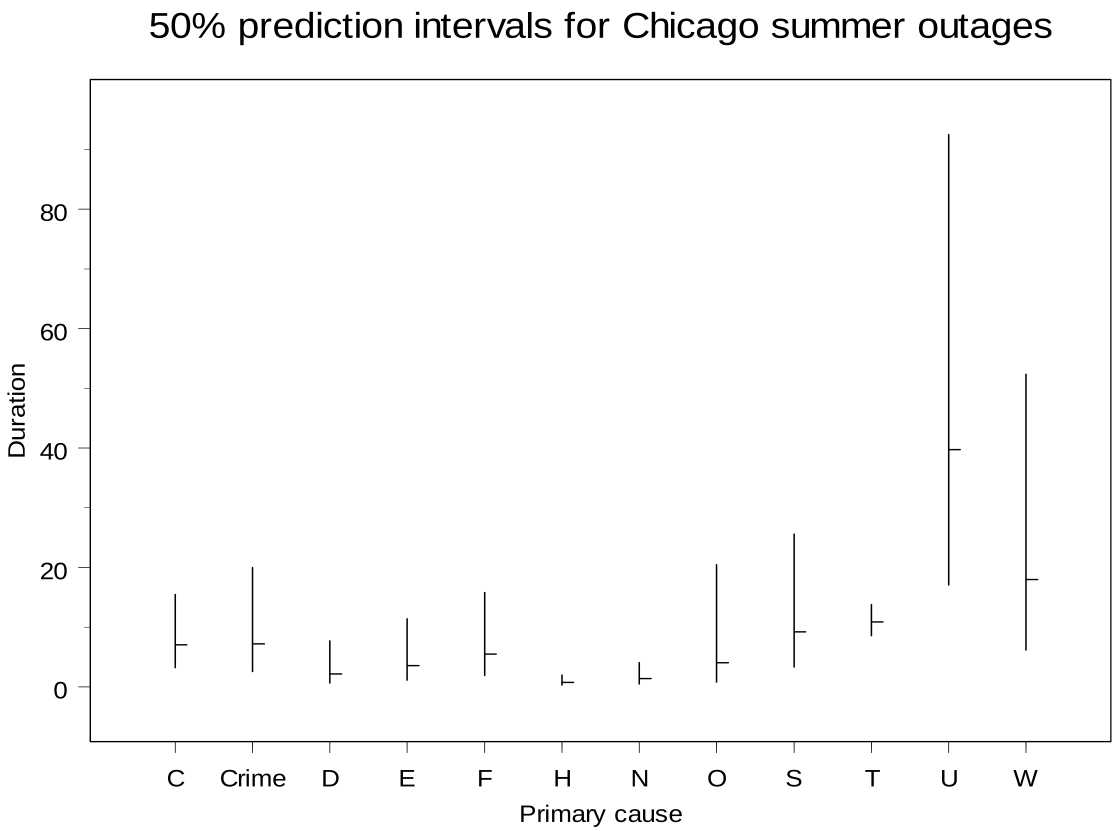
The horizontal tick on each line is the estimated expected duration for a summer New York City outage with that cause, while the vertical line gives the 50% prediction interval. The figure shows that the cause of the incident is related to both the level of duration (e.g., human error and demand reduction associated with shorter incidents and weather and unknown cause associated with longer ones) and the variability in duration (third party cause and system protection have similar expected durations, but durations of incidents caused by system protection are much more variable).

The following plot gives intervals for New York City outages during the winter.

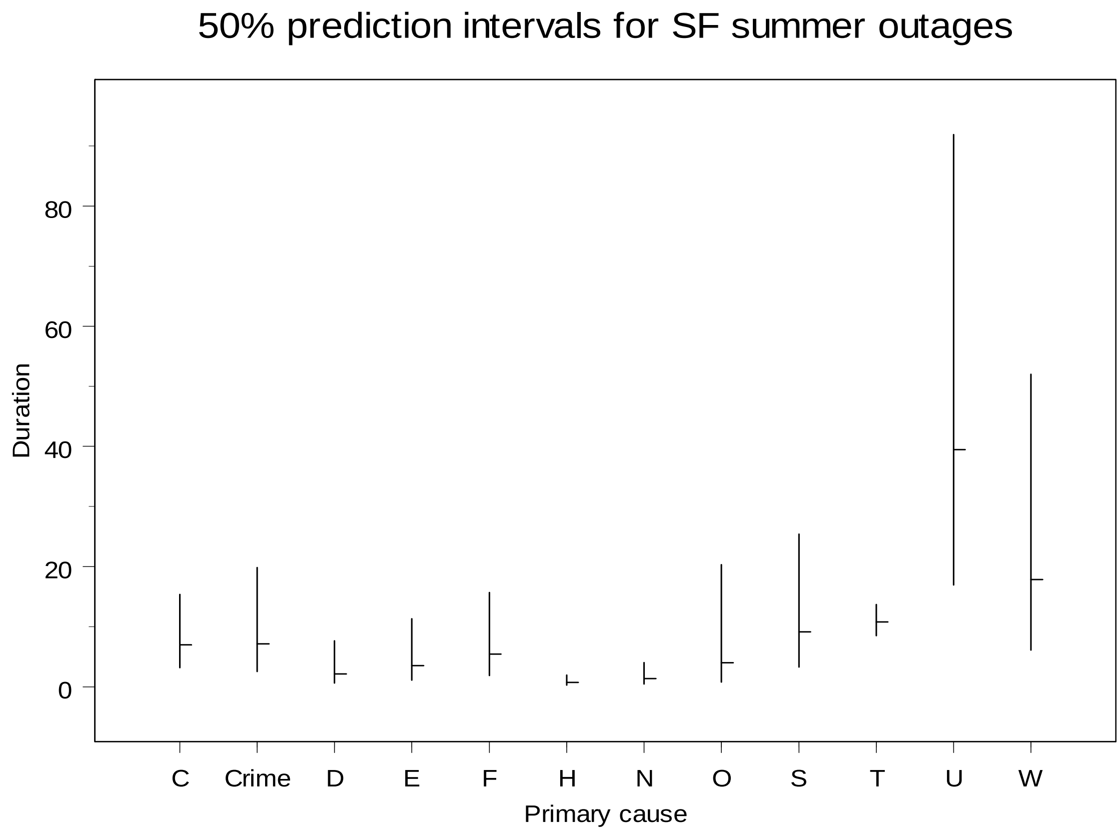


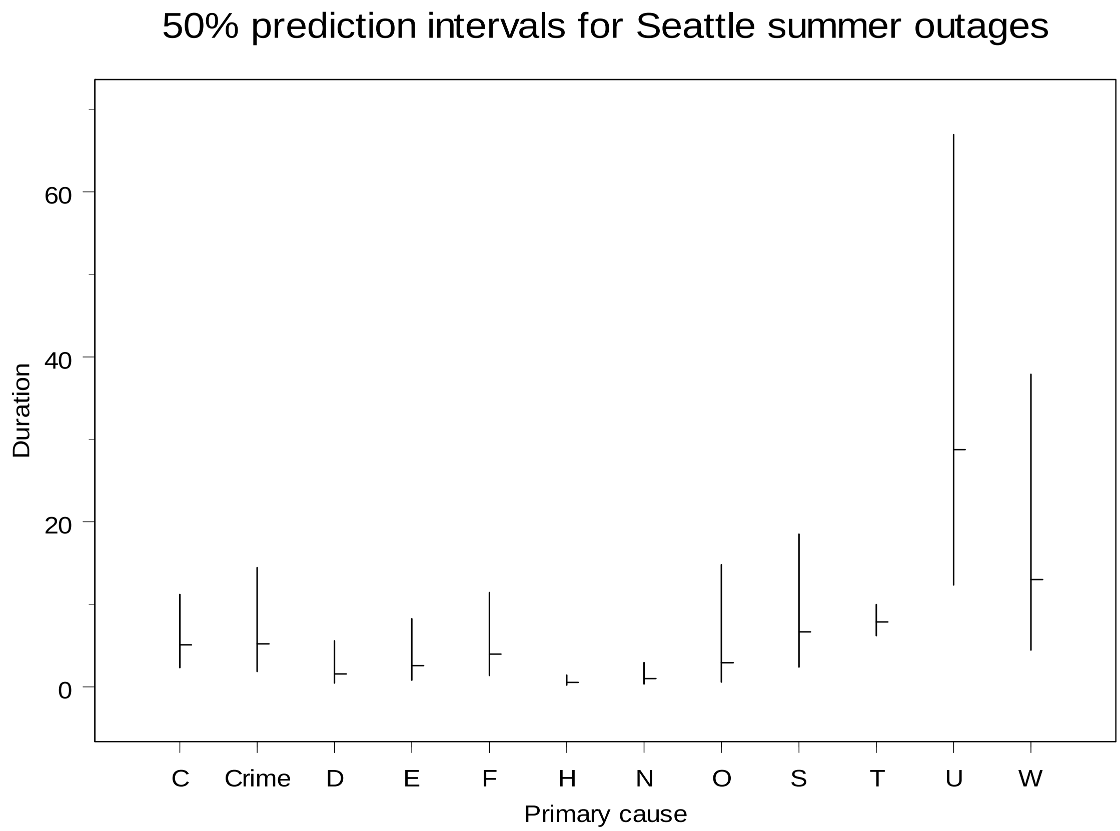
The pattern of relative estimates and prediction intervals is the same as for the summer incidents, but the averages and intervals are shifted up by a factor of two, reflecting that outages are longer on average during the winter.

The pattern of the intervals for a Chicago summer outage is again similar to that of the New York ones (as it must be), except that the intervals are shifted downwards, reflecting that the population density and number of customers serviced in Chicago imply a shorter expected duration of an incident.



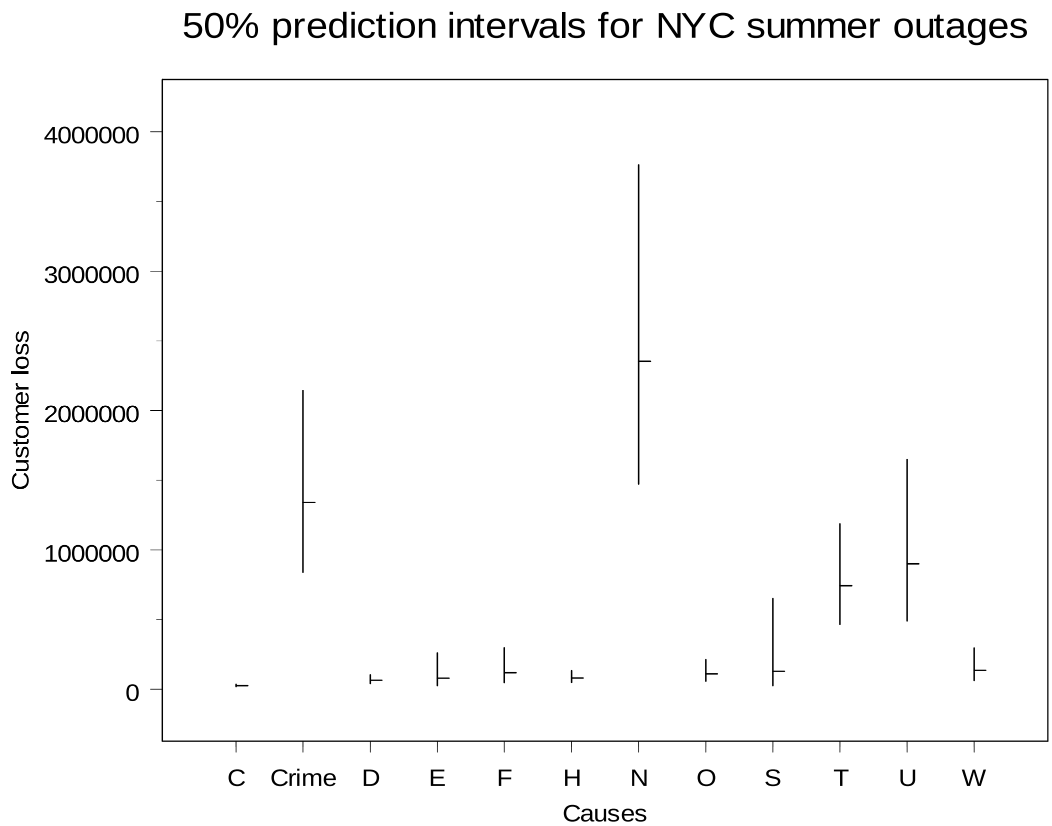
The intervals for San Francisco are similar to those for Chicago, while those for Seattle are centered at somewhat lower values.


50% prediction intervals for SF summer outages
Duration
0
20
40
60
80
C
Crime
D
E
F
H
N
O
S
T
U
W
Primary cause

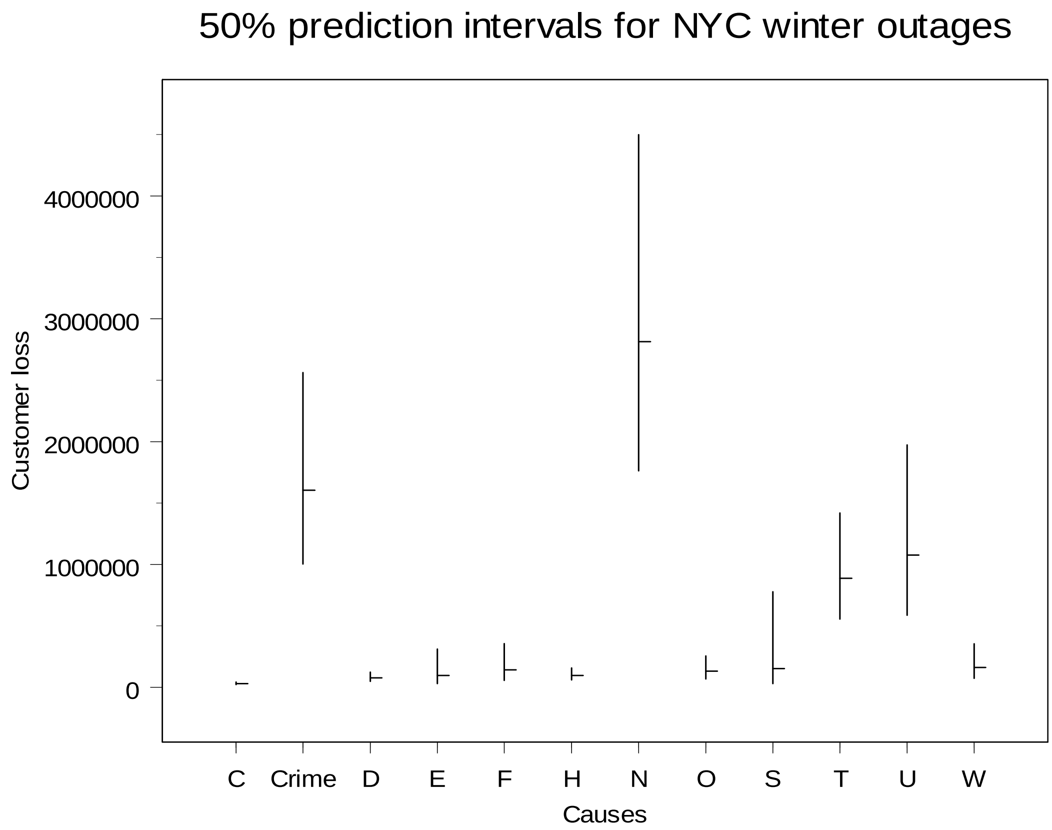


2. Customer loss of an incident, given that it is nonzero

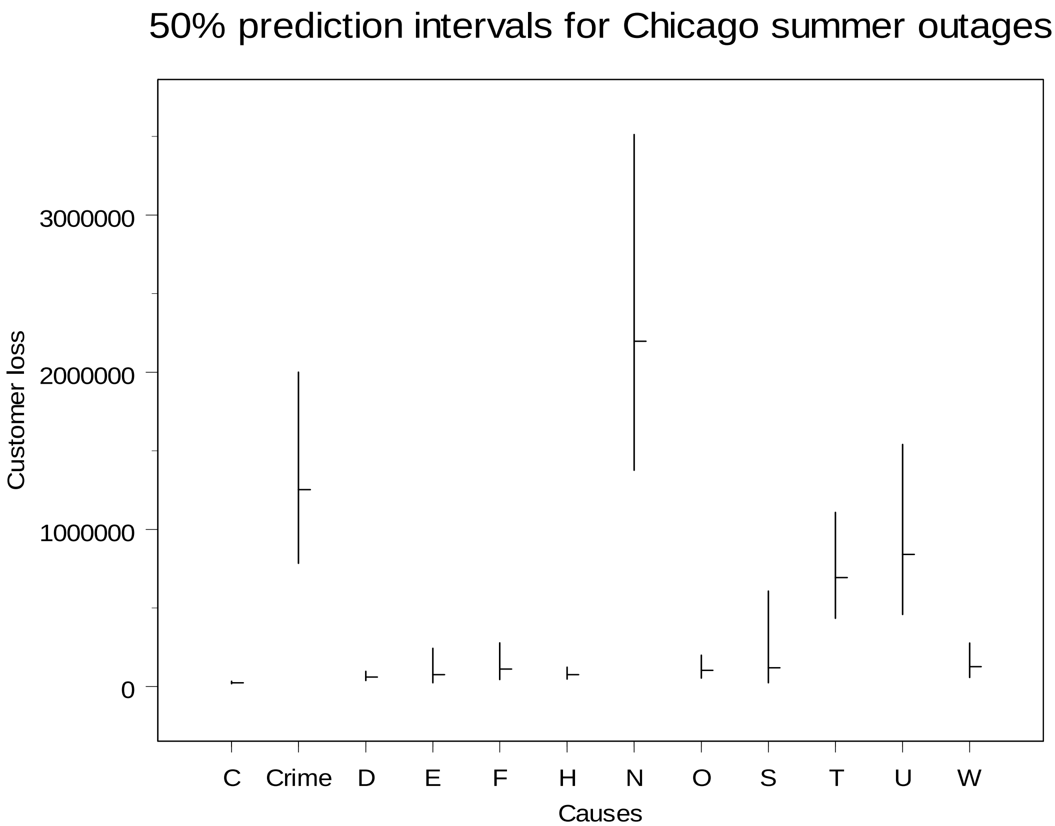
Using the estimated durations as inputs for the model, prediction intervals for customer loss (given that the loss is nonzero) also can be constructed. First, here are intervals for a summer outage in New York City.



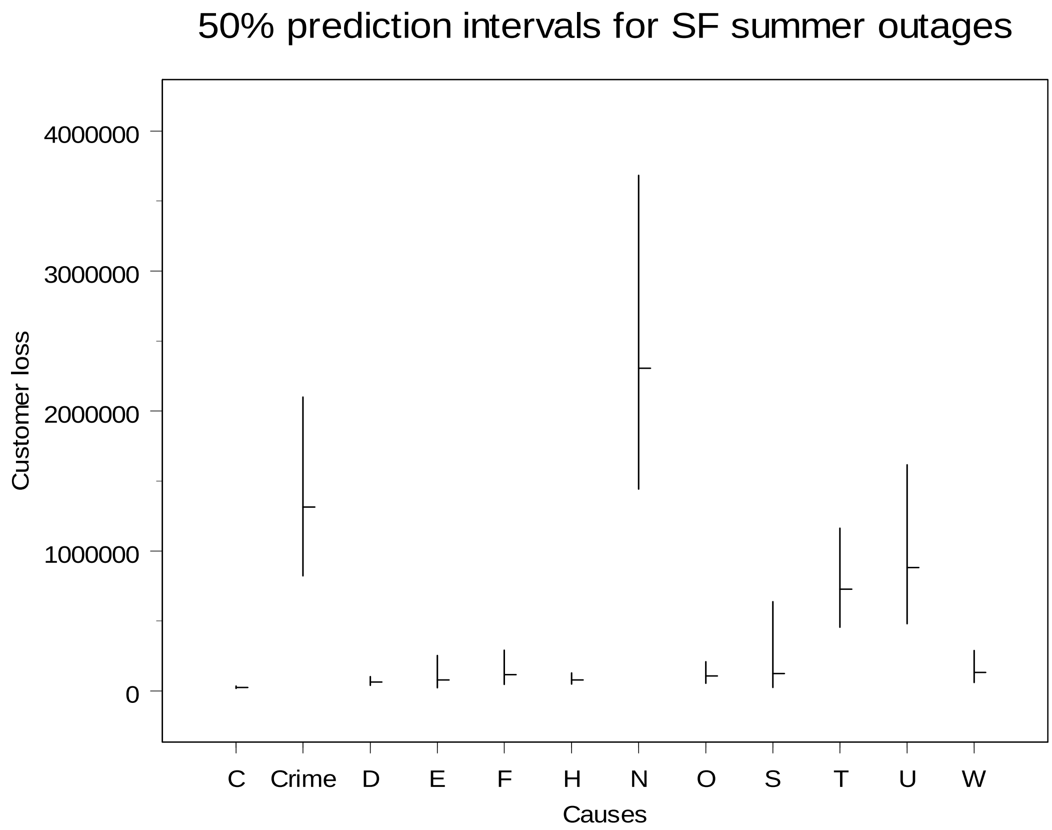
Once again there are considerable differences in both level and variability depending on the cause of the incident. The intervals for winter outages are centered at higher values, but this is an indirect, rather than direct, effect: while there is little difference in expected customer loss for summer and winter given the other predictors, outages are longer on average during the winter than during the summer, and longer outages are associated with more customers being affected.

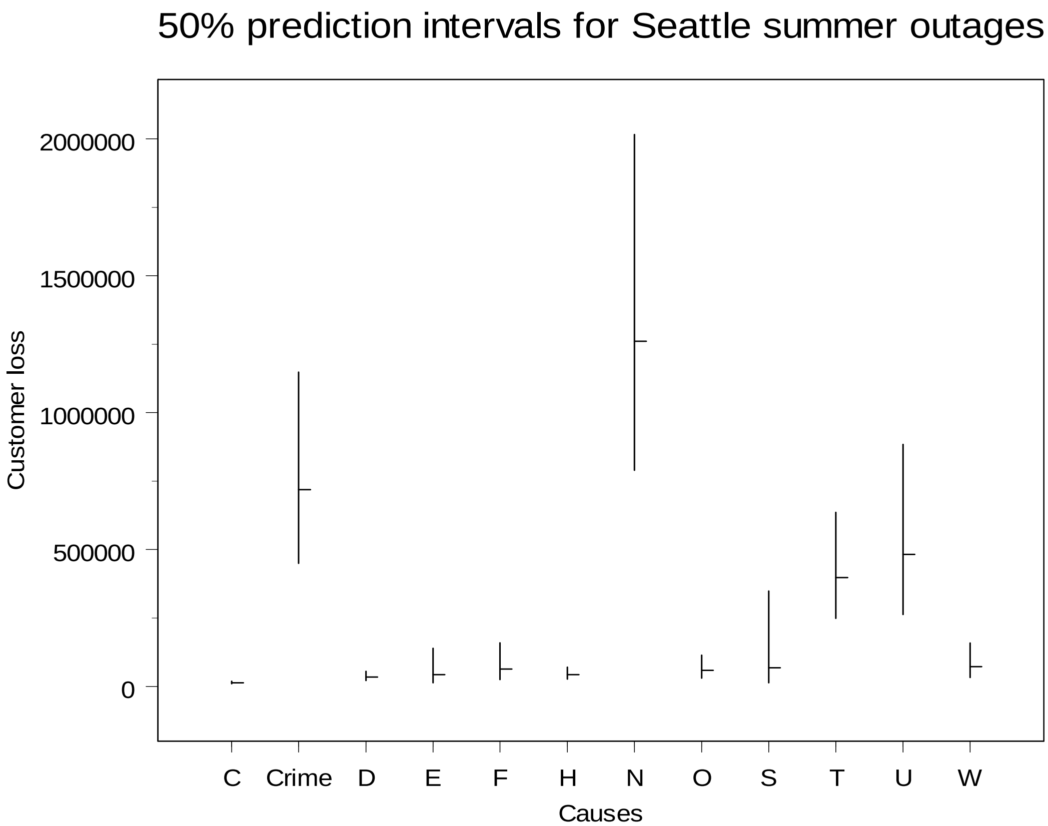


Customer losses in Chicago and San Francisco are expected to be similar to those in New York, while those in Seattle have smaller losses (these patterns are being driven in large part by the number of customers that utilities in those cities serve).



50% prediction intervals for Chicago summer outages
Customer loss
3000000
2000000
1000000
0
C
Crime
D
E
F
H
N
O
S
T
U
W
Causes


50% prediction intervals for SF summer outages
4000000
3000000
2000000
1000000
0
Customer loss
C
Crime
D
E
F
H
N
O
S
T
U
W
Causes


50% prediction intervals for Seattle summer outages
Customer loss
2000000
1500000
1000000
500000
0
C
Crime
D
E
F
H
N
O
S
T
U
W
Causes

Appendix: Expected duration, probability of zero customer loss, and expected customer loss for different cities, seasons, and causes

1. Expected duration of an incident

The following is a table of estimated expected durations (in hours) for New York City scenarios.

	Autumn	*Spring*	*Summer*	*Winter*
Capacity shortage	11.9	12.5	8.5	19.2
Crime	12.2	12.8	8.7	19.6
Demand reduction	3.7	3.9	2.7	6.0
Equipment failure	6.0	6.3	4.3	9.7
Fire	9.3	9.8	6.7	15.0
Human error	1.3	1.3	0.9	2.0
Natural disaster	2.4	2.5	1.7	3.8
Operational error	6.8	7.2	4.9	11.0
System protection	15.5	16.4	11.2	25.1
Third party	18.4	19.4	13.2	29.7
Unknown	67.2	70.7	48.3	108.5
Weather	30.4	32.0	21.8	49.1

The following is a table of estimated expected durations for Chicago scenarios.

	Autumn	*Spring*	*Summer*	*Winter*
Capacity shortage	9.8	10.3	7.0	15.8
Crime	10.0	10.5	7.2	16.1
Demand reduction	3.0	3.2	2.2	4.9
Equipment failure	5.0	5.2	3.6	8.0
Fire	7.7	8.1	5.5	12.4
Human error	1.0	1.1	0.7	1.7
Natural disaster	2.0	2.1	1.4	3.2
Operational error	5.6	5.9	4.0	9.0
System protection	12.8	13.5	9.2	20.7
Third party	15.1	15.9	10.9	24.5
Unknown	55.3	58.2	39.7	89.3
Weather	25.0	26.3	18.0	40.4

The following is a table of estimated expected durations for San Francisco scenarios.

	Autumn	*Spring*	*Summer*	*Winter*
Capacity shortage	9.7	10.2	7.0	15.7
Crime	9.9	10.5	7.1	16.0
Demand reduction	3.0	3.2	2.2	4.9
Equipment failure	4.9	5.2	3.5	8.0
Fire	7.6	8.0	5.5	12.3

Human error	1.0	1.1	0.7	1.7
Natural disaster	1.9	2.0	1.4	3.1
Operational error	5.6	5.9	4.0	9.0
System protection	12.7	13.4	9.1	20.5
Third party	15.0	15.8	10.8	24.3
Unknown	54.9	57.8	39.5	88.7
Weather	24.8	26.1	17.8	40.1

The following is a table of estimated expected durations for Seattle scenarios.

	Autumn	*Spring*	*Summer*	*Winter*
Capacity shortage	7.1	7.5	5.1	11.4
Crime	7.2	7.6	5.2	11.7
Demand reduction	2.2	2.3	1.6	3.6
Equipment failure	3.6	3.8	2.6	5.8
Fire	5.5	5.8	4.0	9.0
Human error	0.7	0.8	0.5	1.2
Natural disaster	1.4	1.5	1.0	2.3
Operational error	4.1	4.3	2.9	6.5
System protection	9.3	9.7	6.7	15.0
Third party	11.0	11.5	7.9	17.7
Unknown	40.0	42.1	28.8	64.6
Weather	18.1	19.0	13.0	29.2

2. Probability of zero customer loss

The following is a table of estimated probabilities that an incident will have zero customer loss for New York City scenarios.

	Autumn	*Spring*	*Summer*	*Winter*
Capacity shortage	.049	.056	.028	.052
Crime	.431	.464	.300	.447
Demand reduction	.542	.575	.401	.558
Equipment failure	.047	.053	.027	.050
Fire	.047	.054	.027	.050
Human error	.059	.066	.034	.0622
Natural disaster	.117	.132	.070	.124
Operational error	.019	.022	.011	.020
System protection	.000	.000	.000	.000
Third party	.485	.519	.348	.502
Unknown	.034	.039	.019	.036
Weather	.007	.008	.004	.007

The following is a table of estimated probabilities that an incident will have zero customer loss for Chicago scenarios.

	Autumn	*Spring*	*Summer*	*Winter*
Capacity shortage	.073	.083	.043	.077
Crime	.535	.568	.395	.551
Demand reduction	.642	.673	.504	.657
Equipment failure	.069	.078	.040	.073
Fire	.070	.079	.041	.074
Human error	.086	.098	.051	.092
Natural disaster	.167	.187	.102	.177
Operational error	.029	.033	.016	.031
System protection	.000	.000	.000	.000
Third party	.621	.621	.448	.605
Unknown	.057	.057	.029	.054
Weather	.012	.012	.006	.011

The following is a table of estimated probabilities that an incident will have zero customer loss for San Francisco scenarios.

	Autumn	*Spring*	*Summer*	*Winter*
Capacity shortage	.074	.084	.043	.079
Crime	.539	.573	.399	.556
Demand reduction	.647	.677	.509	.662
Equipment failure	.070	.080	.041	.075
Fire	.071	.081	.042	.076
Human error	.088	.099	.052	.093
Natural disaster	.170	.190	.104	.180
Operational error	.029	.033	.017	.031
System protection	.000	.000	.000	.000
Third party	.593	.626	.453	.609
Unknown	.051	.058	.030	.055
Weather	.010	.012	.006	.011

The following is a table of estimated probabilities that an incident will have zero customer loss for Seattle scenarios.

	Autumn	*Spring*	*Summer*	*Winter*
Capacity shortage	.131	.148	.079	.139
Crime	.689	.718	.557	.703
Demand reduction	.776	.799	.663	.787
Equipment failure	.125	.141	.075	.132
Fire	.127	.143	.076	.134
Human error	.154	.172	.093	.163
Natural disaster	.280	.308	.180	.293

Operational error	.054	.061	.031	.057
System protection	.000	.000	.000	.000
Third party	.734	.760	.610	.747
Unknown	.093	.105	.055	.099
Weather	.020	.022	.011	.021

3. Expected customer loss of incident given nonzero customer loss

The following is a table of estimated expected customer losses (given nonzero customer loss) for New York City scenarios.

	Autumn	*Spring*	*Summer*	*Winter*
Capacity shortage	31,998	42,984	25,448	30,434
Crime	1,686,511	2,265,524	1,341,245	1,604,029
Demand reduction	81,903	110,022	65,136	77,897
Equipment failure	100,974	135,641	80,302	96,036
Fire	149,381	200,667	118,800	142,076
Human error	102,244	137,347	81,313	97,244
Natural disaster	2,959,504	3,975,563	2,353,628	2,814,765
Operational error	138,930	186,627	110,488	132,135
System protection	160,942	216,197	127,994	153,071
Third party	934,651	1,255,536	743,308	888,941
Unknown	1,131,190	1,519,551	899,611	1,075,867
Weather	170,352	228,837	135,477	162,021

The following is a table of estimated expected customer losses (given nonzero customer loss) for Chicago scenarios.

	Autumn	*Spring*	*Summer*	*Winter*
Capacity shortage	29,876	40,133	23,760	28,415
Crime	1,574,661	2,115,275	1,252,293	1,497,650
Demand reduction	76,471	102,725	60,816	72,731
Equipment failure	94,277	126,645	74,977	89,667
Fire	139,474	187,359	110,921	132,653
Human error	95,463	128,238	75,920	90,795
Natural disaster	2,763,230	3,711,903	2,197,536	2,628,089
Operational error	129,716	174,250	103,160	123,372
System protection	150,269	201,859	119,505	142,920
Third party	872,665	1,172,269	694,011	829,986
Unknown	1,056,169	1,418,774	839,948	1,004,516
Weather	159,054	213,661	126,492	151,275

The following is a table of estimated expected customer losses (given nonzero customer loss) for San Francisco scenarios.

	Autumn	*Spring*	*Summer*	*Winter*
Capacity shortage	31,342	42,103	24,926	29,809
Crime	1,651,928	2,219,069	1,313,742	1,571,138
Demand reduction	80,224	107,766	63,800	76,300
Equipment failure	98,904	132,859	78,656	94,067
Fire	146,318	196,552	116,364	139,162
Human error	100,148	134,530	79,645	95,250
Natural disaster	2,898,818	3,894,042	2,305,366	2,757,046
Operational error	136,081	182,800	108,222	129,426
System protection	157,642	211,764	125,369	149,933
Third party	915,486	1,229,791	728,066	870,712
Unknown	1,107,994	1,488,392	881,164	1,053,806
Weather	166,859	224,145	132,699	158,698

The following is a table of estimated expected customer losses (given nonzero customer loss) for Seattle scenarios.

	Autumn	*Spring*	*Summer*	*Winter*
Capacity shortage	17,144	23,030	13,634	16,305
Crime	903,585	1,213,804	718,601	859,394
Demand reduction	43,881	58,947	34,898	41,735
Equipment failure	54,099	72,672	43,024	51,453
Fire	80,034	107,512	63,650	76,120
Human error	54,780	73,587	43,565	52,101
Natural disaster	1,585,619	2,129,995	1,261,008	1,508,072
Operational error	74,435	99,990	59,196	70,794
System protection	86,228	115,832	68,576	82,011
Third party	500,760	672,681	398,243	476,269
Unknown	606,060	814,133	481,986	576,419
Weather	91,270	122,605	72,585	86,806

These estimates can be combined to estimate the overall (unconditional) expected number of customers lost for a given scenario. If p is the probability of zero customer loss, the expected number of customers lost is

$$E(\text{Customers lost}) = (p)(0) + (1-p)(E[\text{Customers lost given nonzero customer loss}])$$

So, for example, since an incident in New York City during the winter caused by crime has zero customer loss with probability p=.447 and nonzero loss with probability 1-p=.553, and an expected 1,604,029 customers lost if there is nonzero loss, the overall expected customers lost for such an incident is

$$E(\text{Customers lost}) = (.447)(0) + (.553)(1,604,029) = 887,028.$$

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.