Lab3

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Lab 3

Part 1 - Modeling House Values

Exploratory Data Analysis

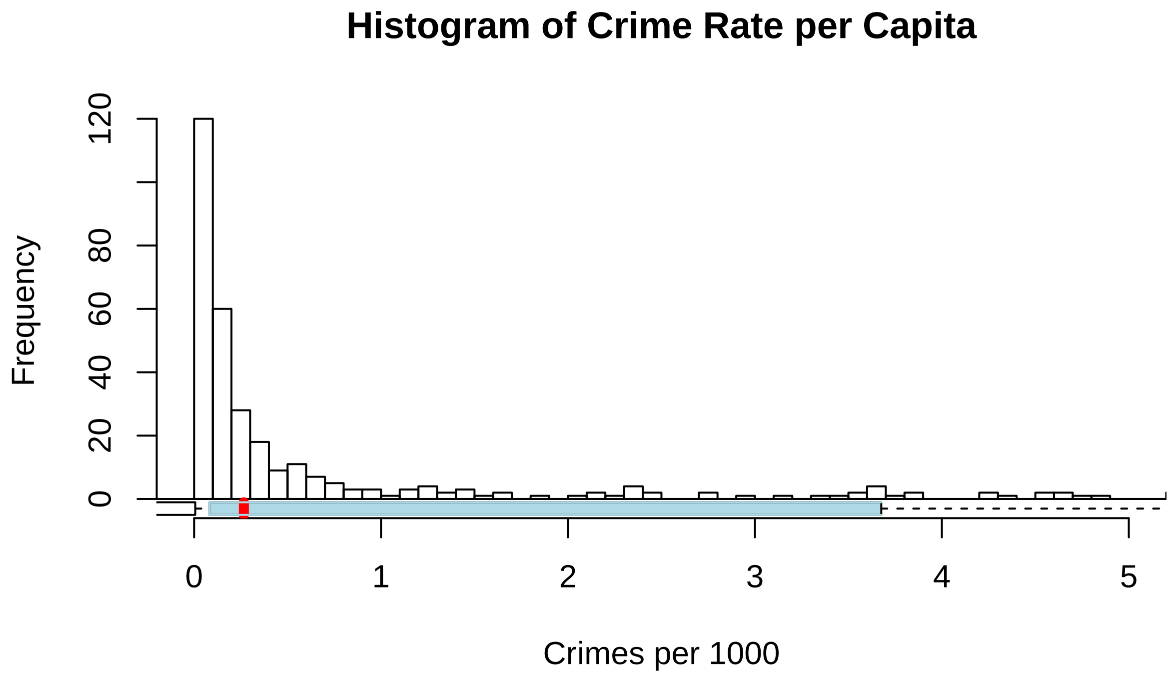
An examination of the provided data set reveals 11 variables of which *withWater* is binary and rest are continuous. There are no NA's in the data set, however the *distanceToHighway* variable appears to have a coding issue. We'll examine this variable in more detail a bit later, but first we summarize the variables in the following table.

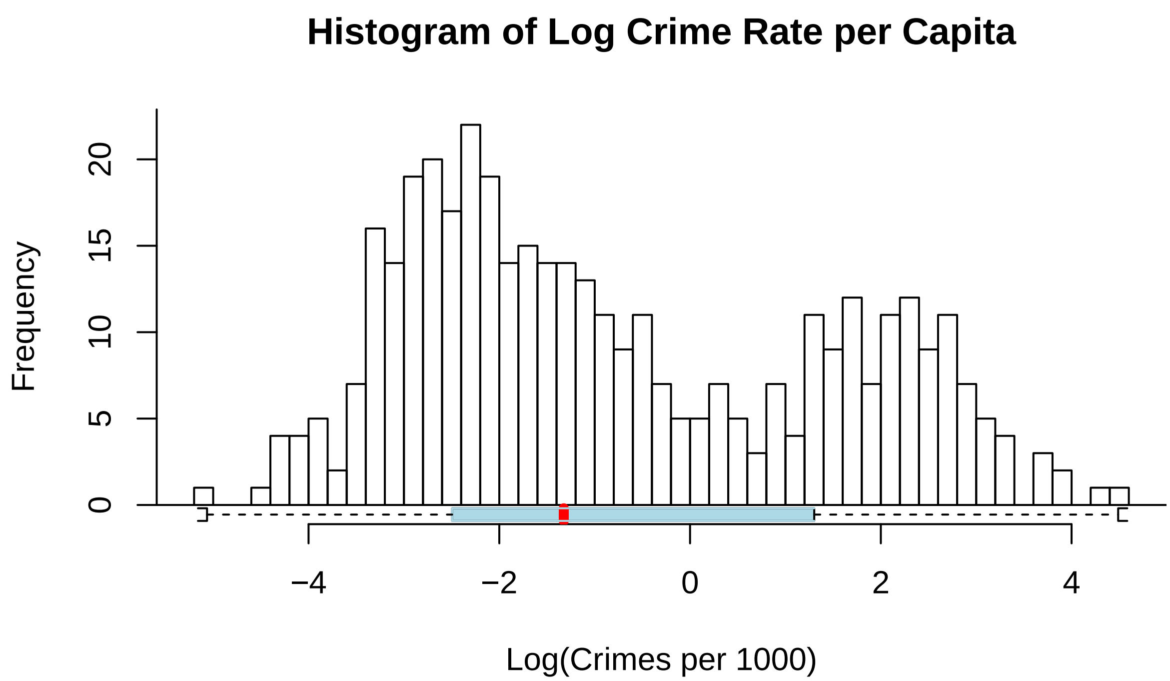
Table 1: Summary of Data

Statistic	N	Mean	St. Dev.	Min	Max
crimeRate_pc	400	3.763	8.872	0.006	88.976
nonRetailBusiness	400	0.112	0.070	0.007	0.277
withWater	400	0.068	0.251	0	1
ageHouse	400	68.932	27.977	2.900	100.000
distanceToCity	400	9.638	8.786	1.228	54.197
distanceToHighway	400	9.582	8.672	1	24
pupilTeacherRatio	400	21.391	2.168	15.600	25.000
pctLowIncome	400	15.795	9.341	2	49
homeValue	400	499,584.400	196,115.700	112,500	1,125,000
pollutionIndex	400	40.615	11.825	23.500	72.100
nBedRooms	400	4.266	0.719	1.561	6.780

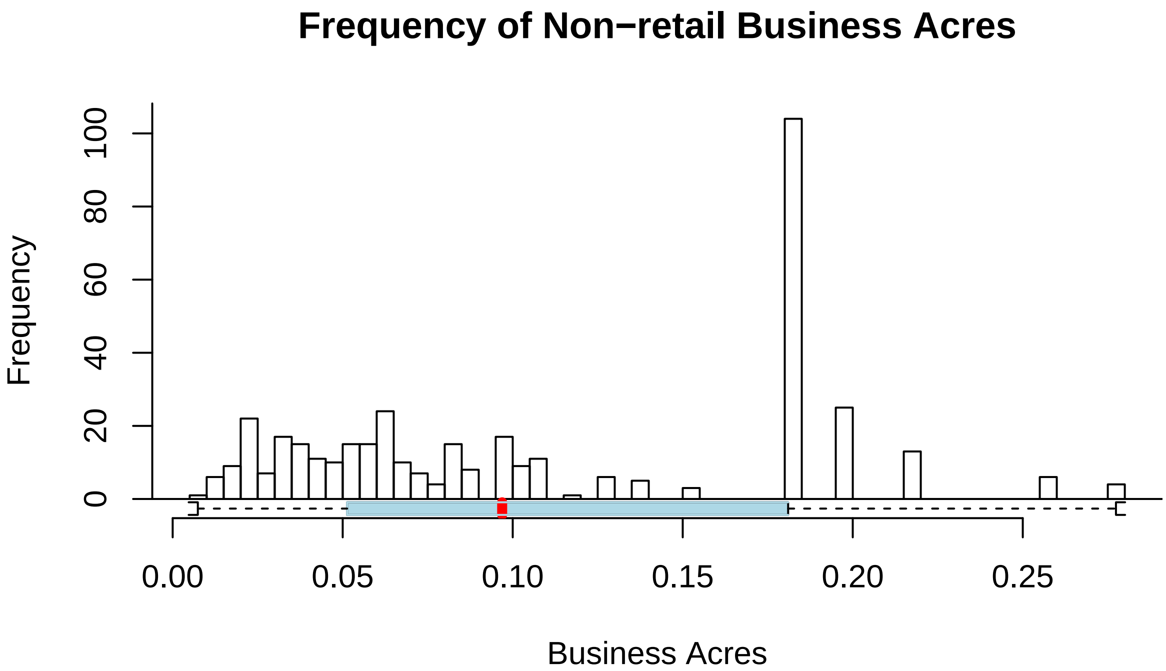
For the purposes of this analysis we categorize the variables *crimeRate_pc*, *nonRetailBusiness*, *withWater*, *distanceToCity*, *distanceToHighway*, *pollutionIndex*, *pupilTeacherRation* and *pctLowHousing* to be environmental variables. The variables *ageHouse* and *nBedRooms* are attributes of the house. The variable *homeValue* is the dependent variable we would like to explain in terms of primarily the environment variables but we will compare to explanations in terms of house attributes as well.

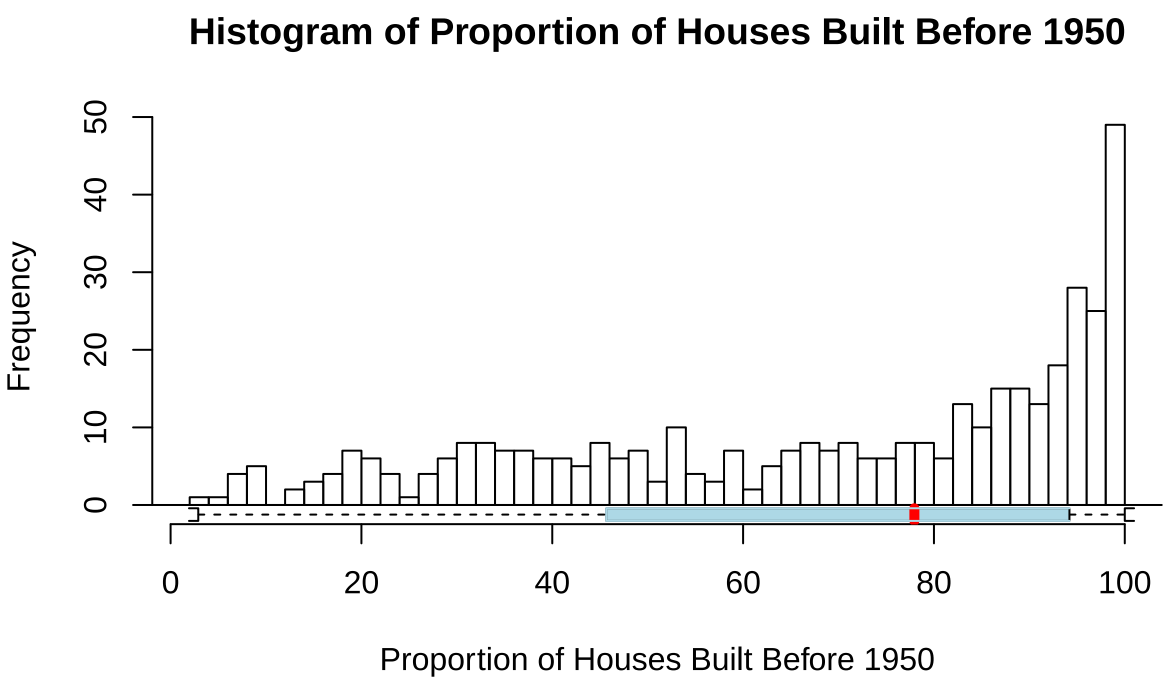
In the next several pages we examine the distribution of each of the variables and, where indicated, the distribution of the log(variable) as well.





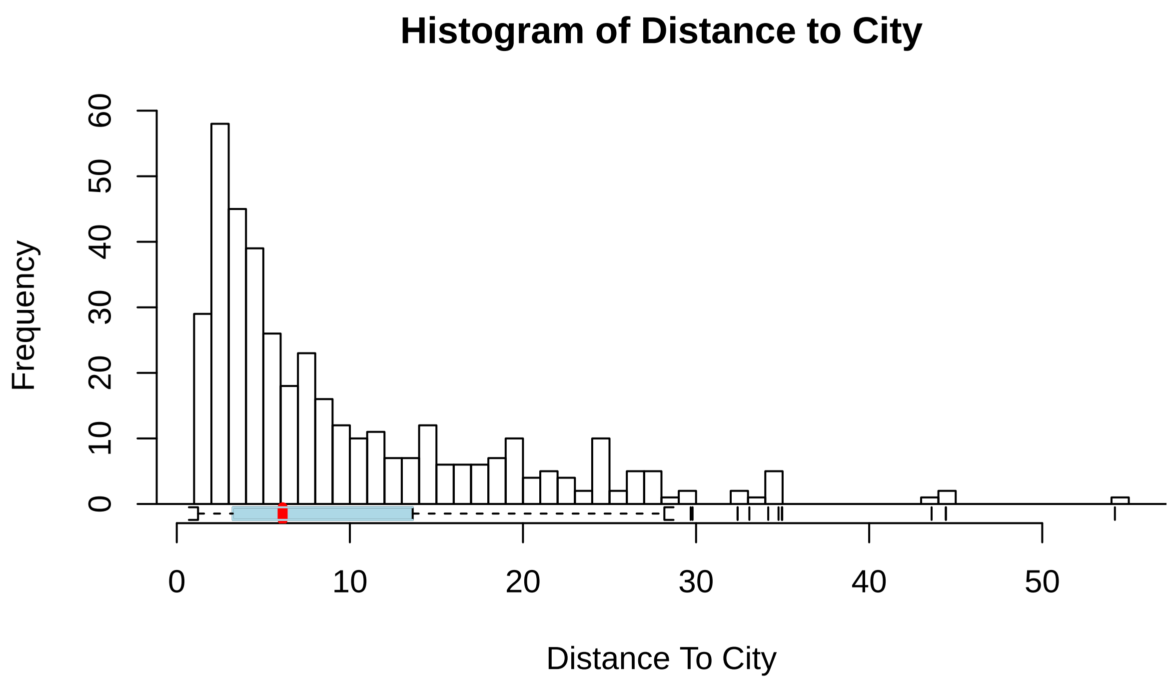
The distribution of *crimeRate_pc* is highly right-skewed with a very long tail. This makes sense as most neighborhoods are very low crime neighborhoods. The distribution of *log(crimeRate_pc)* appears almost bi-modal; however the analysis of skew and kurtosis show a significant improvement of each with a log transformation.

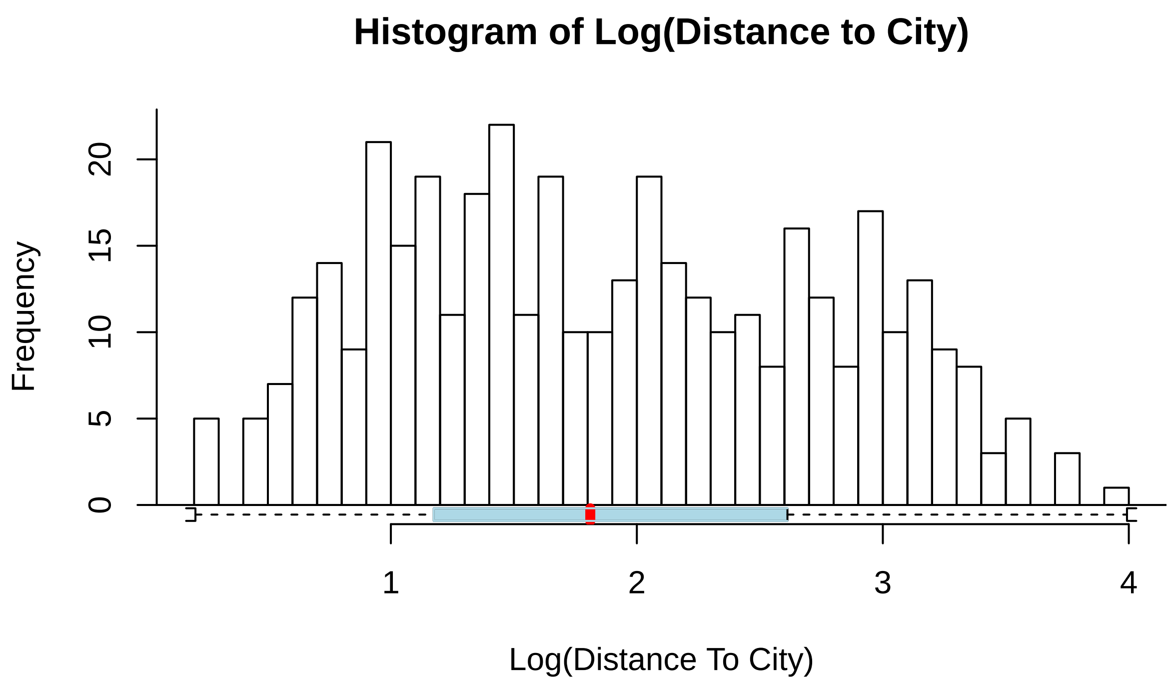




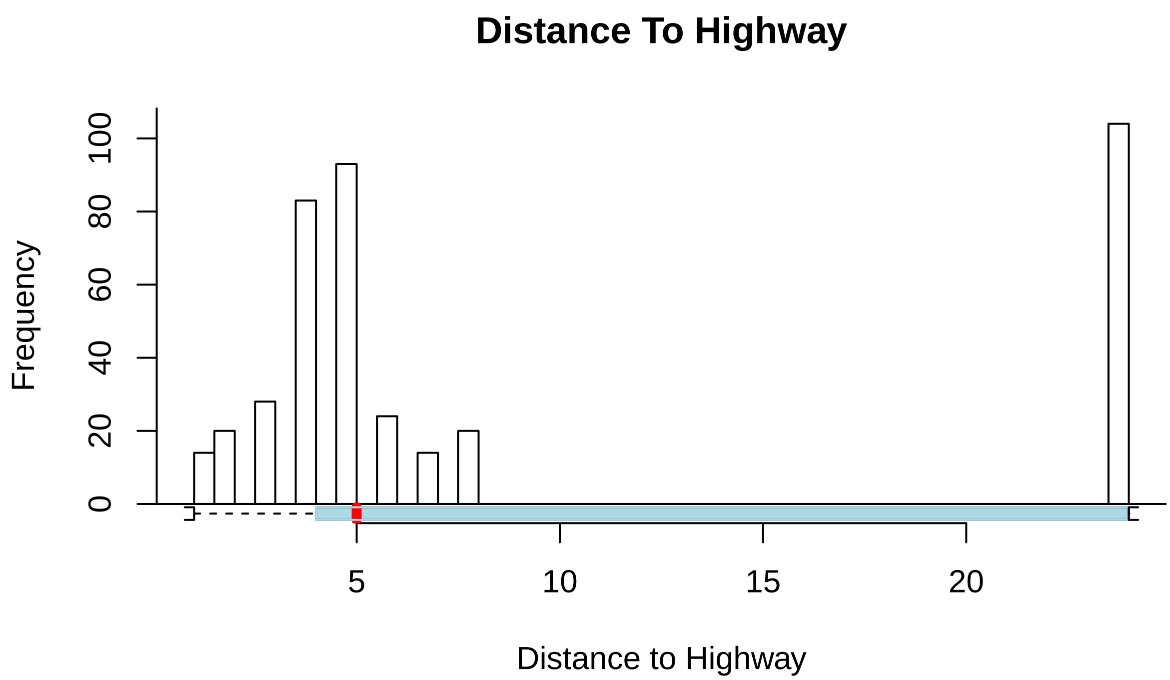
The variable *nonRetailBusiness* is a measure of the footprint of industy in a neaghborhood. This may range from light industrial to manufacturing but that information is not given. The distribution of *nonRetailBusiness* shows a spike at 0.18 business-acres but is otherwise somewhat uniform. There was no transform that improved skew or kurtosis for this variable.

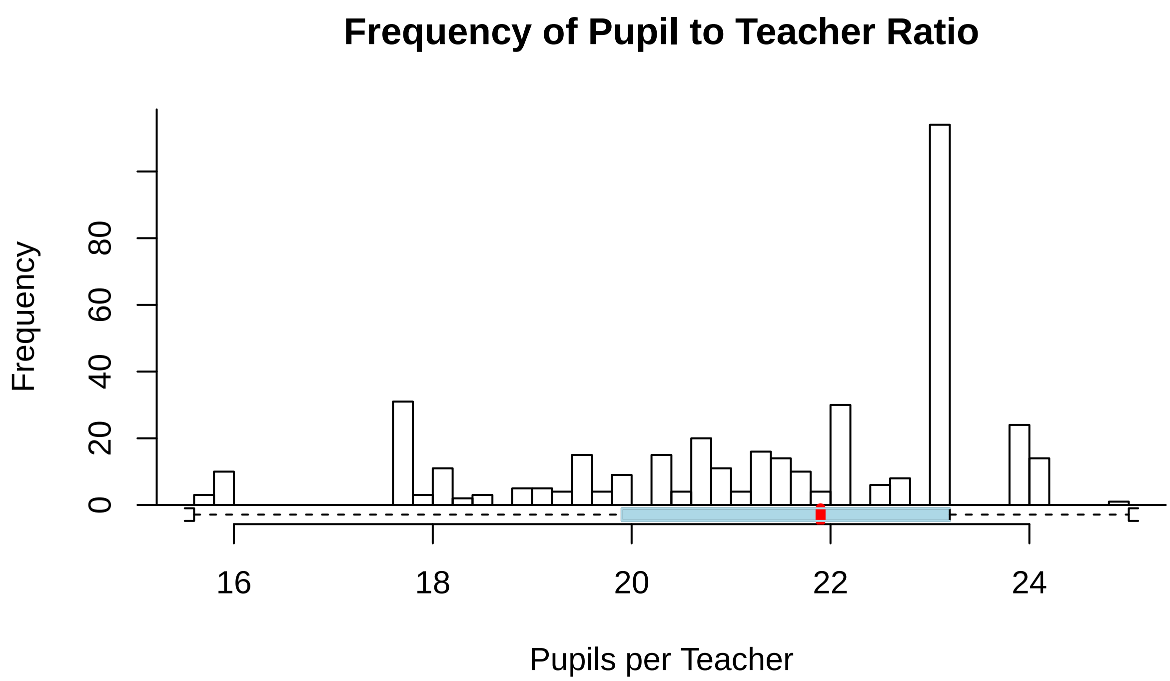
The variable *ageHouse* is the percentage of houses in a neighborhood built before 1950 and shows a significant left-skew with a long tail to the left. However no transformation was found that normalized the skew and kurtosis of this variable.





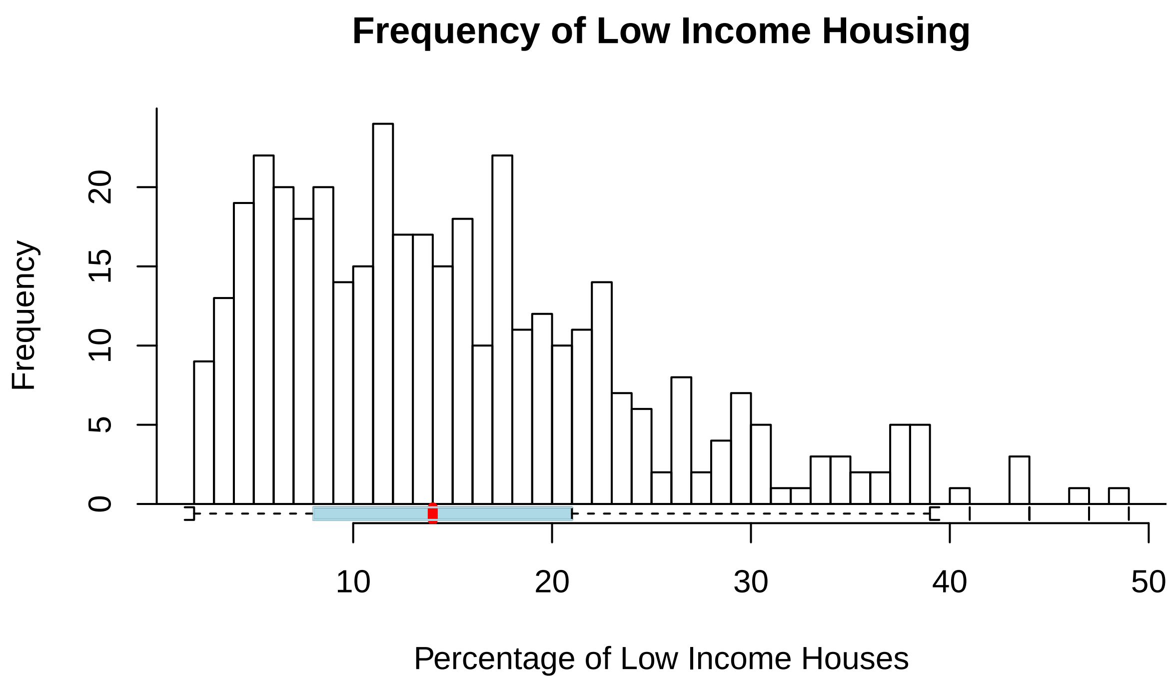
The *distanceToCity* variable shows a right-skewed distrubution that is much improved by a log transformation.

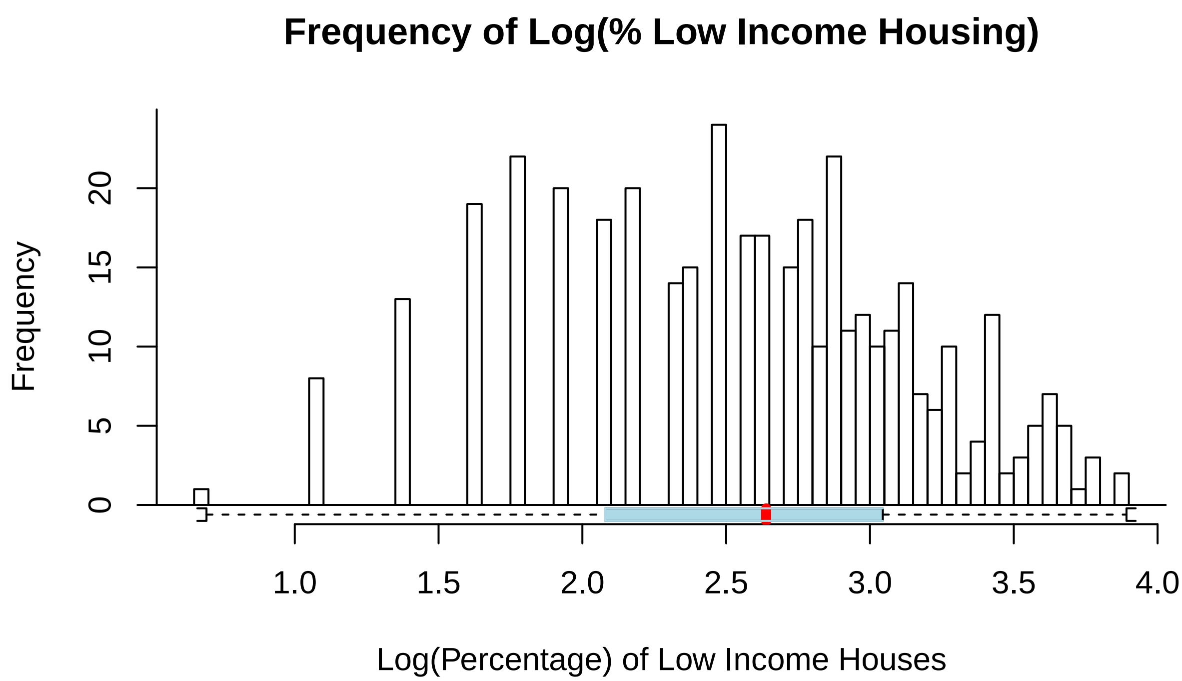




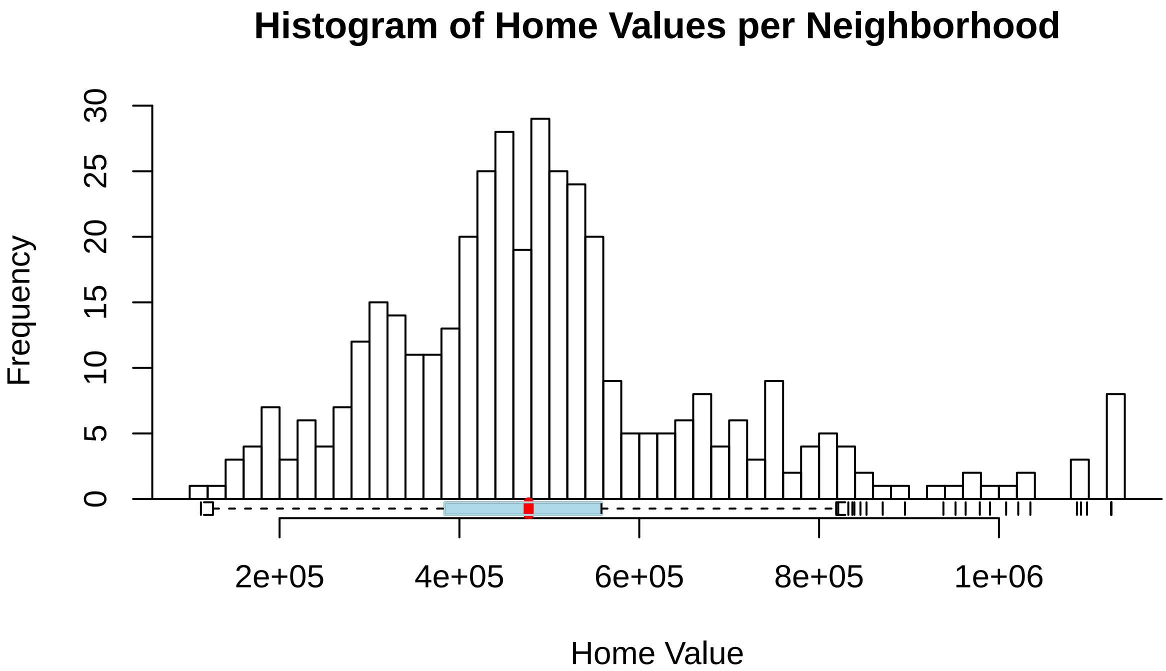
The *distanceToHighway* variable shows the concern with coding error in this histogram as there is a large occurance of the value *24*. About 25% of the dataset have this value, some of which may be correct but it seems unlikely that the *distanceToHighway* variable would be much greater than the *distanceToCity* variable.

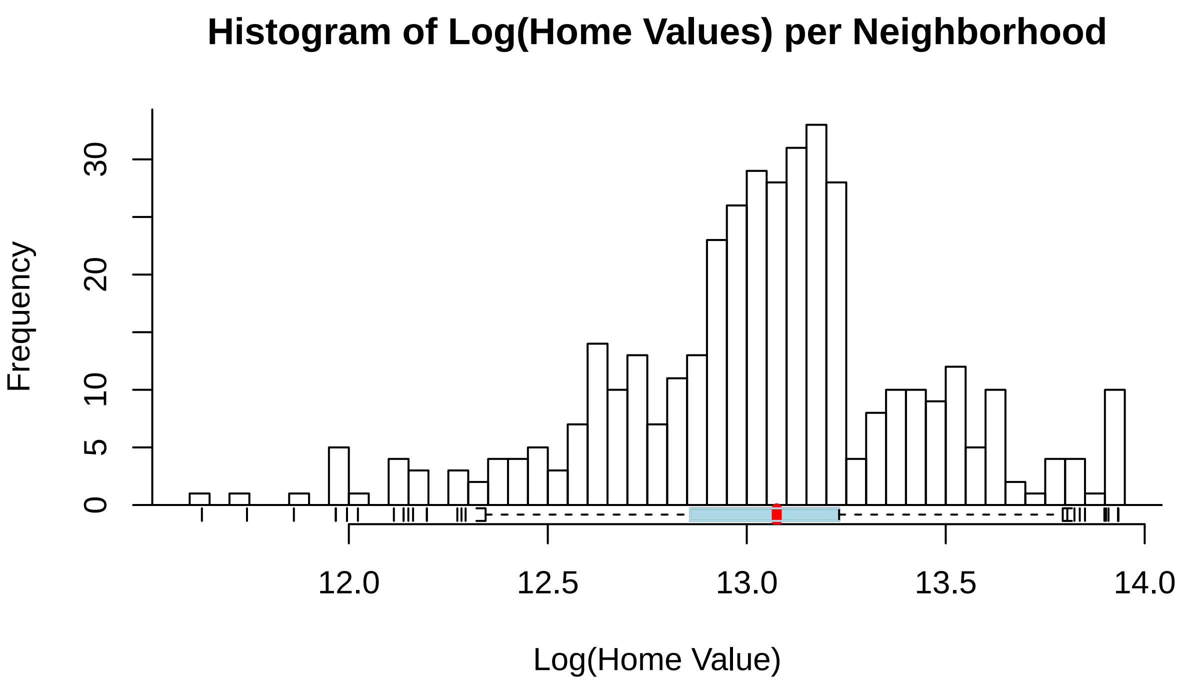
The *pupilTeacherRatio* variable shows a roughly uniform distribution except for a large number of occurances of the value *23*, which must be a more common classroom size.



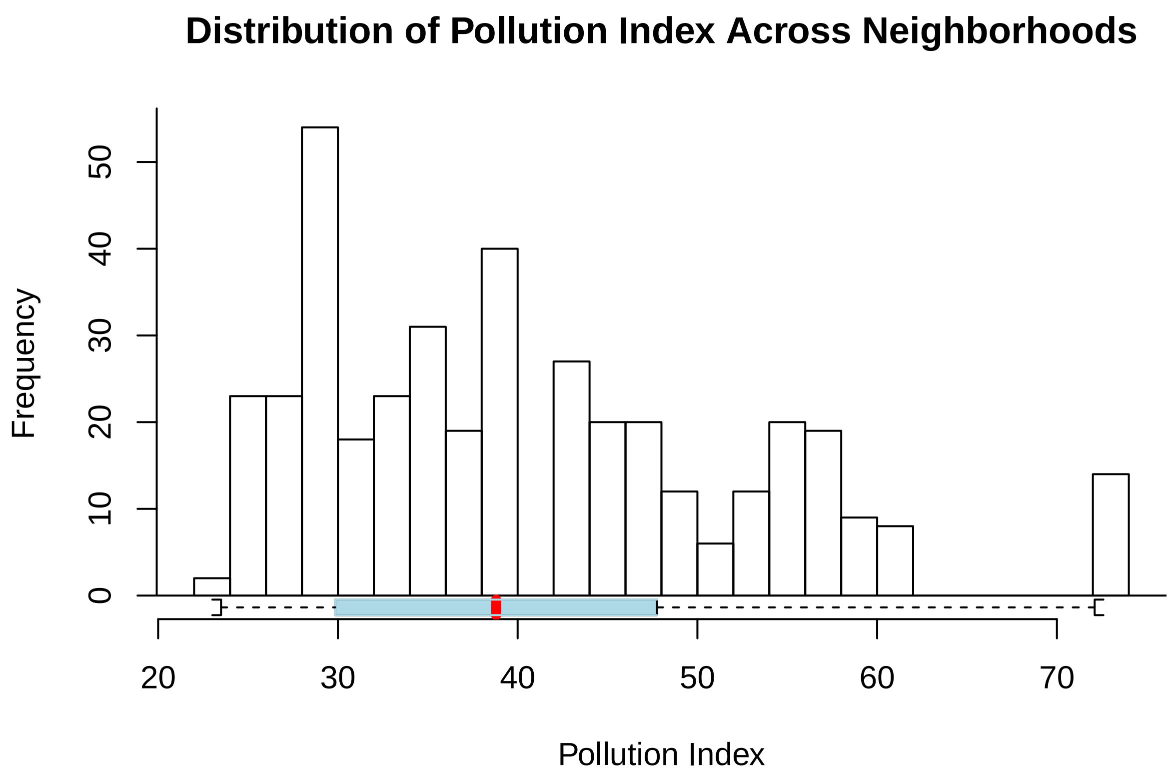


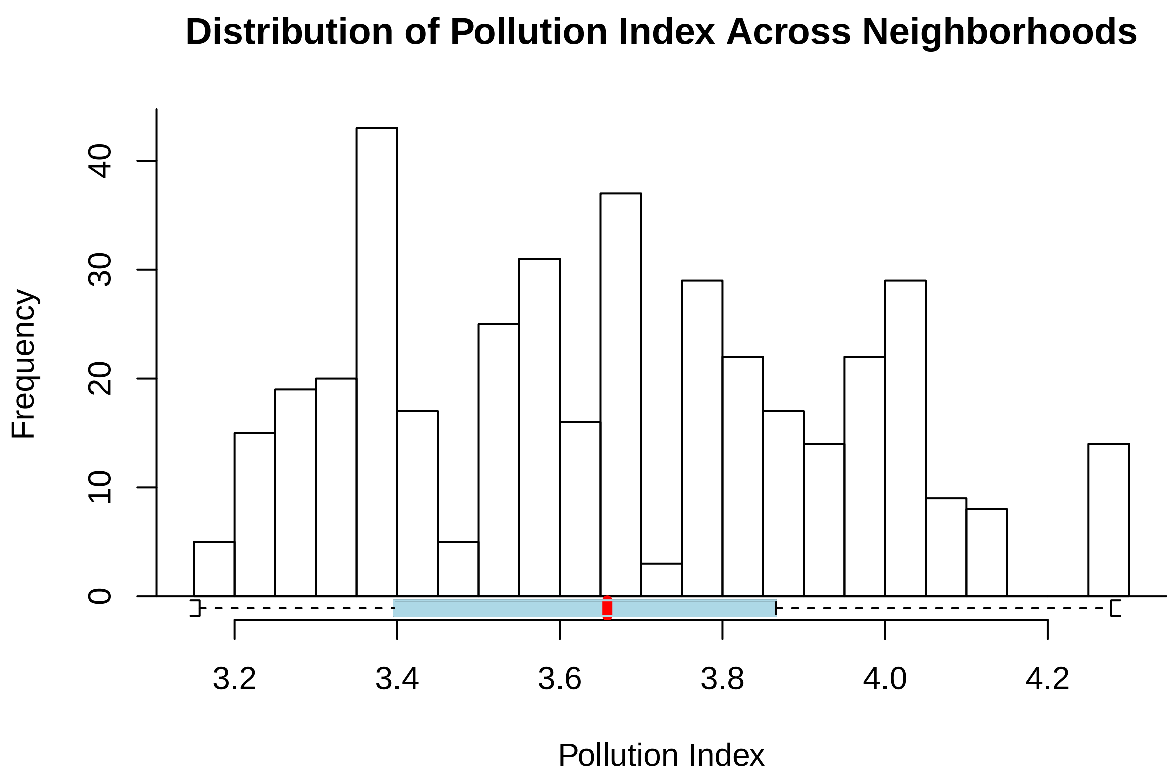
The *pctLowIncome* variable has a right-skewed distribution that tapers off to the right relatively quickly. A log transformation greatly improves the skew and kurtosis of the distribution.



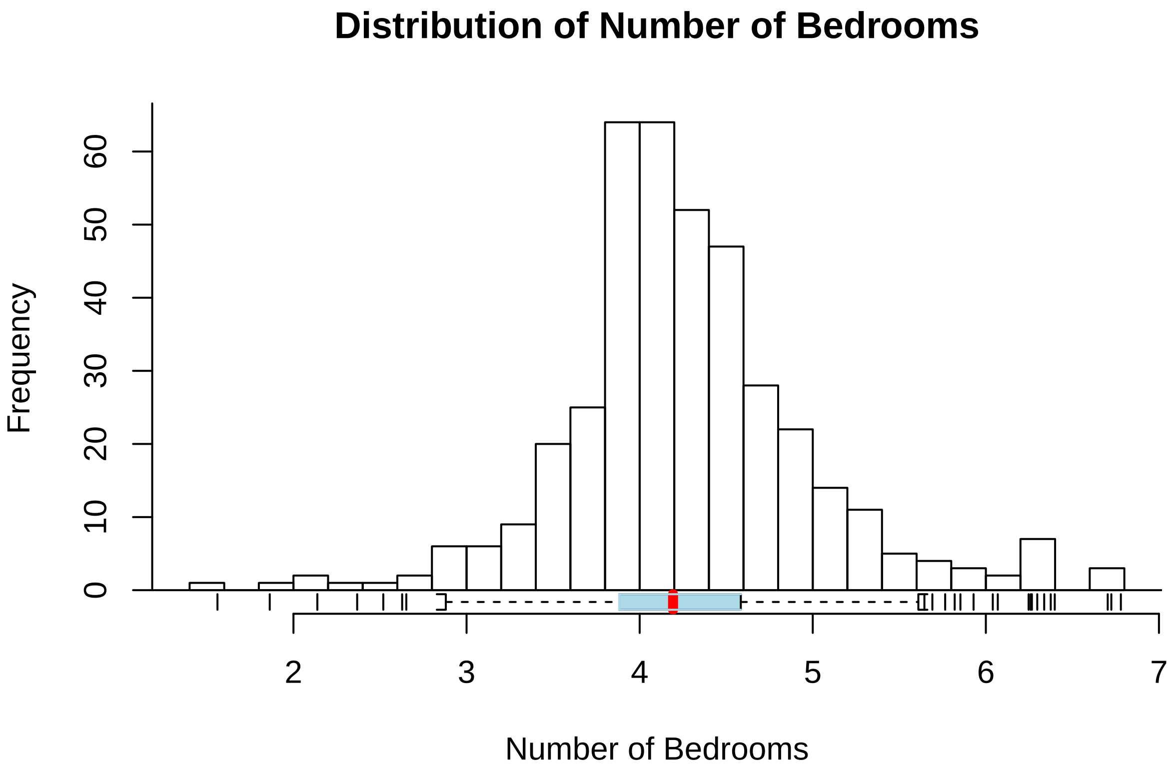


The *homeValue* variable shows a slight right-skew and a log transformation is used to help with this. It also allows discussion in terms of percentage change of home value when controlling for other variables.



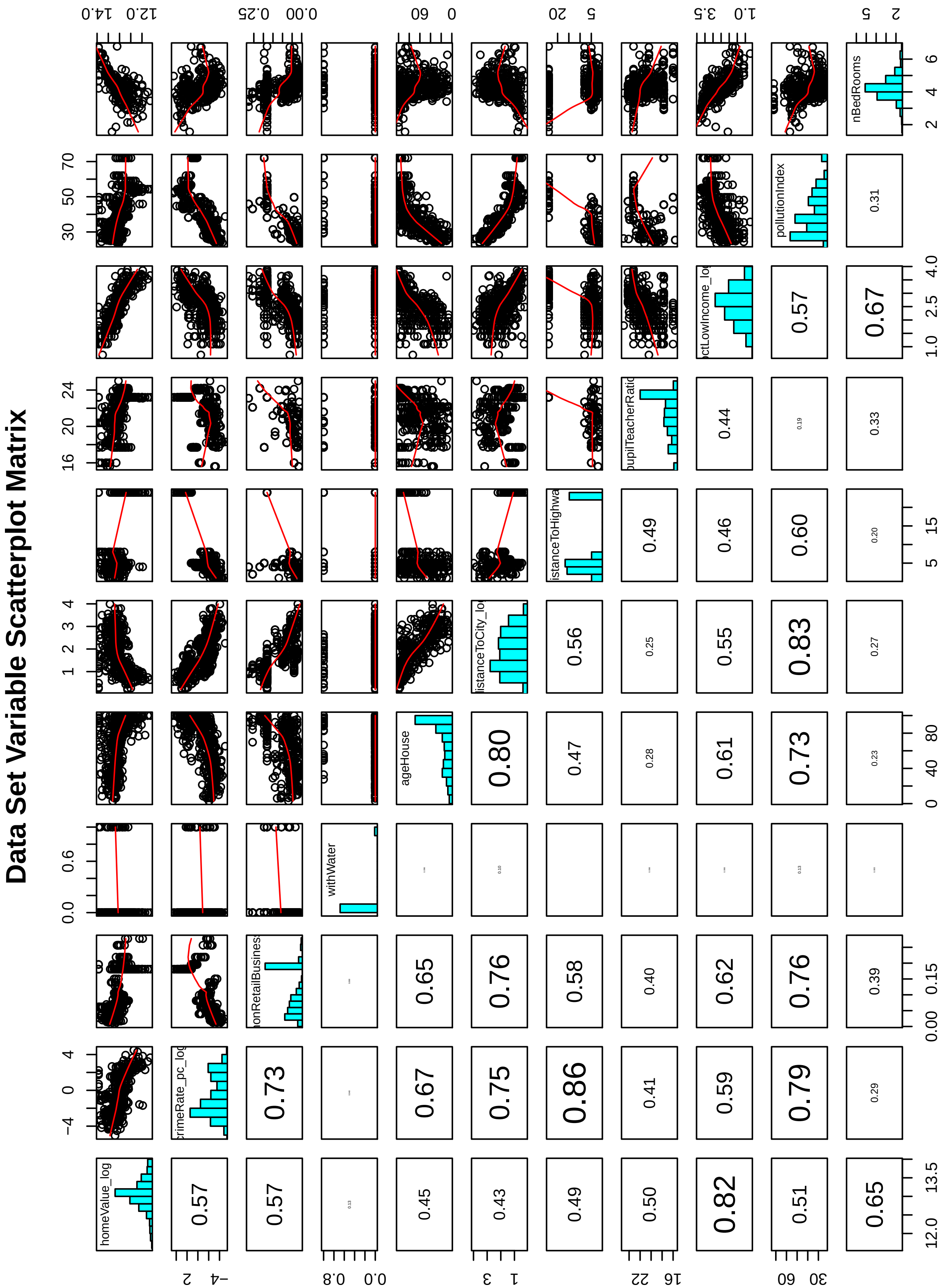


The *pollutionIndex* variable shows a right-skewed distribution upon which we perform a log transform.



The *nBedRooms* variable appears amazingly normal-like in its distribution.

The next page brings all the variables into a single matrix for comparison and to get a first look at correlations to explore further.


Data Set Variable Scatterplot Matrix
homeValue_log
withWater
ageHouse
pollutionIndex
nBedRooms

DistanceToHighway Variable Detailed Examination

We saw previously that the *distanceToHighway* variable looked suspicious so in this section we look at how to address a possible coding issue. The number of rows in the dataset that have the *distanceToHighway* variable as 24 is 25% of the dataset. Removing these rows would remove a significant amount of data, reducing *N=400* to *N=296*. We examine two strategies and compare them to the row-removal option: replacing values of 24 with the mean of the filtered values or with the value of *distanceToCity*.

The following two tables compare the summaries of the filtered dataset with the summaries of the dataset with transformed values. Comparing the *distanceToHighway_meanMod* and *distanceToHighway_cityMod* shows that the latter is much closer to the values of the filtered dataset. This indicates that replacing the value of 24 with the value of *distanceToCity* is a reasonable transformation to deal with the coding issue. The idea is further substantiated by the proposition that the distance to a city is usually not greater than the distance to a highway as cities are generally located on highways.

The following page shows a set of comparison histograms for the *distanceToHighway* variable with the different transformations. A histogram of *distanceToCity* is included as a reference.

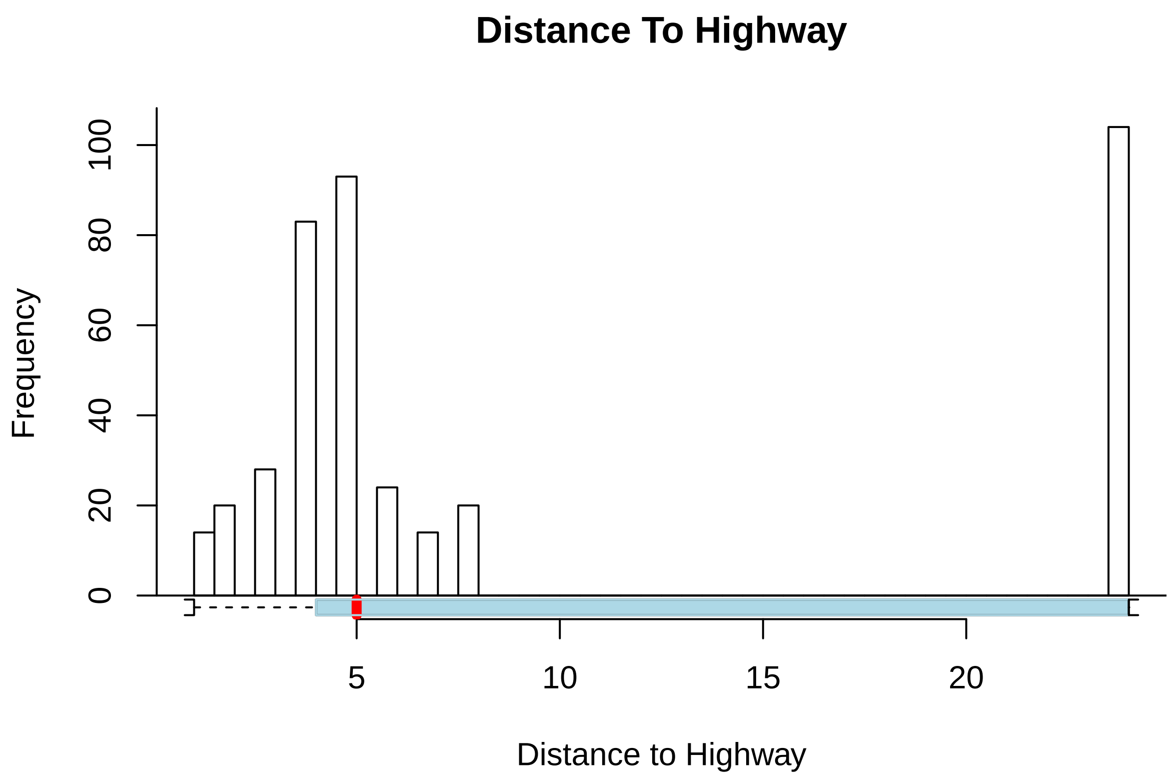
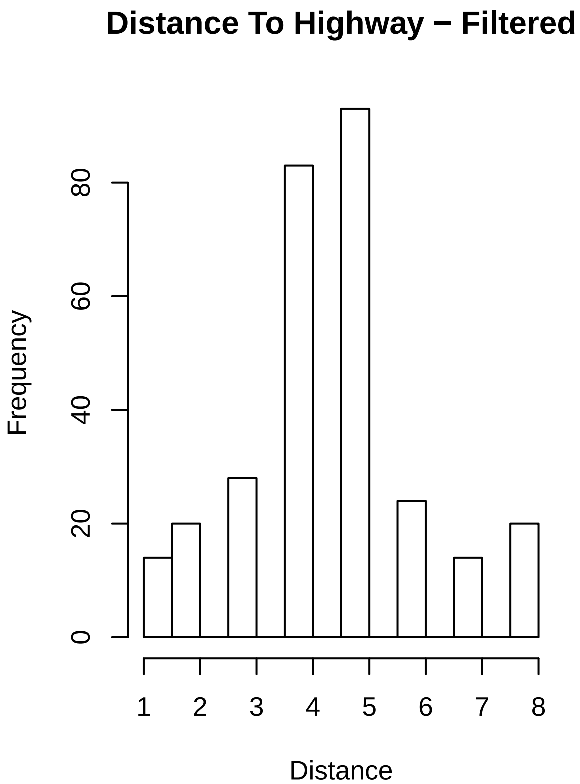


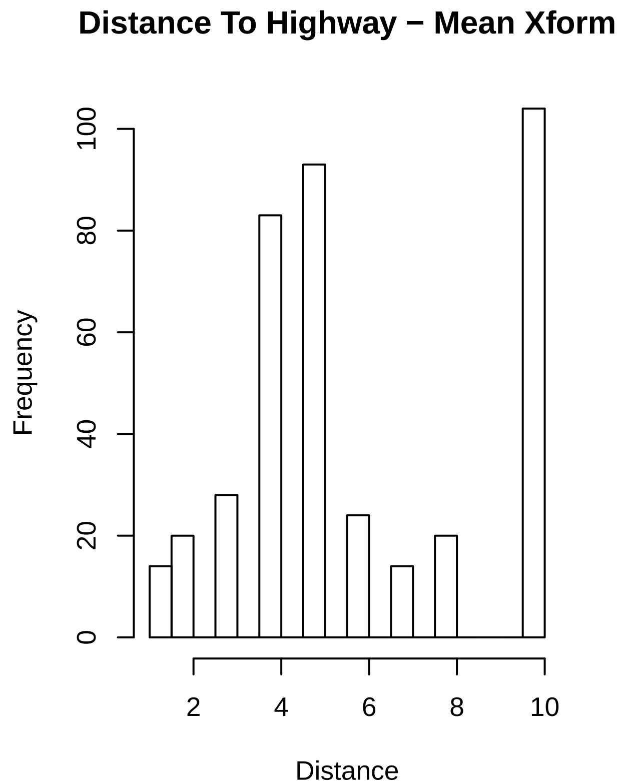
Table 2: Filtered Dataset

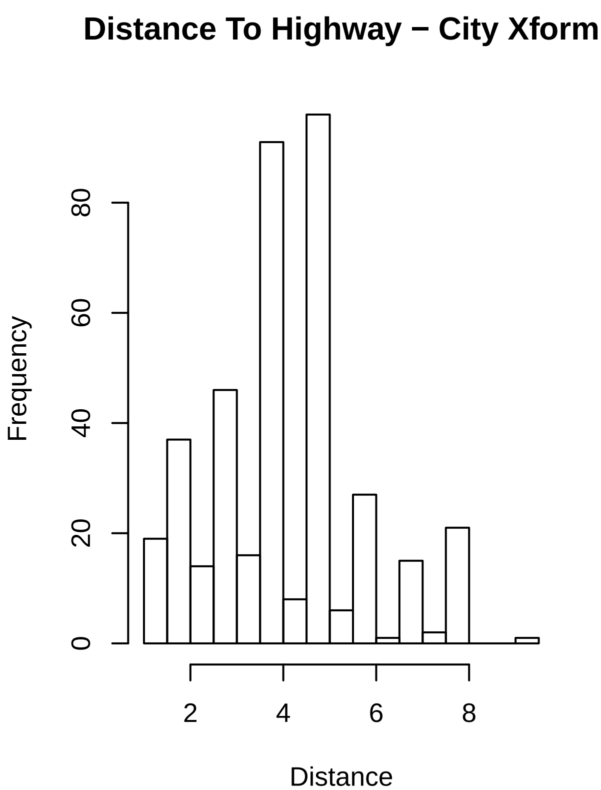
Statistic	N	Mean	St. Dev.	Min	Max
crimeRate_pc	296	0.381	0.610	0.006	3.535
nonRetailBusiness	296	0.087	0.065	0.007	0.277
withWater	296	0.068	0.251	0	1
ageHouse	296	61.367	28.205	2.900	100.000
distanceToCity	296	11.877	9.178	1.562	54.197
distanceToHighway	296	4.517	1.636	1	8
pupilTeacherRatio	296	20.756	2.191	15.600	25.000
pctLowIncome	296	13.037	7.690	2	44
homeValue	296	547,487.300	178,890.300	157,500	1,125,000
pollutionIndex	296	36.438	10.450	23.500	72.100
nBedRooms	296	4.356	0.676	2.903	6.725
crimeRate_pc_log	296	−1.840	1.297	−5.064	1.263
distanceToCity_log	296	2.175	0.802	0.446	3.993
pctLowIncome_log	296	2.403	0.587	0.693	3.784
ageHouse_log	296	3.959	0.643	1.065	4.605
homeValue_log	296	13.165	0.306	11.967	13.933
pollutionIndex_log	296	3.562	0.250	3.157	4.278

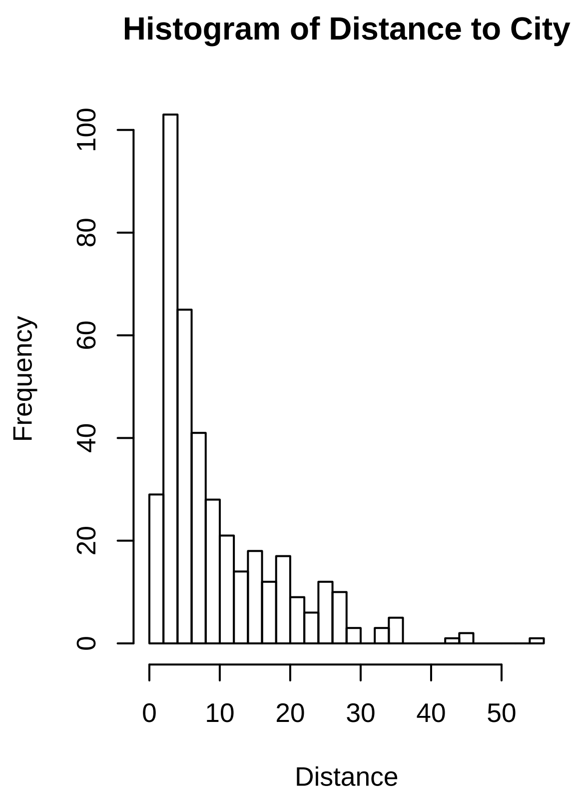
Table 3: Full Dataset

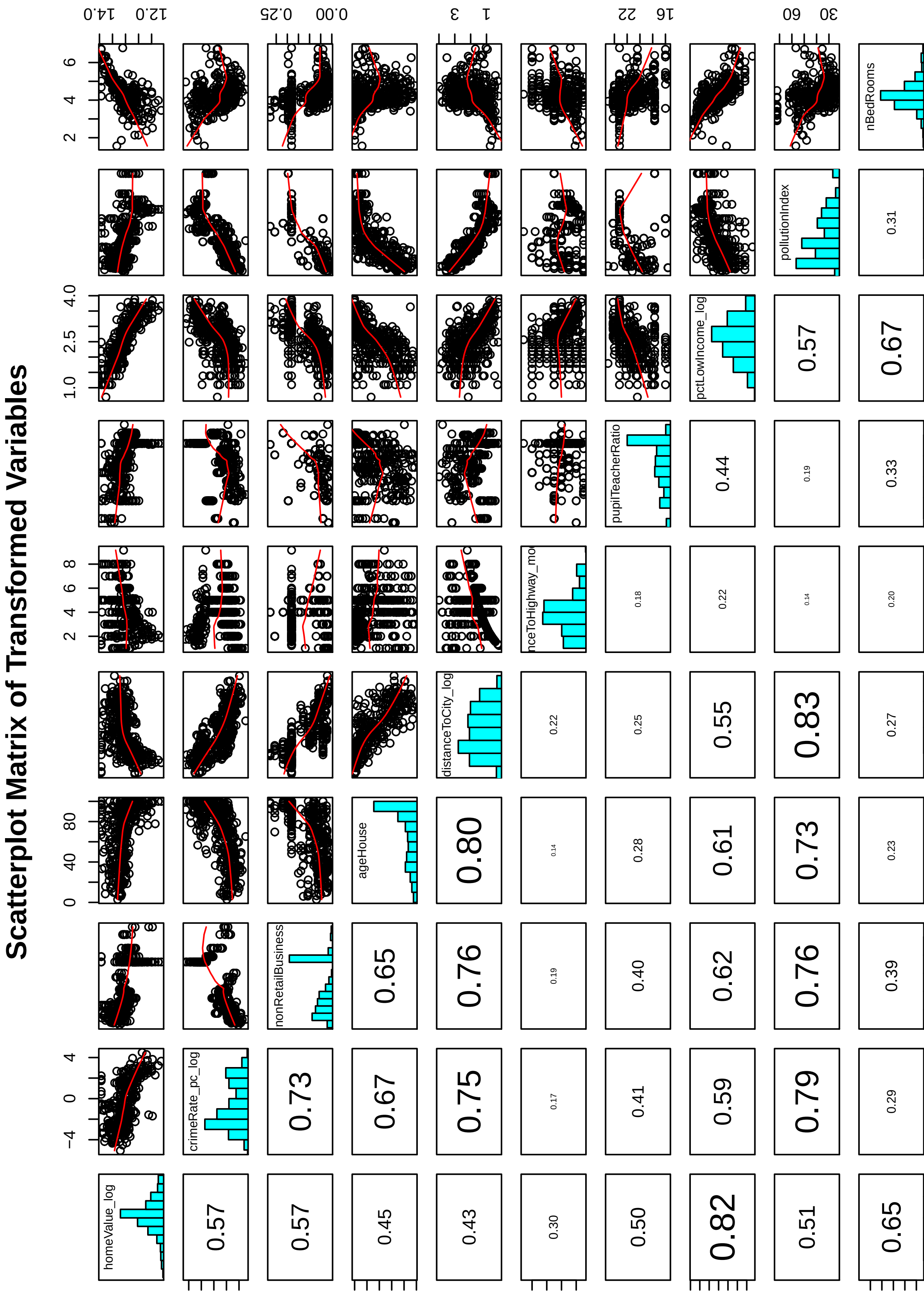
Statistic	N	Mean	St. Dev.	Min	Max
crimeRate_pc	400	3.763	8.872	0.006	88.976
nonRetailBusiness	400	0.112	0.070	0.007	0.277
withWater	400	0.068	0.251	0	1
ageHouse	400	68.932	27.977	2.900	100.000
distanceToCity	400	9.638	8.786	1.228	54.197
distanceToHighway	400	9.582	8.672	1	24
pupilTeacherRatio	400	21.391	2.168	15.600	25.000
pctLowIncome	400	15.795	9.341	2	49
homeValue	400	499,584.400	196,115.700	112,500	1,125,000
pollutionIndex	400	40.615	11.825	23.500	72.100
nBedRooms	400	4.266	0.719	1.561	6.780
crimeRate_pc_log	400	−0.763	2.164	−5.064	4.488
distanceToCity_log	400	1.892	0.868	0.205	3.993
pctLowIncome_log	400	2.577	0.631	0.693	3.892
ageHouse_log	400	4.099	0.605	1.065	4.605
homeValue_log	400	13.046	0.397	11.631	13.933
pollutionIndex_log	400	3.664	0.282	3.157	4.278
distanceToHighway_modMean	400	5.834	2.632	1.000	9.582
distanceToHighway_modCity	400	4.192	1.698	1.000	9.159


Distance To Highway − Filtered
Frequency
0
20
40
60
80
1 2 3 4 5 6 7 8
Distance


Distance To Highway − Mean Xform
Frequency
0
20
40
60
80
100
2 4 6 8 10
Distance


Distance To Highway − City Xform
Frequency
0
20
40
60
80
2 4 6 8
Distance

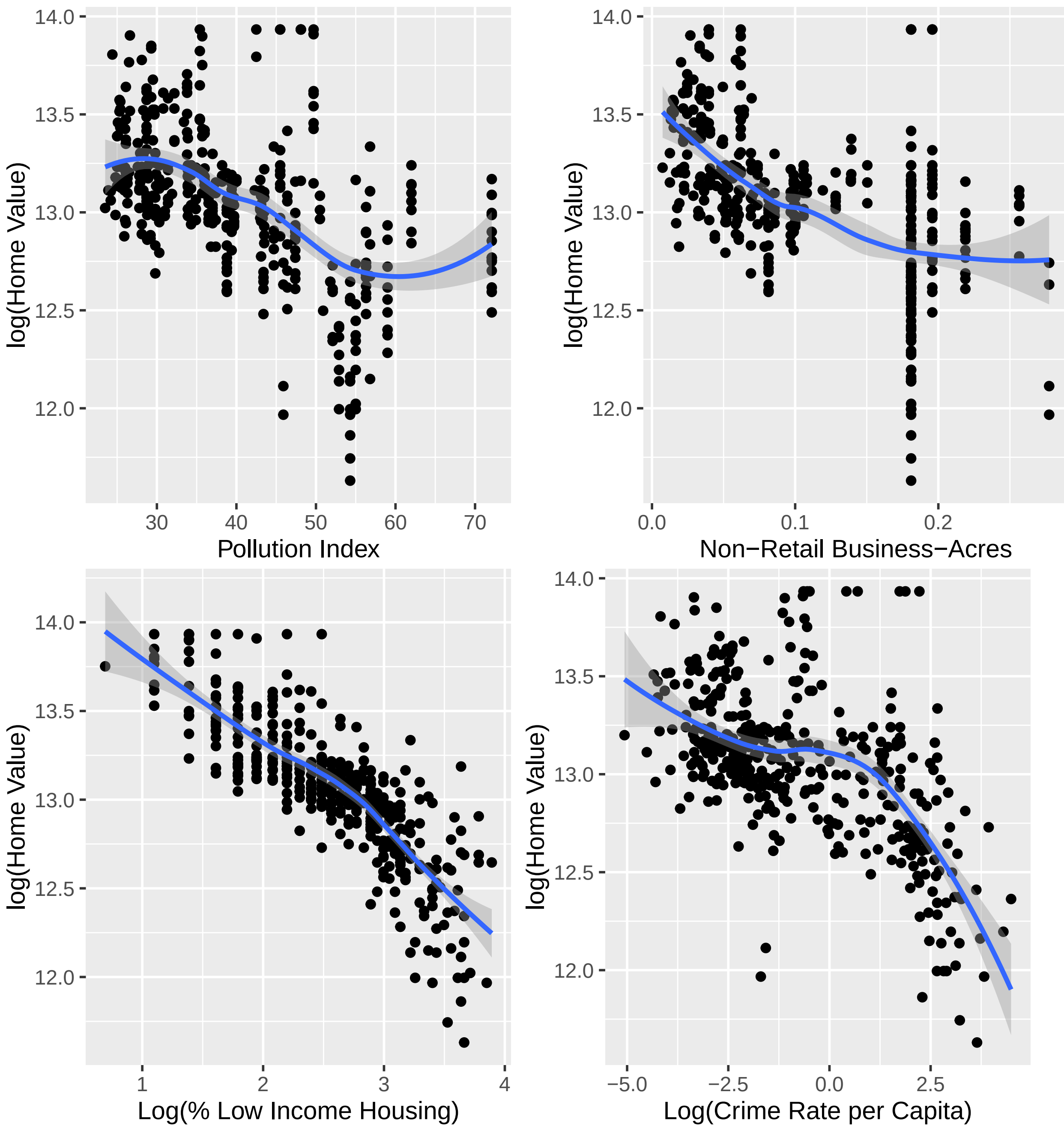

Histogram of Distance to City
Frequency
0
20
40
60
80
100
0 10 20 30 40 50
Distance

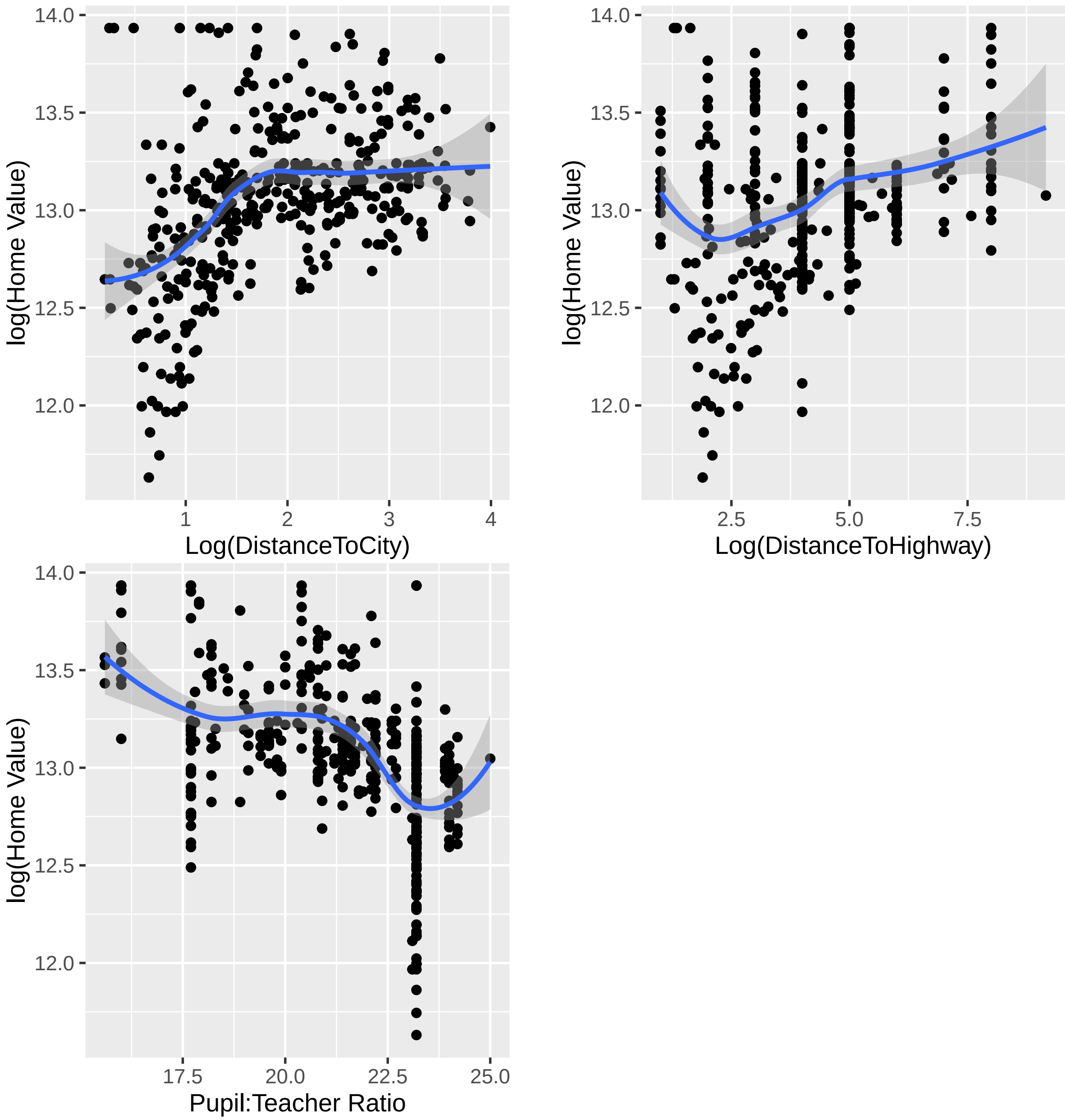


Scatterplot Matrix of Transformed Variables
homeValue_log
crimeRate_pc_log
nonRetailBusiness
ageHouse
distanceToCity_log
nceToHighway_mo
pupilTeacherRatio
pctLowIncome_log
pollutionIndex
nBedRooms

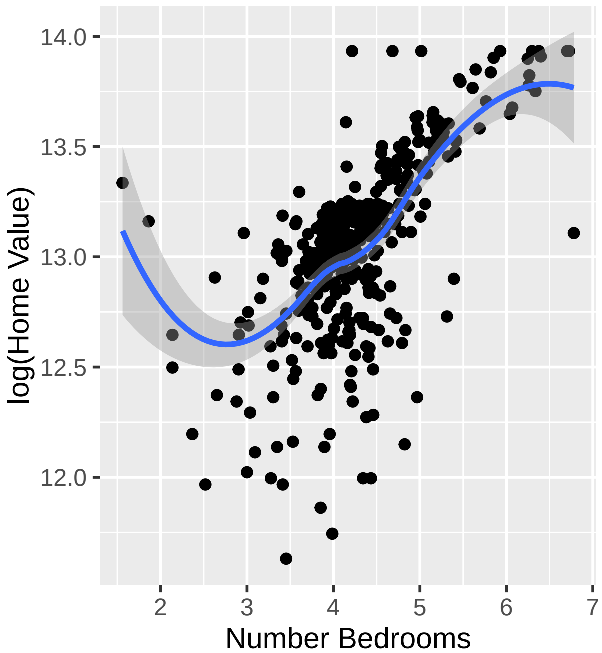
Multivariate Data Analysis

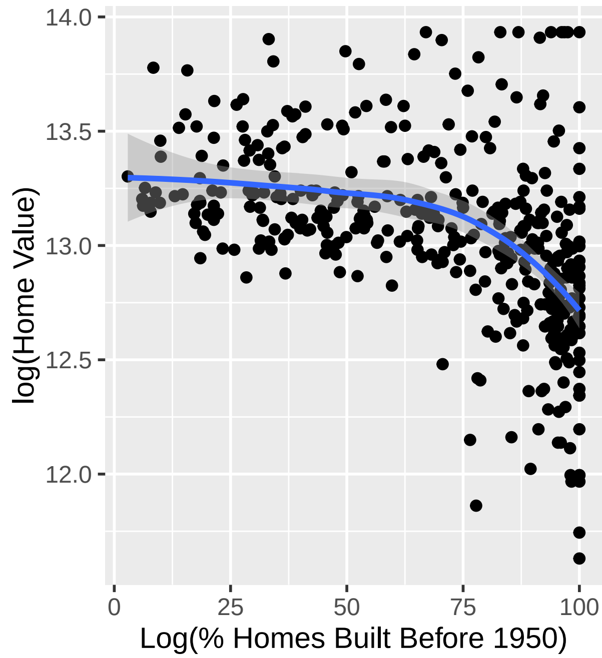
First we will examine the relationships of the environment variables on home values graphically. We can see that there are definitely relationships between most of the environmental variables and home values, as shown on the next two pages of graphs.




log(Home Value)
14.0
13.5
13.0
12.5
12.0
1
2
3
4
Log(DistanceToCity)
log(Home Value)
14.0
13.5
13.0
12.5
12.0
2.5
5.0
7.5
Log(DistanceToHighway)
log(Home Value)
14.0
13.5
13.0
12.5
12.0
17.5
20.0
22.5
25.0
Pupil:Teacher Ratio

These final two graphs show relationships between home attributes and home values.





Models Incorporating Environment Variables

Put something here about all the different models that were tried.

Include models with interaction terms

Discuss omitted variables and how they bias the models

What hypotheses can we test?

Choose the best model(s) and explain the parameters for them.

Table 4: Regression Model Comparison

	Dependent variable:				
	log(Home Values)				
	(1)	(2)	(3)	(4)	(5)
log(Low Income Housing)	−0.518***	−0.469***	−0.474***	−0.461***	−0.448***
	(0.018)	(0.022)	(0.022)	(0.022)	(0.022)
log(Crime Rate)		−0.024***	−0.030***	−0.026***	−0.024***
		(0.006)	(0.009)	(0.006)	(0.006)
Pollution Index			0.002		
			(0.002)		
Close To Water					0.027***
					(0.007)
Distance To Highway				0.144***	0.137***
				(0.044)	(0.043)
Constant	14.380***	14.238***	14.181***	14.205***	14.060***
	(0.048)	(0.061)	(0.082)	(0.061)	(0.069)
Observations	400	400	400	400	400
R^2	0.677	0.688	0.689	0.696	0.709
Adjusted R^2	0.676	0.686	0.686	0.694	0.706
Residual Std. Error	0.226	0.222	0.222	0.220	0.215
F Statistic	834.337***	437.399***	291.964***	302.291***	240.388***
Note:					*p<0.1; **p<0.05; ***p<0.01

Part 2 - Modeling and Forecasting a Real-World Macroeconomic Financial Time Series

Exploratory Data Analysis

In order to better understand the time series and analyze the possible underlying processes we must first observe and explore the time series. A summary of the time series is:

[1] "function"

Table 5: Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Max
DXCM Series	2,332	23.2	23.4	1.4	101.9

The first set of plots reveals:

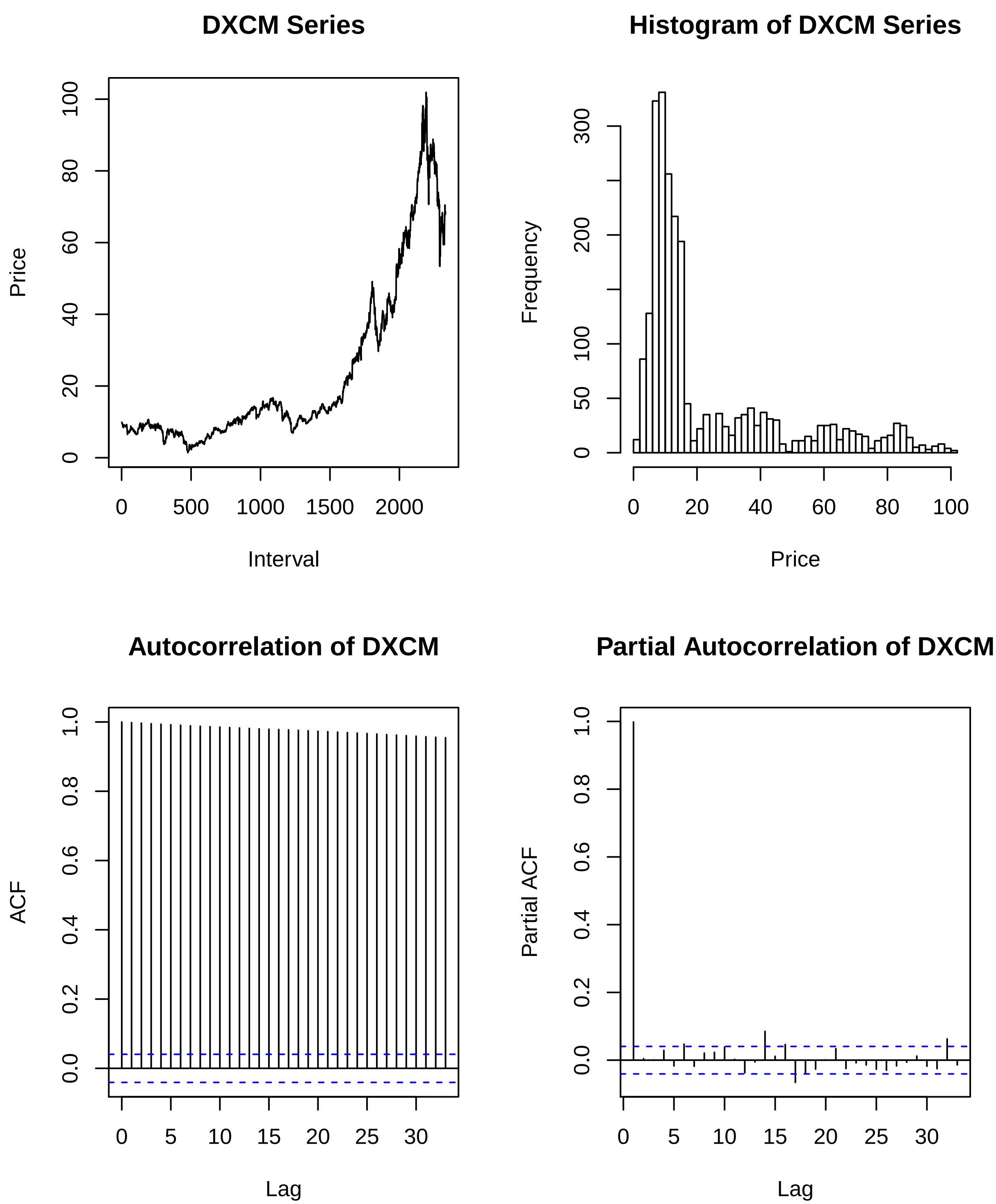
- The series is non-stationary; it has a persistent upward trend, interrupted by shocks;
- There are shocks at approximately time periods 500, 1200, 1800 and 2200;
- There appears to be seasonality in the series;
- The autocorrelation shows a very slight decay over the entire correlagram;
- The partial autocorrelation shows barely significant results at lags 14 and 32;
- We do not know the frequency of the time series;
- The series is of closing prices of DXCM

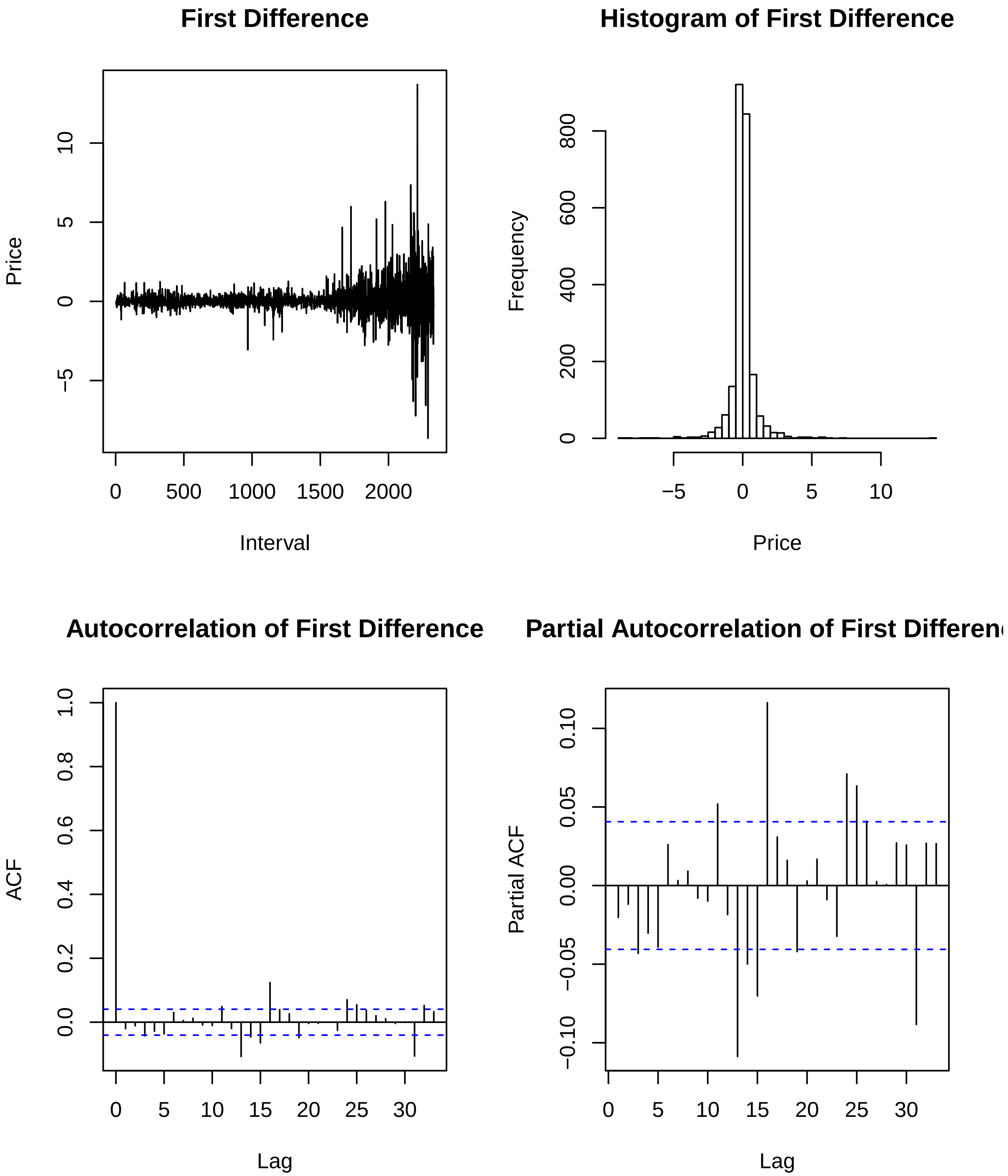
Since this is a time series of the closing price of a stock or other NYSE symbol we infer that these are daily closings and that they have a weekly frequency. Therefore to work with seasonality we reform the time series object in R as follows:

```
ts1 <- ts(ts1.csv_load$DXCM.Close, frequency = 365.25/7)
```

To remove the trend from the series we take the first difference and replot to check the results. In the differenced series we observe:

- The first difference series has a more or less white noise appearance until approximately time interval 1600 where the volatility of the series increases dramatically. This corresponds to the sudden, persistent upward trend in the original series.
- The autocorrelation shows marginally significant results at lags 13, 15, 16, 24, 31
- The partial autocorrelation shows a cyclic behavior that doesn't appear to decline, with significant results at lags 11, 13, 14, 15, 16, 24, 25, 31


DXCM Series
Price
Interval
0
20
40
60
80
100
0
500
1000
1500
2000
Histogram of DXCM Series
Frequency
Price
0
50
100
200
300
0
20
40
60
80
100
Autocorrelation of DXCM
ACF
Lag
0.0
0.2
0.4
0.6
0.8
1.0
0
5
10
15
20
25
30
Partial Autocorrelation of DXCM
Partial ACF
Lag
0.0
0.2
0.4
0.6
0.8
1.0
0
5
10
15
20
25
30

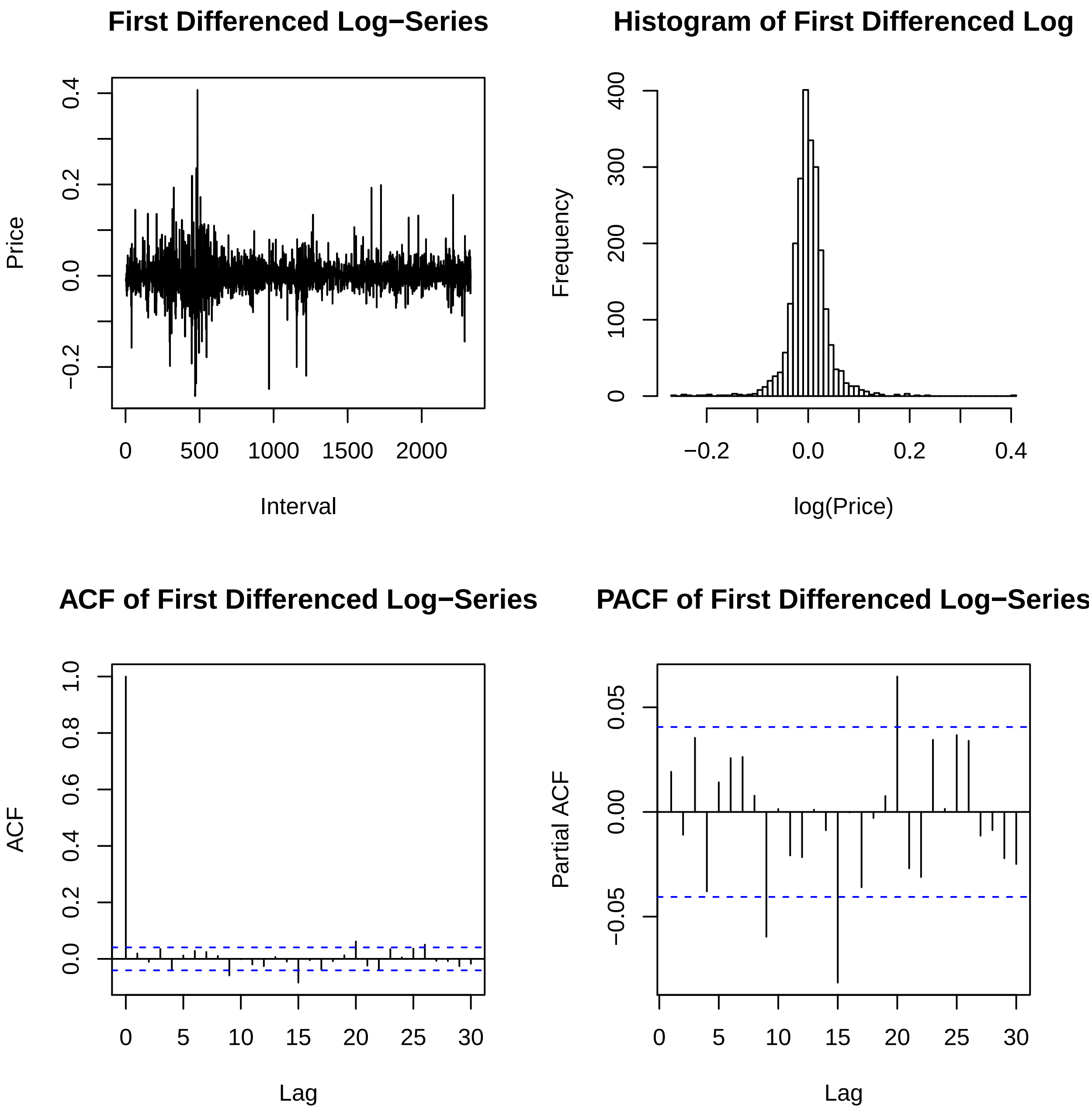


First Difference
Price
Interval
10
5
0
−5
0
500
1000
1500
2000
Histogram of First Difference
Frequency
Price
800
600
400
200
0
−5
0
5
10
Autocorrelation of First Difference
ACF
Lag
1.0
0.8
0.6
0.4
0.2
0.0
0
5
10
15
20
25
30
Partial Autocorrelation of First Differen
Partial ACF
Lag
0.10
0.05
0.00
−0.05
−0.10
0
5
10
15
20
25
30

We also examine the first difference of the log of the series and replot to check results. In the differenced log series we observe:

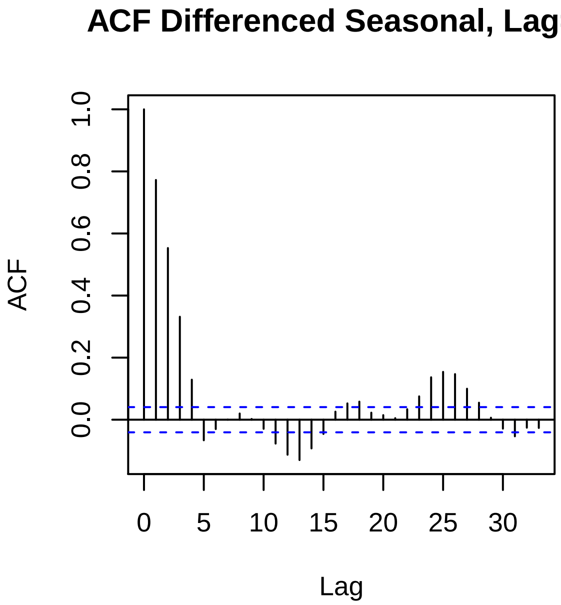
- The volatility appears to be reversed such that it is around interval 300-500, and overall the volatility of the differenced log series is higher.
- The ACF shows only a small results at lag 15 and 20.
- The PACF shows a cyclic behavior with significant results at lags 9, 15, 20

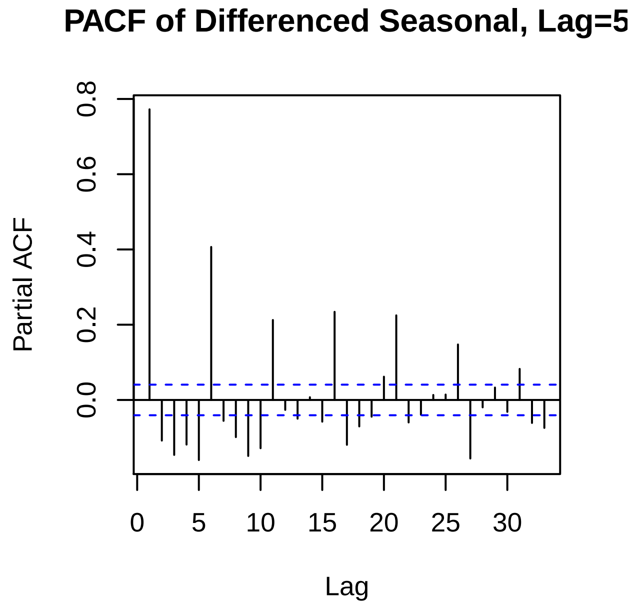
We choose to use the diffenced log-series since this is a financial time series and we can discuss returns in terms of percentage-changes to the closing price.

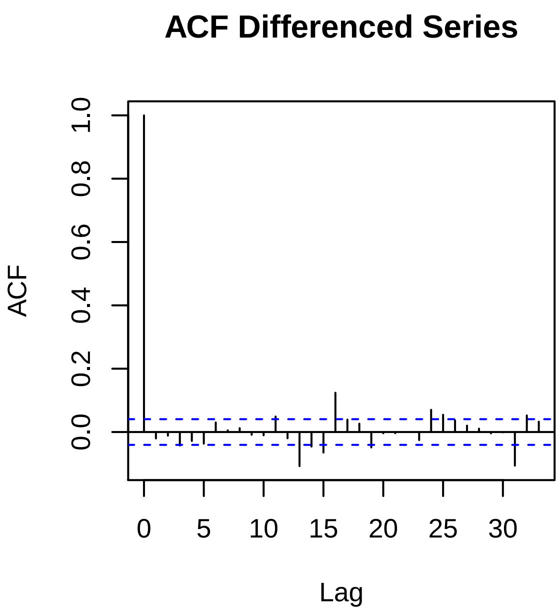


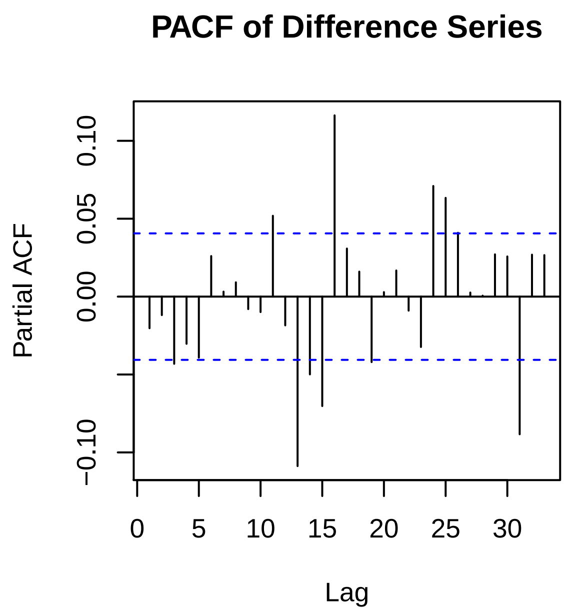
The seasonality of the series is not strong in the ACF of the differenced series. However, there are hints of a 5 day cycle that corresponds to the weekly frequency. There are stronger spikes that appear in lags 15 and 30 that support a multiple or harmonic of 5. We will use a seasonality factor of 365.25/7 in order to deal with the varying number of weeks per year.

The ACF and PACF of the differenced seasonal series show evidence of an underlying AR process





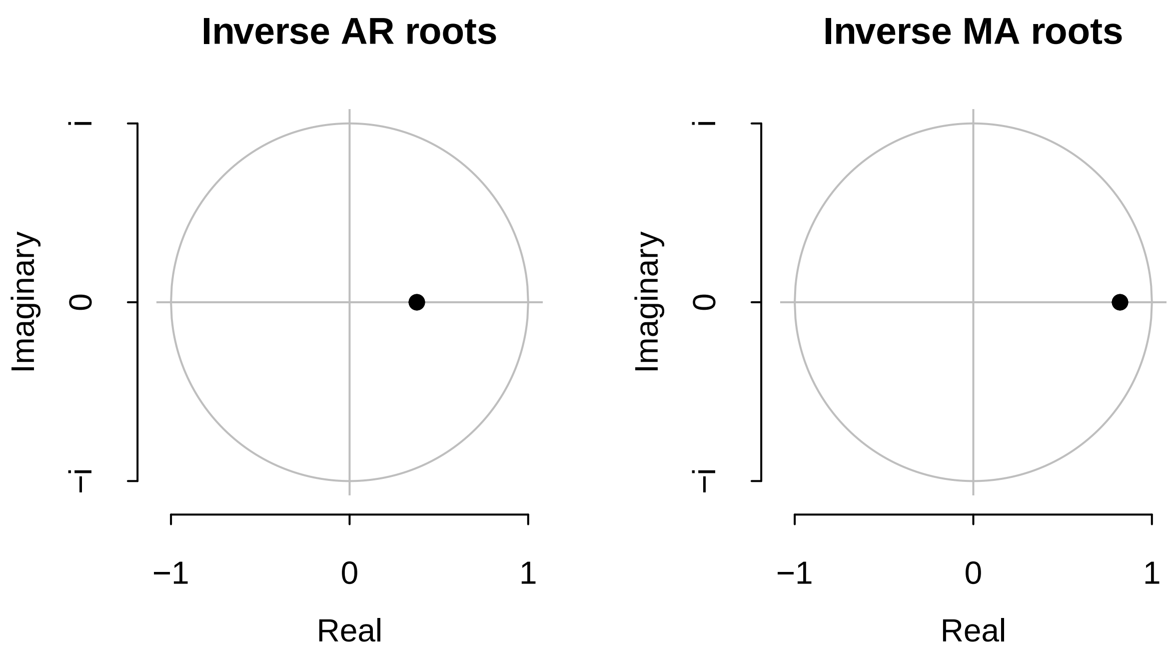




Model Selection

We build a model grid of SARIMA models to from SARIMA(0,1,1)(0,1,0) to SARIMA(2,1,1)(1,1,1) and use the model results to present the parameters in tabular format for comparison. All models use a seasonal value of 365.25/7, or just a bit over 52.

The parameters of the 24 models are split into 3 tables of 8 models; each successive table contains models with more parameters. Comparing the AICc and Log Likelihood values reveals that there are a cluster of models around the AICc value of 8610. The most parsimonious model is the SARIMA(0,1,1)(0,1,0)[52] model but the model is not stationary because the lagged coefficient polynomial root is on the unit circle. In fact, the only models in this grid that do not have roots on the unit circle are the SARIMA(1,1,0)(0,1,0)[52] and SARIMA(1,1,1)(1,1,1)[52] models, with AICc values of -7673 and -8469, respectively. Therefore we choose the SARIMA(1,1,1)(1,1,1)[52] model as the most appropriate. The root plot for this model is shown below; the tables for the model parameters follow on the next two pages.



	(0,1,1)|(0,1,0)	(0,1,1)|(0,1,1)	(0,1,1)|(1,1,0)	(0,1,1)|(1,1,1)	(1,1,0)|(0,1,0)	(1,1,0)|(1,1,1)	(1,1,0)|(1,1,0)	(1,1,0)|(1,1,1)
ar1					−0.48	0.02	−0.30	0.01
					(0.02)	(0.02)	(0.03)	(0.14)
ma1	−1.00	−0.49	−1.00	−1.00				
	(0.00)		(0.00)					
sar1			0.02	0.99			−0.30	0.01
			(0.02)	(0.01)			(0.03)	(0.14)
sma1		−0.49		−1.00		−1.00		−1.00
						(0.00)		(0.00)
AIC	-8611.22	-8220.38	-8610.12	-8607.72	-7673.27	-8610.12	-7789.59	-8608.13
AICc	-8611.22	-8220.37	-8610.11	-8607.71	-7673.27	-8610.11	-7789.58	-8608.11
BIC	-8599.71	-8203.12	-8592.86	-8584.71	-7661.77	-8592.86	-7772.33	-8585.11
Log Likelihood	4307.61	4113.19	4308.06	4307.86	3838.64	4308.06	3897.80	4308.06

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 6: Statistical models

	(1,1,1)|(0,1,0)	(1,1,1)|(0,1,1)	(1,1,1)|(1,1,0)	(1,1,1)|(1,1,1)	(0,1,2)|(0,1,0)	(0,1,2)|(1,1,1)	(0,1,2)|(1,1,0)	(0,1,2)|(1,1,1)
ar1	0.02	0.99	0.01	0.38				
	(0.02)	(0.01)	(0.14)					
ma1	−1.00	−1.00	−1.00	−0.82	−0.98	−0.87	−0.31	−0.39
	(0.00)		(0.00)		(0.02)	(0.09)	(0.14)	(0.23)
ma2					−0.02	−0.13	−0.69	−0.61
					(0.02)	(0.09)	(0.14)	(0.23)
sar1			0.01	0.38			−0.66	−0.56
			(0.14)				(0.15)	(0.25)
sma1		−1.00		−0.82		−0.11		−0.02
						(0.09)		(0.04)
AIC	-8610.12	-8607.72	-8608.13	-8468.69	-8610.14	-8608.48	-8610.79	-8609.12
AICc	-8610.11	-8607.71	-8608.11	-8468.66	-8610.13	-8608.46	-8610.77	-8609.09
BIC	-8592.86	-8584.71	-8585.11	-8439.92	-8592.88	-8585.46	-8587.77	-8580.35
Log Likelihood	4308.06	4307.86	4308.06	4239.34	4308.07	4308.24	4309.39	4309.56

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 7: Statistical models

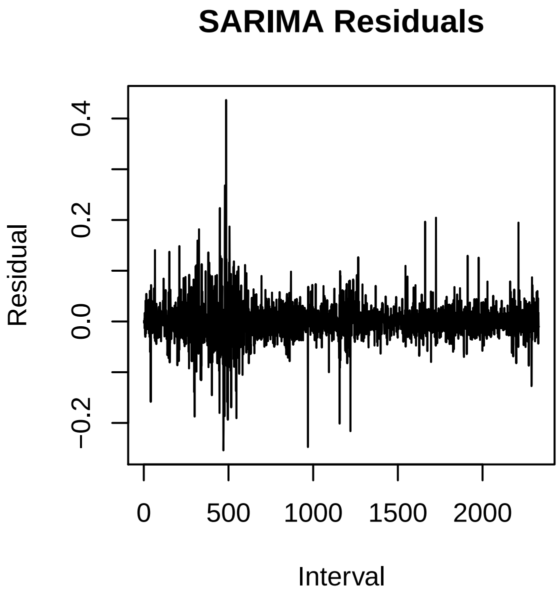
<table>
<tr><th></th><th>(1,1,2)|(0,1,0)</th><th>(1,1,2)|(0,1,1)</th><th>(1,1,2)|(1,1,0)</th><th>(1,1,2)|(1,1,1)</th><th>(2,1,2)|(0,1,0)</th><th>(2,1,2)|(1,1,1)</th><th>(2,1,2)|(1,1,0)</th><th>(2,1,2)|(1,1,1)</th></tr>
<tr><td>ar1</td><td>−0.66</td><td>−0.56</td><td>−0.16</td><td>−0.43</td><td>−0.62</td><td>0.05</td><td>−0.25</td><td>−0.97</td></tr>
<tr><td></td><td>(0.15)</td><td>(0.25)</td><td></td><td>(0.33)</td><td>(0.16)</td><td>(0.72)</td><td>(0.28)</td><td>(0.04)</td></tr>
<tr><td>ar2</td><td></td><td></td><td></td><td></td><td>−0.02</td><td>0.47</td><td>0.08</td><td>−0.03</td></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td>(0.02)</td><td>(0.57)</td><td>(0.05)</td><td>(0.03)</td></tr>
<tr><td>ma1</td><td>−0.31</td><td>−0.39</td><td>−0.66</td><td>−0.41</td><td>−0.36</td><td>−0.31</td><td>−0.41</td><td>−0.15</td></tr>
<tr><td></td><td>(0.14)</td><td>(0.23)</td><td>(0.13)</td><td>(0.13)</td><td>(0.16)</td><td>(0.18)</td><td>(0.09)</td><td>(0.10)</td></tr>
<tr><td>ma2</td><td>−0.69</td><td>−0.61</td><td>−0.34</td><td>−0.59</td><td>−0.64</td><td>−0.69</td><td>−0.59</td><td>−0.85</td></tr>
<tr><td></td><td>(0.14)</td><td>(0.23)</td><td>(0.13)</td><td>(0.13)</td><td>(0.16)</td><td>(0.17)</td><td>(0.09)</td><td>(0.10)</td></tr>
<tr><td>sar1</td><td></td><td></td><td>−0.16</td><td>−0.43</td><td></td><td></td><td>−0.32</td><td>−0.72</td></tr>
<tr><td></td><td></td><td></td><td></td><td>(0.33)</td><td></td><td></td><td>(0.23)</td><td>(0.07)</td></tr>
<tr><td>sma1</td><td></td><td>−0.02</td><td></td><td>0.30</td><td></td><td>−0.71</td><td></td><td>0.85</td></tr>
<tr><td></td><td></td><td>(0.04)</td><td></td><td>(0.20)</td><td></td><td>(0.78)</td><td></td><td>(0.10)</td></tr>
<tr><td>AIC</td><td>-8610.79</td><td>-8609.12</td><td>-8607.50</td><td>-8607.87</td><td>-8609.23</td><td>-8606.81</td><td>-8609.32</td><td>-8610.37</td></tr>
<tr><td>AICc</td><td>-8610.77</td><td>-8609.09</td><td>-8607.47</td><td>-8607.83</td><td>-8609.20</td><td>-8606.77</td><td>-8609.28</td><td>-8610.32</td></tr>
<tr><td>BIC</td><td>-8587.77</td><td>-8580.35</td><td>-8578.73</td><td>-8573.34</td><td>-8580.46</td><td>-8572.28</td><td>-8574.80</td><td>-8570.09</td></tr>
<tr><td>Log Likelihood</td><td>4309.39</td><td>4309.56</td><td>4308.75</td><td>4309.93</td><td>4309.61</td><td>4309.40</td><td>4310.66</td><td>4312.18</td></tr>
</table>

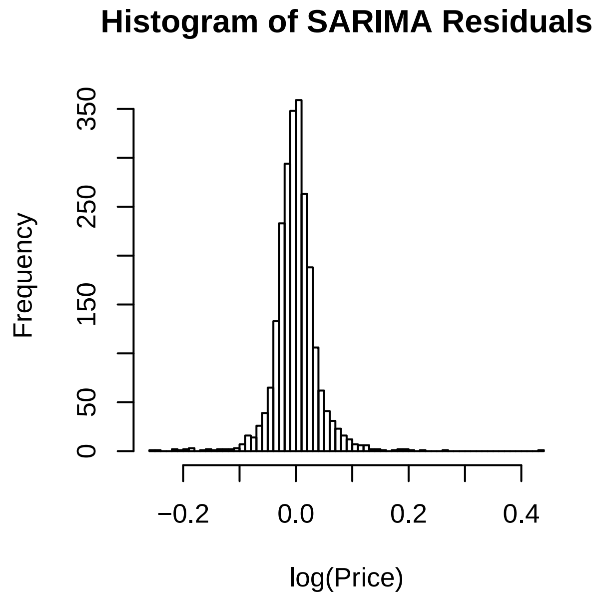
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

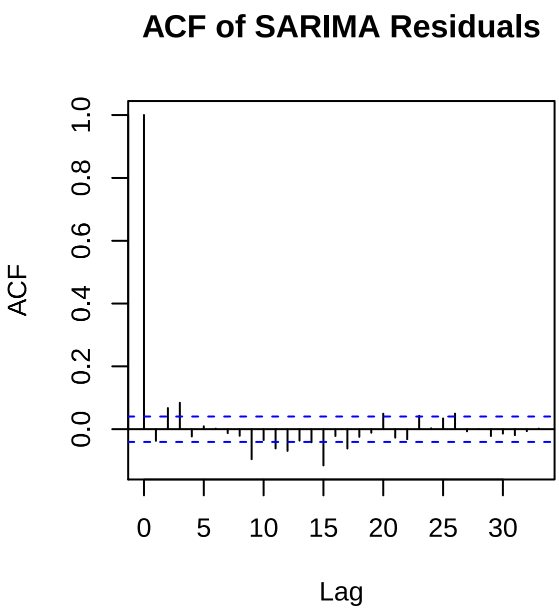
Table 8: Statistical models

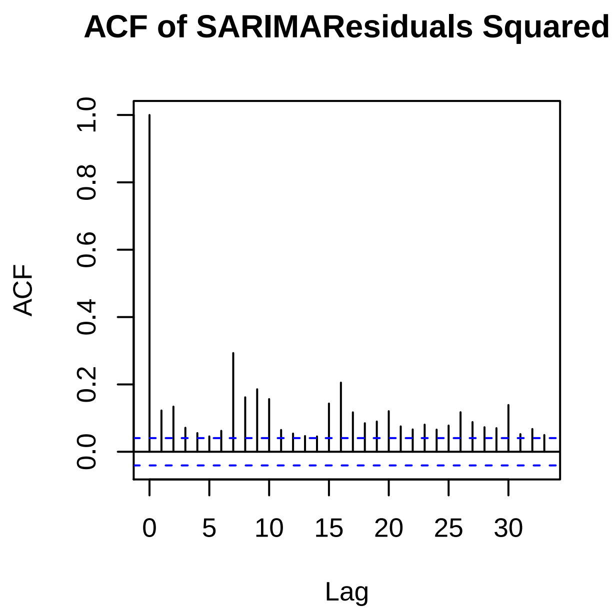
SARIMA (1,1,1)(1,1,1)[52] Model Residual Analysis

The residual plots of the SARIMA(1,1,1)(1,1,1)[52] model show that the residual has a volatility that changes over time. The PACF of the squared residuals show that a ARCH model could be used for the residuals.







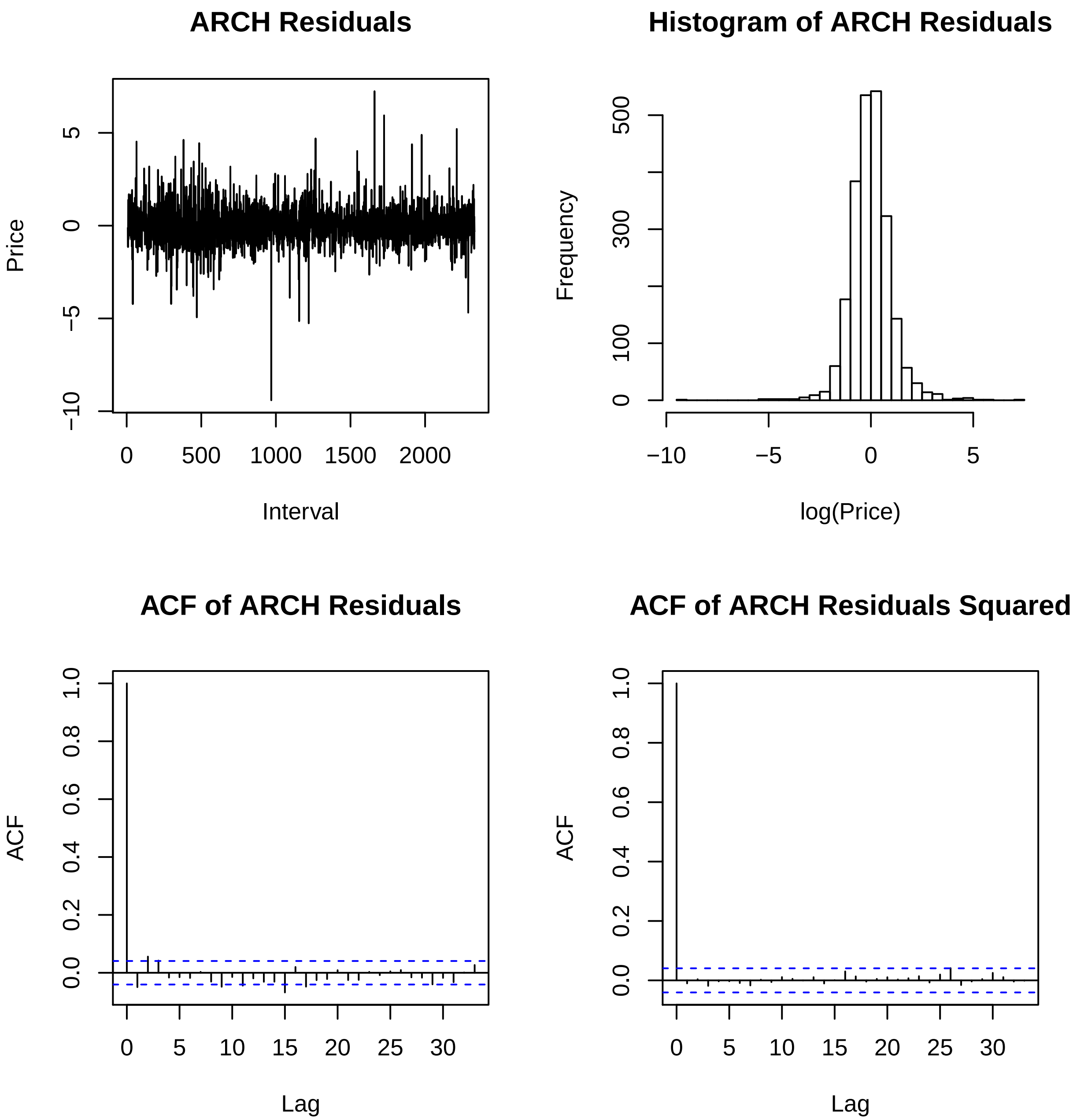


ARCH Model Analysis

We analyse potential ARCH models by constructing models of increasing order and plotting the squared residuals. Once the squared residuals have no statistically significant lags we select the result ARCH model order. Using this process we arrive at an ARCH(7)/GARCH(0,7) model.

	a0	a1	a2	a3	a4	a5	a6	a7
2.5 %	0.00	0.16	0.07	0.10	-0.02	-0.02	0.01	0.09
97.5 %	0.00	0.24	0.11	0.17	0.02	0.02	0.07	0.14

Table 9: ARCH(7) Coefficient Confidence Intervals



Part 3 - Forecast Web Search Activity for "Global Warming"

Part 4 - Forecast Inflation-Adjusted Gas Price