

# Do Seat Belt Laws Predict a Reduction in Road Casualties?

DATA 606 Final Project  
Spring 2022

By Julian Adames-Ng

# Abstract

To answer the proposed question, I gathered data using the “UKDriverDeaths” time-series from the R Documentation which includes monthly statistics on road deaths in the United Kingdom from January 1969 to December 1984. The mandatory seat belt law was introduced on January 1983. In order to manipulate the data to perform analyses, I created a data-frame from this data set. This allows me to parse the data as needed and analyze measures of center and variation as well as perform correlation analyses on the data prior to and after the passing of the seat belt law. Visualization of these analyses are provided.

# Loading the Data

## Time Series

- “UKDriverDeaths is a time series giving the monthly totals of car drivers in Great Britain killed or seriously injured Jan 1969 to Dec 1984. Compulsory wearing of seat belts was introduced on 31 Jan 1983.” - R Documentation
- Seatbelts is a multiple time series, with the columns:
  - DriversKilled - car drivers killed
  - drivers - same as UKDriverDeaths (total road deaths)
  - front - front-seat passengers killed or seriously injured
  - rear - rear-seat passengers killed or seriously injured
  - kms - distance driven
  - PetrolPrice - petrol price
  - VanKilled - number of van ('light goods vehicle') drivers
  - law - 0/1: was the law in effect that month?

UKDriverDeaths												
##	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
## 1969	1687	1508	1507	1385	1632	1511	1559	1630	1579	1653	2152	2148
## 1970	1752	1765	1717	1558	1575	1520	1805	1800	1719	2008	2242	2478
## 1971	2030	1655	1693	1623	1805	1746	1795	1926	1619	1992	2233	2192
## 1972	2080	1768	1835	1569	1976	1853	1965	1689	1778	1976	2397	2654
## 1973	2097	1963	1677	1941	2003	1813	2012	1912	2084	2080	2118	2150
## 1974	1608	1503	1548	1382	1731	1798	1779	1887	2004	2077	2092	2051
## 1975	1577	1356	1652	1382	1519	1421	1442	1543	1656	1561	1905	2199
## 1976	1473	1655	1407	1395	1530	1309	1526	1327	1627	1748	1958	2274
## 1977	1648	1401	1411	1403	1394	1520	1528	1643	1515	1685	2000	2215
## 1978	1956	1462	1563	1459	1446	1622	1657	1638	1643	1683	2050	2262
## 1979	1813	1445	1762	1461	1556	1431	1427	1554	1645	1653	2016	2207
## 1980	1665	1361	1506	1360	1453	1522	1460	1552	1548	1827	1737	1941
## 1981	1474	1458	1542	1404	1522	1385	1641	1510	1681	1938	1868	1726
## 1982	1456	1445	1456	1365	1487	1558	1488	1684	1594	1850	1998	2079
## 1983	1494	1057	1218	1168	1236	1076	1174	1139	1427	1487	1483	1513
## 1984	1357	1165	1282	1110	1297	1185	1222	1284	1444	1575	1737	1763

Source - Harvey A.C. (1989). Forecasting, Structural Time Series Models and the Kalman Filter. Cambridge University Press, pp. 519-523.

Durbin, J. And Koopman, S. J. (2001). Time Series Analysis by State Space Methods. Oxford University Press. <http://www.ssfpack.com/dkbook/>

# Loading the Data

## Creating a Data-Frame

- “Seatbelts is more information on the same problem.” - R Documentation
- This data-frame shows the previously mentioned variables involved in the study as column vectors with corresponding monthly dates for each data entry.

Seatbelts										
##	DriversKilled	drivers	front	rear	kms	PetrolPrice	VanKilled	law		
## Jan 1969	107	1687	867	269	9059	0.10297181	12	0		
## Feb 1969	97	1508	825	265	7685	0.10236300	6	0		
## Mar 1969	102	1507	806	319	9963	0.10206249	12	0		
## Apr 1969	87	1385	814	407	10955	0.10087330	8	0		
## May 1969	119	1632	991	454	11823	0.10101967	10	0		
## Jun 1969	106	1511	945	427	12391	0.10058119	13	0		
## Jul 1969	110	1559	1004	522	13460	0.10377398	11	0		
## Aug 1969	106	1630	1091	536	14055	0.10407640	6	0		
## Sep 1969	107	1579	958	405	12106	0.10377398	10	0		
## Oct 1969	134	1653	850	437	11372	0.10302640	16	0		
## Nov 1969	147	2152	1109	434	9834	0.10273011	13	0		
## Dec 1969	180	2148	1113	437	9267	0.10199719	14	0		
## Jan 1970	125	1752	925	316	9130	0.10127456	14	0		
## Feb 1970	134	1765	903	311	8933	0.10070398	6	0		
## Mar 1970	110	1717	1006	351	11000	0.10013961	8	0		
## Apr 1970	102	1558	892	362	10733	0.09862110	11	0		
## May 1970	103	1575	990	486	12912	0.09834929	7	0		
## Jun 1970	111	1520	866	429	12926	0.09808018	13	0		
## Jul 1970	120	1805	1095	551	13990	0.09727921	13	0		
## Aug 1970	129	1800	1204	646	14926	0.09741062	11	0		
## Sep 1970	122	1719	1029	456	12900	0.09742524	11	0		
## Oct 1970	183	2008	1147	475	12034	0.09638063	14	0		
## Nov 1970	169	2242	1171	456	10643	0.09573896	16	0		
## Dec 1970	190	2478	1299	468	10742	0.09510631	14	0		
## Jan 1971	134	2030	944	356	10266	0.09673597	17	0		
## Feb 1971	108	1655	874	271	10281	0.09610922	16	0		
## Mar 1971	104	1693	840	354	11527	0.09536725	15	0		

# Loading the Data

## Creating a Data-Frame continued

```
#Create a data frame from Seatbelts  
sbelts <- data.frame(Seatbelts)  
  
sbelts
```

##	DriversKilled	drivers	front	rear	kms	PetrolPrice	VanKilled	law
## 1	107	1687	867	269	9059	0.10297181	12	0
## 2	97	1508	825	265	7685	0.10236300	6	0
## 3	102	1507	806	319	9963	0.10206249	12	0
## 4	87	1385	814	407	10955	0.10087330	8	0
## 5	119	1632	991	454	11823	0.10101967	10	0
## 6	106	1511	945	427	12391	0.10058119	13	0
## 7	110	1559	1004	522	13460	0.10377398	11	0
## 8	106	1630	1091	536	14055	0.10407640	6	0
## 9	107	1579	958	405	12106	0.10377398	10	0
## 10	134	1653	850	437	11372	0.10302640	16	0
## 11	147	2152	1109	434	9834	0.10273011	13	0
## 12	180	2148	1113	437	9267	0.10199719	14	0
## 13	125	1752	925	316	9130	0.10127456	14	0
## 14	134	1765	903	311	8933	0.10070398	6	0
## 15	110	1717	1006	351	11000	0.10013961	8	0
## 16	102	1558	892	362	10733	0.09862110	11	0
## 17	103	1575	990	486	12912	0.09834929	7	0
## 18	111	1520	866	429	12926	0.09808018	13	0
## 19	120	1805	1095	551	13990	0.09727921	13	0
## 20	129	1800	1204	646	14926	0.09741062	11	0
## 21	122	1719	1029	456	12900	0.09742524	11	0
## 22	183	2008	1147	475	12034	0.09638063	14	0
## 23	169	2242	1171	456	10643	0.09573896	16	0

- I decided to use the previous data-frame to create a duplicate called “sbelts” that was easier for me to work with for parsing.
- The difference between “Seatbelts” and “sbelts” is that the row titles have been changed from a month/year date format in the former to indexed values in the latter.

# Parsing the Data

- I parsed the “sbelts” data-frame and created two subsets:
  - “DnoLaw” shows the data BEFORE the seat belt law was introduced. This is indicated in the “law” column where 0 means that the law was not yet passed.
  - “DLaw” shows the data AFTER the seat belt law was introduced. This is indicated in the “law” column where 1 means that the law had been passed.

```
DnoLaw <- sbelts %>% filter(law == 0)
DLaw <- sbelts %>% filter(law == 1)

DnoLaw
```

##	DriversKilled	drivers	front	rear	kms	PetrolPrice	VanKilled	law
## 1	107	1687	867	269	9059	0.10297181	12	0
## 2	97	1508	825	265	7685	0.10236300	6	0
## 3	102	1507	806	319	9963	0.10206249	12	0
## 4	87	1385	814	407	10955	0.10087330	8	0
## 5	119	1632	991	454	11823	0.10101967	10	0
## 6	106	1511	945	427	12391	0.10058119	13	0
## 7	110	1559	1004	522	13460	0.10377398	11	0
## 8	106	1630	1091	536	14055	0.10407640	6	0
## 9	107	1579	958	405	12106	0.10377398	10	0
## 10	134	1653	850	437	11372	0.10302640	16	0

```
DLaw
```

##	DriversKilled	drivers	front	rear	kms	PetrolPrice	VanKilled	law
## 1	95	1057	426	300	15511	0.1136570	3	1
## 2	100	1218	475	318	18308	0.1131444	2	1
## 3	89	1168	556	391	17793	0.1184955	6	1
## 4	82	1236	559	398	19205	0.1179694	3	1
## 5	89	1076	483	337	19162	0.1176866	7	1
## 6	60	1174	587	477	20997	0.1200592	6	1
## 7	84	1139	615	422	20705	0.1194377	8	1
## 8	113	1427	618	495	18759	0.1188813	8	1
## 9	126	1487	662	471	19240	0.1184624	4	1
## 10	122	1483	519	368	17504	0.1180166	3	1
## 11	118	1513	585	345	16591	0.1177066	5	1
## 12	92	1357	483	296	16224	0.1177761	5	1
## 13	86	1165	434	319	16670	0.1147970	3	1

```

cat(" Overall Mean: \n", mean(sbelts$drivers),
  "\n Mean (Pre-Law): \n", mean(DnoLaw$drivers),
  "\n Mean (Post-Law): \n", mean(DLaw$drivers),

"\n\n Mean - Driver Deaths (Pre-Law): \n", mean(DnoLaw$DriversKilled),
"\n Mean - Driver Deaths (Post-Law): \n", mean(DLaw$DriversKilled),

"\n\n Mean - Front Seat Passenger Deaths/Serious Injuries (Pre-Law): \n", mean(DnoLaw$front),
"\n Mean - Front Seat Passenger Deaths/Serious Injuries (Post-Law): \n", mean(DLaw$front),

"\n\n Mean - Rear Seat Passenger Deaths/Serious Injuries (Pre-Law): \n", mean(DnoLaw$rear),
"\n Mean - Rear Seat Passenger Deaths/Serious Injuries (Post-Law): \n", mean(DLaw$rear))

```

```

## Overall Mean:
## 1670.307
## Mean (Pre-Law):
## 1717.751
## Mean (Post-Law):
## 1321.696
##
## Mean - Driver Deaths (Pre-Law):
## 125.8698
## Mean - Driver Deaths (Post-Law):
## 100.2609
##
## Mean - Front Seat Passenger Deaths/Serious Injuries (Pre-Law):
## 873.4556
## Mean - Front Seat Passenger Deaths/Serious Injuries (Post-Law):
## 570.9565
##
## Mean - Rear Seat Passenger Deaths/Serious Injuries (Pre-Law):
## 400.3195
## Mean - Rear Seat Passenger Deaths/Serious Injuries (Post-Law):
## 407.7391

```

# Comparing Averages

- We see that there is a significant reduction in the average amount of deaths after the seat belt law was introduced.
- The mean for ALL deaths before the introduction of the law was 1717.751. After the law, the mean decreased to 1321.696.
- Parsing the data, we see that the mean for DRIVER deaths before the introduction of the law was 125.8698. After the law, the mean decreased to 100.2609.
- Parsing the data further, we can also compare the average FRONT SEAT passenger deaths/serious injuries. We see a significant reduction from 873.4556 to 570.9565.
- However, the average REAR SEAT passenger deaths/ serious injuries increased from 400.3195 to 407.7391. When compared to the reduction in overall or front seat deaths, this increase is negligible.

# Comparing Variability

- We also see that the variability of road death data had reduced significantly post-law. This indicates more consistency in the data.
- The standard deviation for front seat passenger deaths decreased significantly and the standard deviation for rear seat passenger deaths decrease less so.

```
cat(" Overall Standard Deviation: \n", sd(sbelts$drivers),
  "\n Standard Deviation (Pre-Law): \n", sd(DnoLaw$drivers),
  "\n Standard Deviation (Post-Law): \n",sd(DLaw$drivers),

  "\n\n Standard Deviation - Driver Deaths (Pre-Law): \n", sd(DnoLaw$DriversKilled),
  "\n Standard Deviation - Driver Deaths (Post-Law): \n",sd(DLaw$DriversKilled),

  "\n\n Standard Deviation - Front (Pre-Law):\n", sd(DnoLaw$front),
  "\n Standard Deviation - Front (Post-Law):\n", sd(DLaw$front),

  "\n\n Standard Deviation - Rear (Pre-Law): \n", sd(DnoLaw$rear),
  "\n Standard Deviation - Rear (Post-Law): \n", sd(DLaw$rear))
```

```
## Overall Standard Deviation:
## 289.611
## Standard Deviation (Pre-Law):
## 266.892
## Standard Deviation (Post-Law):
## 199.7233
##
## Standard Deviation - Driver Deaths (Pre-Law):
## 24.26088
## Standard Deviation - Driver Deaths (Post-Law):
## 22.2286
##
## Standard Deviation - Front (Pre-Law):
## 151.5416
## Standard Deviation - Front (Post-Law):
## 81.29099
##
## Standard Deviation - Rear (Pre-Law):
## 84.88012
## Standard Deviation - Rear (Post-Law):
## 69.91828
```

# Comparing Variability continued

- This reduction in variation is also evidenced by the range of road deaths in each scenario. After the law, the maximum and minimum road deaths decreased by a good amount each.

```
cat(" Maximum (Pre-Law):", max(range(DnoLaw$drivers)),
    "\n Maximum (Post-Law)", max(range(DLaw$drivers)),

    "\n\n Minimum (Pre-Law):", min(range(DnoLaw$drivers)),
    "\n Minimum (Post-Law)", min(range(DLaw$drivers)),

    "\n\n Range (Pre-Law):", max(range(DnoLaw$drivers))-min(range(DnoLaw$drivers)),
    "\n Range (Post-Law)", max(range(DLaw$drivers))-min(range(DLaw$drivers)))

## Maximum (Pre-Law): 2654
## Maximum (Post-Law) 1763
##
## Minimum (Pre-Law): 1309
## Minimum (Post-Law) 1057
##
## Range (Pre-Law): 1345
## Range (Post-Law) 706
```

# Rate of Fewer Deaths

- We can compare the average reduction in deaths to the average number of deaths prior to the law's introduction using a ratio:

$$\text{Reduction Rate} = \frac{\text{Mean Deaths (Before Law)} - \text{Mean Deaths (After Law)}}{\text{Mean Deaths (Before Law)}}$$

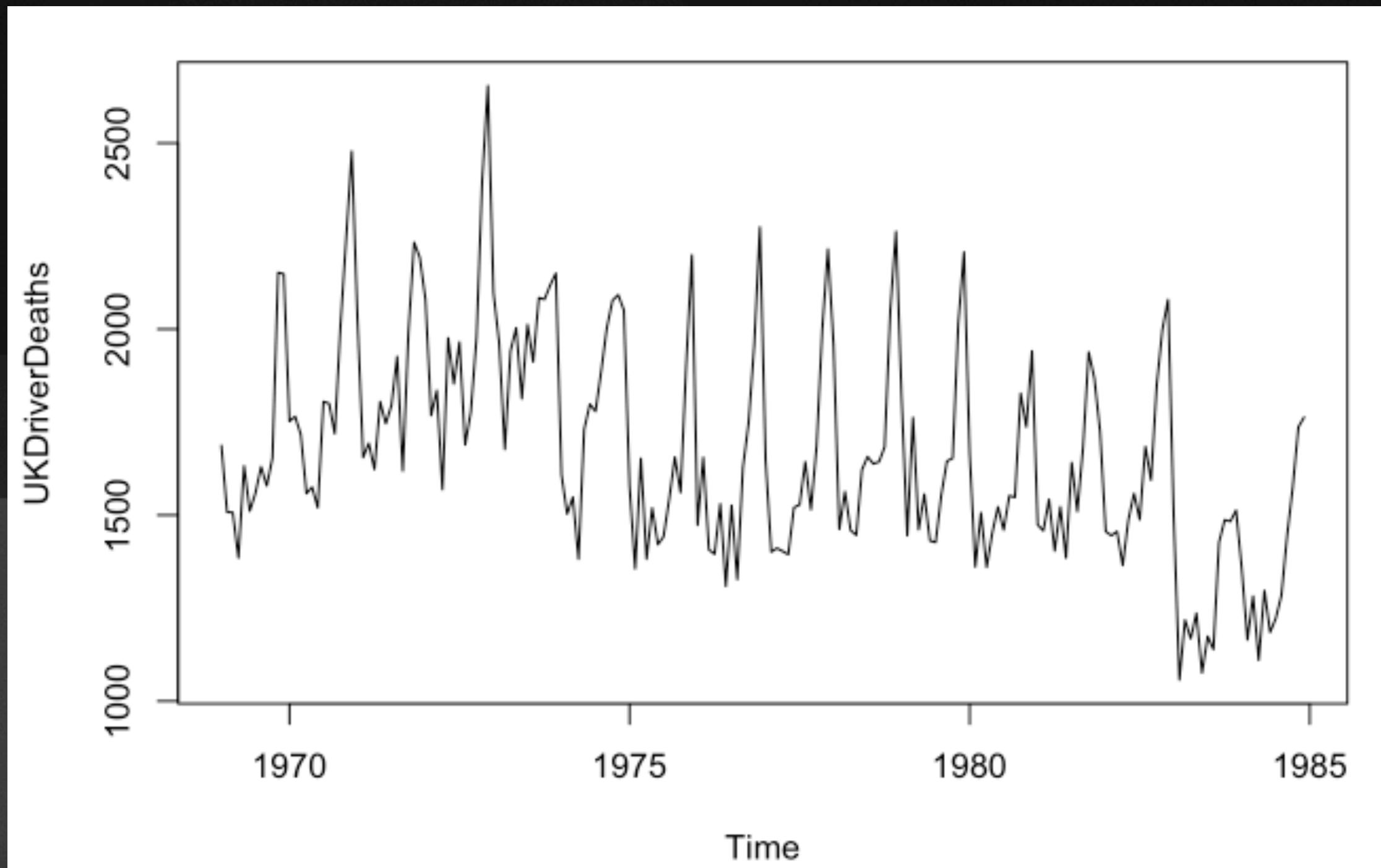
```
reduc_rate <- (mean(DnoLaw$drivers)-mean(DLaw$drivers))/mean(DnoLaw$drivers)
reduc_drivers <- (mean(DnoLaw$DriversKilled)-mean(DLaw$DriversKilled))/mean(DnoLaw$DriversKilled)
reduc_front <- (mean(DnoLaw$front)-mean(DLaw$front))/mean(DnoLaw$front)
reduc_rear <- (mean(DnoLaw$rear)-mean(DLaw$rear))/mean(DnoLaw$rear)

cat(" Average Total Death Reduction Rate: ", "\n", reduc_rate,
    "\n\n Average Reduction Rate in Driver Deaths: \n", reduc_drivers,
    "\n\n Average Reduction Rate in Front Seat Deaths: \n", reduc_front,
    "\n\n Average Reduction Rate in Rear Seat Deaths: \n", reduc_rear)
```

```
## Average Total Death Reduction Rate:
## 0.2305664
##
## Average Reduction Rate in Driver Deaths:
## 0.2034559
##
## Average Reduction Rate in Front Seat Deaths:
## 0.3463245
##
## Average Reduction Rate in Rear Seat Deaths:
## -0.0185342
```

# Visualizing the Data

```
plot.ts(UKDriverDeaths)
```

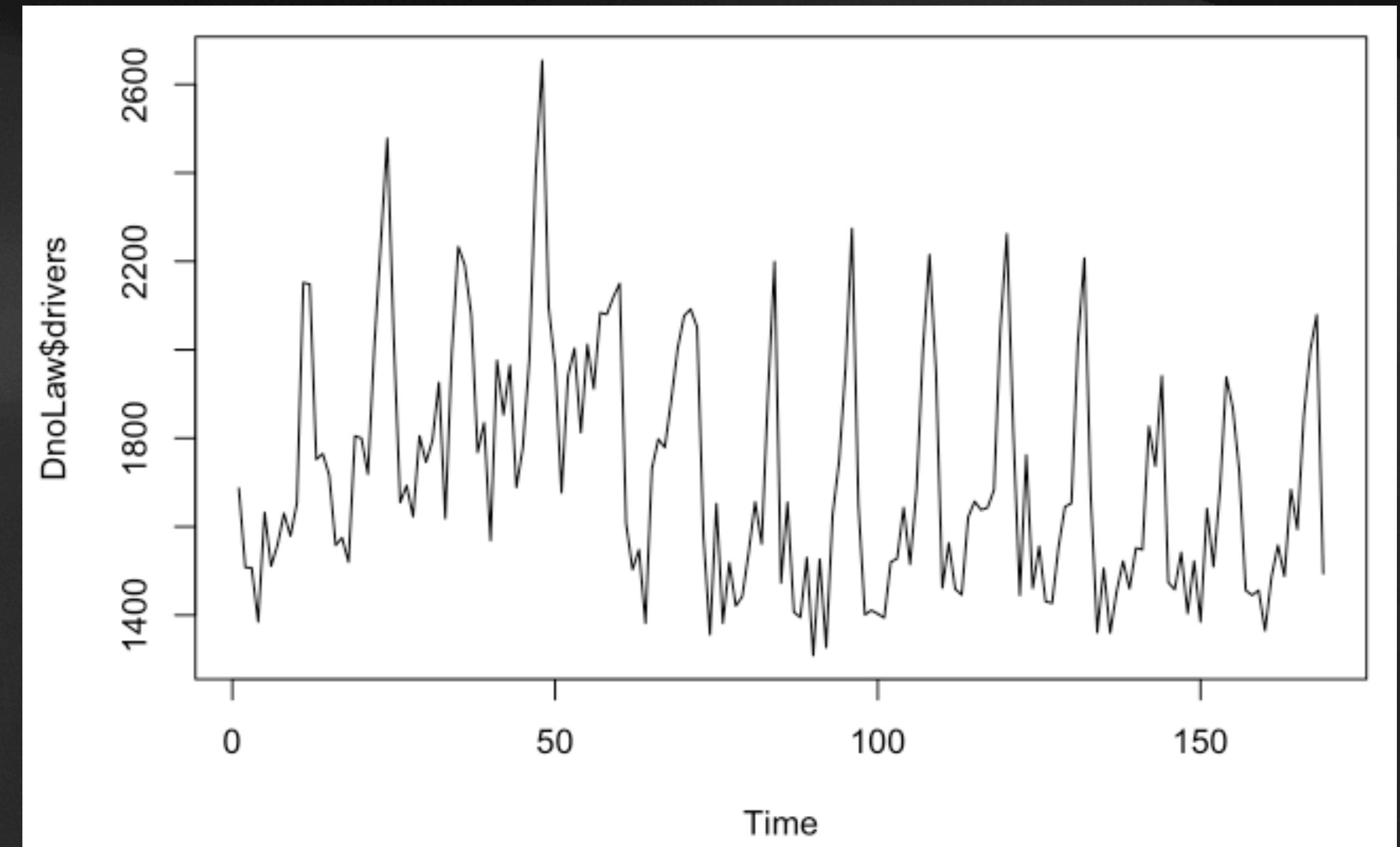


- In the first graph to the left, we see the visualized time-series data on total road casualties.
- It shows the entire timeline of data with Time (in years) on the horizontal axis.

# Visualizing the Data

```
plot.ts(DnoLaw$drivers)
```

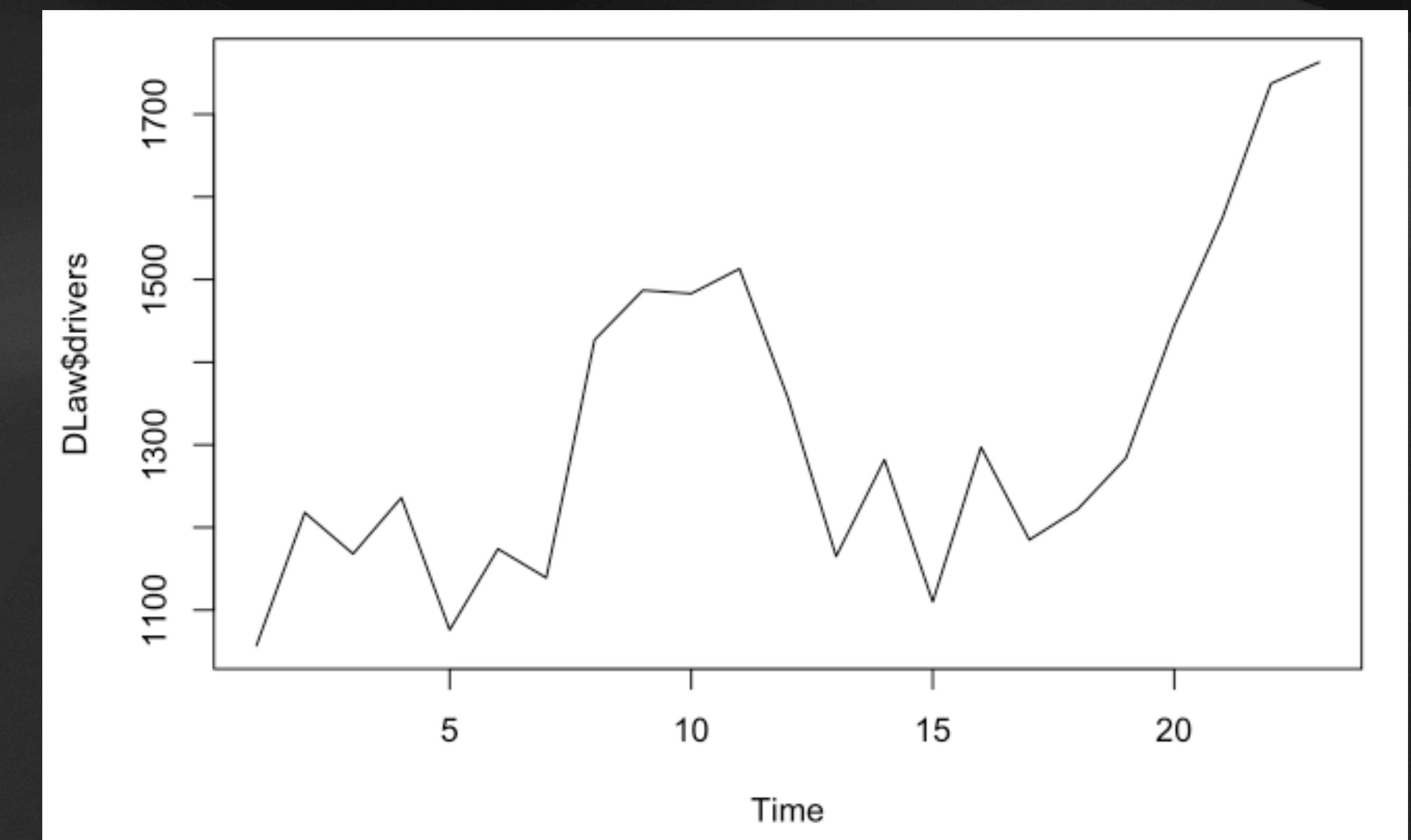
- The second graph shows the timeline of data BEFORE the law was enacted (the first 169 months), with Time (in months SINCE THE START OF THE STUDY) on the horizontal axis.



# Visualizing the Data

```
plot.ts(DLaw$drivers)
```

- The third graph shows the timeline of data AFTER the law was enacted (the last 23 months), with Time (in months SINCE ENACTMENT OF THE LAW) on the horizontal axis.

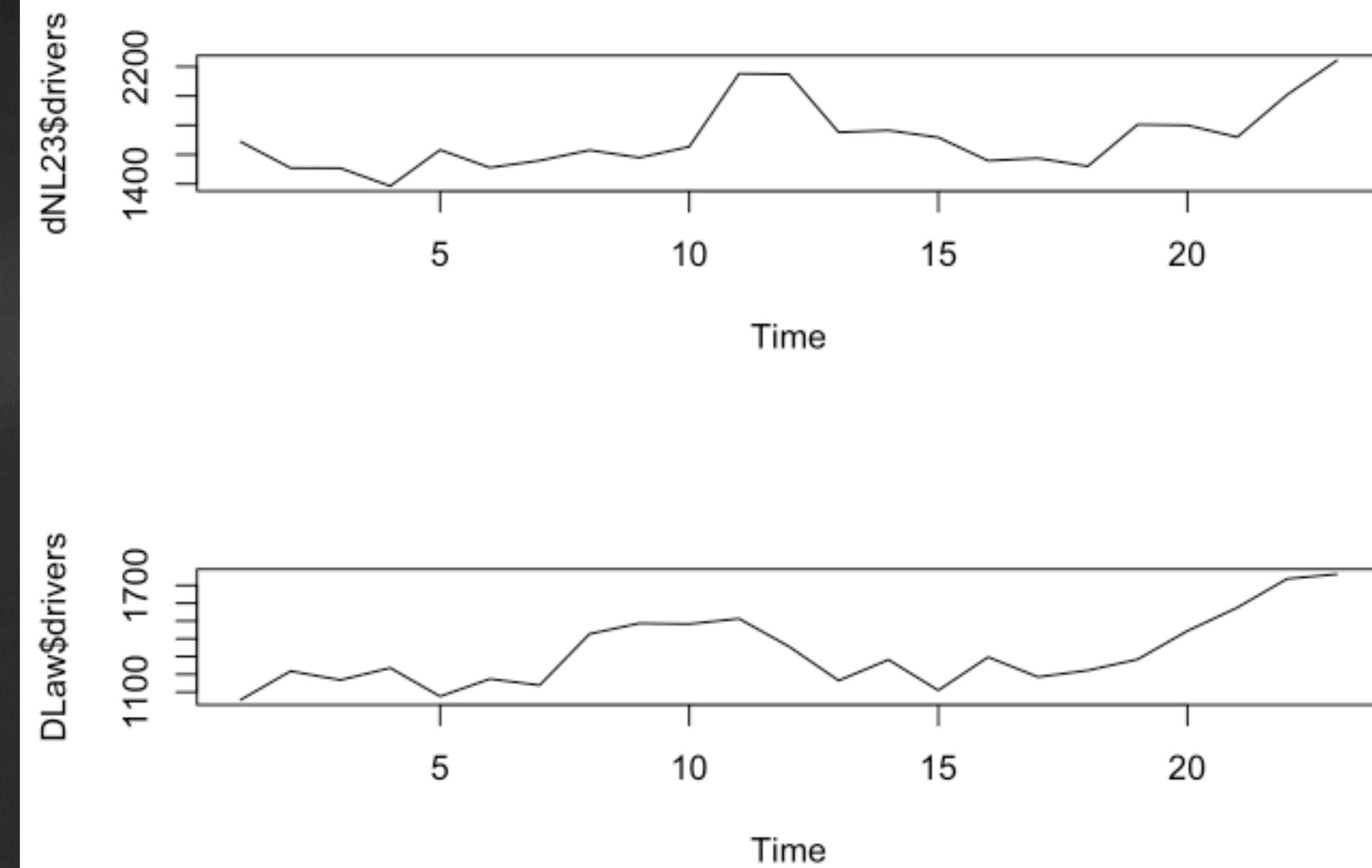


# Visualizing the Data

- Since we're limited to 23 months worth of data after the law was enacted, for the following graphs I chose to zoom in on four particular 22-26 month time periods before the enactment of the law. I did this in hopes of having a more comparable amount of data points, being sure to include the lowest dips in road deaths for each period. I paired each 22-26 month pre-law period with the 23 month post-law for comparison.
- We can visually see that the scaling for the number of deaths, regardless of time frame, decreases significantly after the passing of the seat belt law.

First 23 Months (Pre-Law) vs Final 23 Months (Post-Law)

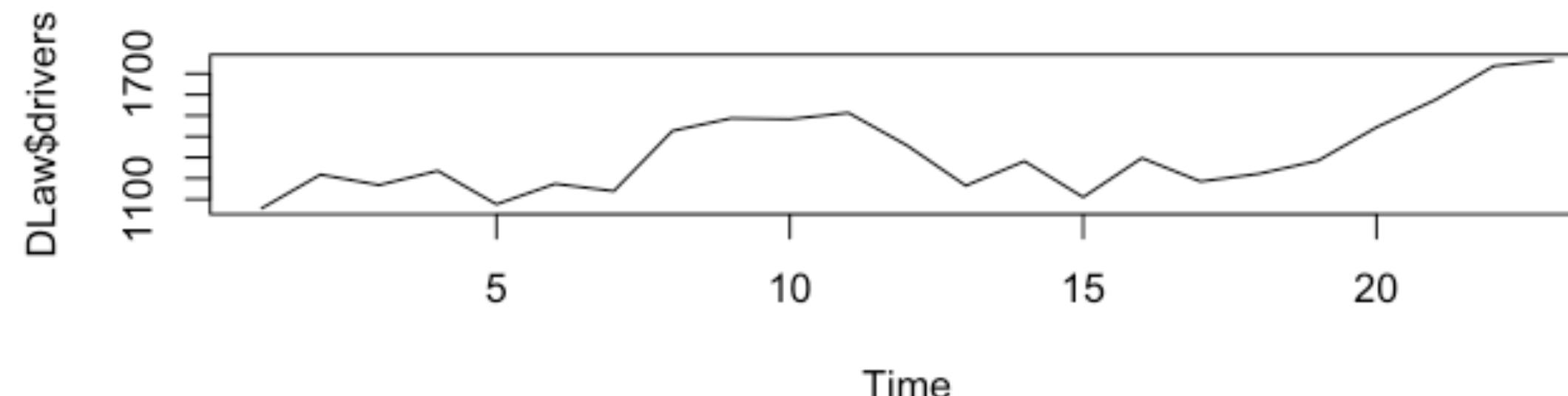
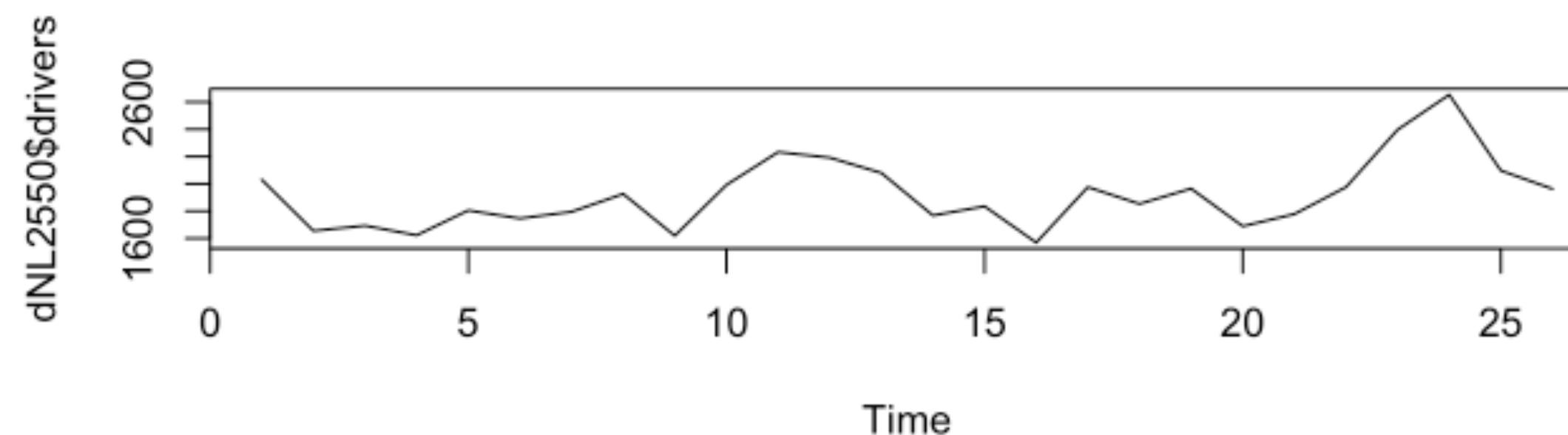
```
#first 23 months
dNL23 <- DnoLaw %>% slice(1:23)
par(mfrow=c(2,1))
plot.ts(dNL23$drivers)
plot.ts(DLaw$drivers)
```



# Visualizing the Data

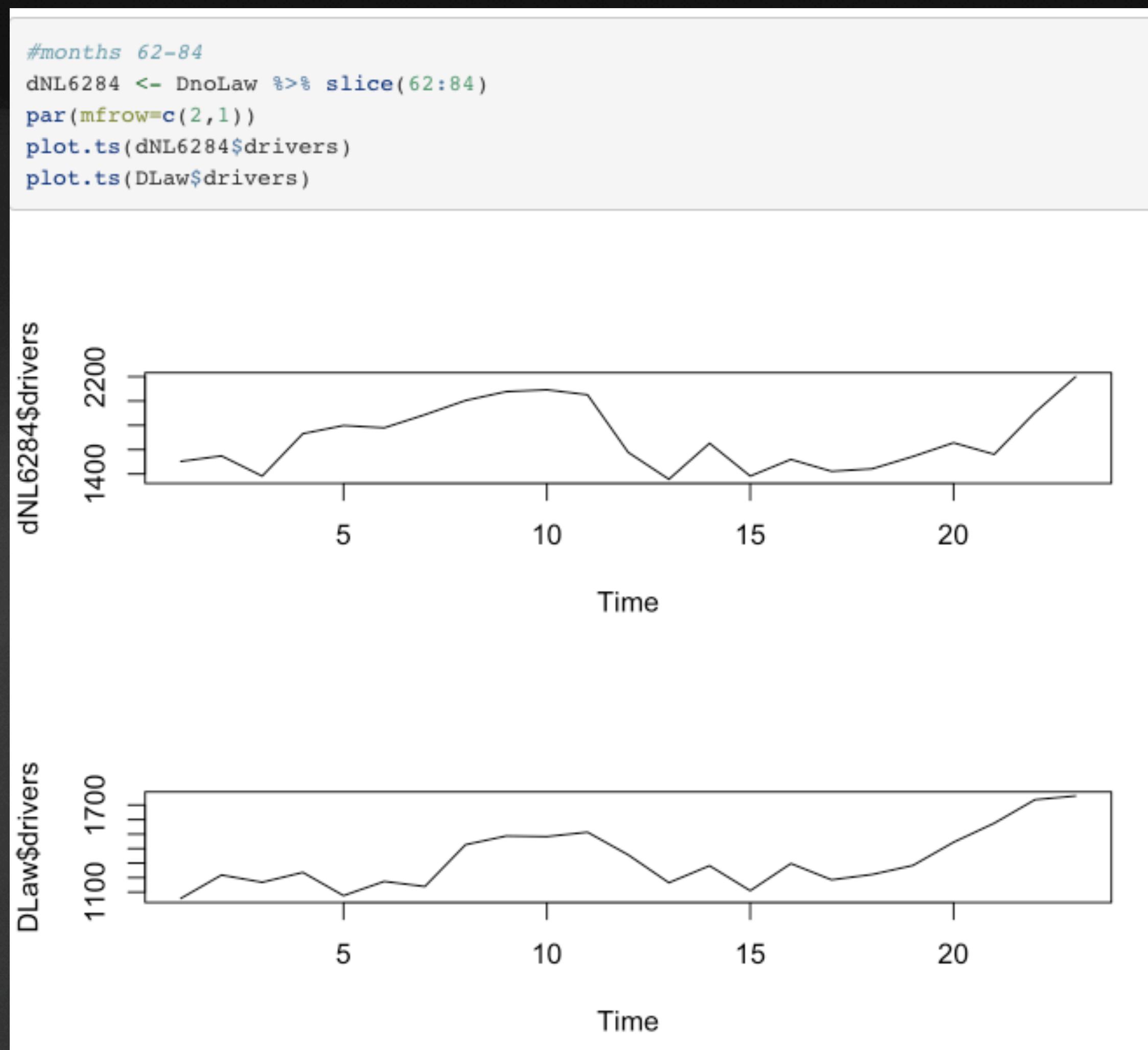
Months 25-50 (Pre-Law) vs Final 23 Months (Post-Law)

```
#months 25-50
dNL2550 <- DnoLaw %>% slice(25:50)
par(mfrow=c(2,1))
plot.ts(dNL2550$drivers)
plot.ts(DLaw$drivers)
```



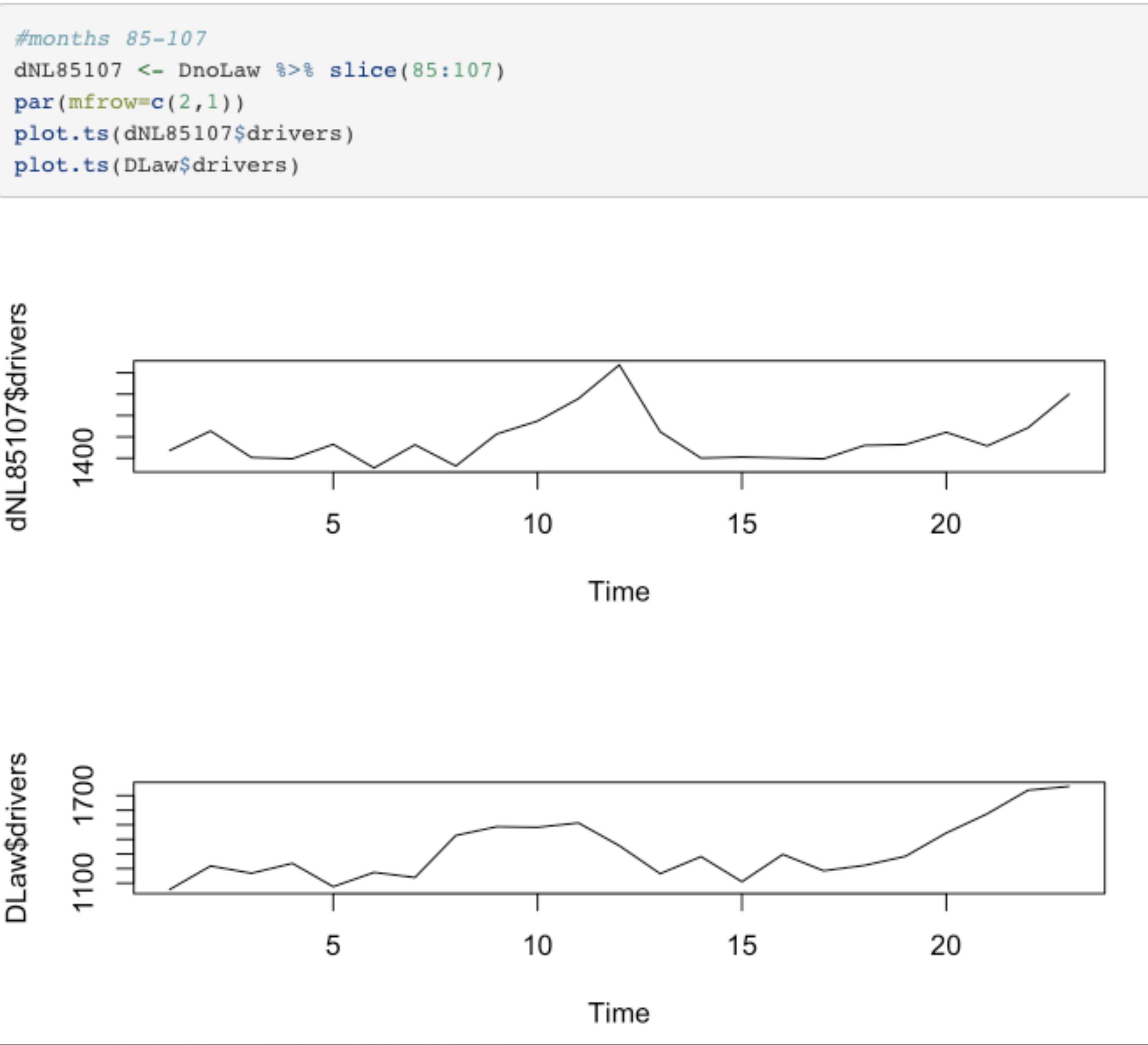
# Visualizing the Data

Months 62-84 (Pre-Law) vs Final 23 Months (Post-Law)



# Visualizing the Data

Months 85-107 (Pre-Law) vs Final 23 Months (Post-Law)



# Visualizing the Data

## Boxplots of Summary Data

- The boxplot to the left is a comparison of the summary data pre-law and post law.
- Within the image, the plot on the left represents the data corresponding to pre-law statistics.
- The plot on the right represents data corresponding to post-law statistics.
- We see that the data before the law was passed is centered around much higher values than after it was passed. The third quartile indicator for the post-law data is smaller than the first quartile indicator for the pre-law data. This signifies to me a dramatic reduction in casualties.



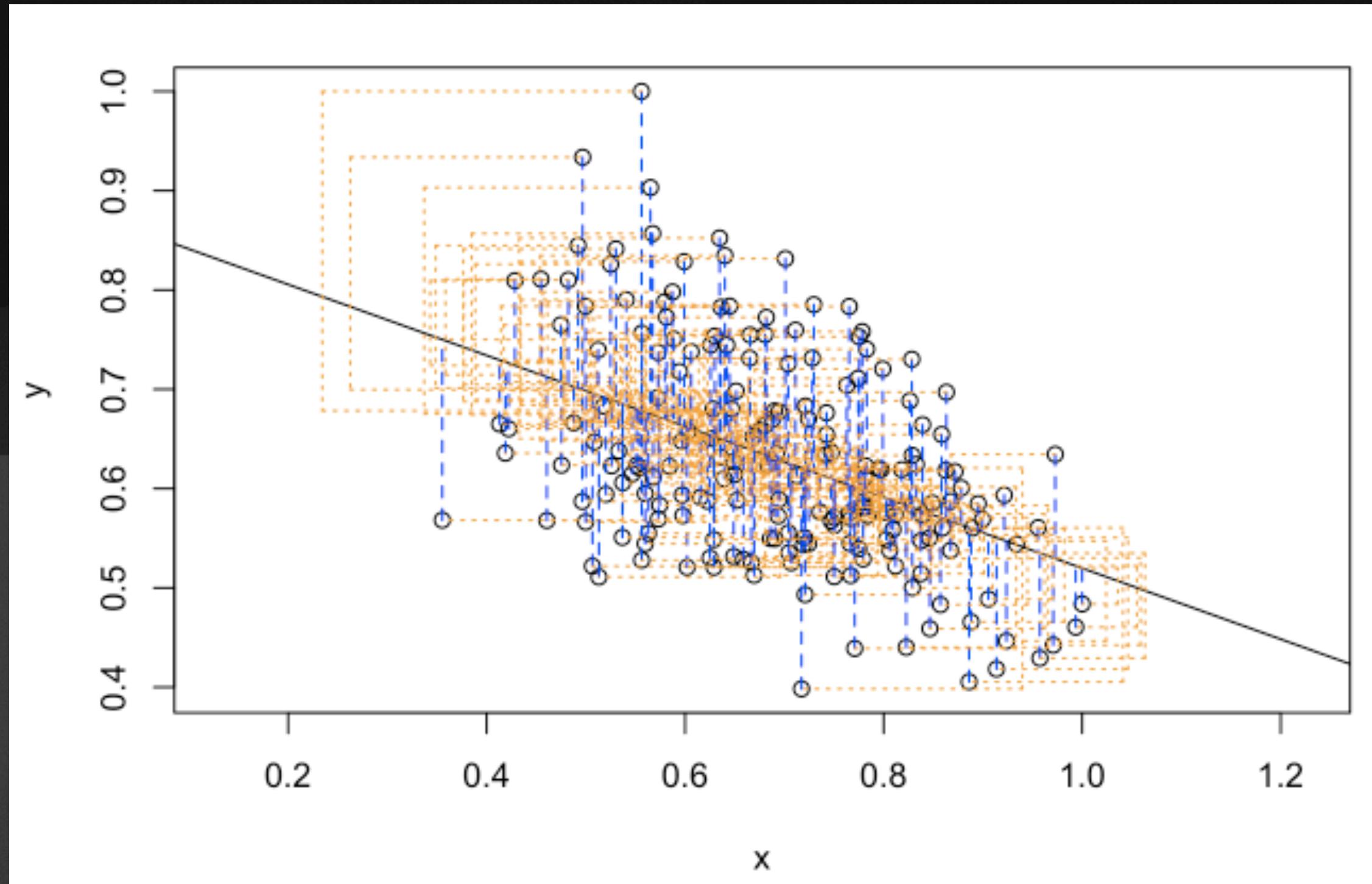
```

sbelts <- sbelts %>%
  mutate(deaths_norm = sbelts$drivers/max(sbelts$drivers))
sbelts <- sbelts %>%
  mutate(kms_norm = sbelts$kms/max(sbelts$kms))
sbelts <- sbelts %>%
  mutate(p_norm = sbelts$PetrolPrice/max(sbelts$PetrolPrice))

DATA606::plot_ss(x = sbelts$kms_norm, y = sbelts$deaths_norm, showSquares =TRUE)

```

## Road Casualties vs Distance Traveled Scatterplot



```

cor(sbelts$kms, sbelts$drivers)

## [1] -0.4447631

```

# Comparison of Other Variables Using Scatterplots

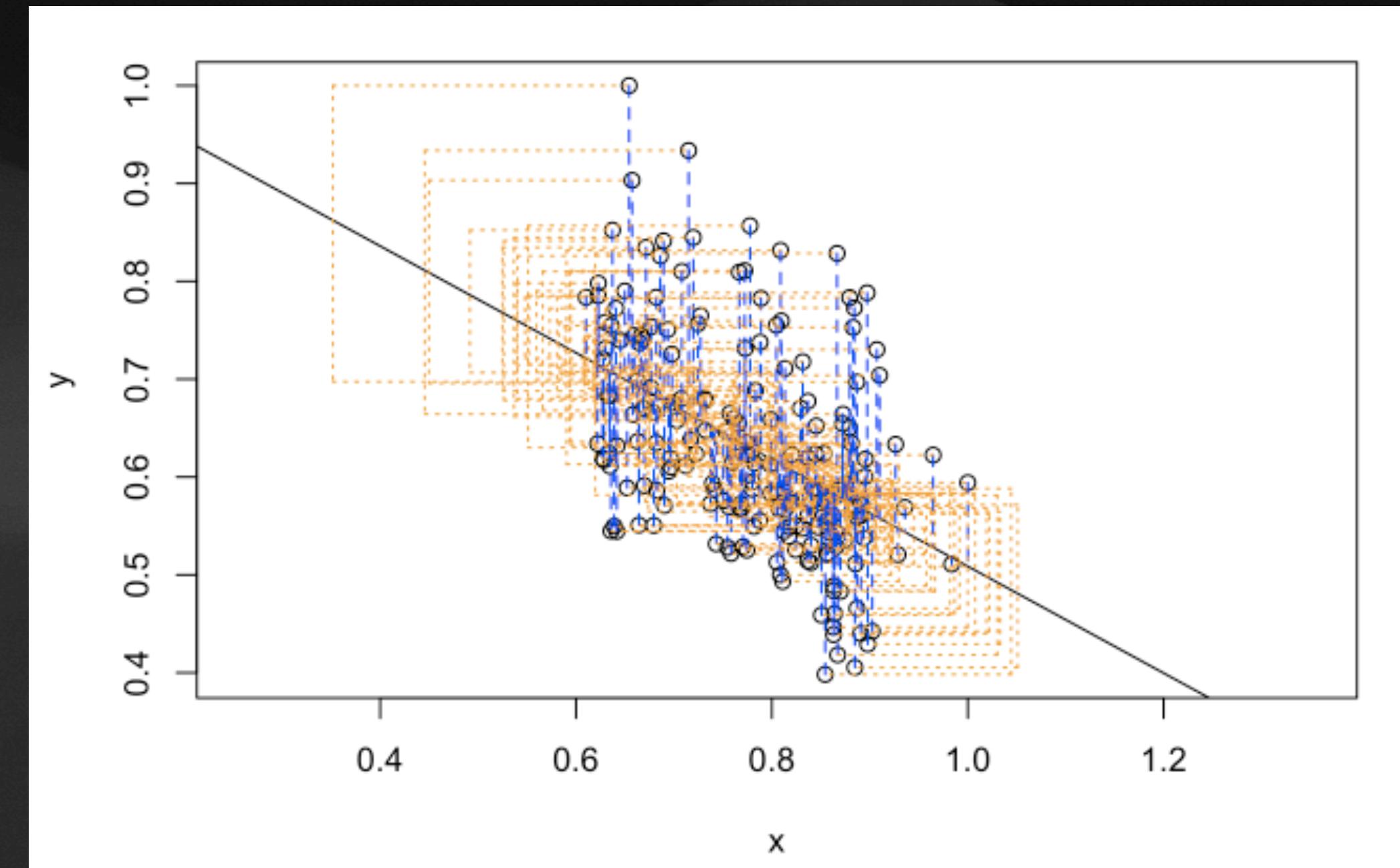
- In addition to casualty count, the data set also included information on distance traveled and price of petroleum.
- There was another variable called “VanKilled” which represents the number of van (‘light goods vehicle’) drivers killed, but I left that out of my analysis as it would not give any additional information that the other variables already give.
- I used scatterplots to visualize the correlation between these variables and road deaths. I also normalized the data to get a better visual. There seems to be a linear correlation between both distance traveled vs road deaths and petroleum price vs road deaths, using the cor() function gives us the correlation coefficient for the Least Squares Regression line of each.
- We see that the values for r are -0.04447631 and -0.4576675, respectively. Although there seems to be a linear relationship in each case, the values for r indicate a weak correlation. This still does not rule out their involvement in the reduction of road casualties.
- The graph to the left shows a negative linear relationship between casualties and distance traveled. In other words, more distance traveled (ie. driving experience) correlates to lower death.

# Comparison of Other Variables

```
DATA606::plot_ss(x = sbelts$p_norm, y = sbelts$deaths_norm, showSquares =TRUE)
```

Road Casualties vs Petrol Price Scatterplot

- The graph to the right shows a negative linear relationship between casualties and petrol price. In other words, higher petrol prices (ie. driving experience) correlates to lower death.



```
cor(sbelts$PetrolPrice, sbelts$drivers)
```

```
## [1] -0.4576675
```

# Conclusion

The analysis involved in this study determined that, with regard to measures of central tendency, there was a significant reduction in the average overall number of road casualties after the passing of the seat belt law. This is consistent with the mean data for front seat passenger and driver deaths. Although the mean rear seat passenger deaths increased, it was very slight and is negligible when compared to the overall data. The mean analysis was verified with the visualization of the summary data using box plots. In my analysis of the spread of data, the standard deviation and range decreased after the passing of the law, regardless of the type of casualty. This indicates a narrowing of the data meaning more consistent values that are easier to rely on. I also used narrowed down time frames for the comparison of time series graphs to have much more comparable visualizations. In the visualizations for all comparisons, the scaling for the number of deaths decreased after the law was passed. Finally, there were two previously unused variables that were included in the study. I considered these as possible influencers in road death casualties and used scatterplots, least squares regression, and the correlation coefficient function in R Studio to determine the strength of the linear correlation. Given the values of  $r$ , I determined that there is a linear correlation between both of these variables and road casualties. Although the strengths of these correlations were weak, it may still represent a degree of influence on survival outcomes, but based on my findings, there is sufficient evidence to conclude that seat belt laws *predict* a reduction in road casualties.