

# **Regression Analysis of Air Pollution and Mortality**

STA-6013 Regression Analysis

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# 1. Problem Description

The objective of this project is to seek to find the association between air pollution and mortality as well as to obtain a prediction equation for mortality as a function of the predictor variables. The dataset used is named 'Pollution Data 12rev n57 Version 2018' with all numeric data collected from 57 US cities. Below is the variable description and the header of the dataset:

$y$  = Total age-adjusted mortality from all causes in deaths per 100,000 population

$x_1$  = Mean annual precipitation (in inches)

$x_2$  = Median number of school years completed for persons of age 25 years or older

$x_3$  = Percentage of the population that is nonwhite

$x_4$  = Relative pollution potential of oxides of nitrogen

$x_5$  = Relative pollution potential of sulfur dioxide

**Note:** Relative pollution potential is the product of the tons emitted per day per square kilometer and a factor correcting for the dimensions of and exposure to the given area.

Obs	City	y	x1	x2	x3	x4	x5
1	San Jose, CA	790.73	13	12.2	3	32	3
2	Wichita, KS	829.76	28	12.1	7.5	2	1
3	San Diego, CA	839.71	10	12.1	5.9	66	20
4	Lancaster, PA	844.05	43	9.5	2.9	7	32
5	Minneapolis, MN	857.62	25	12.1	3	11	26

We follow the *PISEAS* (Planning, Investigating, Specification, Estimation, Assess, and Selection) rule, a general system for performing a regression analysis except for '*P*' since the data is designated here. MLR (multiple linear regression) is started with the most common OLS (ordinary least square) model. After investigation of the data, an increased power transformation on  $y$  is conducted based on Box-Cox test and estimate parameters are then obtained for specification of the fitted model. However, MSE (mean squared error) and  $R^2_{Adj}$  of the model are not desirable. Also, adequacy checking using diagnostic measures indicate the assumptions on error term do not hold well. To improve the fit, possible outliers and influential points are identified by influential analyses. After removing one outlier, the model is refitted, making the assumptions on error term hold while MSE and  $R^2_{Adj}$  do not improve much. Another transformation on  $y$  did not help much, likewise. Hence, we conclude that OLS model does not perform well on the data.

Since a model is supposed to be as informative as possible, deleting an outlier is not preferred or recommended. We try to accommodate it, such as downweighting it to a less impactful point, or almost to zero, by using WLS (weighted least square) model. Thus, the WLS model is fitted instead of the OLS one. To our delight, MSE,  $R^2_{Adj}$  and even CV (coefficient variance) improved significantly with all observations kept. Finally, variable selection measures were performed to obtain the optimal model, and the prediction equation is

$$\hat{y} = 803.64449 + 2.33451x_1 + 2.28908x_3 - 0.12425x_4 + 0.42937x_5$$

We conclude *Mortality* is positively associated with mean annual precipitation, percentage of the population that is nonwhite, relative pollution potential of sulfur dioxide, and is negatively related to relative pollution potential of oxides of nitrogen.

Fortunately, multicollinearity was not observed throughout the whole regression analysis.

## 2. Investigation of the Data

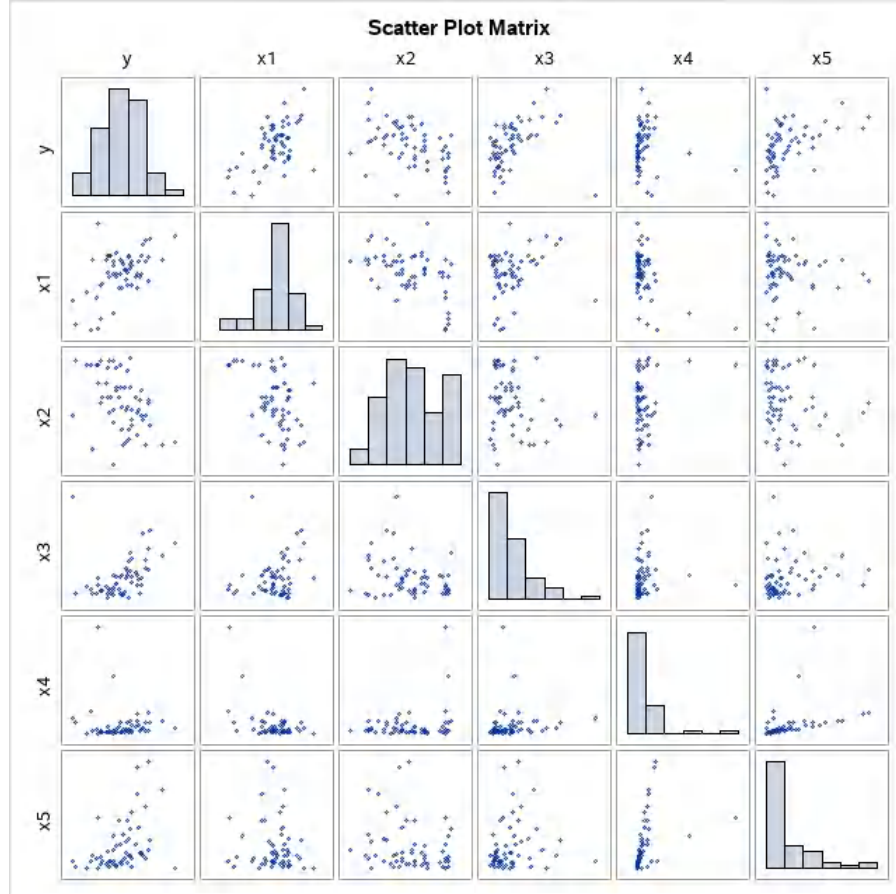
The summary statistics for response and all predictors are shown in Table 1.  $x_3$ ,  $x_4$  and  $x_5$  show large standard deviance compared to the mean.

Table 1 Simple Summary Statistics

Simple Statistics						
Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
y	57	938.89702	65.79181	53517	782.37000	1113
x1	57	36.96491	10.21023	2107	10.00000	80.00000
x2	57	10.93333	0.85802	623.20000	9.00000	12.30000
x3	57	12.18246	10.72046	694.40000	0.80000	57.60000
x4	57	24.59649	47.40210	1402	1.00000	319.00000
x5	57	56.45614	63.89726	3218	1.00000	278.00000

The pairwise scatter plots are shown in Fig.1, suggesting  $y$  is positively associated with  $x_1, x_3$  and  $x_5$ , negatively associated with  $x_2$ , and not obviously related to  $x_4$ . However, considering the two leverage points in the plot of  $y$  vs  $x_4$ , there might be association between the two variables. Moreover, there appear to no or little linear pairwise association among the five predictors.

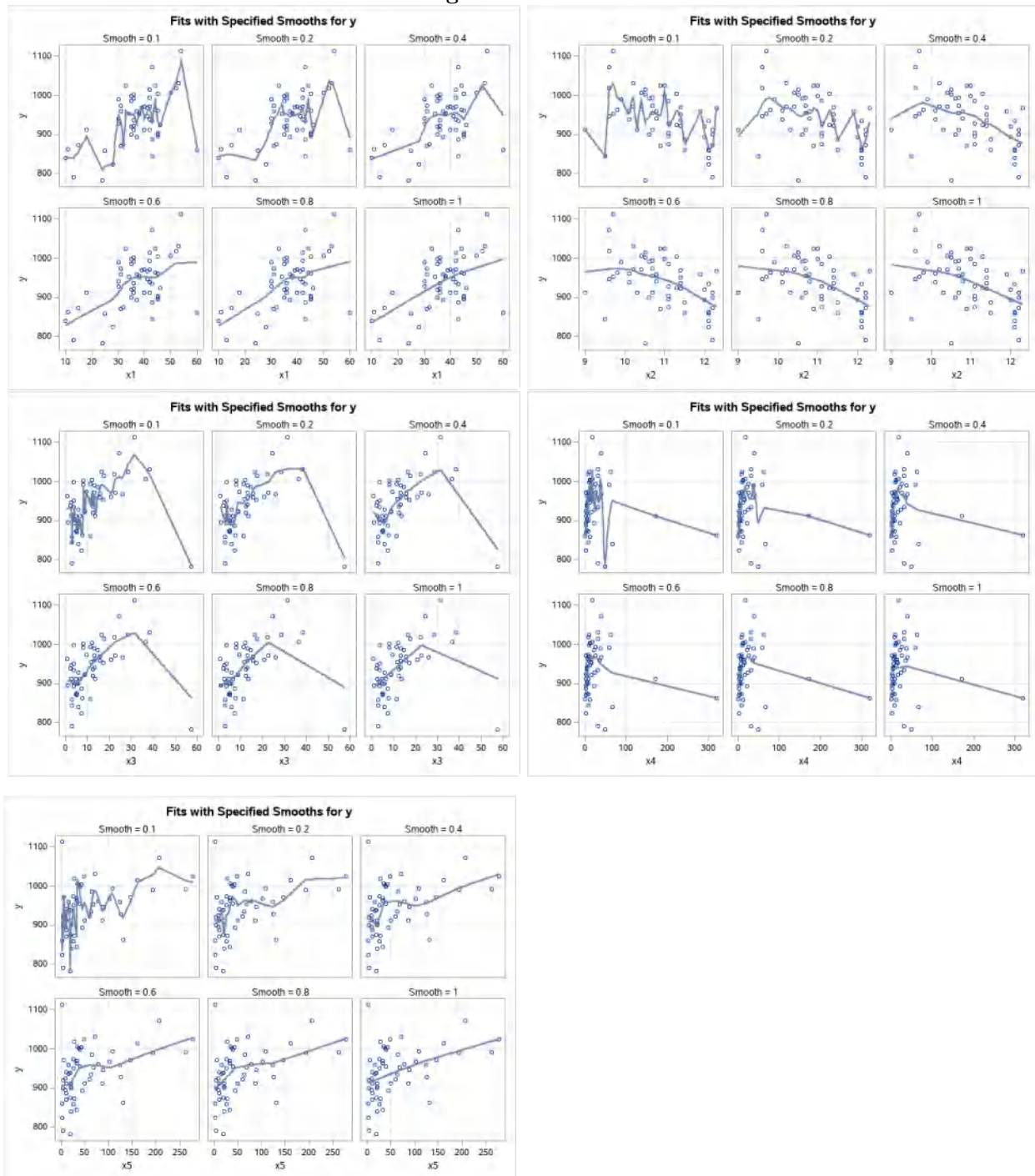
Fig. 1 Paired Scatter Plots



Loess plots are obtained for all predictors using various smoothing parameters of 0.1, 0.2, 0.4, 0.6, 0.8 and 1. As seen in Fig.2, all predictors achieve the best Loess fit with *smooth* equals 0.6 or 0.8. However, the strong nonlinear trend with  $x_3$  and  $x_4$  suggests transformation of the original data, commonly on the power of response. To obtain the appropriate  $\lambda$  for  $y$  in the transformed form  $y^\lambda$ , Box-Cox analysis is recommended.

Observation 7, 17, 57 should be carefully scrutinized as possible outliers since they have a large  $x_4$  or  $x_3$  value and are off the trend of the majority data.

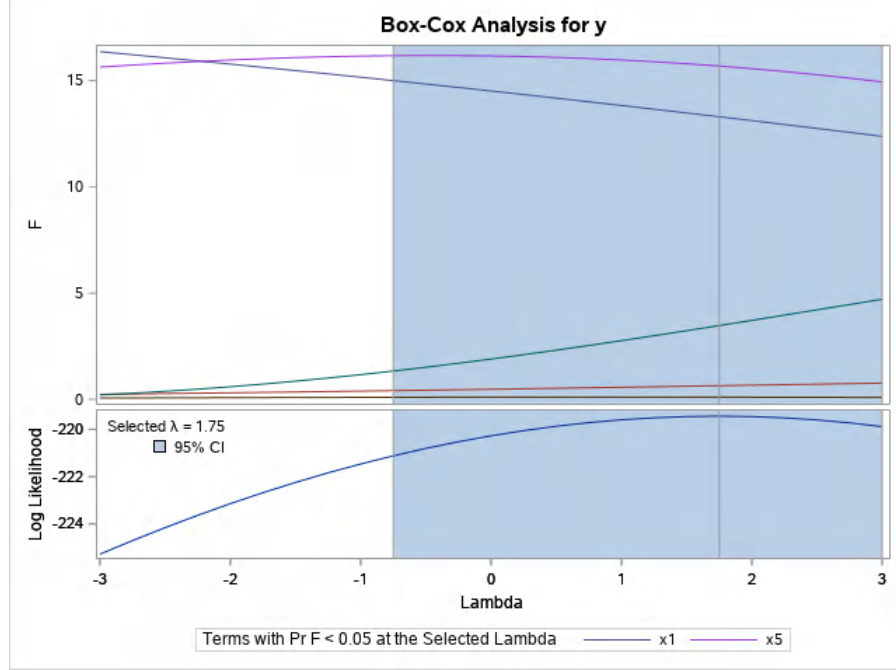
Fig. 2 Loess Plots



### 3. Specification of the Model

Base on preliminary judgments from the Investigation stage in Section 2 above, Box-Cox analysis suggests  $y^{1.75}$  is a good transformation of the response. To simplify the prediction equation, we take value of 2, the nearest integer around 1.75, to be the proper order transformation on the response variable.

**Fig. 3 Box-Cox Analysis for  $y$**



Therefore, the initial proposed MLR model is

$$y_i^2 = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_4 x_{i4} + \beta_5 x_{i5} + \epsilon_i, \quad i = 1, \dots, n$$

For  $i$ th observation,  $y_i^2$  is the response variable, all  $x_{ij}$ s are predictors for  $j = 1, 2, 3, 4, 5$ , and  $\epsilon_i$  is the error term.  $\beta_{ij}$ s are parameters where  $\beta_{0j}$  is the response value when all predictors are set to zero, and other  $\beta_{ij}$ s represent the change in  $y_i$  per unit change in  $x_{ij}$ .

The model assumptions are:

1. Linear relationship between response and predictors in coefficient  $\beta_{ij}$ , or  $\beta_{ij} \neq 0$  for at least one  $j$
2. Error term  $\epsilon_i$  follows  $N(0, \sigma^2)$ . In other words, the probability distribution of  $\epsilon_i$  shows normality and constant variance.
3. No or light multicollinearity among all predictors  $x_{ij}$ .

## 4. Estimation of the Appropriate Model

According to Table 2, the prediction equation is obtained with the parameter estimates as

$$\hat{y}^2 = 139629 + 866.83842x_1 - 2122.80478x_2 + 343.27633x_3 - 16.63512x_4 + 133.20095x_5$$

The ANOVA analysis result given in Table 2 shows the  $p$ -value for  $F$ -test is smaller than 0.0001, indicating rejection of the  $H_0$  that all  $\beta_{ijs} = 0$ . The assumption (1) in Section 3 holds. A good CV of 8.71% shows the ratio of standard deviation to mean is low, suggesting a low variability in the data. However, a  $R^2_{Adj}$  of 49.04% means less than 50% of the variability in the data can be explained by the model. Also, the MSE is  $13922^2$ , which is extremely large.

**Table 2 ANOVA Analysis for the Initial Model**

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	5	11413879112	2282775822	11.78	<.0001
Error	51	9884331014	193810412		
Corrected Total	56	21298210126			
Root MSE		13922	R-Square	0.5359	
Dependent Mean		159755	Adj R-Sq	0.4904	
Coeff Var		8.71432			

Read from the parameter estimates Table 3, the  $p$ -values obtained for  $x_2$  and  $x_4$  in  $t$ -test are greater than 0.05, indicating insignificant of these two variables at 0.05 level. The absolute value of  $\hat{\beta}_2$  is extremely large while that of  $\hat{\beta}_4$  is too small in magnitude compared with other predictor coefficients, suggesting the model does not fit well.

All VIFs (variance inflation factors) are smaller than 2, meaning only moderate correlations are observed among the predictors. Therefore, the assumption (3) in Section 3 holds. Multicollinearity is not a concern for the data.

**Table 3 Parameter Estimates for the Initial Model**

Parameter Estimates									
Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr >  t	Standardized Estimate	Variance Inflation	95% Confidence Limits
Intercept	Intercept	1	139629	33991	4.11	0.0001	0	0	71389 207870
x1	x1	1	866.83842	237.71280	3.65	0.0006	0.45383	1.70211	389.61006 1344.06678
x2	x2	1	-2122.80478	2642.57367	-0.80	0.4255	-0.09340	1.48544	-7427.99279 3182.38322
x3	x3	1	343.27633	184.15581	1.86	0.0681	0.18870	1.12619	-26.43189 712.98455
x4	x4	1	-16.63512	50.81421	-0.33	0.7447	-0.04043	1.67540	-113.84890 85.57885
x5	x5	1	133.20095	33.63467	3.96	0.0002	0.43643	1.33460	65.67653 200.72537

Also, the collinearity diagnostics table with intercept adjusted in Table 4 further confirms it as

$$\kappa = \frac{\lambda_{max}}{\lambda_{min}} = \frac{1.90269}{0.37954} = 1.32 < 10$$

**Table 4 Collinearity Diagnostics (intercept adjusted)**

Collinearity Diagnostics (intercept adjusted)							
Number	Eigenvalue	Condition Index	Proportion of Variation				
			x1	x2	x3	x4	x5
1	1.90269	1.00000	0.12268	0.09064	0.02132	0.08798	0.00850
2	1.44511	1.14745	0.00071289	0.06619	0.14254	0.07239	0.23271
3	0.83232	1.51195	0.00146	0.08551	0.71547	0.00625	0.19161
4	0.44034	2.07869	0.33870	0.75730	0.00188	0.04940	0.36311
5	0.37954	2.23899	0.53705	0.00015162	0.11880	0.76356	0.20406

Overall, the assumption (2) in Section 3 does not hold with the initial model. The poor  $R^2_{Adj}$  and MSE indicate poor adequacy of the model.

## 5. Assessment of the Chosen Prediction Equation

Shapiro-Wilk test result and QQ-plot of R-student residual vs predicted value in Table 5 suggests rejection of  $H_0$  in normality test and we conclude the normality assumption on the error term does not hold.

Table 5 Shapiro-Wilk Test on Normality

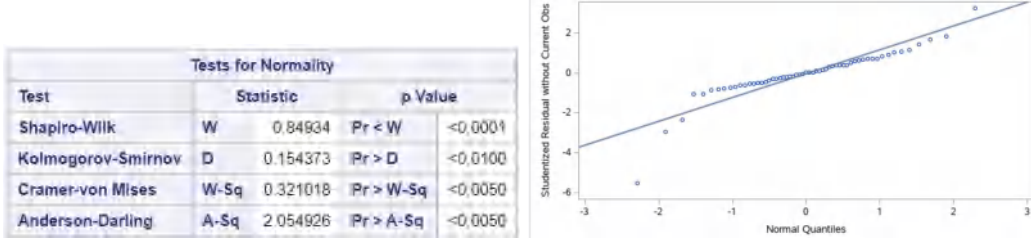
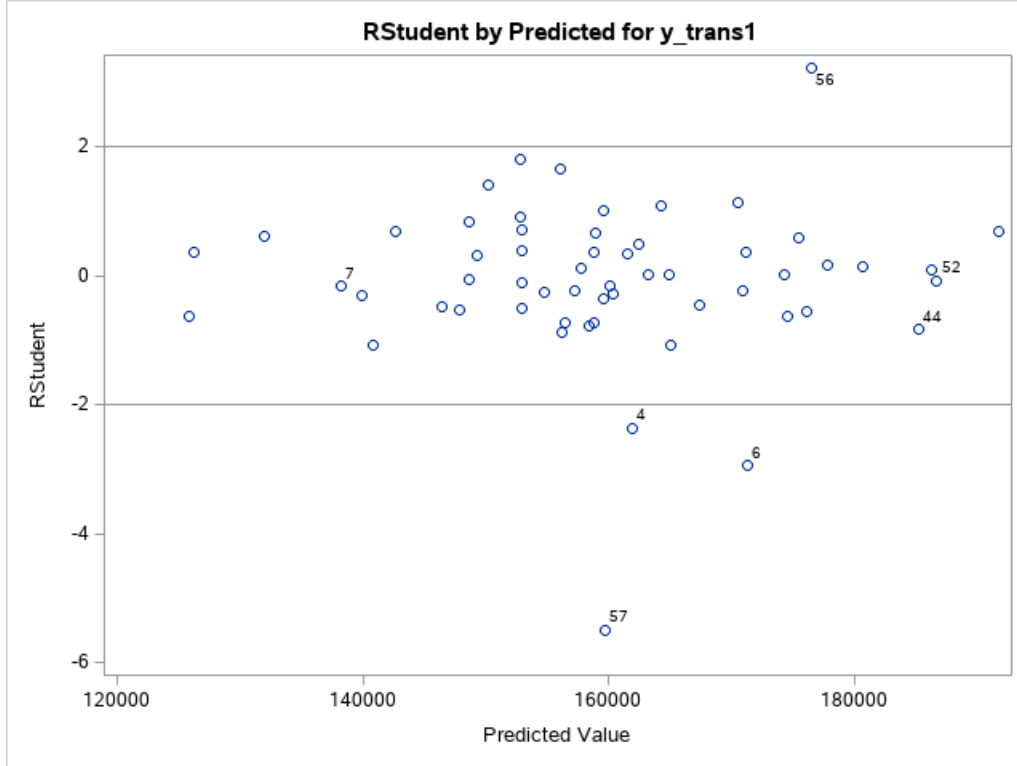


Fig. 4 shows the of R-student residual vs predicted value. The variance on error term has an outward-funnel pattern, likely caused by observation 57, a possible outlier with R-student residual value of less than -4. Therefore, we conclude the constant variance assumption on the error term does not hold, and the assumption (2) in Section 3 does not hold.

Fig. 4 R-student Residual vs Predicted Value



Influential analysis is summarized in Table 6. According to  $RStudent$  values in Fig. 4, observation 57 is an outlier. Next,  $H_{ii}$ ,  $Cook'sD$ ,  $DFFITs$ , and  $DFBETAS$  are evaluated to find out possible influential points.

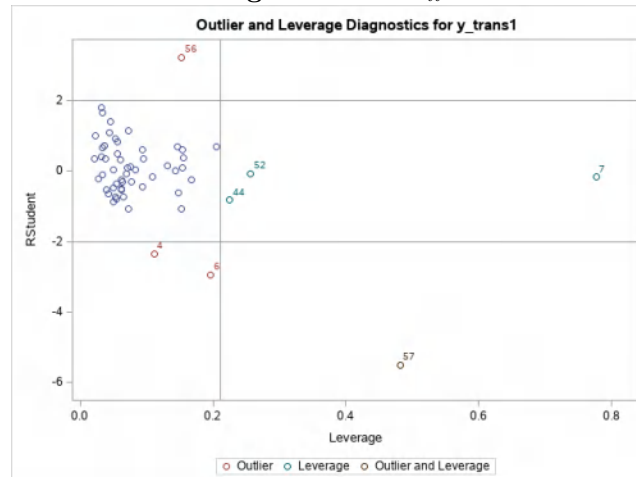


### Table 6 Influential Analysis Summary

Case	Dependent Variable	Predicted Value	Site Error Mean	Output Statistics										DIPBETA									
				95% CL Mean	95% CL Predict	Residual	Site Error Residual	Student Residual	Cook's D	H Measure	Hot Ling D	Cov Ratio	DIPHTS	Intercept	x1	x2	x3	x4	x5				
1	11719	15562	3842	15562	15562	3842	15562	3842	0.822	0.031	-0.018	1.449	1.267	0.254	0.064	0.919	0.017	0.606	0.019	0.047			
2	12665	12665	0	12665	12665	11807	12665	14235	1561	0.019	0.007	0.007	1.063	0.008	0.076	0.767	0.168	0.016	0.016	0.007			
3	13068	13623	555	13067	13067	14888	13068	18007	0.021	0.004	0.308	0.158	1.217	0.168	0.010	0.106	0.008	0.007	0.005	0.004			
4	13117	16173	3056	13057	13116	13041	13041	18705	2076	0.127	0.040	0.101	0.673	0.031	0.060	0.004	0.008	0.004	0.004	0.004			
5	13245	13694	3649	13245	13694	15762	13694	18819	4910	0.188	-0.006	0.167	1.082	0.009	0.009	0.009	0.009	0.015	0.008	0.004			
6	13897	17267	3370	13897	13898	14025	13898	3416	0.042	0.245	0.307	2.948	0.176	0.031	1.469	0.006	1.007	-0.044	0.177	0.004			
7	12704	13616	1026	12701	12623	13089	12701	17540	0.001	0.877	0.16	0.467	0.008	0.009	0.015	0.003	0.2247	0.049	0.382	0.004			
8	13972	14035	663	14035	14035	15003	13975	15025	0.003	0.014	-0.002	-0.084	0.449	0.151	0.108	0.002	0.002	0.008	0.003	0.019			
9	13863	13194	3435	13863	13863	15056	13863	1803	0.004	0.016	0.012	0.815	0.155	0.217	0.007	0.003	0.001	0.048	0.180	0.011			
10	14526	16762	2236	14526	14526	15367	14526	1744	0.049	0.234	0.022	-0.069	0.001	0.106	0.104	0.008	0.047	0.105	0.033	0.002			
11	14401	15045	1644	14401	14401	15201	14401	16668	1544	0.006	-0.007	-0.079	0.064	0.081	0.003	0.196	-0.094	-0.1034	0.040	0.003			
12	15010	15279	2669	15010	15010	15175	15010	1777	0.001	0.005	0.003	0.017	0.001	0.104	0.008	0.048	0.029	0.047	0.000	-0.004			
13	14651	15613	1062	14651	14651	15356	14651	1805	0.009	0.727	0.002	0.724	0.003	0.119	0.012	0.024	0.1072	0.029	0.146	0.004			
14	14187	14876	689	14187	14187	14663	14187	1657	0.007	0.007	0.008	0.060	0.004	0.010	0.010	0.017	0.003	0.017	0.000	0.004			
15	14730	15847	1117	14730	14730	15031	14731	15031	0.004	0.788	-0.000	0.255	0.006	0.188	0.001	0.002	0.000	0.029	0.005	0.006			
16	14900	14900	0	14900	14900	15051	14900	1679	0.005	0.641	-0.706	0.188	0.006	0.191	0.016	0.080	0.1034	0.077	0.004	0.003			
17	15126	14905	1321	15126	15126	15149	15126	1615	0.014	0.004	0.021	0.008	0.254	0.003	0.009	0.009	0.048	0.010	0.257	0.001			
18	15100	14697	2403	15100	15100	15100	15100	1507	0.004	0.560	0.004	0.004	0.157	0.160	0.003	0.001	0.009	0.008	0.105	0.001			
19	15141	15470	3284	15141	15141	15190	15141	15024	0.007	0.486	0.246	0.017	0.016	0.195	0.								

Leverage points are determined by  $h_{ii} > 2p/n = (2)(6)/57 = 0.2105$ , suggesting point 7, 44, 52 and 57 to be leverage points. Combined with previous finding the point 57 is an outlier, then it is likely to be influential.

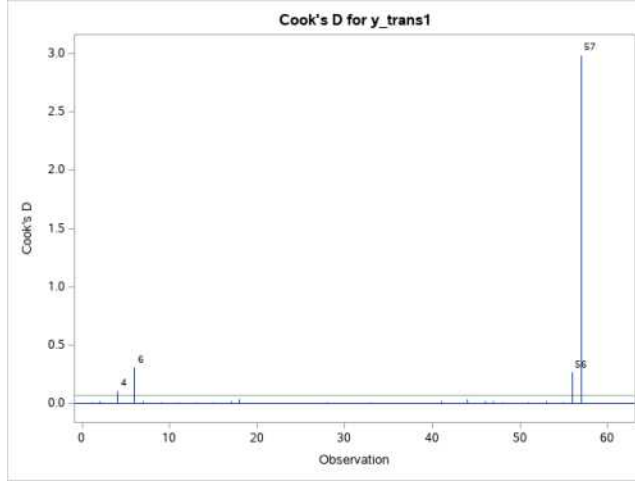
Fig. 5 Plot of  $h_{ii}$





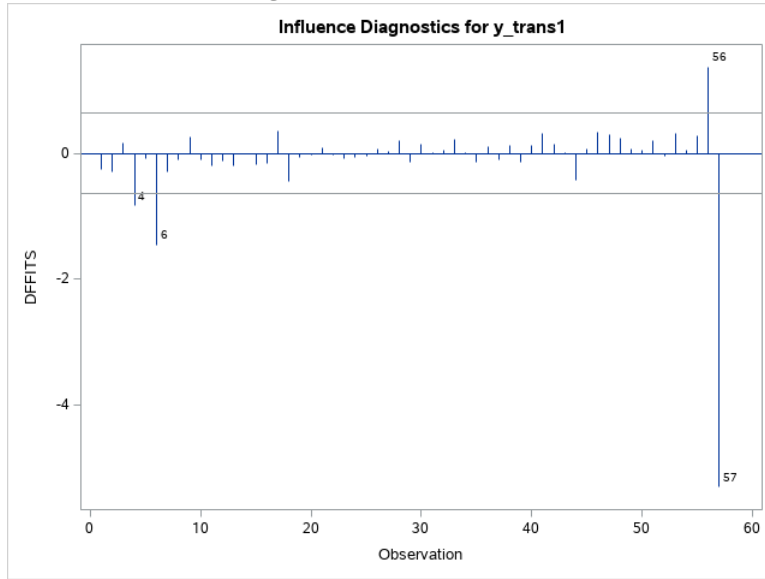
$Cook's D$  value greatly exceeds  $Di > 1$  for observation 57, suggesting it is influential.

**Fig. 6 Plot of  $CookD$**



The cutoff for  $DFFITs_i$  is  $|DFFITs_i| > 2\sqrt{p/n} = 2\sqrt{5/57} = 0.5923$ . Observations 4, 6, 56, and 57 have values of  $|DFFITs_i|$  that exceed this value, therefore are most likely influential.

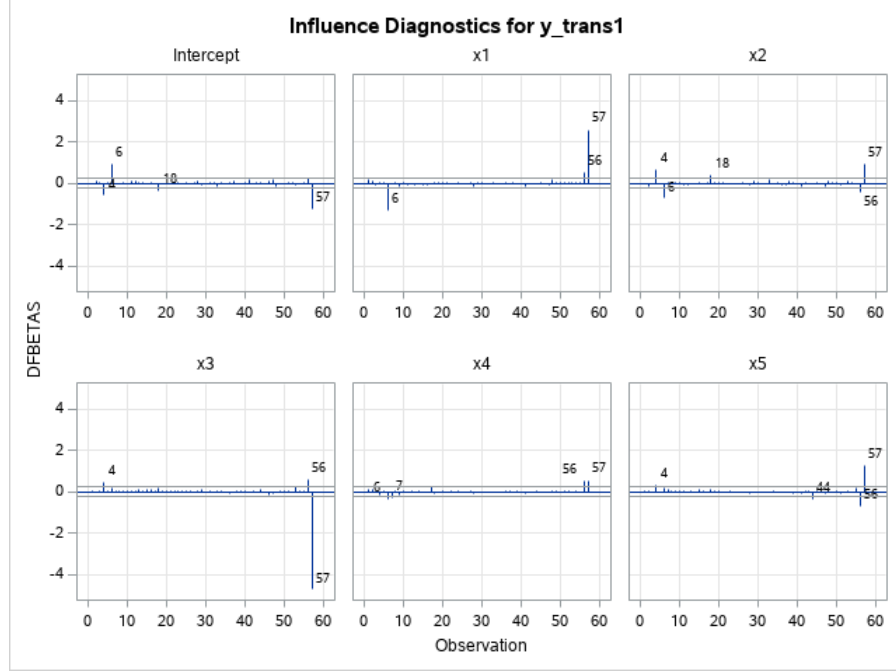
**Fig. 7 Plot of  $DFFITs$**



The cutoff for  $DFBETAS_i$  is  $|DFBETAS_i| > 2/\sqrt{n} = 2/\sqrt{57} = 0.2649$ , we immediately noticed that observation 57 has effect on all five parameters and intercept, and its effect on  $\hat{\beta}_1$  and  $\hat{\beta}_3$  is large. Point 56 has effect on all five parameters other than intercept. Point 4 has effect on intercept,  $\hat{\beta}_2$ ,  $\hat{\beta}_3$  and  $\hat{\beta}_5$ , especially for  $\hat{\beta}_2$ . Point 6 has effect on intercept,  $\hat{\beta}_1$ ,  $\hat{\beta}_2$  and  $\hat{\beta}_4$ , especially for intercept and  $\hat{\beta}_1$ . Point 18 has small effect on intercept and  $\hat{\beta}_2$ . Point 7 has small effect on  $\hat{\beta}_4$ . Point 44 has small effect on  $\hat{\beta}_5$ .

The cutoff for  $COVRATIO_i$  is  $1 \pm 3p/n = 1 \pm (3)(6)/57$ , or 1.316 and 0.684. Note that the values of observation 6, 8, 15, 52, 56, and 57 clearly exceed these limits, indicating these points are influential. However, point 4 barely exceed the cutoff, so the influence of it, from a practically point of view, is fairly small.

**Fig. 8 Plot of  $DFBETA$**



Adopting a diagnostic view, point 57 is clearly influential since it has effect on  $H_{ii}$ ,  $RStudent$ ,  $Cook'sD$ ,  $\hat{\beta}$ ,  $\hat{Y}_i$  and  $COVRATIO_i$ , point 56 have effect on  $\hat{\beta}$ ,  $\hat{Y}_i$  and  $COVRATIO_i$ , and point 4, 6 have moderate effect on  $\hat{\beta}$  and  $\hat{Y}_i$ . Hence, we conclude that point 57 are influential.

After removing the influential point 57, the model specified in Section 3 is refitted and analyzed as follows.

The ANOVA analysis result given in Table 7 shows the  $p$ -value for  $F$ -test is smaller than 0.0001, indicating rejection of the  $H_0$  that all  $\beta_{ijs} = 0$ . The assumption (1) in Section 3 holds. A slightly decreased CV of 6.91% shows the ratio of standard deviation to mean is low, suggesting a low variability in the data. However, a slightly higher  $R^2_{Adj}$  of 64.94% means only less than 70% of the variability in the data can be explained by the model. Also, the MSE of 11100<sup>2</sup> remains extremely large.

**Table 7 ANOVA Analysis after Deleting the Outlier**

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	5	1316558677	2633117335	21.37	<.0001
Error	50	6160393749	123207875		
Corrected Total	55	19325980426			

Root MSE	11100	R-Square	0.6812
Dependent Mean	160541	Adj R-Sq	0.6494
Coeff Var	6.91405		

Read from the parameter estimates Table 8, the  $p$ -values obtained for  $x_1$ ,  $x_2$  and  $x_4$  in  $t$ -test are greater than 0.05, indicating insignificant of these three variables at 0.05 level, which will cause the model to be less informative due to great loss of predictors. The absolute value of  $\hat{\beta}_2$  is extremely large while that of  $\hat{\beta}_4$  and  $\hat{\beta}_5$  are too small in magnitude compared with other predictor coefficients, suggesting the model does not fit well.

All VIFs are smaller than 3, meaning only moderate correlations are observed among the predictors. Therefore, the assumption (3) in Section 3 holds. Multicollinearity is not a concern for the data.

**Table 8 Parameter Estimates after Deleting the Outlier**

Parameter Estimates									
Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr >  t	Standardized Estimate	Variance Inflation	95% Confidence Limits
Intercept	Intercept	1	173851	27808	6.25	< .0001	0	0	117998 229705
x1	x1	1	378.71431	209.29784	1.81	0.0764	0.20507	2.01480	-41.67278 799.10140
x2	x2	1	-4013.61088	2134.85271	-1.88	0.0659	-0.18495	1.51795	-8301.58885 274.36688
x3	x3	1	1036.70608	193.56682	5.36	< .0001	0.48108	1.31872	647.91569 1425.49647
x4	x4	1	-38.62336	40.71193	-0.95	0.3473	-0.09833	1.68523	-120.39568 43.14896
x5	x5	1	99.10320	27.52533	3.60	0.0007	0.33981	1.39720	43.81695 154.38945

Shapiro-Wilk test result and QQ-plot of R-student residual vs predicted value in Table 9 indicates we fail to reject  $H_0$  in normality test and we conclude the normality assumption on the error term hold.

**Table 9 Shapiro-Wilk Test on Normality**

Tests for Normality				
Test	Statistic	p Value		
Shapiro-Wilk	W	0.963682	Pr < W	0.0898
Kolmogorov-Smirnov	D	0.099041	Pr > D	> 0.1500
Cramer-von Mises	W-Sq	0.129012	Pr > W-Sq	0.0453
Anderson-Darling	A-Sq	0.760501	Pr > A-Sq	0.0460

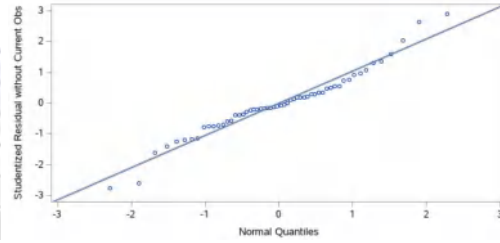
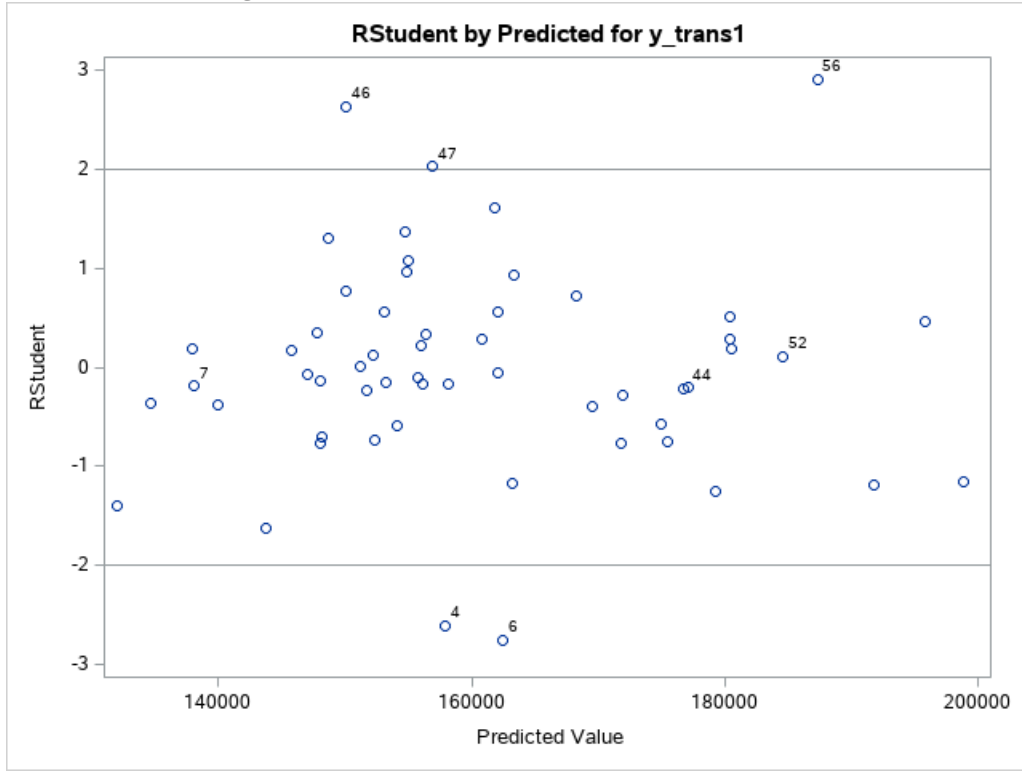


Fig. 9 shows the of R-student residual vs predicted value. The variance on error term has an decent even pattern along size the zero line, suggesting the constant variance assumption on the error term holds. Therefore, the assumption (2) in Section 3 holds.

Fig. 9 R-student Residual vs Predicted Value



Overall, the assumptions (1), (2) and (3) in Section 3 all hold with the refitted model after deleting the outlier. And there is no sign of strong multicollinearity among the predictors. However, the decent  $R^2_{Adj}$  of 64.94% and the poor MSE of 11100<sup>2</sup> indicate lack of adequacy of the refitted model.

Box-Cox analysis is performed again, and the result in Fig. 10 suggests  $y^{1.5}$  is a proper transformation of the response after deleting the outlier. However, the  $R^2_{Adj}$  and MSE do not improve much as shown in Table 10.

Fig. 10 Box-Cox Analysis after Deleting the Outlier

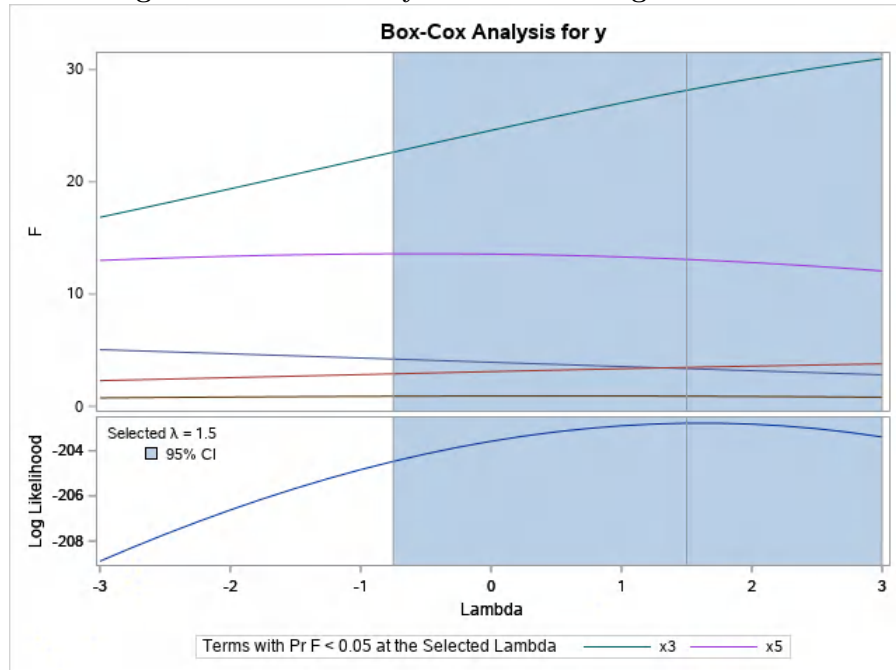


Table 10 ANOVA Analysis after Second Transformation on Response

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	5	314016453	62803291	21.27	<.0001
Error	50	147645256	2952905		
Corrected Total	55	461661709			

Root MSE	1718.40191	R-Square	0.6802
Dependent Mean	28945	Adj R-Sq	0.6482
Coeff Var	5.93675		

Hence, we conclude MLR with an OLS model does not provide a desirable fit for the data, especially for the complete data. To make the model as informative as possible, we want to keep all the observations and consider WLS as a method to accommodate the outlier via downweighting it to a less impactful point, or almost to zero.

To our delight, read from Tabel 11 and Table 12, the ANOVA analysis shows the  $p$ -value for  $F$ -test is smaller than 0.0001, indicating rejection of the  $H_0$  that all  $\beta_{ijs} = 0$ . A smaller CV of 0.17%, a higher  $R^2_{Adj}$  of 71.62%, and a profoundly decreased MSE of 1.5448<sup>2</sup> are obtained. All VIFs are smaller than 3, meaning only moderate correlations are observed among the predictors. Therefore, multicollinearity is not a concern for the data. We conclude the WLS model provides a better fit to the data than the OLS model.

Table 11 ANOVA Analysis of the WLS Model

Weight: wt2					
Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	5	349.11200	69.82240	29.26	<.0001
Error	51	121.70630	2.38640		
Corrected Total	56	470.81830			

Root MSE	1.54480	R-Square	0.7415
Dependent Mean	934.69189	Adj R-Sq	0.7162
Coeff Var	0.16527		

Table 12 Parameter Estimates of the WLS Model

Parameter Estimates									
Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr >  t	Standardized Estimate	Variance Inflation	95% Confidence Limits
Intercept	Intercept	1	823.10440	50.03136	16.45	<.0001	0	0	722.66226 923.54654
x1	x1	1	2.41085	0.48239	5.00	<.0001	0.61271	2.96529	1.44242 3.37928
x2	x2	1	-1.85437	4.29649	-0.43	0.6671	-0.04260	1.93109	-10.45986 6.75112
x3	x3	1	2.15583	0.77624	2.78	0.0076	0.28730	2.11127	0.59747 3.71419
x4	x4	1	-0.11054	0.06666	-1.61	0.1137	-0.19447	2.88061	-0.24842 0.02735
x5	x5	1	0.42484	0.06398	6.64	<.0001	0.65790	1.93689	0.29639 0.55328

The weights obtained for the WLS model are listed in the below Table 13.

Table 13 Weights of the WLS Model

Output Statistics												
Obs	Weight	Dependent Variable	Predicted value	Std Error Mean Predict	95% CL Mean		95% CL Predict		Residual	Std Error Residual	Student Residual	Cook's D
1	9.80E-04	791	836.0270	15.2656	805.3795	866.6744	732.6233	909.2307	-45.2970	46.654	-0.971	0.017
2	9.61E-04	824	804.5426	16.6461	663.1700	905.9157	703.7501	905.3367	60.7029	47.896	1.269	0.017
3	-0.04E-04	840	836.6960	14.9086	806.7951	866.6264	725.5140	882.0775	-1.0142	52.393	-0.019	0.000
4	1.59E-03	846	826.2275	11.0367	808.0242	850.4300	647.3407	1009	84.1775	37.151	2.267	0.026
5	2.54E-02	865	877.2562	10.1023	866.9619	887.5185	812.4088	942.0616	-19.8152	20.889	-0.977	0.009
6	2.10E-03	881	871.6067	11.3160	848.0886	894.2648	600.1605	1043	110.0967	31.785	3.467	0.254
7	1.67E-02	882	883.9691	11.6077	840.2741	887.6641	830.2330	887.7101	2.1291	1.864	1.089	7.154
8	9.75E-04	871	852.3087	6.1221	818.2359	906.8456	791.5117	960.1677	21.1967	18.790	0.935	0.001
9	1.22E-03	872	857.7674	19.2249	627.2022	898.3526	763.9337	991.5711	15.9829	41.513	0.307	0.003
10	1.05E-03	874	857.0523	7.0266	830.0000	910.2345	802.8050	905.4945	23.0721	42.557	0.549	0.001
11	1.82E-02	887	874.8844	3.3632	834.1174	935.6517	867.4655	968.3036	-77.4146	35.776	-1.048	0.004
12	1.14E-02	884	844.1861	5.8788	807.0013	881.3708	684.2489	844.1292	20.1961	14.026	1.440	0.022
13	5.05E-03	880	816.2322	5.7699	804.0468	827.8156	671.0993	961.3721	20.5322	26.882	0.980	0.012
14	2.86E-03	869	804.6722	6.5988	681.0826	918.1617	645.3052	964.4381	5.8122	28.189	0.199	0.000
15	1.44E-03	900	824.6196	7.3945	809.7746	939.4640	641.4360	1006	36.0896	40.083	0.625	0.003
16	4.01E-03	904	826.0807	4.8520	816.4516	936.5250	676.4175	976.3094	22.2337	21.659	0.931	0.006
17	1.44E-03	912	851.0456	4.9380	871.0897	910.9974	606.9576	975.1206	20.6544	19.467	0.920	0.002
18	1.16E-03	912	837.6616	13.2788	813.3046	862.6684	644.4567	1031	36.1396	13.212	0.605	0.005
19	1.95E-03	912	810.2902	6.2099	883.7954	926.7620	830.0146	960.5450	7.9190	16.236	0.480	0.000
20	1.06E-03	912	910.0204	6.8096	660.5496	965.6910	615.9897	1000	0.1296	46.659	0.000	0.000
21	7.66E-04	920	910.6826	10.5306	889.5114	934.7905	790.8000	1.020	6.0779	56.185	0.110	0.000
22	3.32E-03	922	931.1340	4.9179	921.2609	941.0070	806.0780	986.1080	9.2540	31.050	0.290	0.000
23	1.46E-03	923	935.6676	6.6816	921.0747	948.3008	682.7688	1017	11.8576	19.635	0.597	0.000
24	7.16E-05	926	937.9126	3.2322	925.2002	950.6250	913.5490	962.4766	6.7030	0.237	1.051	0.106
25	2.67E-04	905	924.6813	0.2999	924.0810	925.2817	918.8327	905.5205	0.0107	0.00782	2.447	1504.321
26	7.29E-04	908	921.8420	6.9541	900.0657	939.6190	805.6160	1089	14.3872	58.492	0.255	0.000
27	1.94E-03	906	917.3790	6.3269	898.6572	935.5004	842.1805	961.3973	20.9212	14.853	0.800	0.004
28	4.26E-04	941	907.6752	0.0702	886.3817	899.3580	750.1163	1029	33.3040	23.045	0.845	0.001
29	5.16E-03	846	946.9820	10.1118	905.2924	956.6832	902.1697	969.6959	0.3620	16.643	0.020	0.000
30	3.40E-02	881	911.8074	4.8304	902.5416	921.1302	856.3890	968.3400	36.6030	27.389	1.420	0.046
31	4.26E-04	964	951.3972	10.3811	800.5383	972.2682	801.6666	1101	2.1828	73.009	0.000	0.000
32	8.66E-04	964	935.2000	7.2810	800.0126	949.6471	626.2181	1042	12.2100	52.300	0.367	0.000
33	3.59E-04	969	923.8881	9.7017	804.3612	943.5250	816.2779	1001	24.9819	51.801	0.675	0.000
34	1.43E-03	969	960.6889	7.4810	946.7295	975.6453	677.2449	1044	-1.4699	40.205	-0.036	0.000
35	5.62E-04	961	959.7259	12.3012	805.0303	1014	556.9887	1123	28.7159	64.005	0.449	0.001
36	3.02E-03	962	936.0590	10.8584	904.8923	947.2670	846.7943	986.3956	36.2596	26.095	1.391	0.013
37	9.71E-04	989	994.1097	16.7379	880.5068	1020	689.0337	1099	36.3057	48.670	0.594	0.007
38	7.05E-04	989	942.3647	8.6660	923.0679	960.6715	826.2947	1059	26.7552	56.361	0.459	0.001
39	4.45E-03	970	967.8021	6.8261	974.7004	1001	939.4829	1036	17.3021	22.226	0.780	0.009
40	2.65E-04	971	955.6047	15.7740	824.1371	947.4724	762.6592	1149	16.0153	63.624	0.164	0.000
41	6.69E-04	972	905.2067	6.3802	891.6024	925.1508	766.8435	1029	64.1232	58.273	1.101	0.004
42	9.12E-04	986	943.4690	6.0641	927.2291	956.6905	639.4920	1047	42.4902	50.510	0.841	0.003
43	5.46E-03	969	983.2189	7.8331	887.4913	949.9425	939.4736	1029	6.0521	19.836	0.313	0.003
44	2.34E-03	981	1013	16.9763	891.0766	1005	945.2482	1001	21.6216	29.891	0.721	0.011
45	4.29E-03	995	971.6679	5.2158	981.4173	982.3584	923.3699	1020	22.7521	22.014	0.989	0.000
46	2.75E-03	990	910.0849	5.8949	898.6819	921.5073	845.6749	970.5140	87.7951	28.999	3.027	0.059
47	1.05E-03	1002	922.6799	6.7257	909.7767	935.7013	826.6152	1016	79.6210	47.201	1.667	0.010
48	1.97E-03	1004	953.3512	6.6483	909.4019	967.3005	671.8382	1083	56.1400	20.869	1.307	0.009
49	1.76E-04	1008	1010	26.3307	984.9618	1067	776.1094	1254	8.4456	112.9	0.084	0.000
50	3.76E-03	1015	1037	6.1949	891.0463	1024	854.4112	1001	7.5419	23.747	0.319	0.000
51	3.35E-04	1010	999.1126	16.6715	966.6431	1000	676.4466	1163	28.4474	62.712	0.345	0.000
52	1.16E-02	1025	1029	10.4390	1000	1060	992.3236	1064	5.8410	9.650	0.598	0.031
53	3.08E-04	1020	909.0000	18.6070	852.4946	1027	800.2747	1170	36.6620	88.008	0.615	0.001
54	2.11E-04	1000	1042	35.9990	989.0205	1094	621.9826	1263	11.6037	103.2	0.113	0.000
55	1.94E-02	1071	1045	13.6696	1019	1070	964.2921	1125	26.4024	35.951	0.735	0.011
56	1.76E-04	1113	1062	23.7037	853.9546	1049	764.6821	1239	115.5181	112.2	0.985	0.007
57	5.70E-05	782	986.4381	41.1131	866.7776	1071	589.3054	1406	208.0981	280.5	1.029	0.007



## 6. Selection of Variable Subset

Stepwise selection and all possible regressions are used for variable selection of the WLS model at 0.05 level, the outputs are shown in Table 14 and Table 15, respectively. All of the three statistics,  $R_p^2$ ,  $C_p$  (close to  $p + 1 = 6$ ), and  $MS_{Res}$  optimize when  $x_1$ ,  $x_3$ ,  $x_4$  and  $x_5$  are included in the model, indicating we should remove  $x_2$  in the final model.

Table 14 Backward Selection

Weight: wt2									
Summary of Stepwise Selection									
Step	Variable Entered	Variable Removed	Label	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	x5		x5	1	0.2545	0.2545	94.0797	18.78	<.0001
2	x1		x1	2	0.3988	0.6533	17.4088	62.10	<.0001
3	x3		x3	3	0.0662	0.7195	6.3446	12.51	0.0009
4	x4		x4	4	0.0211	0.7406	4.1872	4.22	0.0449

Table 15 All Possible Regressions

C(p) Selection Method

Number of Observations Read	57
Number of Observations Used	57

Weight: wt2

Number in Model	C(p)	R-Square	Adjusted R-Square	MSE	Variables in Model
4	4.1872	0.7406	0.7206	2.34909	x1 x3 x4 x5
5	6.0000	0.7415	0.7162	2.38640	x1 x2 x3 x4 x5
3	6.3446	0.7195	0.7036	2.49197	x1 x3 x5
4	6.5901	0.7284	0.7075	2.45937	x1 x2 x3 x5
4	11.7133	0.7024	0.6795	2.69449	x1 x2 x4 x5
3	11.9304	0.6912	0.6737	2.74347	x1 x2 x5
3	12.5085	0.6882	0.6706	2.76950	x1 x4 x5
2	17.4088	0.6533	0.6404	3.02316	x1 x5
4	28.9774	0.6149	0.5853	3.48677	x2 x3 x4 x5
3	29.2262	0.6035	0.5811	3.52224	x3 x4 x5

## 7. Conclusion

After using the OLS and WLS models, WLS is chosen as the best estimation method. And the final prediction equation is

$$\hat{y} = 803.64449 + 2.33451x_1 + 2.28908x_3 - 0.12425x_4 + 0.42937x_5$$

We conclude *Mortality* is positively associated with mean annual precipitation ( $x_1$ ), percentage of the population that is nonwhite ( $x_3$ ), relative pollution potential of sulfur dioxide ( $x_5$ ), and is negatively related to relative pollution potential of oxides of nitrogen ( $x_4$ ). However, *Mortality* is not associated with Median number of school years completed for persons of age 25 years or older ( $x_2$ ). An advantage of the WLS model is relatively even magnitudes of the predictor coefficients. A concern is the negative association between  $y$  and  $x_4$ , but a reasonable explanation maybe the existed large composition of nitrogen oxides in the air we breathe. Further investigation should be focused on whether the outlier data is reliable, because it is influential to modeling.

## 8. Appendix

```
/* 1. import database */  
  
filename reffile '/home/u49400069/Regression Analysis/Final_Project/Pollution_Mortality.xls';  
  
proc import datafile=reffile  
    dbms=xls  
    out=work.pollution;  
    getnames=yes;  
run;  
  
proc print data=work.pollution;run;  
proc contents data=work.pollution; run;  
  
/* 2. investigation of the data */  
  
/* Boxplots */  
  
data long;  
    set pollution;  
    array tm(*) x1 - x5;  
  
    do i=1 to dim(tm);  
        hour=compress(vname(tm(i)), 'kd');  
        Value=tm(i);  
        output;  
    end;  
    keep hour value;  
run;  
  
proc sgplot data=long;
```

```
vbox value / group=hour;  
run;
```

```
proc sgplot data=have;  
    vbox x1 x2 x3 x4 x5;  
run;
```

```
* correlation table & scatter plots ;  
proc corr data=pollution plots=matrix(histogram nvar=all);  
run;
```

```
* loess plots ;  
proc sgplot data=pollution;  
    reg x=x1 y=y / clm cli;  
run;
```

```
proc loess data=pollution;  
    model y=x1/smooth=0.1 0.2 0.4 0.6 0.8 1.0;  
run;
```

```
proc sgplot data=pollution;  
    reg x=x2 y=y / clm cli;  
run;
```

```
proc loess data=pollution;  
    model y=x2/smooth=0.1 0.2 0.4 0.6 0.8 1.0;  
run;
```

```
proc sgplot data=pollution;
```

```

        reg x=x3 y=y / clm cli;
run;

proc loess data=pollution;
        model y=x3/smooth=0.1 0.2 0.4 0.6 0.8 1.0;
run;

proc sgplot data=pollution;
        reg x=x4 y=y / clm cli;
run;

proc loess data=pollution;
        model y=x4/smooth=0.1 0.2 0.4 0.6 0.8 1.0;
run;

proc sgplot data=pollution;
        reg x=x5 y=y / clm cli;
run;

proc loess data=pollution;
        model y=x5/smooth=0.1 0.2 0.4 0.6 0.8 1.0;
run;

/* 3. specification of the model */
* box-cox analysis and transformation on y ;
proc transreg data=pollution;
        model boxcox(y)=identity(x1 x2 x3 x4 x5);
run;

```

```
data trans1;
    set pollution;
    y_trans1=y**2;
run;
```

```
/* 4. estimation of the appropriate model */
```

```
proc reg data=trans1 plots(label)=(cooksd RSTUDENTBYPREDICTED dfbetas dffits diagnostics
    observedbypredicted);
    model y_trans1=x1 x2 x3 x4 x5/
    alpha=.05 r p clb cli clm stb vif partial influence collinoint collin;
    output out=one r=resid student=sresid p=pred rstudent=rs r=y_res;
run;

proc univariate data=one plot normal;
    var rs; * qqplot r-student residual vs predicted ;
run;
```

```
/* 5. assessment of the chosen prediction equation */
```

```
* delete an outlier ;
```

```
data pollution_new;
    set trans1 end=last;
    if not last then
        output;
run;
```

```
* refit the model ;
```

```
proc reg data=pollution_new plots(label)=(cooksd RSTUDENTBYPREDICTED dfbetas dffits diagnostics
```



```

        observedbypredicted);

model y_trans1=x1 x2 x3 x4 x5/alpha=.05 r p clb cli clm stb vif partial
        influence collinoint collin;

output out=one r=resid student=sresid p=pred rstudent=rs r=y_res;

run;

proc univariate normal plot data=one;

        var rs; * qqplot r-student vs predicted ;

run;

* box-cox analysis and transformation on y ;

proc transreg data=pollution_new;

        model boxcox(y)=identity(x1 x2 x3 x4 x5);

run;

data trans2;

        set pollution_new;

        y_trans2=y**1.5;

run;

* refit the model ;

proc reg data=trans2 plots(label)=(cooksd dfbetas dffits RSTUDENTBYPREDICTED diagnostics
observedbypredicted);

        model y_trans2=x1 x2 x3 x4 x5/alpha=.05 r p clb cli clm stb vif partial

        influence collinoint collin;

        output out=one r=resid student=sresid p=pred rstudent=rs r=y_res;

run;

proc univariate normal plot data=one;

```

```
var rs; * qqplot r-student vs predicted ;  
run;
```

```
/* weighted ls est */
```

```
* step0: initial step ;
```

```
proc reg data=pollution;  
    model y=x1 x2 x3 x4 x5 / clb;  
    output out=result1 p=yhat r=resid;  
run;
```

```
* step1: estimate standard dev. function ;
```

```
data result1;  
    set result1;  
    absres=abs(resid);  
run;
```

```
proc reg data=result1;  
    model absres=x1 x2 x3 x4 x5;  
    output out=step1 p=preds1 r=ress;  
run;
```

```
data step1;  
    set step1;  
    wt1=1/(preds1)**2;  
run;
```

```
proc reg data=step1;  
    model y=x1 x2 x3 x4 x5 /p clb;  
    weight wt1;
```

```
output out=result2 p=wyhat r=wres;  
run;
```

\* step2: estimate the standard dev. function ;

```
data result2;  
    set result2;  
    abswres=abs(wres);  
run;
```

```
proc reg data=result2;  
    model abswres=x1 x2 x3 x4 x5;  
    output out=step2 p=preds2;  
run;
```

```
data step2;  
    set step2;  
    wt2=1/(preds2)**2;  
run;
```

```
proc reg data=step2 plots(label)=(RSTUDENTBYPREDICTED);  
    model y=x1 x2 x3 x4 x5 /p r clb cli clm stb vif partial collino int collin;  
    weight wt2;  
    output out=one r=resid student=sresid p=pred rstudent=rs r=y_res;  
run;
```

/\* 6. variable selection \*/

\* forward selection ;

```
proc reg data=step2;
```

```
model y=x1 x2 x3 x4 x5 / selection=forward slentry=0.25;  
weight wt2;  
run;
```

\* backward selection ;

```
proc reg data=step2;  
    model y=x1 x2 x3 x4 x5 / selection=backward slstay=0.1;  
    weight wt2;  
run;
```

\* stepwise selection ;

```
proc reg data=step2;  
    model y=x1 x2 x3 x4 x5 / selection=stepwise slentry=0.15 slstay=0.15;  
    weight wt2;  
run;
```

\* all possible selection ;

```
proc reg data=step2;  
    model y=x1 x2 x3 x4 x5 / selection=cp rsquare mse adjrsq p clm cli best=10;  
    weight wt2;  
run;
```