Project Key Part 1 (90 pts.)
due April 18

A reminder – Please do not hand in any unlabeled or unedited SAS output. Include in your write-up only those results that are necessary to present a complete solution (what you want the grader to grade). In particular, questions must be answered in order (including graphs), and all graphs must be fully labeled. Don't forget to put all necessary information (see course policies) on the first page including names for each group member. Include the SAS input for all questions at the very end of your project; this could be important even though it won't be graded.

This project is concerning the complete analysis using multiple regression of the Real Estate Sales Data set described in Data Set C.7 (APPENC07.DAT). In brief, a city tax assessor is interested in what factors are affecting residential home sale prices. In this project, no interaction terms will be used (until 8.e).

Note: there are five qualitative variables in this data set. Three of them are correctly coded: Air conditional, Pool and Highway. Quality has 3 choices so that would be two additional variables, I am calling them qual1 and qual2. Style has possible values of 1 – 11 with no 8 so that is 9 additional variables which I am calling style1 to style10 with no style8. My results reflect this choice of the variables.

Because of the length of the project, I will provide the code in a separate file.

1. **(4 pts.) The project begins by determining if a multiple regression is appropriate. Remember, if there are qualitative variables with more than two options, you will need to make dummy variables before you run the regression. To perform this step, test the regression relation using all of the explanatory variables. State the hypotheses, test statistic and degrees of freedom, the p-value, the decision and the conclusion in words.**

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	20	8.27019E12	4.135095E11	126.27	<.0001
Error	501	1.640722E12	3274893675		
Corrected Total	521	9.910912E12			

H_0: $\beta_i = 0$ for i = 1, …, 20 H_a: at least one $\beta_i \neq 0$ for i = 1, …, 20

F = 126.27, df(numerator) = 20, df(denominator) = 501, p-value < 0.0001, decision: reject H_0

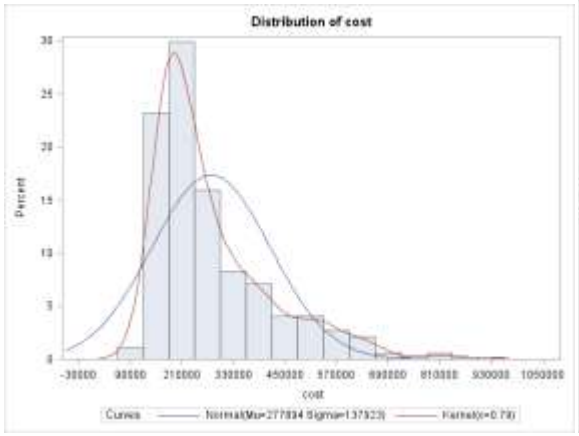
This data strongly supports that at least one of the predictor variables is important in the regression.

2. **(7 pts.) The next step is to check the assumptions and look at the original variables. Use all of the "usual plots" (no partial residual plots). It is acceptable to just show the histograms for the explanatory variables. This step does not require any quantitative analysis. (You may use the automated plots generated in SAS.) Be sure to list all of the assumptions and whether they are appropriate or not using the graphs displayed in this step.**

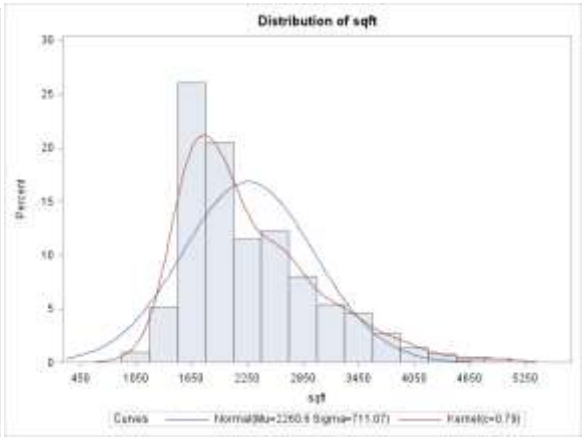
   Each of the assumptions will be discussed for the individual plots except for Independent Observations which has to be assumed from the experimental data. The results will be summarized at the end.

   Original Variables:

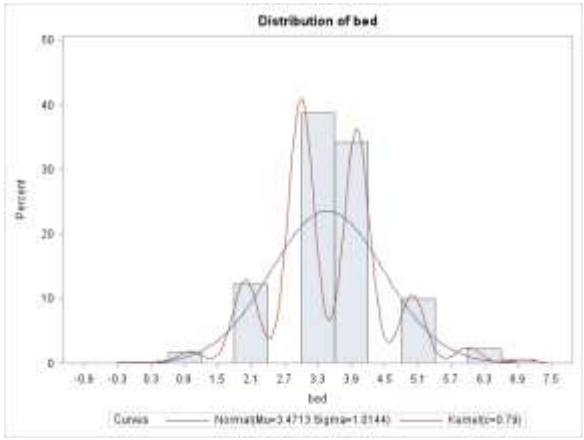
   Note: I am only going to comment on the non-qualitative variables except if they are so lopsided, that the 'other' value is considered an outlier.



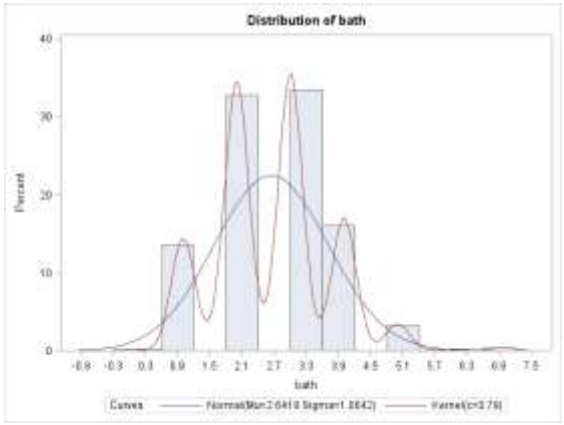
right skewed



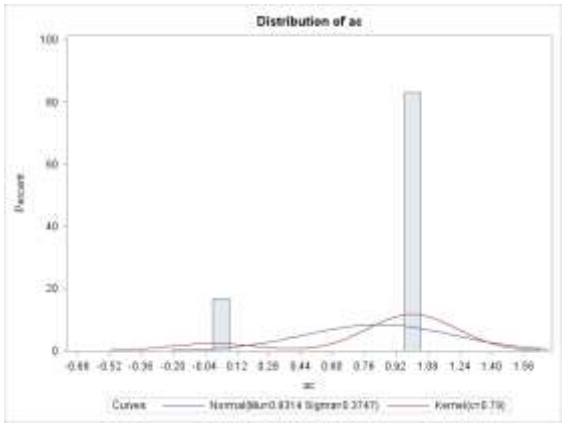
right skewed



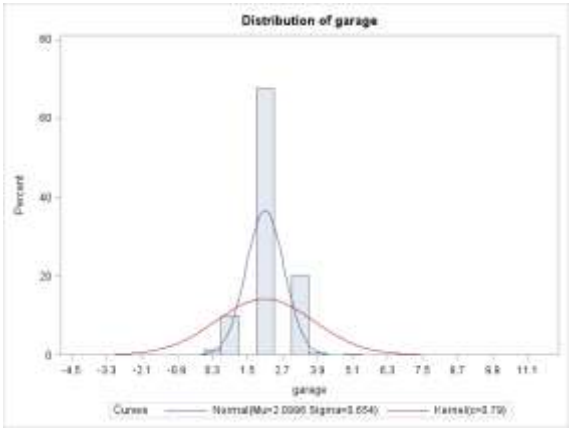
looks approximately normal



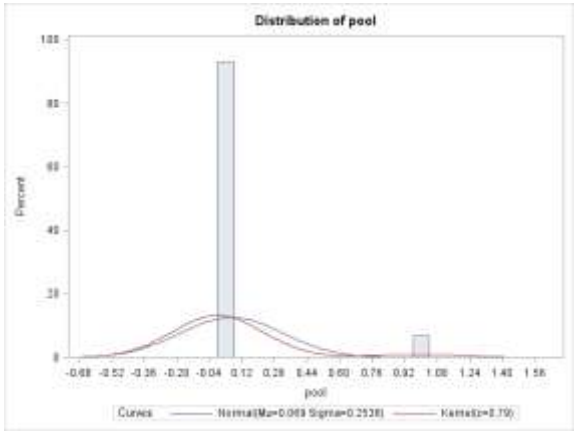
looks approximately normal



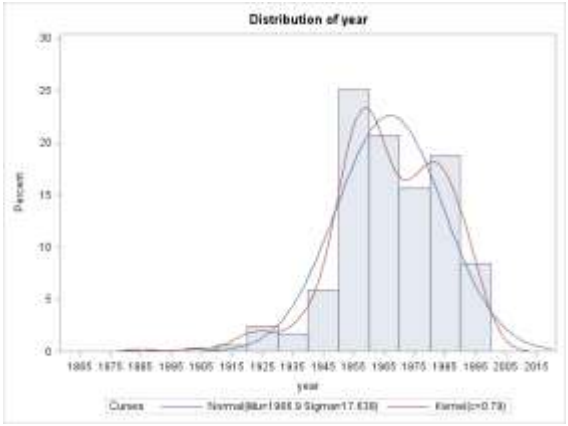
qualitative



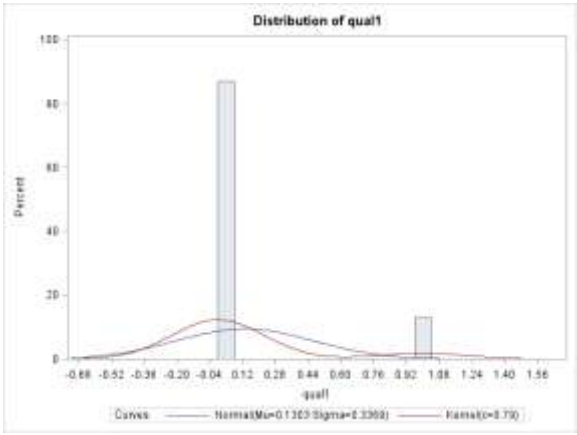
looks approximately normal



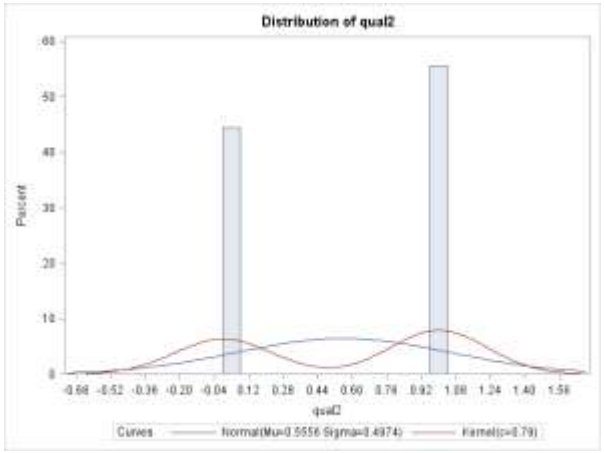
qualitative – maybe outliers



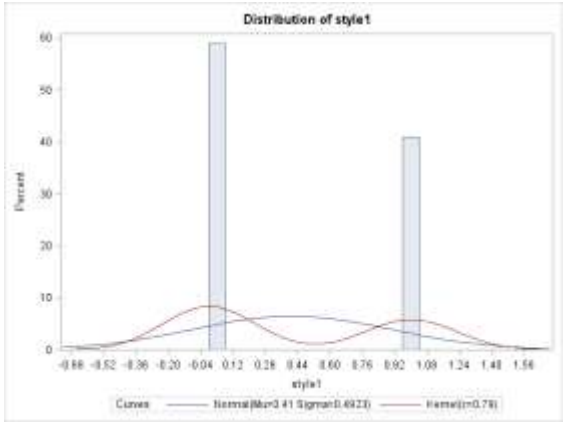
left skewed



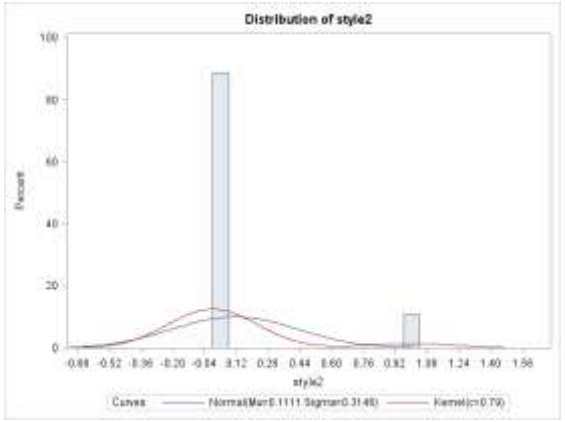
qualitative



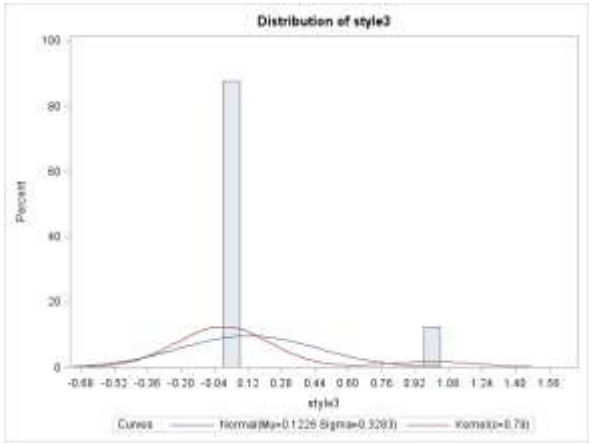
qualitative



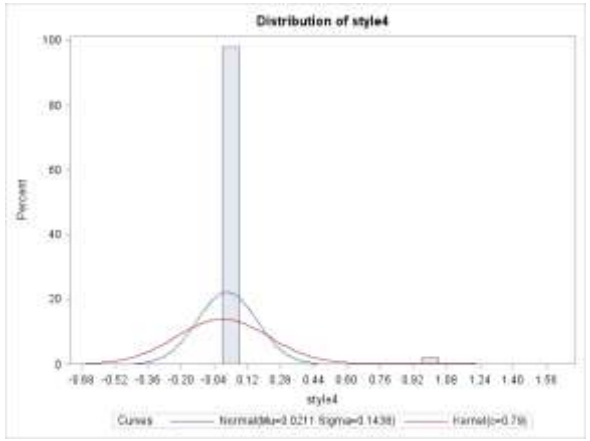
qualitative



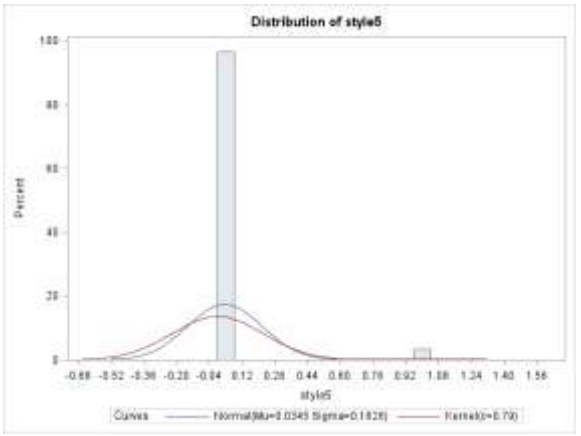
qualitative



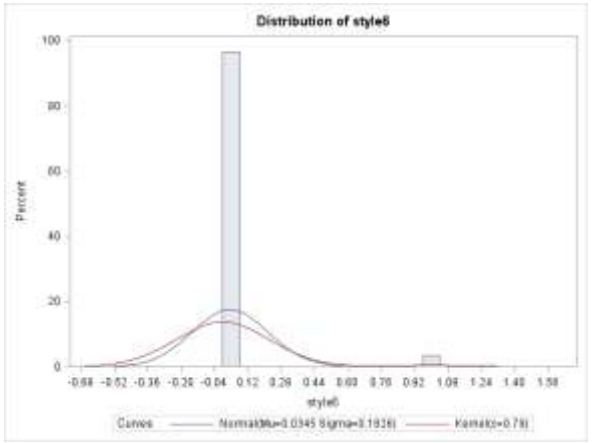
qualitative



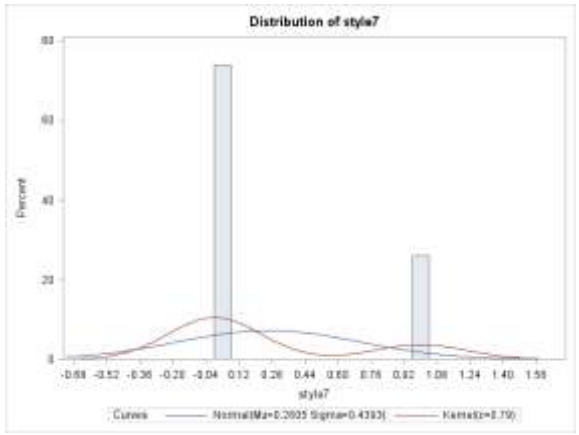
qualitative – maybe outliers



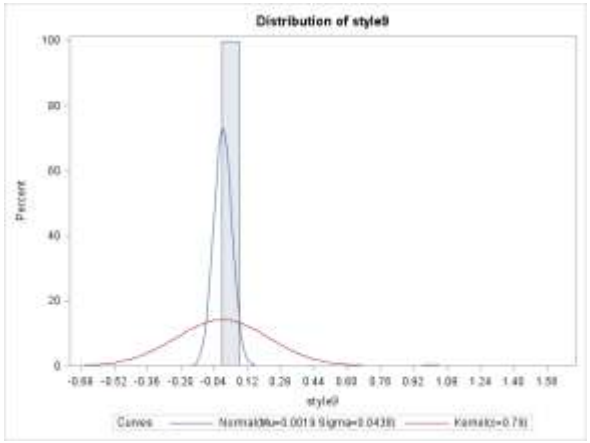
qualitative – maybe outliers



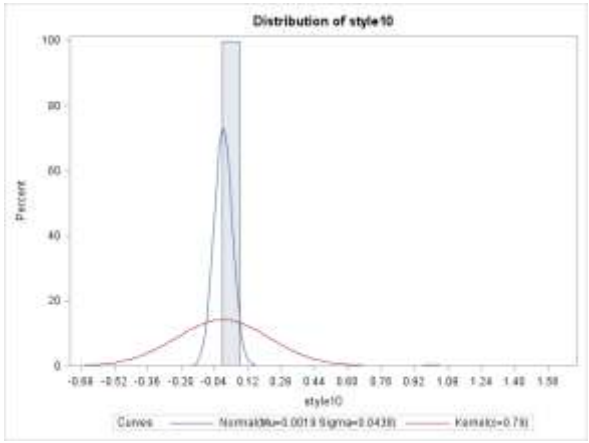
qualitative – maybe outliers

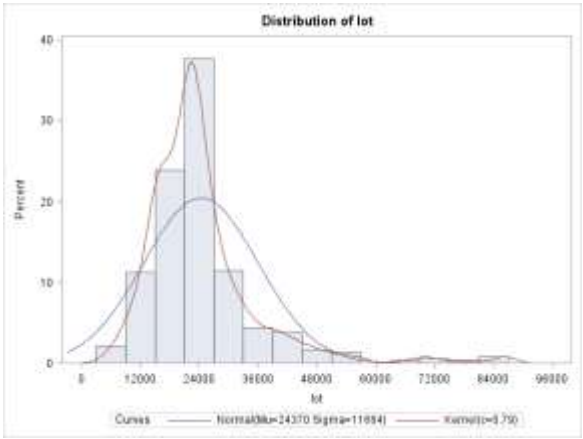


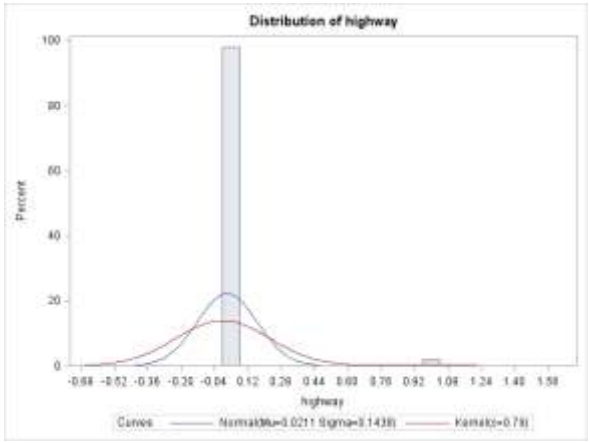
qualitative



qualitative – maybe outliers





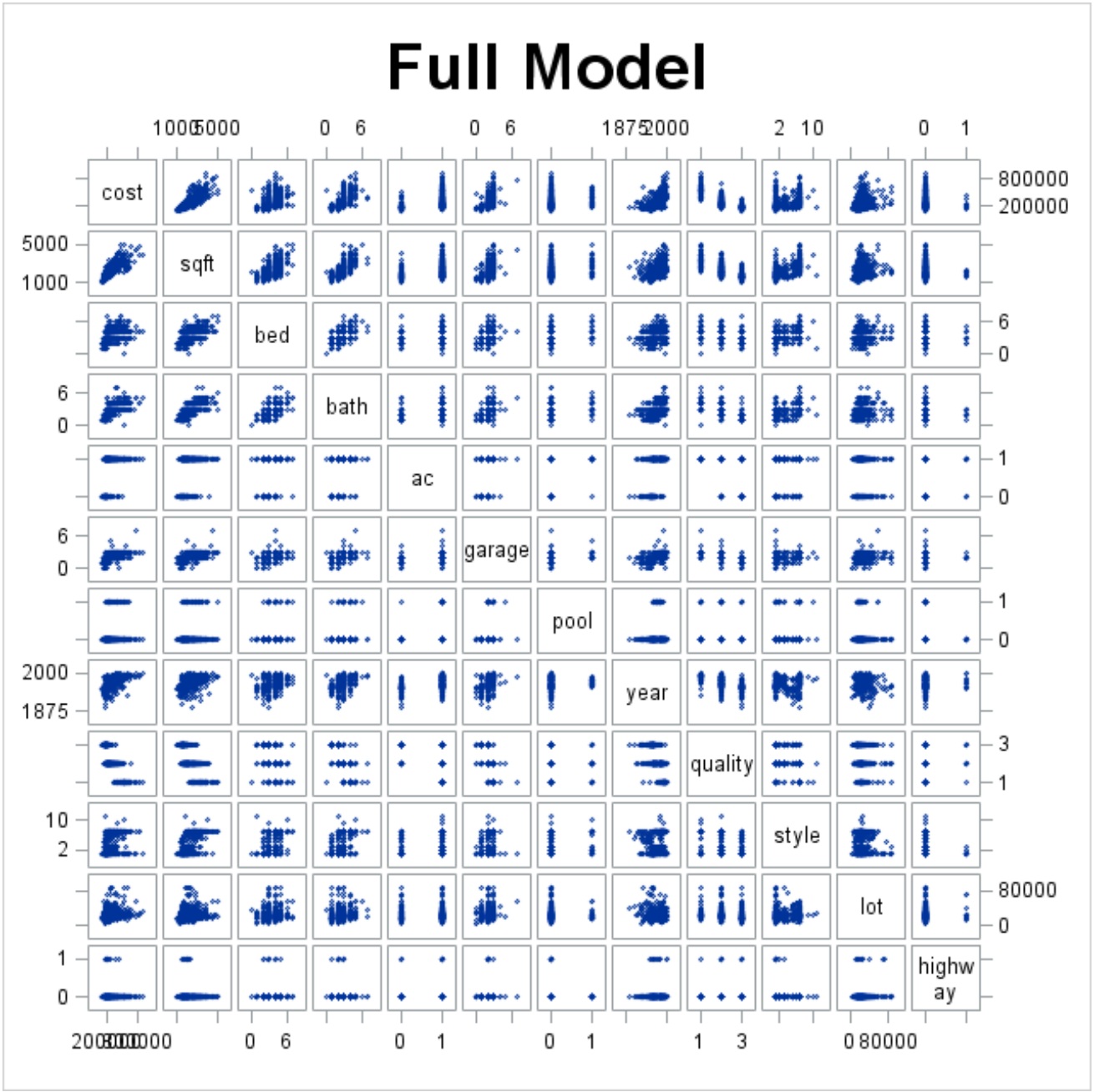


qualitative – maybe outliers right skewed qualitative – maybe outliers

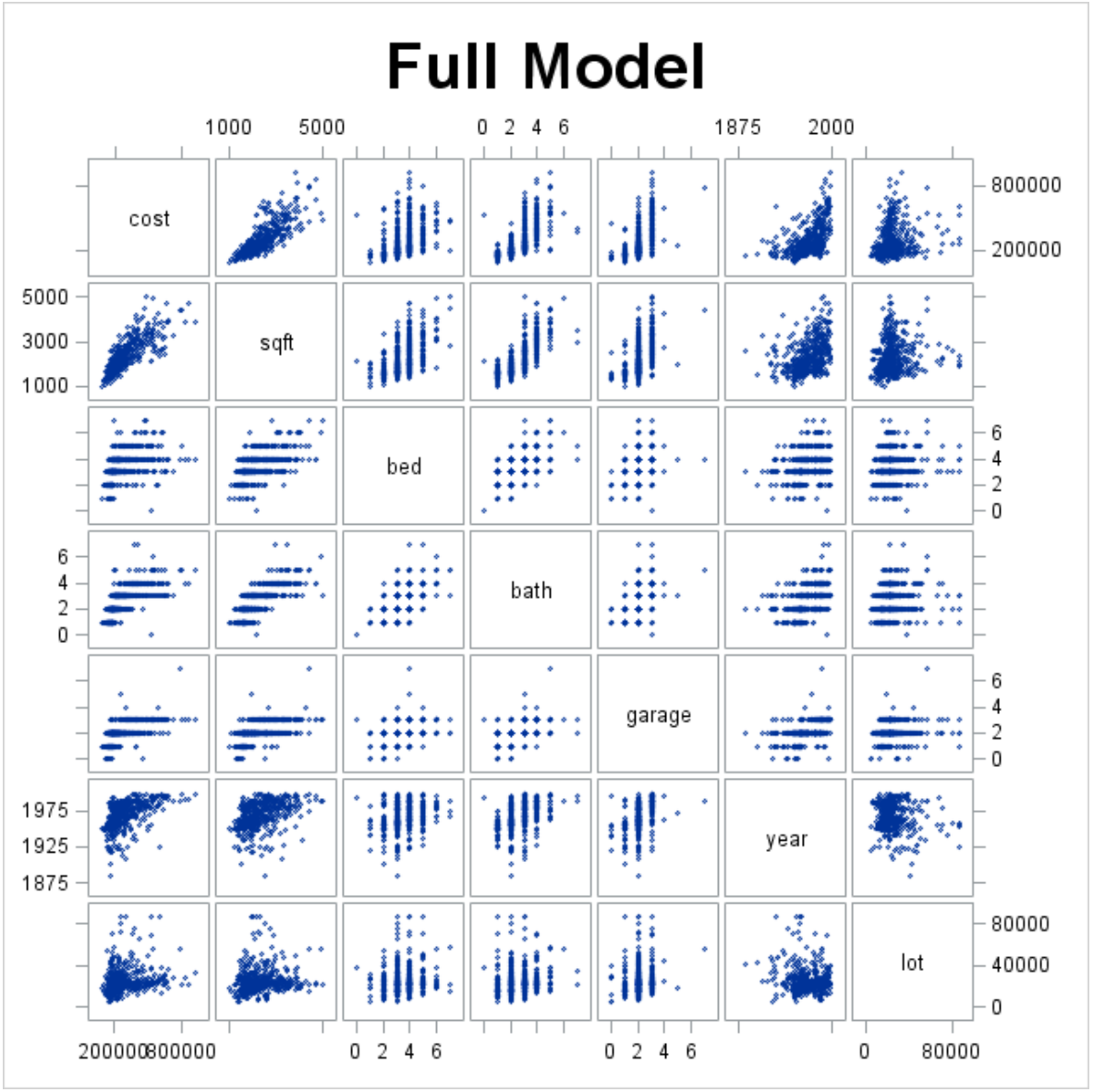
Conclusion: possible outliers in X_i's.

Scatterplot:

To make this easier to look at, I have am using the original variables for style and quality. It is hard to see linearity with a qualitative variable so the only thing that can be looked for is outliers

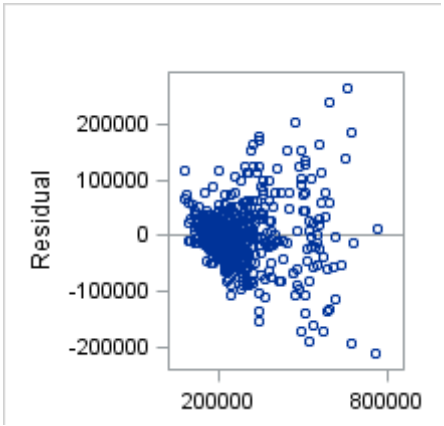

Full Model
cost
sqft
bed
bath
ac
garage
pool
year
quality
style
lot
highway

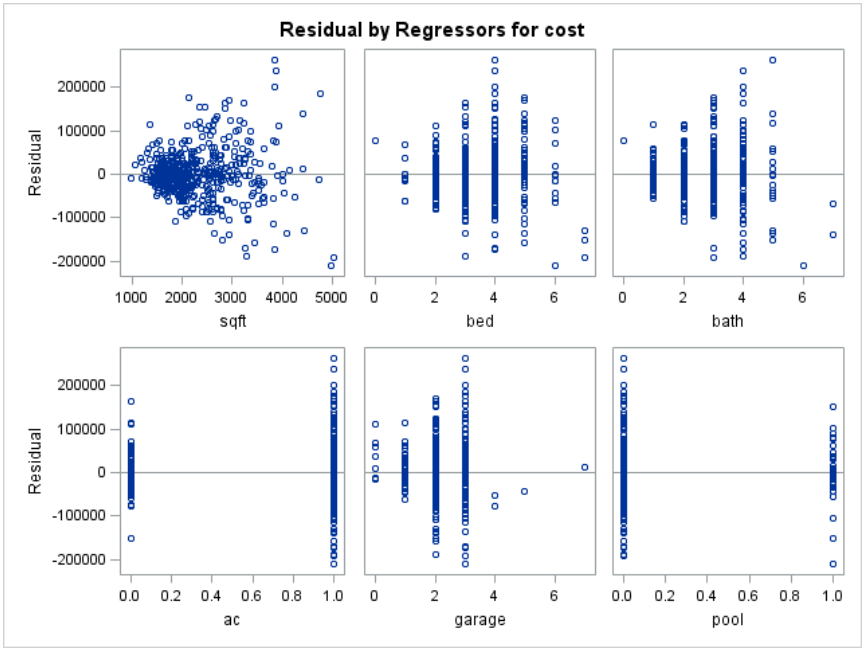
problems with constant variance with: sqft, bed, bath, year.
problems with outliers with: garage, style and maybe bed and bath.
To look at linearity, I will regenerate the scatterplot with only quantitative variables:

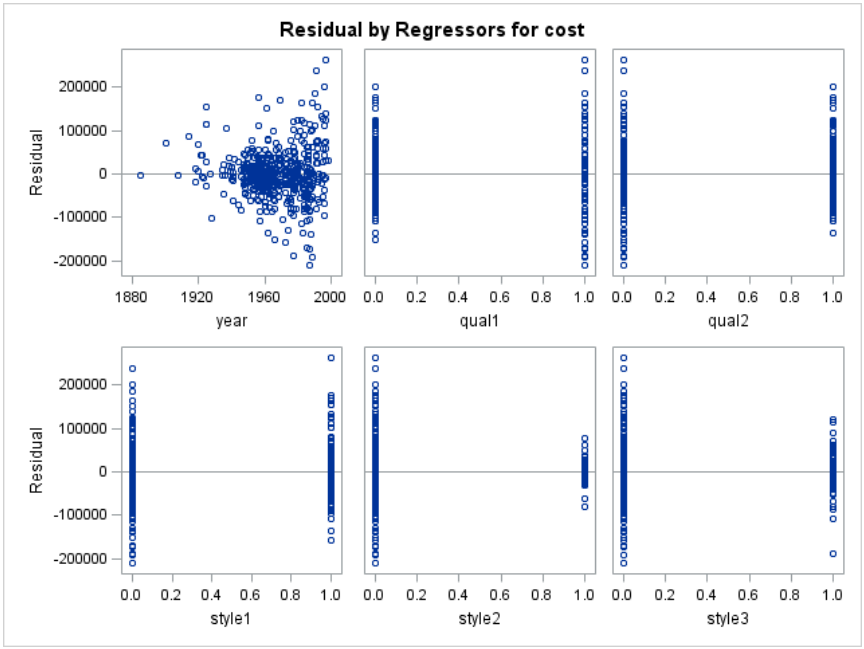


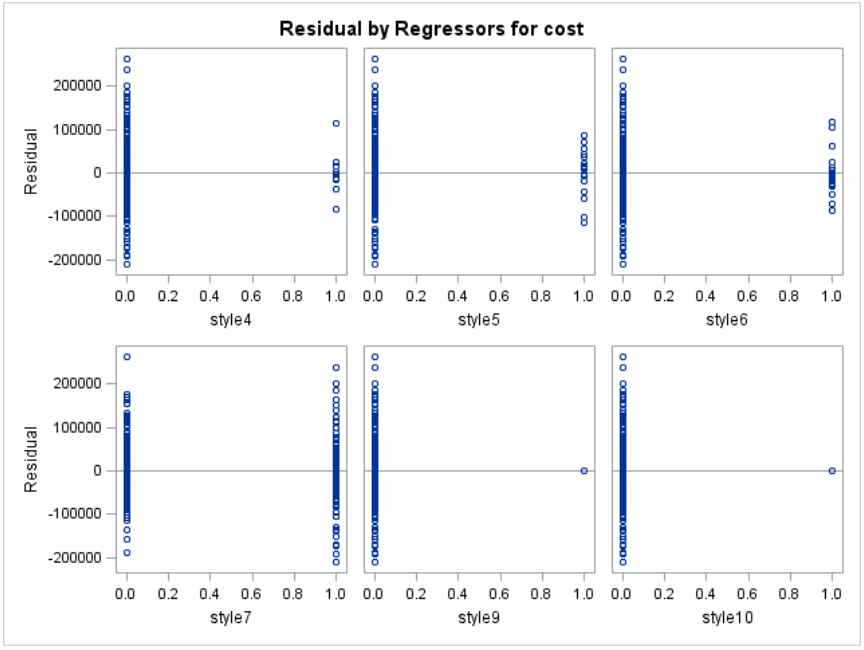
Possible problems with linearity: bed, bath, year, lot.

Residual Plots:






Residual by Regressors for cost
Residual
year
qual1
qual2
style1
style2
style3


Residual by Regressors for cost
Residual
style4
style5
style6
style7
style9
style10

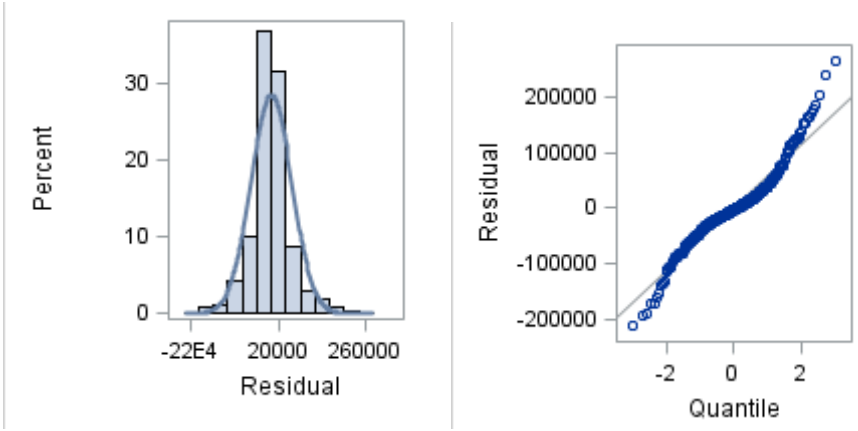
Comments:

It looks like there is a problem with constant variance in the residual vs. predicted value, sqft, bed, bath, garage, year, some of the style quantitative variables, highway and maybe ac, lot.

I cannot tell if there is a problem with linearity on these plots.

It looks like there is a problem with outliers in the following plots: bed, bath, garage, year. There might be a problem in: predicted value, sq ft, lot. Since there is only one style9 and style10, by definition these are outliers.

Normality plots



From these plots, it looks like there might be a problem with normality of the residuals due to long tails. Note that this might be caused by the outlier problem mentioned above.

Conclusion:

linearity: problem
constant variance: a problem
outliers: a problem
normality: a problem
independence: assumed

3. (4 pts.) The next step is to look at multicollinearity.

(a) Do the results from the regression indicate that there might be a problem with multicollinearity? Explain your answer. You might need to include additional output from what you displayed in part 1.

This is the output from part 1)

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	**1**	-2886487	406877	-7.09	<.0001
sqft	**1**	99.92248	7.61615	13.12	<.0001
bed	**1**	-4483.24551	3254.24167	-1.38	0.1689
bath	**1**	10115	4217.24827	2.40	0.0168
ac	**1**	2164.50354	7938.13709	0.27	0.7852
garage	**1**	9113.19604	4953.47083	1.84	0.0664
pool	**1**	12527	10337	1.21	0.2261
year	**1**	1406.35732	205.61821	6.84	<.0001
qual1	**1**	143036	14187	10.08	<.0001
qual2	**1**	10751	8078.28525	1.33	0.1838
style1	**1**	100125	57955	1.73	0.0847
style2	**1**	72886	58313	1.25	0.2119
style3	**1**	85781	58186	1.47	0.1410
style4	**1**	115098	60575	1.90	0.0580
style5	**1**	74984	59909	1.25	0.2113
style6	**1**	94069	59832	1.57	0.1165
style7	**1**	56874	58344	0.97	0.3301
style9	**1**	11943	81606	0.15	0.8837
style10	**1**	13081	83159	0.16	0.8751
lot	**1**	1.34315	0.23433	5.73	<.0001
highway	**1**	-35839	17721	-2.02	0.0437

Since at least one of these is significant, we cannot determine if there is a problem with multicollinearity from this data.

The two possible methods of testing this are using the SS's and VIF (Tol). I will show both, though only one of the two methods is required. Note: VIF is much better than looking at the SS's

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Type I SS	Type II SS	Variance Inflation
Intercept	**1**	-2886487	406877	-7.09	<.0001	4.031153E13	1.648197E11	0
sqft	**1**	99.92248	7.61615	13.12	<.0001	6.655486E12	5.637065E11	4.66585
bed	**1**	-4483.24551	3254.24167	-1.38	0.1689	27612564716	6215594105	1.73350
bath	**1**	10115	4217.24827	2.40	0.0168	1.427102E11	18840321852	3.20420
ac	**1**	2164.50354	7938.13709	0.27	0.7852	33417146001	243487468	1.40780
garage	**1**	9113.19604	4953.47083	1.84	0.0664	2.001904E11	11084584306	1.66946
pool	**1**	12527	10337	1.21	0.2261	123140234	4809893561	1.09352
year	**1**	1406.35732	205.61821	6.84	<.0001	2.352098E11	1.532023E11	2.09247
qual1	**1**	143036	14187	10.08	<.0001	6.954309E11	3.328922E11	3.63480
qual2	**1**	10751	8078.28525	1.33	0.1838	6843097373	5800827317	2.56836
style1	**1**	100125	57955	1.73	0.0847	76594239754	9774679192	129.50097
style2	**1**	72886	58313	1.25	0.2119	52624538	5116358792	53.53091
style3	**1**	85781	58186	1.47	0.1410	15915626022	7117773942	58.05187
style4	**1**	115098	60575	1.90	0.0580	27618229488	11823303159	12.06533
style5	**1**	74984	59909	1.25	0.2113	3600622620	5130437942	19.04656
style6	**1**	94069	59832	1.57	0.1165	28385447805	8095036280	18.99777
style7	**1**	56874	58344	0.97	0.3301	5066977228	3111930262	104.53207
style9	**1**	11943	81606	0.15	0.8837	67730682	70140204	2.02964
style10	**1**	13081	83159	0.16	0.8751	38407398	81030802	2.10759
lot	**1**	1.34315	0.23433	5.73	<.0001	1.024325E11	1.075968E11	1.19255
highway	**1**	-35839	17721	-2.02	0.0437	13394228041	13394228041	1.03262

From the SS1 and SS2: The predictors which look like they are different are: bed, bath, ac, garage, pool, and the styles.

From VIF: It looks like there is a problem with style1 – style7, remember, there is only one non-zero value for style9 and style10. There might be a problem with sqft.

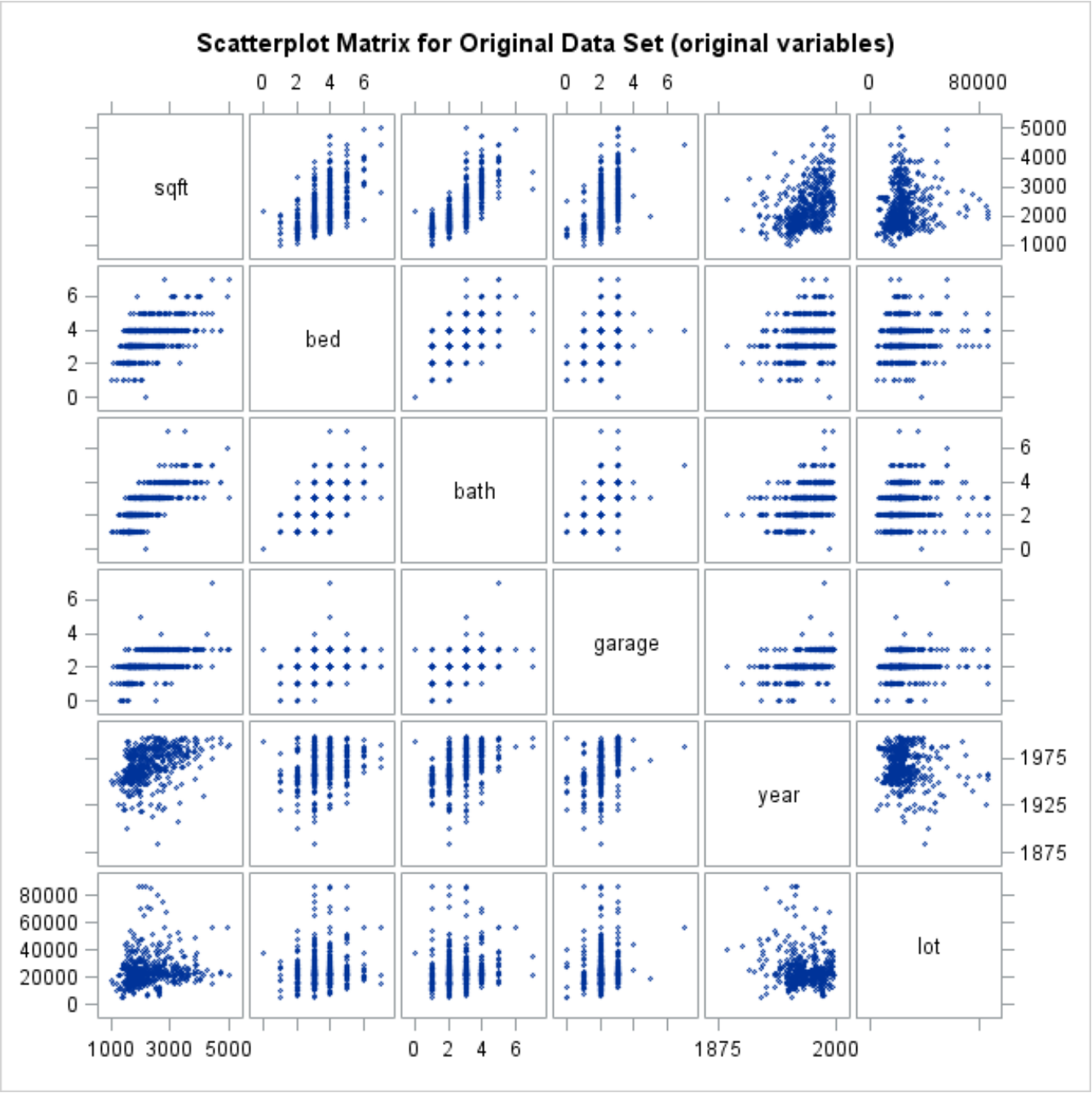
My conclusion is that the style information is contained in the other data.

(b) Roughly determine which variables (if any) might cause a problem with multicollinearity by looking at the correlations between the explanatory variables both visually (scatterplot) and quantitatively (proc corr). The scatterplot should be repeated from question 2. Which variables do you think might be causing problems? Explain your answer.

Since we are only looking at multicollinearity, I do not need to include the 'cost' in the output.

scatterplot:

Since it is very hard to see if qualitative predictors are correlated, I will only included quantitative variables below.


Scatterplot Matrix for Original Data Set (original variables)
sqft
bed
bath
garage
year
lot
0 2 4 6
0 80000
5000
4000
3000
2000
1000
6
4
2
0
1975
1925
1875
80000
60000
40000
20000
0
1000 3000 5000
0 2 4 6
1875 2000

variable	correlation
sqft	bed, bath, garage, year, lot
bed	sqft, bath, maybe garage, year
bath	sqft, bed, year
garage,	sqft, bed
year	sqft, lot
lot	sqft, year

I am including all of the predictor variables in the proc corr.

Pearson Correlation Coefficients, N = 522									
	sqft	**bed**	**bath**	**ac**	**garage**	**pool**	**year**	**qual1**	**qual2**
sqft	1.00000	0.55784	0.75527	0.26795	0.53377	0.16240	0.44120	0.59178	0.09524
bed	0.55784	1.00000	0.58345	0.23465	0.31681	0.13454	0.26869	0.21316	0.19909
bath	0.75527	0.58345	1.00000	0.32476	0.48990	0.18415	0.51284	0.44625	0.27520
ac	0.26795	0.23465	0.32476	1.00000	0.31928	0.10236	0.42559	0.17427	0.29749
garage	0.53377	0.31681	0.48990	0.31928	1.00000	0.10893	0.46176	0.45495	0.08917
pool	0.16240	0.13454	0.18415	0.10236	0.10893	1.00000	0.05983	0.09681	0.03043
year	0.44120	0.26869	0.51284	0.42559	0.46176	0.05983	1.00000	0.42005	0.22727
qual1	0.59178	0.21316	0.44625	0.17427	0.45495	0.09681	0.42005	1.00000	-0.43269
qual2	0.09524	0.19909	0.27520	0.29749	0.08917	0.03043	0.22727	-0.43269	1.00000
style1	-0.38008	-0.32998	-0.35662	-0.16567	-0.14498	-0.08852	-0.22779	-0.03330	-0.32836
style2	-0.18221	0.02206	-0.04714	0.11036	-0.02592	0.09623	0.08425	-0.11872	0.19355
style3	-0.12147	-0.03551	-0.04435	0.05912	-0.03912	-0.03259	0.09982	-0.10997	0.18154
style4	-0.06288	-0.05507	-0.13875	-0.04081	-0.10403	-0.03993	-0.17179	-0.05678	-0.05667
style5	0.03833	0.04680	-0.03507	-0.16729	-0.07702	-0.05143	-0.20334	-0.01076	-0.08452
style6	0.06627	0.06752	0.02418	-0.05512	-0.01274	-0.01000	-0.15210	-0.07314	-0.02113
style7	0.61412	0.35277	0.50791	0.16236	0.27691	0.07959	0.31259	0.23707	0.16201
style9	0.02272	-0.02037	0.01476	0.01973	-0.00668	-0.01192	0.05494	0.11320	-0.04898
style10	0.10727	0.10932	0.09718	0.01973	0.06038	0.16097	0.03007	0.11320	-0.04898
lot	0.15752	0.12654	0.14701	-0.10530	0.15222	-0.03685	-0.10045	0.08049	0.04062
highway	-0.06063	-0.02874	-0.05093	-0.04081	-0.00196	-0.03993	0.02578	-0.01716	-0.00298

Pearson Correlation Coefficients, N = 522											
	style1	**style2**	**style3**	**style4**	**style5**	**style6**	**style7**	**style9**	**style10**	**lot**	**highway**
sqft	-0.38008	-0.18221	-0.12147	-0.06288	0.03833	0.06627	0.61412	0.02272	0.10727	0.15752	-0.06063
bed	-0.32998	0.02206	-0.03551	-0.05507	0.04680	0.06752	0.35277	-0.02037	0.10932	0.12654	-0.02874
bath	-0.35662	-0.04714	-0.04435	-0.13875	-0.03507	0.02418	0.50791	0.01476	0.09718	0.14701	-0.05093
ac	-0.16567	0.11036	0.05912	-0.04081	-0.16729	-0.05512	0.16236	0.01973	0.01973	-0.10530	-0.04081
garage	-0.14498	-0.02592	-0.03912	-0.10403	-0.07702	-0.01274	0.27691	-0.00668	0.06038	0.15222	-0.00196
pool	-0.08852	0.09623	-0.03259	-0.03993	-0.05143	-0.01000	0.07959	-0.01192	0.16097	-0.03685	-0.03993
year	-0.22779	0.08425	0.09982	-0.17179	-0.20334	-0.15210	0.31259	0.05494	0.03007	-0.10045	0.02578
qual1	-0.03330	-0.11872	-0.10997	-0.05678	-0.01076	-0.07314	0.23707	0.11320	0.11320	0.08049	-0.01716
qual2	-0.32836	0.19355	0.18154	-0.05667	-0.08452	-0.02113	0.16201	-0.04898	-0.04898	0.04062	-0.00298
style1	1.00000	-0.29470	-0.31159	-0.12230	-0.15753	-0.15753	-0.49477	-0.03652	-0.03652	0.07336	0.12178
style2	-0.29470	1.00000	-0.13216	-0.05187	-0.06682	-0.06682	-0.20986	-0.01549	-0.01549	-0.07117	-0.00943
style3	-0.31159	-0.13216	1.00000	-0.05485	-0.07064	-0.07064	-0.22189	-0.01638	-0.01638	-0.08161	-0.01418
style4	-0.12230	-0.05187	-0.05485	1.00000	-0.02773	-0.02773	-0.08709	-0.00643	-0.00643	0.00480	-0.02153
style5	-0.15753	-0.06682	-0.07064	-0.02773	1.00000	-0.03571	-0.11218	-0.00828	-0.00828	0.06192	-0.02773
style6	-0.15753	-0.06682	-0.07064	-0.02773	-0.03571	1.00000	-0.11218	-0.00828	-0.00828	0.06818	-0.02773
style7	-0.49477	-0.20986	-0.22189	-0.08709	-0.11218	-0.11218	1.00000	-0.02601	-0.02601	-0.02657	-0.08709
style9	-0.03652	-0.01549	-0.01638	-0.00643	-0.00828	-0.00828	-0.02601	1.00000	-0.00192	0.00153	-0.00643
style10	-0.03652	-0.01549	-0.01638	-0.00643	-0.00828	-0.00828	-0.02601	-0.00192	1.00000	-0.00291	-0.00643
lot	0.07336	-0.07117	-0.08161	0.00480	0.06192	0.06818	-0.02657	0.00153	-0.00291	1.00000	0.07845
highway	0.12178	-0.00943	-0.01418	-0.02153	-0.02773	-0.02773	-0.08709	-0.00643	-0.00643	0.07845	1.00000

I used an arbitrary cutoff of 0.5 to determine correlation.

variable	correlation
sqft	bed, bath, garage, qual1, style7
bed	sqft, bath
bath	sqft, bed, year, style7
garage	sqft
year	bath, quality
qual1	sqft
style7	sqft, bath
not correlated: ac, pool, qual2, $style_i$ ($i \neq 7$), lot, highway	

(c) Is your analysis consistent in parts a) and b)? Explain your answer.

Some of the correlations are the same and some are different. In general, it looks like sqft, bed, bath, year and garage are correlated. The only qualitative variables that are correlated are qual1 (high quality) and style7.

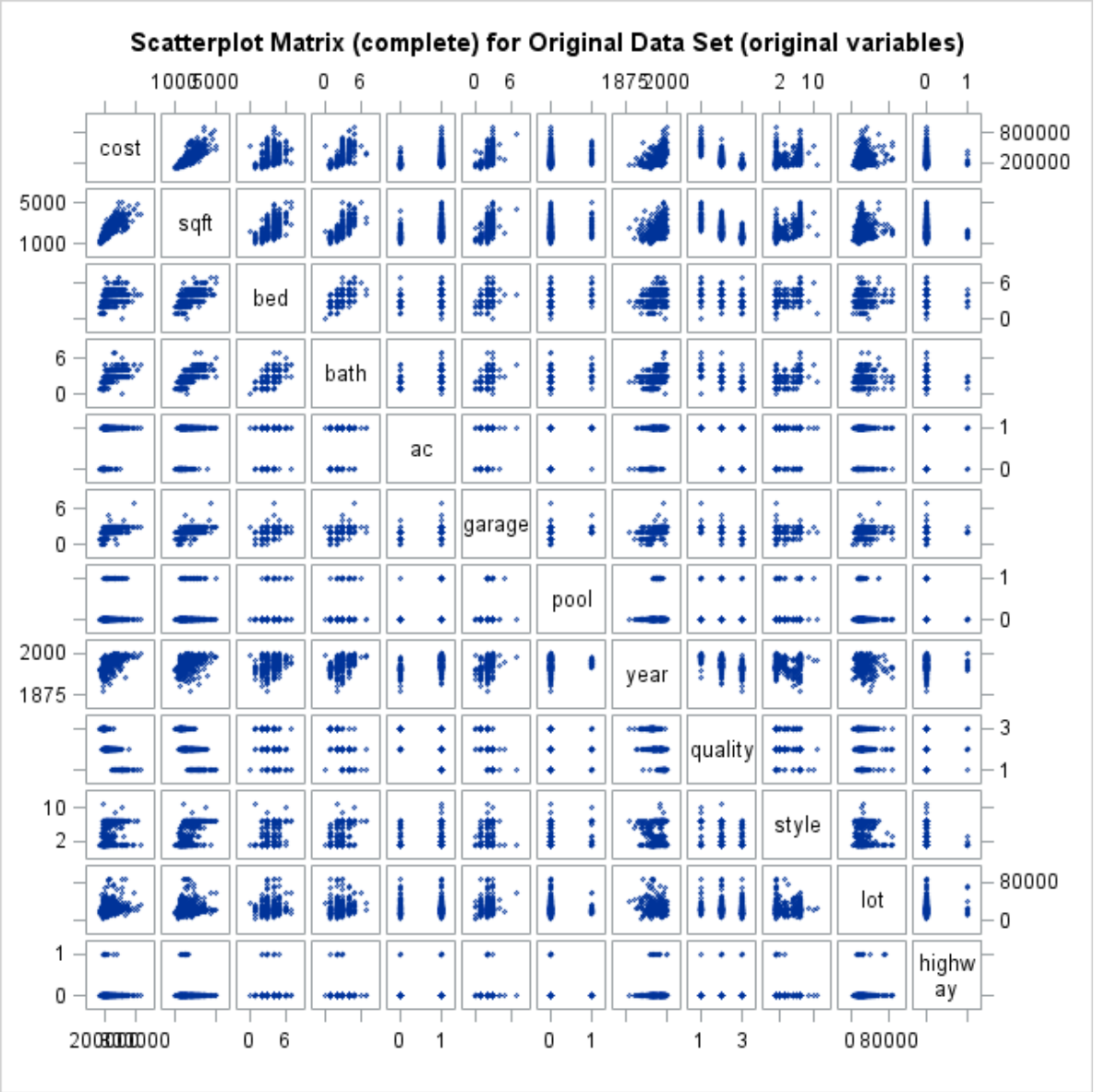
4. (11.5 pts.) Before we run model selection, it is a good idea to make some predictions on which variables might be included in the final model.

(a) From the regression analysis, which variables do you think might be important in the final model. Explain your answer.

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	**1**	-2886487	406877	-7.09	<.0001
sqft	**1**	99.92248	7.61615	13.12	<.0001
bed	**1**	-4483.24551	3254.24167	-1.38	0.1689
bath	**1**	10115	4217.24827	2.40	0.0168
ac	**1**	2164.50354	7938.13709	0.27	0.7852
garage	**1**	9113.19604	4953.47083	1.84	0.0664
pool	**1**	12527	10337	1.21	0.2261
year	**1**	1406.35732	205.61821	6.84	<.0001
qual1	**1**	143036	14187	10.08	<.0001
qual2	**1**	10751	8078.28525	1.33	0.1838
style1	**1**	100125	57955	1.73	0.0847
style2	**1**	72886	58313	1.25	0.2119
style3	**1**	85781	58186	1.47	0.1410
style4	**1**	115098	60575	1.90	0.0580
style5	**1**	74984	59909	1.25	0.2113
style6	**1**	94069	59832	1.57	0.1165
style7	**1**	56874	58344	0.97	0.3301
style9	**1**	11943	81606	0.15	0.8837
style10	**1**	13081	83159	0.16	0.8751
lot	**1**	1.34315	0.23433	5.73	<.0001
highway	**1**	-35839	17721	-2.02	0.0437

The predictor variables that have low P-values are: sqft, bath, garage (maybe), year, qual1, style1 (maybe), style4 (maybe), lot and highway.

(b) Which variables do you think might be important by looking at the correlations between the sales price and each of the explanatory variables. Your SAS output should include both a visual representation (scatterplot) and quantitative data (proc corr). Which variables do you think should be included in the final model and which variables do you think might be dropped. Explain your answer.



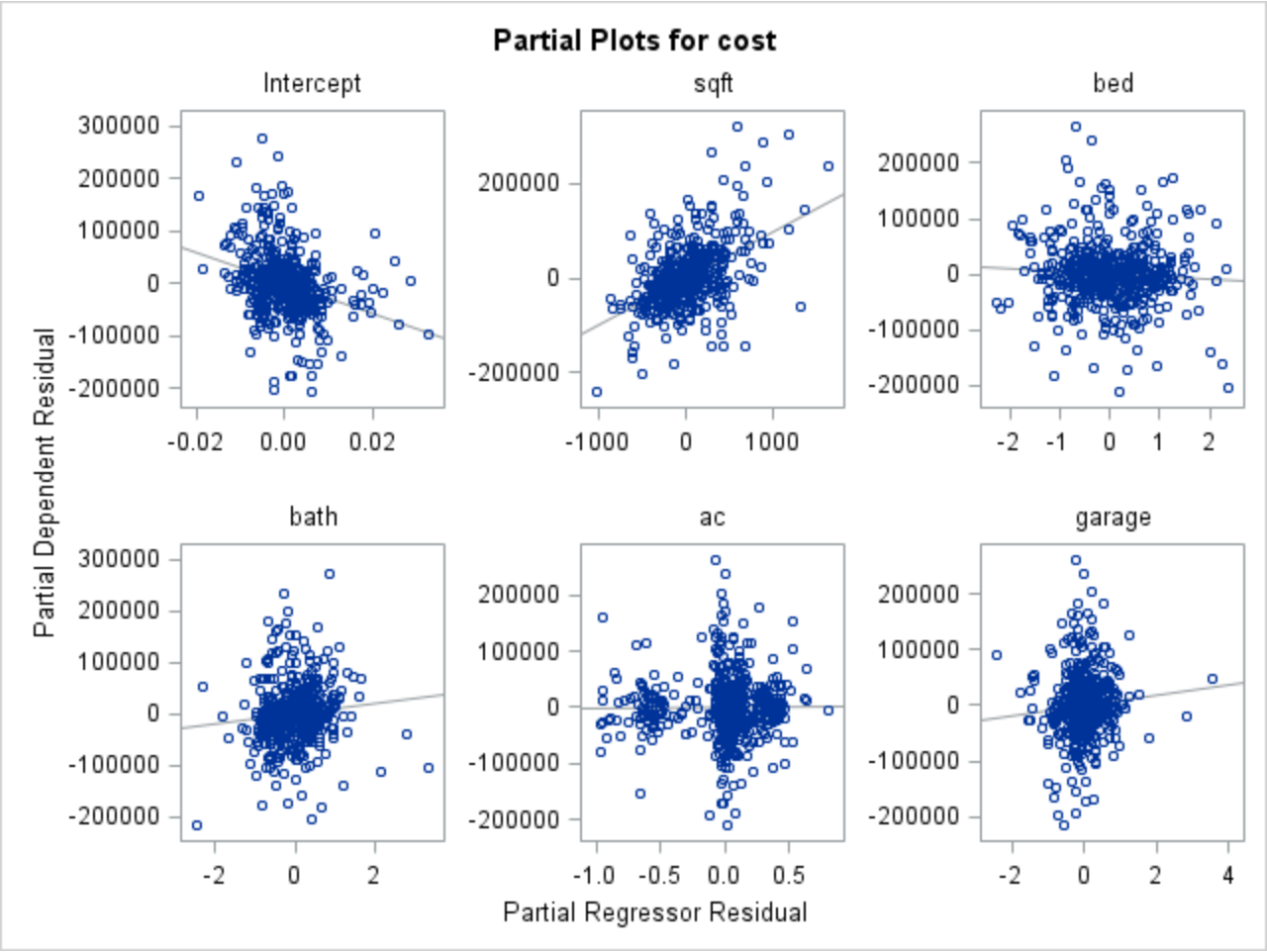
From the scatterplot: sqft, bed, bath, ac (maybe), pool (maybe), year (looks quadratic), and lot are correlated, therefore quality (can't tell), style (can't tell) and highway (looks like outliers) should be dropped. It is difficult to tell if a qualitative variable is correlated using this method.

Pearson Correlation Coefficients, N = 522									
	sqft	**bed**	**bath**	**ac**	**garage**	**pool**	**year**	**qual1**	**qual2**
cost	0.81947	0.41332	0.68369	0.28860	0.57779	0.14661	0.55552	0.74632	-0.03349

Pearson Correlation Coefficients, N = 522											
	style1	**style2**	**style3**	**style4**	**style5**	**style6**	**style7**	**style9**	**style10**	**lot**	**highway**
cost	-0.17866	-0.14849	-0.08102	-0.06423	-0.03625	0.00323	0.39308	0.03851	0.08648	0.22417	-0.05097

It looks like sqft, bed (maybe), bath, garage, year, qual1 are correlated, therefore ac, pool, qual2, styles, lot and highway should be dropped.

(c) Generate partial regression plots (it is extremely useful to have the best fit line on the plot). Which variables do you think should be included in the final model. Explain your answer. Please comment on each of the plots.



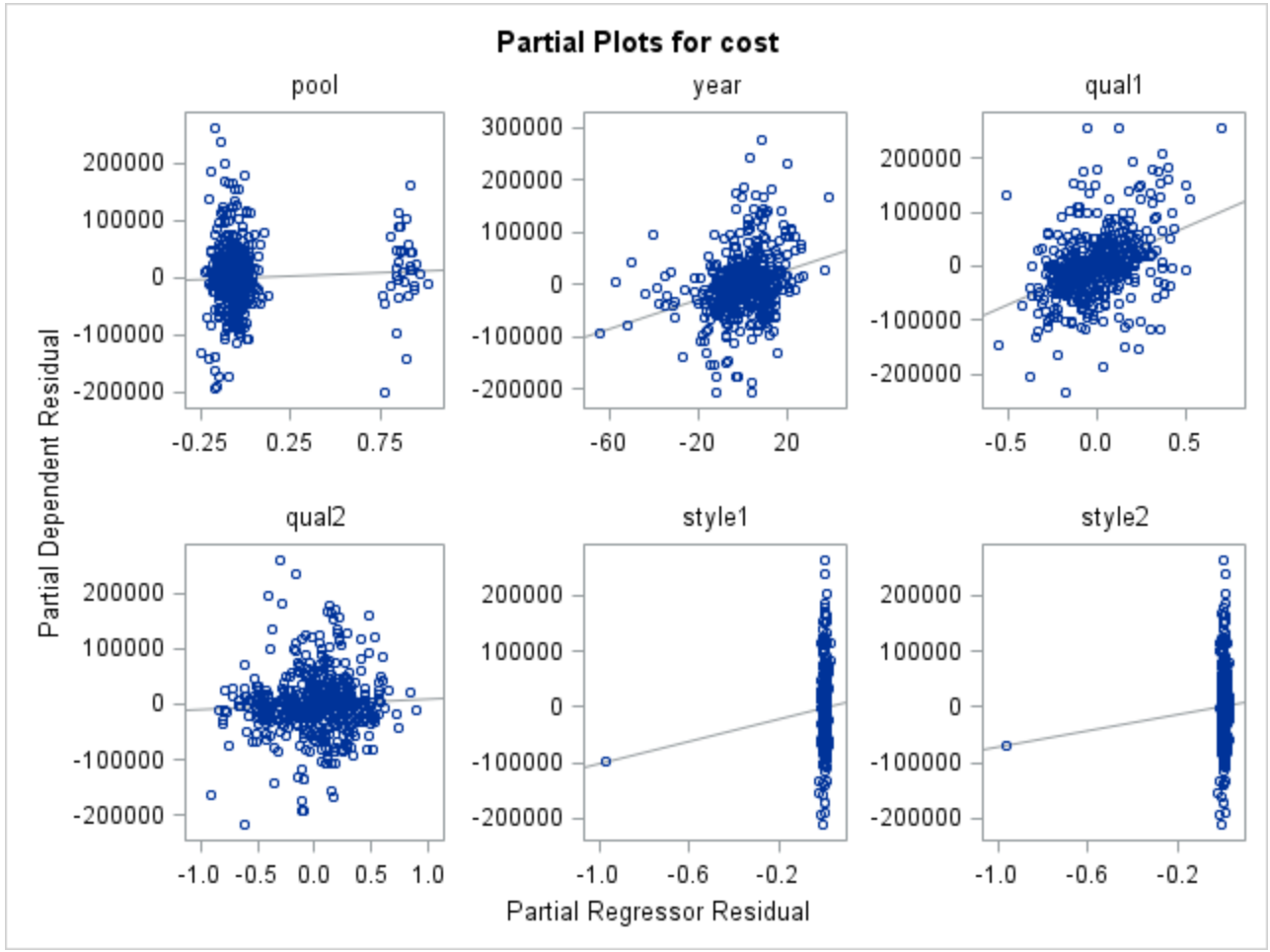
sqft: definitely significant

bed: might or might not be significant especially since the cost goes down as the number of bedrooms increases.

bath: might or might not be significant but more likely

ac: not significant

garage: might or might not be significant



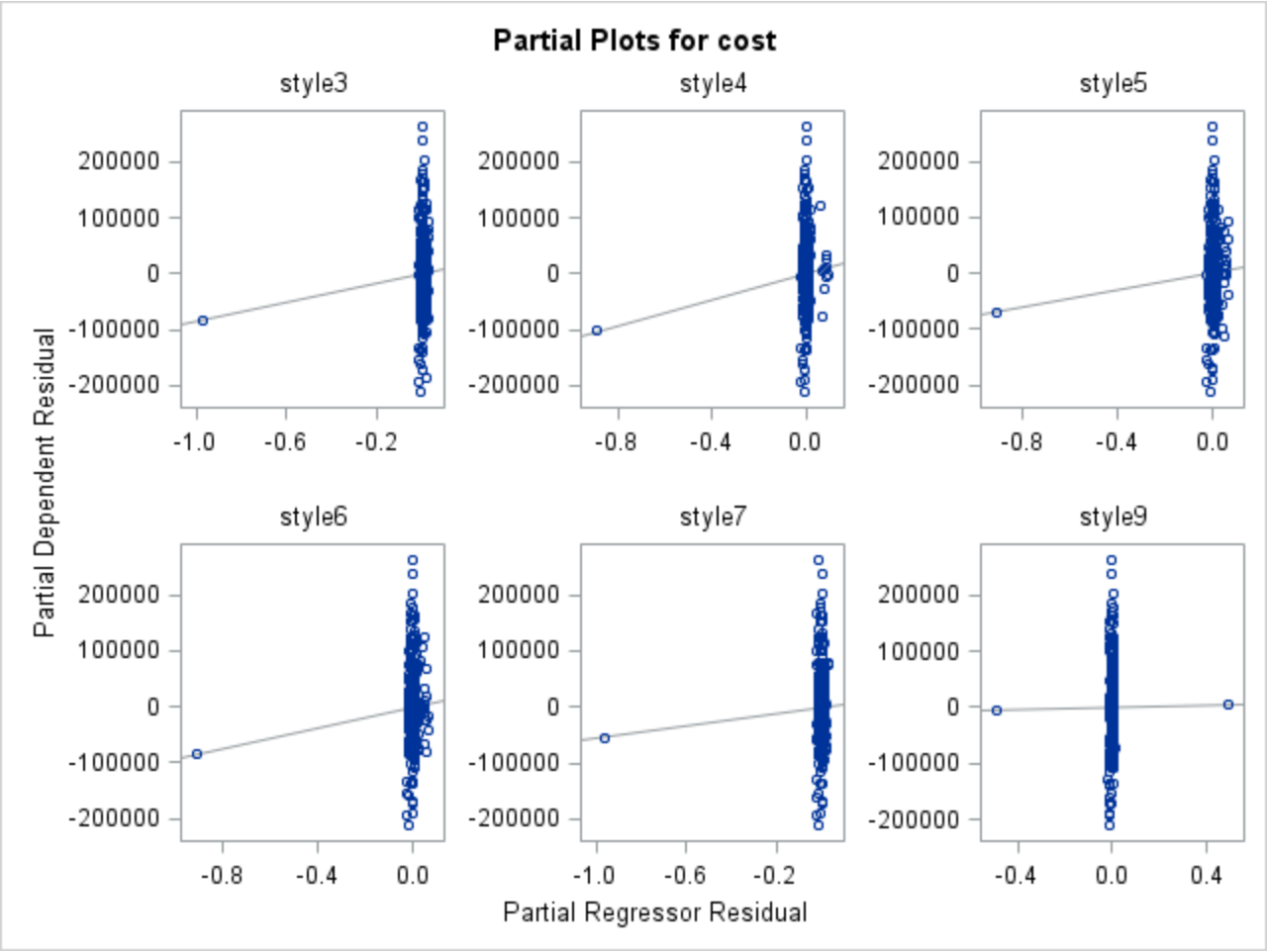
pool: probably not significant

year: significant

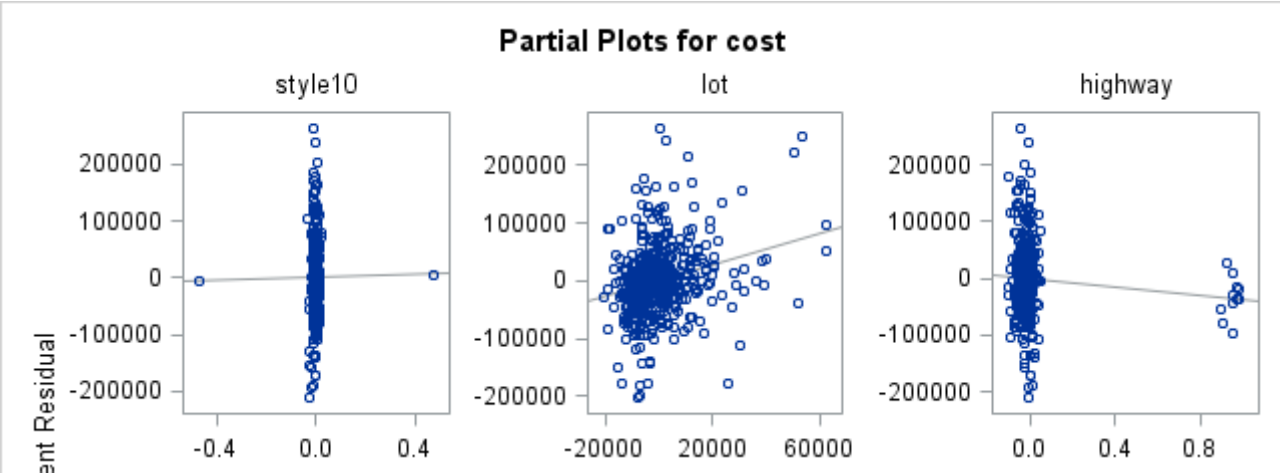
qual1 significant

qual2: not significant

style1, style2: curve due to outliers



style3, style4, style5, style6, style7, style9: curve due to outliers



style10: curve due to outliers

lot: significant or is there a problem with outliers

highway: might be significant, is the curve due to outliers?

(d) Compare the methods used in parts a), b) and c). Are the results the same? different? Which variables do you think should be included in the final model?

procedure	significance
t-tests	sqft, bed, garage, year, qual1, style1, style4, lot, highway
scatterplot	sqrt, bed, bath, ac, pool, year, lot
proc corr	sqrt, bed, bath, garage, year, qual1
partial residual plots	sqrt, bath, garage, year, qual1, lot, highway

The results are generally the same. Remember that I did not include any qualitative variables from the scatterplot. From the above information, I would expect sqft, bed or bath, garage, year, qual1, lot and highway to be in the final model. There is a possibility of both bed and bath and some of the style dummy variables.

(e) Does multicollinearity (question 3) affect your answer in part d)? Explain your answer.

Multicollinearity could be a problem. From the VIF's, it shows that the style dummy variables are correlated with the other variables so that could be a problem. From the SS, bed, bath, garage and year might also have difficulties. The pairwise correlations might be showing some problems here also since sqft should be included in the model and it is correlated with bed, bath, garage, year and lot.

5. (9.5 pts.) In this step, we will run the model selection. Remember, the best model has the least number of explanatory variables that can adequately predict the response variable.

(a) Determine the three best regression models using the Cp criterion. Summarize your results (include the explanatory variables but not their values, and values of R^2, adjusted R^2 and Cp). Explain your answer.

Note: I am including at least one model from each number of predictor variables and all models that are included elsewhere in the discussion.

Number in Model	R-Square	Adjusted R-Square	C(p)	C(p)-p	Variables in Model
1	**0.6715**	0.6709	476.0554	474.0554	sqft
2	**0.7767**	0.7758	159.8867	156.8867	sqft qual1
3	**0.7987**	0.7976	95.1274	91.1274	sqft year qual1
4	**0.8163**	0.8149	43.8837	38.8837	sqft year qual1 lot
5	**0.8219**	0.8201	29.1254	23.1254	sqft year qual1 style7 lot
6	**0.8240**	0.8220	24.5500	17.55	sqft bath year qual1 style7 lot
7	**0.8265**	0.8242	18.9857	10.9857	sqft bath year qual1 style1 style7 lot
8	**0.8279**	0.8253	16.7104	7.7104	sqft bath year qual1 style1 style7 lot highway
9	**0.8293**	0.8263	14.4585	4.4585	sqft bath garage year qual1 style1 style7 lot highway
9	**0.8291**	0.8261	15.1777	5.1777	sqft bath garage year qual1 style1 style4 style7 lot
9	**0.8290**	0.8260	15.3771	5.3771	sqft bath year qual1 style1 style4 style7 lot highway
10	**0.8305**	0.8272	12.9165	1.9165	sqft bath garage year qual1 style1 style4 style7 lot highway
10	**0.8300**	0.8267	14.4116	3.4116	sqft bed bath garage year qual1 style1 style7 lot highway
10	**0.8299**	0.8266	14.6932	3.6932	sqft bath garage year qual1 qual2 style1 style7 lot highway
11	**0.8312**	0.8275	12.9451	0.9451	sqft bed bath garage year qual1 style1 style4 style7 lot highway
11	**0.8311**	0.8275	13.0154	1.0154	sqft bath garage year qual1 qual2 style1 style4 style7 lot highway
11	**0.8311**	0.8274	13.2381	1.2381	sqft bath garage year qual1 style1 style3 style4 style7 lot highway
12	**0.8317**	0.8278	13.2255	0.2255	sqft bath garage year qual1 style1 style2 style3 style4 style6 lot highway

12	**0.8317**	0.8278	13.2438	0.2438	sqft bed bath garage year qual1 qual2 style1 style4 style7 lot highway
12	**0.8317**	0.8277	13.4624	0.4624	sqft bed bath garage year qual1 style1 style3 style4 style7 lot highway
13	**0.8324**	0.8281	13.3098	-0.6902	sqft bath garage year qual1 qual2 style1 style2 style3 style4 style6 lot highway
14	**0.8329**	0.8282	13.8076	-1.1924	sqft bed bath garage year qual1 qual2 style1 style2 style3 style4 style6 lot highway
15	**0.8333**	0.8284	14.4061	-1.5939	sqft bath garage year qual1 qual2 style1 style2 style3 style4 style5 style6 style7 lot highway
16	**0.8339**	0.8286	14.6421	-2.3579	sqft bed bath garage year qual1 qual2 style1 style2 style3 style4 style5 style6 style7 lot highway
17	**0.8344**	0.8288	15.1033	-2.8967	sqft bed bath garage pool year qual1 qual2 style1 style2 style3 style4 style5 style6 style7 lot highway
18	**0.8344**	0.8285	17.0308	-1.9692	sqft bed bath ac garage pool year qual1 qual2 style1 style2 style3 style4 style5 style6 style7 lot highway
19	**0.8344**	0.8282	19.0214	-0.9786	sqft bed bath ac garage pool year qual1 qual2 style1 style2 style3 style4 style5 style6 style7 style10 lot highway
20	**0.8345**	0.8278	21.0000	0	sqft bed bath ac garage pool year qual1 qual2 style1 style2 style3 style4 style5 style6 style7 style9 style10 lot highway

Model	# of variables	C_p	adjusted R^2	R^2	predictors
AA	12	13.2255	0.8278	0.8317	sqft bath garage year qual1 style1 style2 style3 style4 style6 lot highway
B	12	13.2438	0.8278	0.8317	sqft bed bath garage year qual1 qual2 style1 style4 style7 lot highway
C	12	13.4624	0.8277	0.8317	sqft bed bath garage year qual1 style1 style3 style4 style7 lot highway
D	10	12.9165	0.8272	0.8305	sqft bath garage year qual1 style1 style4 style7 lot highway
E	11	12.9451	0.8271	0.8312	sqft bed bath garage year qual1 style1 style4 style7 lot highway
F	11		0.8271	0.8307	sqft bath garage year qual1 style1 style3 style4 style6 lot highway
G	9	14.4585	0.8263	0.8293	sqft bath garage year qual1 style1 style7 lot highway

The answer to part a are the green models. I choose them because they had C_P's closest to the number of parameters which is the number of predictors in the model + 1. To help me with my answer, I placed an extra column in the SAS output above.

(b) Determine the best regression method using each of the automatic methods, forward stepwise regression, forward selection and backward elimination. Again just include the explanatory variables for each of them. Are these models the same or different from each other and of the models chosen in part a)?

forward stepwise

Summary of Stepwise Selection

Step	Variable Entered	Variable Removed	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	sqft		1	0.6715	0.6715	476.055	1063.10	<.0001
2	qual1		2	0.1051	0.7767	159.887	244.32	<.0001
3	year		3	0.0221	0.7987	95.1274	56.77	<.0001
4	lot		4	0.0176	0.8163	43.8837	49.52	<.0001
5	style7		5	0.0055	0.8219	29.1254	16.04	<.0001
6	bath		6	0.0022	0.8240	24.5500	6.36	0.0120
7	style1		7	0.0025	0.8265	18.9857	7.41	0.0067
8	highway		8	0.0014	0.8279	16.7104	4.21	0.0406
9	garage		9	0.0014	0.8293	14.4585	4.22	0.0406
10	style4		10	0.0012	0.8305	12.9165	3.53	0.0609

This is model D above.

forward selection

Summary of Forward Selection

Step	Variable Entered	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	sqft	1	0.6715	0.6715	476.055	1063.10	<.0001
2	qual1	2	0.1051	0.7767	159.887	244.32	<.0001
3	year	3	0.0221	0.7987	95.1274	56.77	<.0001
4	lot	4	0.0176	0.8163	43.8837	49.52	<.0001
5	style7	5	0.0055	0.8219	29.1254	16.04	<.0001
6	bath	6	0.0022	0.8240	24.5500	6.36	0.0120
7	style1	7	0.0025	0.8265	18.9857	7.41	0.0067
8	highway	8	0.0014	0.8279	16.7104	4.21	0.0406
9	garage	9	0.0014	0.8293	14.4585	4.22	0.0406
10	style4	10	0.0012	0.8305	12.9165	3.53	0.0609
11	bed	11	0.0007	0.8312	12.9451	1.97	0.1613
12	qual2	12	0.0006	0.8317	13.2438	1.70	0.1928
13	style9	13	0.0004	0.8322	13.9149	1.33	0.2495
14	style3	14	0.0004	0.8325	14.7781	1.14	0.2867
15	style6	15	0.0006	0.8331	14.9437	1.84	0.1758
16	pool	16	0.0004	0.8336	15.7143	1.23	0.2674
17	style10	17	0.0004	0.8339	16.6540	1.06	0.3030

This is not listed in the above table and it has too many parameters so it will not be considered.

backward elimination

Variable	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	-2872765	369207	1.983577E11	60.54	<.0001
sqft	100.26719	7.20755	6.340619E11	193.53	<.0001
bath	10431	3867.64533	23829565134	7.27	0.0072
garage	9944.21164	4890.66967	13545454701	4.13	0.0425
year	1424.24280	190.00471	1.840894E11	56.19	<.0001
qual1	131339	10025	5.623093E11	171.63	<.0001
style1	41991	7966.28882	91030027055	27.78	<.0001
style2	17832	10251	9914528711	3.03	0.0825
style3	29965	9616.04294	31814945318	9.71	0.0019
style4	55669	18722	28966610963	8.84	0.0031
style6	32452	14634	16112117938	4.92	0.0270
lot	1.34206	0.22887	1.126605E11	34.39	<.0001
highway	-36422	17700	13872192851	4.23	0.0401

This is model A above.

(c) Normally, what we would do is to perform the rest of the project on each of the best models and then determine which model is the best at the end. However, to save time, we will choose the best model first and then only perform diagnostics and remedial actions on that one model.

i. Run a linear regression on each of the best methods from parts a) and b). If necessary, run a manual backwards elimination and repeat the calculation. (p-values of close to 0.05 are still acceptable.) Give the equation of the fitted regression line for your final model. Explain your choice.

A problem occurs because both of the predictors with multiple dummy variables, quality and style are in the final selection. However, it does make sense to not include all of possible permutations. If qual1 is in the model and qual2 is not in the model, that just means that low and medium quality are treated the same. The problem is more complicated with style since we don't know what each of the choices stands for. However, we do not have to include all of the choices, because the ones not included are not relevant to the final sales price.

To run this part, start off with the models with the most predictors and see if they reduce to the ones with lower numbers of predictors.

Note: I am labeling all of my models with letters. If they are on the table above, they will be in grey. I am also not including the adjusted R^2 below, because all of the data is in the table above.

Model A

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	**1**	-2872765	369207	-7.78	<.0001
sqft	**1**	100.26719	7.20755	13.91	<.0001
bath	**1**	10431	3867.64533	2.70	0.0072
garage	**1**	9944.21164	4890.66967	2.03	0.0425
year	**1**	1424.24280	190.00471	7.50	<.0001
qual1	**1**	131339	10025	13.10	<.0001
style1	**1**	41991	7966.28882	5.27	<.0001
style2	**1**	17832	10251	1.74	0.0825
style3	**1**	29965	9616.04294	3.12	0.0019
style4	**1**	55669	18722	2.97	0.0031
style6	**1**	32452	14634	2.22	0.0270
lot	**1**	1.34206	0.22887	5.86	<.0001
highway	**1**	-36422	17700	-2.06	0.0401

In this model nothing should be removed. The largest p-value is 0.0825 which is for style2. See below for what happens when this parameter is removed.

Model B

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	**1**	-2762411	381771	-7.24	<.0001
sqft	**1**	101.74278	7.21604	14.10	<.0001
bed	**1**	-4264.55579	3204.76883	-1.33	0.1839
bath	**1**	10671	4193.19909	2.54	0.0112
garage	**1**	9860.01871	4902.02032	2.01	0.0448
year	**1**	1382.08473	195.39018	7.07	<.0001
qual1	**1**	138635	13781	10.06	<.0001
qual2	**1**	10015	7679.68857	1.30	0.1928
style1	**1**	20664	6446.52641	3.21	0.0014
style4	**1**	34635	18265	1.90	0.0585
style7	**1**	-23497	7998.56259	-2.94	0.0035
lot	**1**	1.30690	0.23057	5.67	<.0001
highway	**1**	-36294	17706	-2.05	0.0409

In this model, qual2 should be removed first because it has the highest p-value. This is Model E.

Model C

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	**1**	-2871904	362734	-7.92	<.0001
sqft	**1**	103.16223	7.16051	14.41	<.0001
bed	**1**	-4270.05951	3205.89622	-1.33	0.1835
bath	**1**	12192	4031.68811	3.02	0.0026
garage	**1**	10488	4881.91382	2.15	0.0322
year	**1**	1434.82774	186.08733	7.71	<.0001
qual1	**1**	126925	10179	12.47	<.0001
style1	**1**	23473	7311.96443	3.21	0.0014
style3	**1**	11401	9367.36243	1.22	0.2241
style4	**1**	38008	18559	2.05	0.0411
style7	**1**	-20157	8740.23561	-2.31	0.0215
lot	**1**	1.34052	0.22966	5.84	<.0001
highway	**1**	-36087	17708	-2.04	0.0421

In this model, style3 should be removed first because it has the highest p-value. This is again Model E.

Model E

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	**1**	-2929927	359757	-8.14	<.0001
sqft	**1**	102.94627	7.16169	14.37	<.0001
bed	**1**	-4491.99679	3202.21622	-1.40	0.1613
bath	**1**	12178	4033.57340	3.02	0.0027
garage	**1**	10454	4884.13900	2.14	0.0328
year	**1**	1467.38746	184.24128	7.96	<.0001
qual1	**1**	126509	10178	12.43	<.0001
style1	**1**	18997	6322.88921	3.00	0.0028
style4	**1**	33986	18271	1.86	0.0634
style7	**1**	-24552	7963.02914	-3.08	0.0022
lot	**1**	1.33491	0.22972	5.81	<.0001
highway	**1**	-36045	17717	-2.03	0.0424

In this model, bed should be removed first because it has the highest p-value. This is again Model D.

Model D

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	**1**	-2952236	359746	-8.21	<.0001
sqft	**1**	100.52514	6.95718	14.45	<.0001
bath	**1**	10581	3873.20977	2.73	0.0065
garage	**1**	10303	4887.57339	2.11	0.0355
year	**1**	1475.54739	184.32372	8.01	<.0001
qual1	**1**	128682	10069	12.78	<.0001
style1	**1**	19984	6289.59900	3.18	0.0016
style4	**1**	34351	18287	1.88	0.0609
style7	**1**	-23737	7949.34070	-2.99	0.0030
lot	**1**	1.32585	0.22985	5.77	<.0001
highway	**1**	-36531	17730	-2.06	0.0399

The P-value for style4 is a little high, but nothing should be removed.

The final models that I obtained for models A and D which are the two models that were obtained by the automatic methods. I would choose D because it has fewer parameters even though model A has less bias (C_P is closer to p).

I am going to continue the backward elimination process on models A and D until there are no further p-values higher than 0.05 for your information even though my final answer is above.

Model F (generated from model A by removing style2)

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	**1**	-2946930	367465	-8.02	<.0001
sqft	**1**	94.95758	6.54232	14.51	<.0001
bath	**1**	10575	3874.42339	2.73	0.0066
garage	**1**	10593	4886.10977	2.17	0.0306
year	**1**	1470.00925	188.54786	7.80	<.0001
qual1	**1**	132634	10018	13.24	<.0001
style1	**1**	34246	6619.01497	5.17	<.0001
style3	**1**	22414	8597.43989	2.61	0.0094
style4	**1**	49248	18391	2.68	0.0077
style6	**1**	28145	14452	1.95	0.0520
lot	**1**	1.36633	0.22889	5.97	<.0001
highway	**1**	-35873	17733	-2.02	0.0436

This model was not generated in part a), however, the C_P value witll be greater than 13.2381 so the difference will be greater than 1.2381 and so it is probability not the best model.

Model G (generated from Model D by removing style4)

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	**1**	-2865457	357647	-8.01	<.0001
sqft	**1**	101.27161	6.96296	14.54	<.0001
bath	**1**	9798.35842	3860.26032	2.54	0.0114
garage	**1**	10056	4897.84752	2.05	0.0406
year	**1**	1432.88644	183.37049	7.81	<.0001
qual1	**1**	129561	10083	12.85	<.0001
style1	**1**	17433	6156.49251	2.83	0.0048
style7	**1**	-25430	7917.57022	-3.21	0.0014
lot	**1**	1.33104	0.23040	5.78	<.0001
highway	**1**	-36594	17774	-2.06	0.0400

There are no p-values here above 0.05.

Even though a better answer would be model D, I am going to complete the analysis using model G because more students would choose this model. Model D is better even though it has one more predictor because the C_P value is closer to p so the answer is less biased. The Adjusted R^2 are approximately the same.

Final Model: $Y_i = \beta_0 + \beta_1$ sqft $+ \beta_2$ bath $+ \beta_3$ garage $+ \beta_4$ year $+ \beta_5$ qual1 $+ \beta_6$ style1 $+ \beta_7$ style7 $+ \beta_8$ lot $+ \beta_9$ highway

Even though it is not required, I am including the complete output from model G:

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	9	8.219565E12	9.13285E11	276.47	<.0001
Error	512	1.691347E12	3303411517		
Corrected Total	521	9.910912E12			

Root MSE	57475	**R-Square**	0.8293
Dependent Mean	277894	**Adj R-Sq**	0.8263
Coeff Var	20.68245		

Parameter Estimates

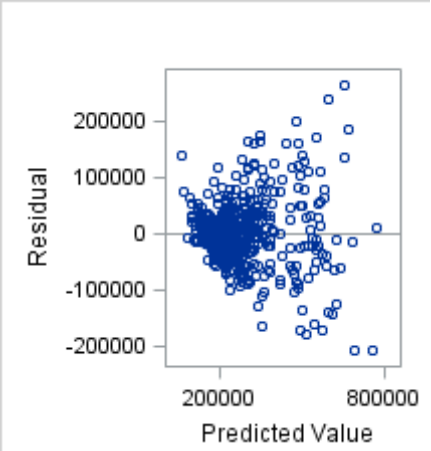
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	**1**	-2865457	357647	-8.01	<.0001
sqft	**1**	101.27161	6.96296	14.54	<.0001
bath	**1**	9798.35842	3860.26032	2.54	0.0114
garage	**1**	10056	4897.84752	2.05	0.0406
year	**1**	1432.88644	183.37049	7.81	<.0001
qual1	**1**	129561	10083	12.85	<.0001
style1	**1**	17433	6156.49251	2.83	0.0048
style7	**1**	-25430	7917.57022	-3.21	0.0014
lot	**1**	1.33104	0.23040	5.78	<.0001
highway	**1**	-36594	17774	-2.06	0.0400

ii. Is your answer in part i) consistent with the results from questions 3 and 4? Do you expect a problem with multicollinearity?

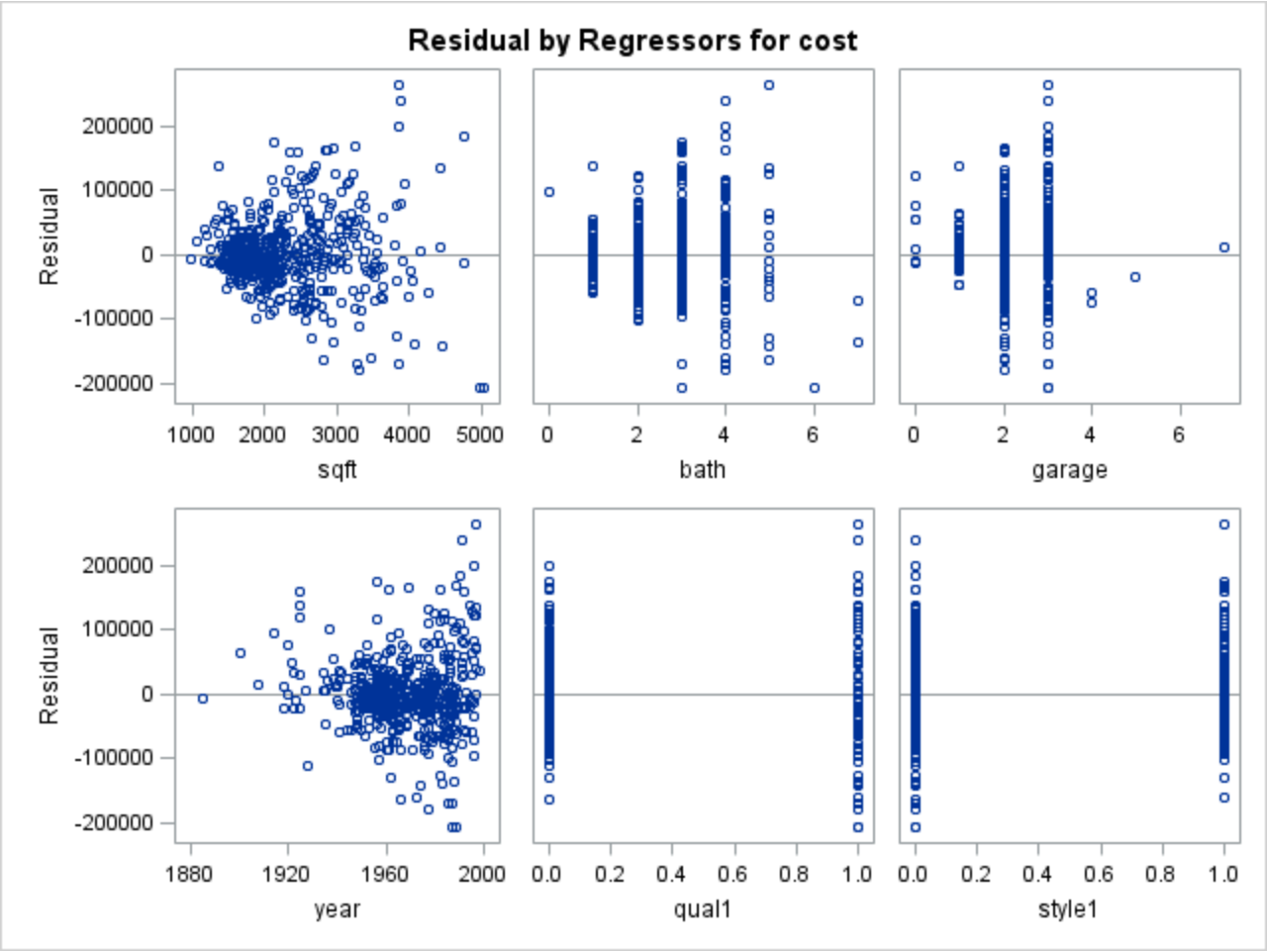
From questions 4, I expected to have sqft, bed or bath, garage, year, qual1, lot and highway. I was not sure about the style dummy variables. Therefore, the previous model is consistent with what was stated before. From question 3, I would expect some problem with multicollinearity because a) style7 has a large VIF and it was not certain which variables this was correlated with and b) sqft, bath, garage, year and lot showed some problems with pairwise correlation.

6. (28 pts.) We are now going to check our assumptions on the best model obtained in Step 5. For ease in grading, I am splitting your answer into the type of information that you are checking. Each assumption will be addressed in at least one (normally more than one) of the parts. Please comment on all graphs shown and write at least one sentence of conclusion for each part. We have already looked at the original variables and the scatterplots between them so you do not need to repeat that here.

(a) residual plots.



predicted value: there is a problem with constant variance and might be a problem with outliers. It is hard to determine if there is a problem with linearity.



sqft: it looks like there might be a problem with outliers and constant variance. There might be a problem with linearity.

bath: it looks like there might be a problem with outliers and constant variance.

garage: it looks like there might be a problem with outliers and constant variance.

year: it looks like there might be a problem with outliers and constant variance.

qual1: looks ok

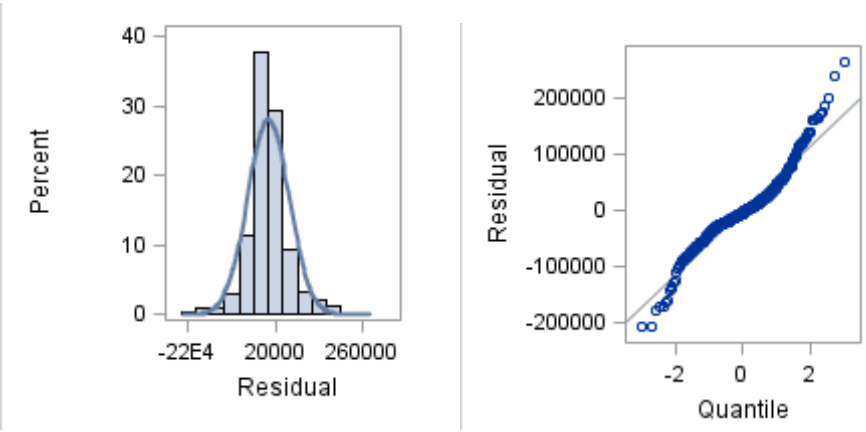
style1: looks ok

style7: looks ok

lot: there might be a problem with outliers, I am not sure about constant variance.

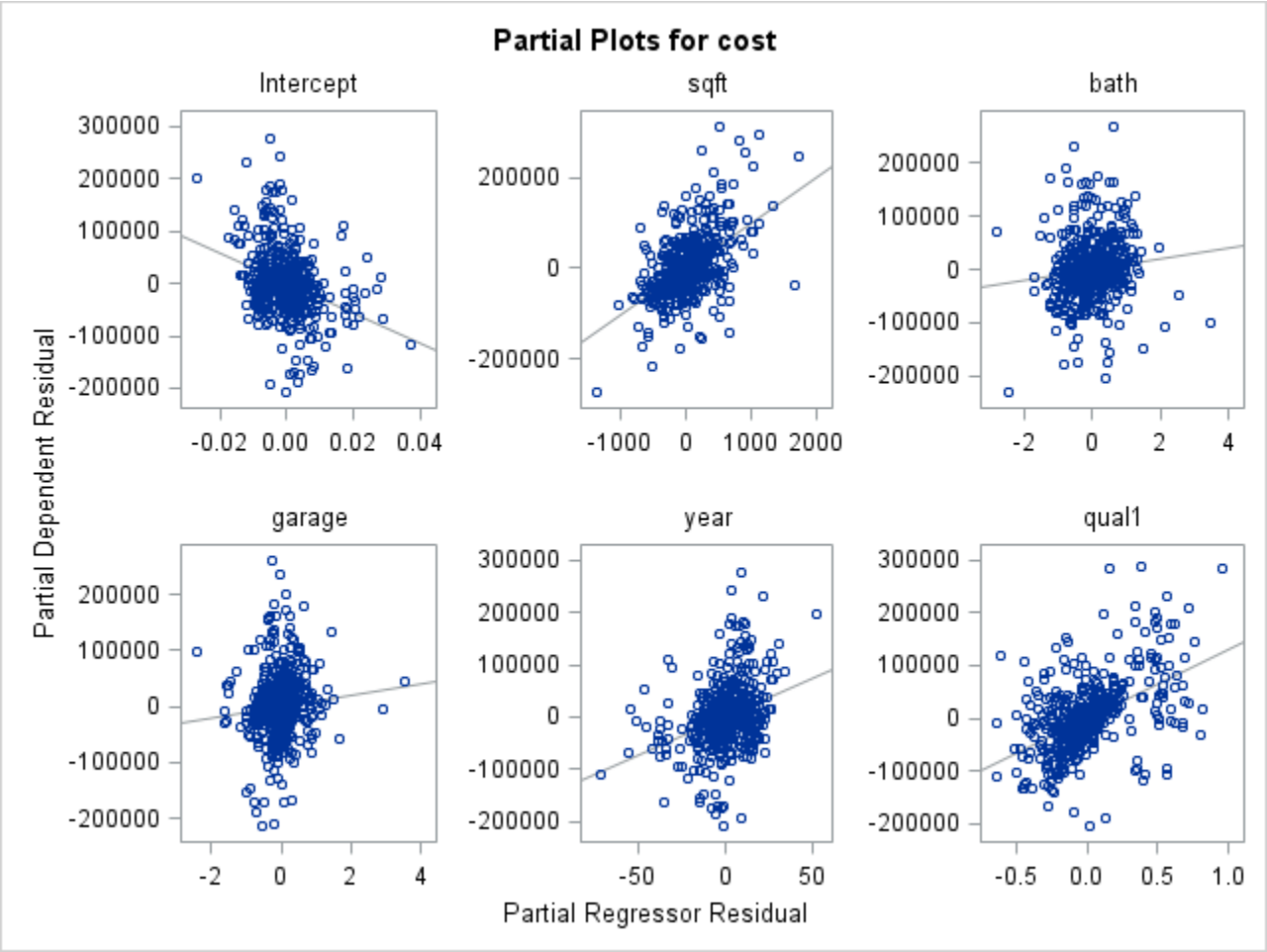
highway: There is a problem with constant variance; are the points at highway=1, outliers?

(b) normality plots.



normality still looks like there is a problem with too long tails which might be due to outliers.

(c) partial regression plots.



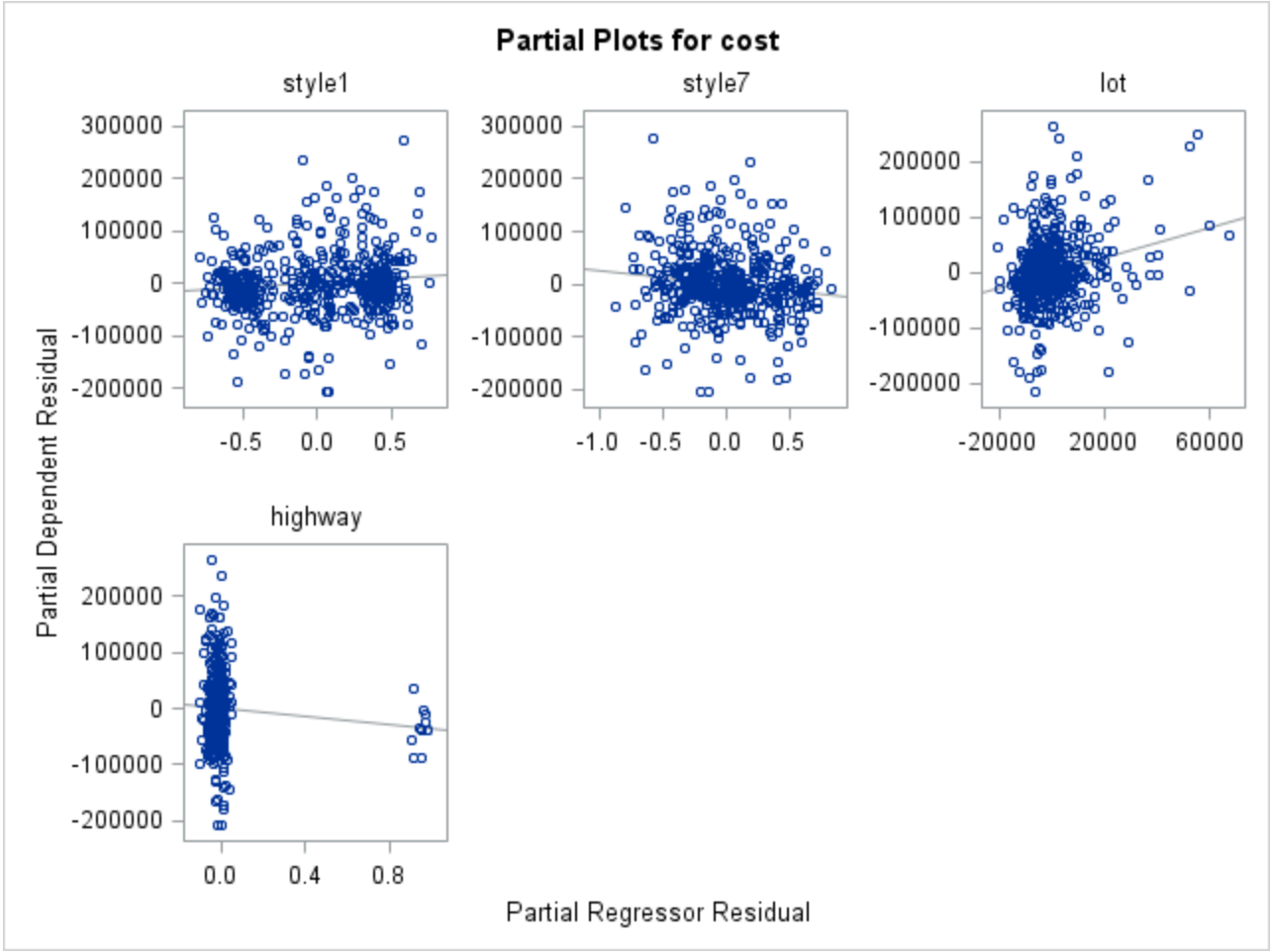
sqft: this is definitely significant and it looks like there is a problem with outliers since the fitted line doesn't look like it goes through the points.

bath: this is significant and again there is a problem with the outliers.

garage: this is significant and again there is a problem with the outliers.

year: this is significant and again there is a problem with the outliers. It also looks like there is some curvature.

qual1: this is significant and again there is a problem with the outliers in this case, the best line isn't close to going through the line of the majority of the points.



style1: this doesn't look significant if you ignore the outliers.

style7: this looks like it might be significant.

lot: this is significant and again there is a problem with the outliers.

highway: this is hard to tell because of the small number of points at 1.

(d) ~~qualitative~~ (quantitative) outlier and influential points (Note: this is considered a large data set). Be sure to include your results from looking at the interactive scatterplot. Do not consider non-outliers as being influential.

type	element	cutoff
Y outliers	RStudent	$t_{n-p-1}(1 - \frac{\alpha}{2n}) = t_{522-9-1}(1 - \frac{0.05}{2(522)}) = t_{512}(1 - 4.79 \times 10^{-5}) = 3.93214$
X outliers	hat diagonal element	$\frac{2p}{n} = \frac{2(10)}{522} = 0.03831$
influential $\hat{Y}$	DFFITS	$2\sqrt{\frac{p}{n}} = 2\sqrt{\frac{10}{522}} = 0.2768$
influential $\hat{Y}$	Cook's Distance	$F_{p,n-p}$ (50th percentile) = $F_{10,522-10}$ (50th) = $F_{10,512}$ (50th) = 0.93541
Influential $\hat{\beta}$	DFBETAS	$\frac{2}{\sqrt{n}} = \frac{2}{\sqrt{522}} = 0.08763$
influential variance	COV RATIO	$\lvert COVRATIO - 1\rvert \geq \frac{3p}{n} = \frac{3(10)}{522} = 0.05747$ $\Longrightarrow COVRATIO \leq -0.9425 \; or \; COVRATIO \geq 1.05747$

Because of the large number of outliers and influential points in this project, I am only going to list the problem points for each of the above types. I did my analysis using Excel by first copying the matrix to a word document and then copying the table into Excel. I then repeatedly used the sort function to find the points that were outside of each of the above cutoffs. After I identified each of the outliers, I then looked at the interactive scatterplot to determine if I thought they were outliers. Both of the Y outliers were really outliers. For the X outliers, the observations that I did not consider outliers have a 'no' in parentheses after the number. For the observations that I thought were outliers, I indicated which predictors, the observation was an outlier for.

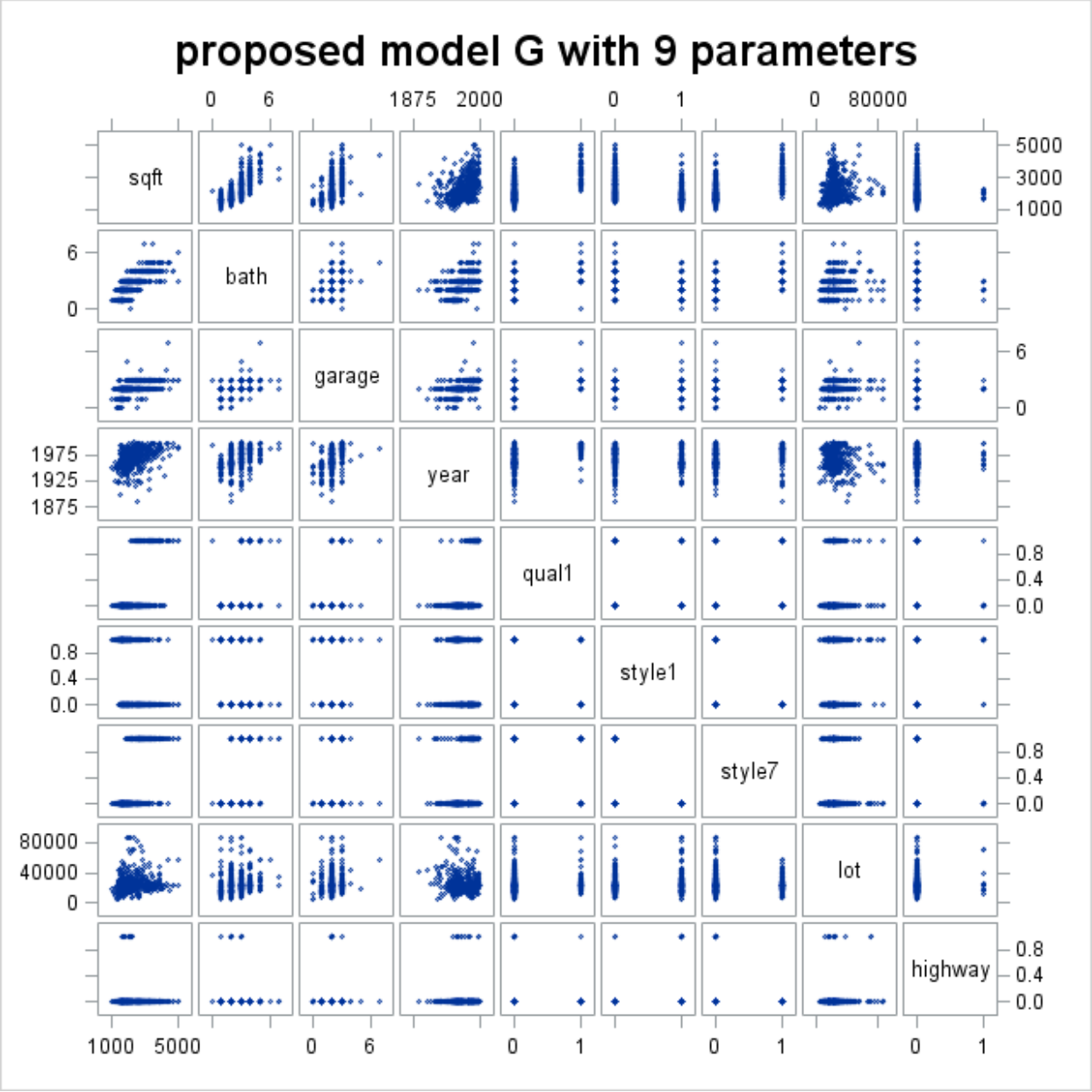
type	problem points
Y outliers	72, 73
X outliers	6 (garage), 25 (no), 37 (no), 49 (no), 50 (no), 52 (no), 55 (year), 56 (lot), 58 (no), 59 (no), 60 (no), 61 (no), 62 (no), 63 (lot), 64 (no), 65 (no), 66 (no), 67 (no), 68 (lot), 81 (many), 96 (year, lot), 103 (sqft), 104 (sqft, bath, lot), 108 (bath), 120 (bath), 123 (lot), 132 (no), 146 (year?), 148 (year), 155 (sqft, year), 161 (garage), 177 (lot), 201 (bath), 203 (sqft, year, lot), 211 (year), 241 (lot), 314 (lot), 344 (no), 466 (lot), 511 (no) (note: it considered all points with highway = 1 as outliers so none were included here)
Outliers to be considered:	6, 55, 56, 68, 72, 73, 81, 96, 103, 104, 108, 120, 123, 146, 148, 155, 161, 177, 201 203, 211, 241, 314, 466

In the following table, I only included the outliers to be considered and I have highlighted the influential points.

					DFBETA								
Obs	**Cook's D**	**Cov Ratio**	**DFFITS**	**Intercept**	**sqft**	**bath**	**garage**	**year**	**qual1**	**style1**	**style7**	**lot**	**highway**
6	0.003	1.0902	-0.1678	-0.0293	0.0358	-0.0164	-0.1569	0.0317	0.0373	-0.031	0.0004	0.0358	0.0078
55	0	1.0996	-0.0435	-0.0372	0.0008	0.0005	-0.0089	0.0372	-0.006	0.0052	-0.0147	-0.0036	-0.0024
56	0.001	1.065	-0.0871	0.0192	0.0161	-0.0229	-0.0148	-0.0178	0.0202	-0.0204	0.0022	-0.0659	0.0123
68	0.014	1.1392	-0.372	-0.0013	-0.0332	0.0894	0.002	0.0028	0.0052	0.0023	-0.0285	-0.1601	-0.3
72	0.033	0.7354	0.5846	-0.0518	0.122	-0.1528	-0.0109	0.0498	0.288	-0.0425	0.1174	0.0457	-0.0041
73	0.073	0.683	0.871	-0.1553	0.2937	0.1979	-0.1134	0.1399	0.1396	0.2987	-0.3862	0.004	-0.0708
81	0.001	1.1841	0.0732	0.0106	0.0101	-0.0039	0.0591	-0.0126	-0.0068	0.0095	-0.016	0.0072	-0.0038
96	0.086	0.9521	0.9326	0.3247	-0.2565	0.1316	-0.0962	-0.323	0.5143	-0.0228	0.0868	0.643	-0.0563
103	0.096	0.8257	-0.9935	0.1265	-0.7929	0.6489	0.0732	-0.1143	-0.0127	-0.024	0.1035	0.0968	-0.0038
104	0.061	0.812	-0.7877	-0.001	-0.3071	-0.0955	0.1831	0.0161	-0.086	-0.0322	0.0703	-0.3351	0.019
108	0.022	1.029	0.4705	-0.1752	0.0214	-0.3463	0.0783	0.1777	0.1967	0.0059	0.0402	0.1463	-0.0466
120	0.054	0.9851	-0.74	-0.1331	0.431	-0.6061	0.1962	0.1253	-0.3628	0.0153	-0.1475	0.044	-0.0178
123	0.005	1.0494	-0.2311	0.0605	0.0455	-0.0202	0.0101	-0.0589	-0.0904	-0.0276	0.0142	-0.1704	0.03
146	0.01	1.0386	0.316	0.0236	0.287	-0.0708	-0.0509	-0.031	-0.1555	0.1136	-0.129	-0.0378	-0.0121
148	0.021	0.9784	0.4611	0.3268	0.0204	-0.0777	0.262	-0.3278	-0.0137	-0.0319	0.1611	-0.1603	0.0303
155	0	1.0805	0.0256	0.0123	0.0172	-0.0078	0.0074	-0.0128	-0.0096	0.0017	0.0001	-0.0064	0.0012
161	0.037	0.9963	0.6083	-0.3868	0.2877	-0.1573	-0.4791	0.3879	-0.1224	0.1646	-0.0927	0.1165	-0.0547
177	0.021	1.0119	-0.46	0.1	-0.1194	0.1387	0.0625	-0.0938	0.0841	-0.073	0.013	-0.405	0.0601
201	0.009	1.0378	-0.2995	0.0153	0.0529	-0.2301	-0.0075	-0.0108	0.108	-0.0484	-0.0208	-0.0208	0.0049
203	0.067	0.8994	0.8281	-0.0321	-0.1305	0.0358	0.1787	0.0205	-0.0897	0.1005	0.0522	0.7239	-0.1035
211	0.011	1.0072	0.3381	0.2957	-0.0687	0.0916	0.0645	-0.2942	0.0467	-0.0283	0.1418	-0.0472	0.0244
241	0.001	1.0718	0.0884	0.02	0.0089	-0.0059	0.0244	-0.0213	-0.0117	-0.0254	-0.0189	0.0644	-0.0053
314	0.002	1.1185	-0.142	0.0397	-0.0133	0.0531	0.047	-0.0401	-0.0072	0.0385	0.0046	-0.1269	0.0125
466	0	1.0882	0.0259	-0.0038	-0.002	-0.0034	-0.0018	0.0036	-0.0006	0.0025	0.0028	0.0247	-0.0034

(e) multicollinearity including visual (scatter plots), pairwise correlation and quantitative information.

Note: this information is the same as in Question 3 but with fewer variables so it should be easier to tell what is happening.



It looks like sqft is correlated with bath, garage, year and lot size. It also looks like bath is correlated with year, year is correlated with lot size.

Pearson Correlation Coefficients, N = 522

	sqft	bath	garage	year	qual1	style1	style7	lot	highway
sqft	1.00000	0.75527	0.53377	0.44120	0.59178	-0.38008	0.61412	0.15752	-0.06063
bath	0.75527	1.00000	0.48990	0.51284	0.44625	-0.35662	0.50791	0.14701	-0.05093
garage	0.53377	0.48990	1.00000	0.46176	0.45495	-0.14498	0.27691	0.15222	-0.00196
year	0.44120	0.51284	0.46176	1.00000	0.42005	-0.22779	0.31259	-0.10045	0.02578
qual1	0.59178	0.44625	0.45495	0.42005	1.00000	-0.03330	0.23707	0.08049	-0.01716
style1	-0.38008	-0.35662	-0.14498	-0.22779	-0.03330	1.00000	-0.49477	0.07336	0.12178
style7	0.61412	0.50791	0.27691	0.31259	0.23707	-0.49477	1.00000	-0.02657	-0.08709
lot	0.15752	0.14701	0.15222	-0.10045	0.08049	0.07336	-0.02657	1.00000	0.07845
highway	-0.06063	-0.05093	-0.00196	0.02578	-0.01716	0.12178	-0.08709	0.07845	1.00000

It still looks like there is a problem between sqft and bath, garage, qual1, style7. But those seem to be the major problems.

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	**1**	-2865457	357647	-8.01	<.0001	0
sqft	**1**	101.27161	6.96296	14.54	<.0001	3.86618
bath	**1**	9798.35842	3860.26032	2.54	0.0114	2.66152
garage	**1**	10056	4897.84752	2.05	0.0406	1.61809
year	**1**	1432.88644	183.37049	7.81	<.0001	1.64979
qual1	**1**	129561	10083	12.85	<.0001	1.82010
style1	**1**	17433	6156.49251	2.83	0.0048	1.44877
style7	**1**	-25430	7917.57022	-3.21	0.0014	1.90843
lot	**1**	1.33104	0.23040	5.78	<.0001	1.14296
highway	**1**	-36594	17774	-2.06	0.0400	1.02976

Whatever the problem was with multicollinearity in the original model, this model does not have any problem with it.

(f) Please summarize your answer by listing each of the assumptions (and multicollinearity) and whether there is a problem or not.

linearity: It is hard to determine if there is a problem with linearity or not with the size of the default graphs but it looks like there might be a problem.

constant variance: there is a problem with constant variance.

outliers: there is a problem with outliers and influential points.

normality: there is a problem with normality.

independence: This can only be determined experimentally.

multicollinearity: there is no problem with multicollinearity.

7. (12.5 pts.) The next step is to perform remedial actions. Please do not correct for influential points.

(a) Only perform one of the following possible actions. Please explain your choice and provide the results of your action.

i. if there is a problem in normality/constant variance and linearity, perform a Y transformation.

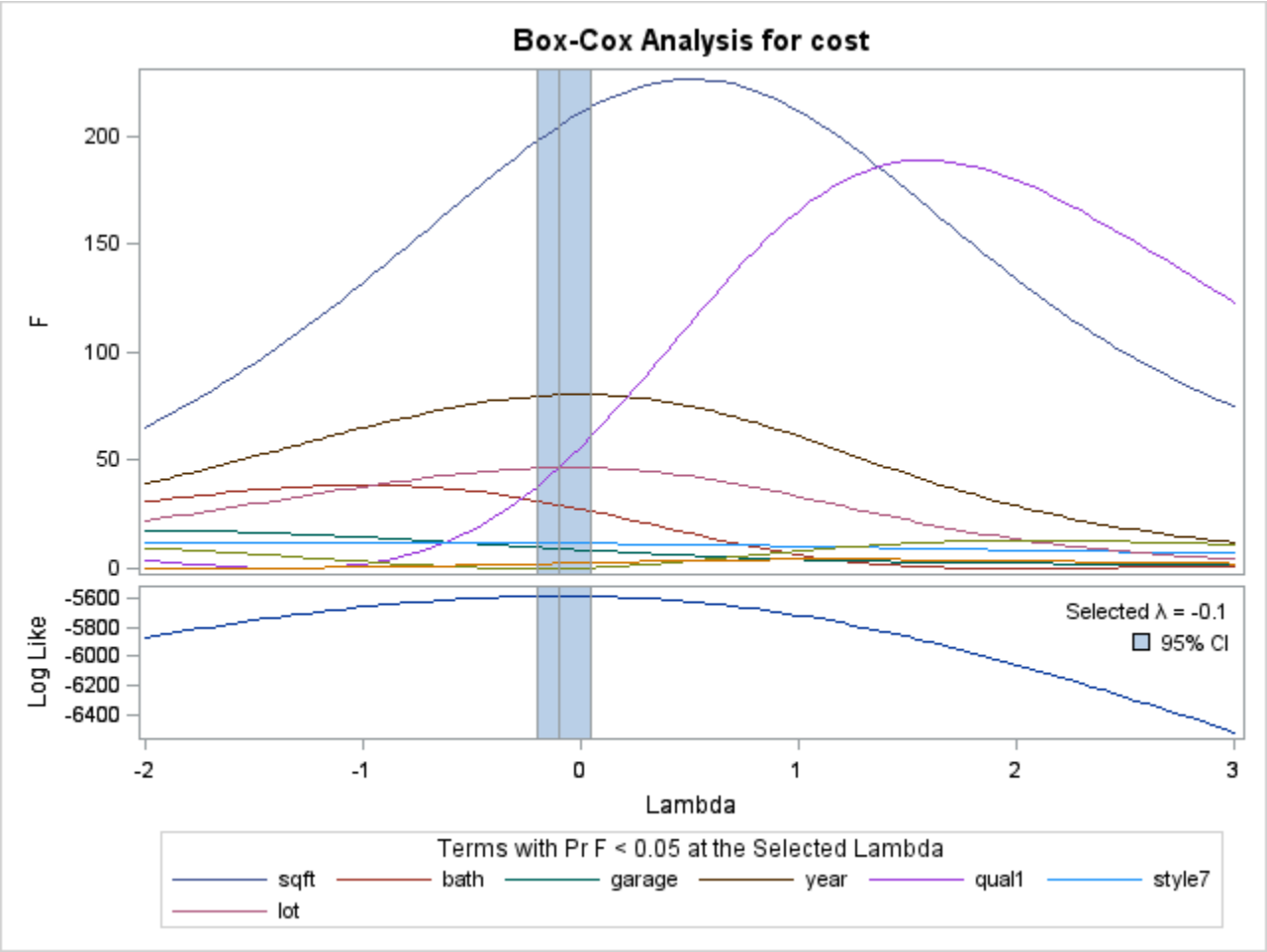
ii. if there is a problem in just constant variance, perform a weighted regression.

iii. If there is a problem with multicollinearity, perform a ridge regression.

iv. if there is a problem with linearity that is due to a curve in one of the explanatory variables, center the variable and include the quadratic term in the regression.

Because there is a problem with constant variance, normality and maybe linearity, I would choose the Y transformation. If you stated that there was no problem with normality and/or linearity, then weighted least squares regression is correct also. Note: if you have a problem with ANY of the assumptions, it is incorrect to choose ridge regression to correct multicollinarity problems. I will give the results of the Y transformation and a weighted regression with all of the predictor variables in the model to determine the weights. In addition, I will provide the answer to ridge regression because a number of students also did that method. It is also acceptable to perform the weighted regression with only the predictor variables that are causing problem but I will not provide that output.

Y-transformation



The best transformation is $Y' = Y^{-0.1}$ but since $\lambda = 0$ is in the confidence interval, I will choose the transformation of $Y' = \log Y$.

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	9	80.65517	8.96169	279.31	<.0001
Error	512	16.42775	0.03209		
Corrected Total	521	97.08292			

Root MSE	0.17912	**R-Square**	0.8308
Dependent Mean	12.43463	**Adj R-Sq**	0.8278
Coeff Var	1.44053		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	**1**	1.24883	1.11462	1.12	0.2631
sqft	**1**	0.00031482	0.00002170	14.51	<.0001
bath	**1**	0.06331	0.01203	5.26	<.0001
garage	**1**	0.04499	0.01526	2.95	0.0034
year	**1**	0.00513	0.00057148	8.97	<.0001
qual1	**1**	0.23533	0.03142	7.49	<.0001
style1	**1**	0.01028	0.01919	0.54	0.5922
style7	**1**	-0.08416	0.02468	-3.41	0.0007
lot	**1**	0.00000490	7.180518E-7	6.83	<.0001
highway	**1**	-0.08961	0.05539	-1.62	0.1063

The F value increased from 276.47 (Model G) to, 279.31.

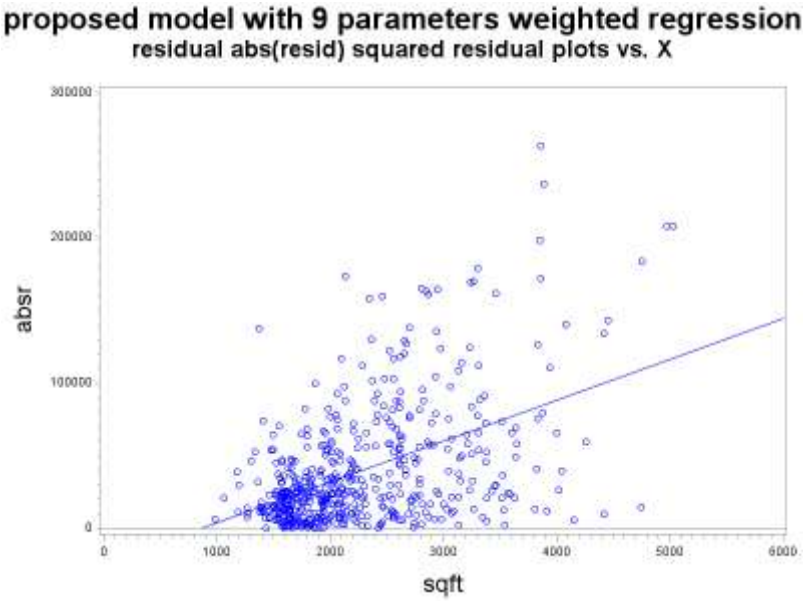
The R^2 also increased from 0.8293 to 0.8308.

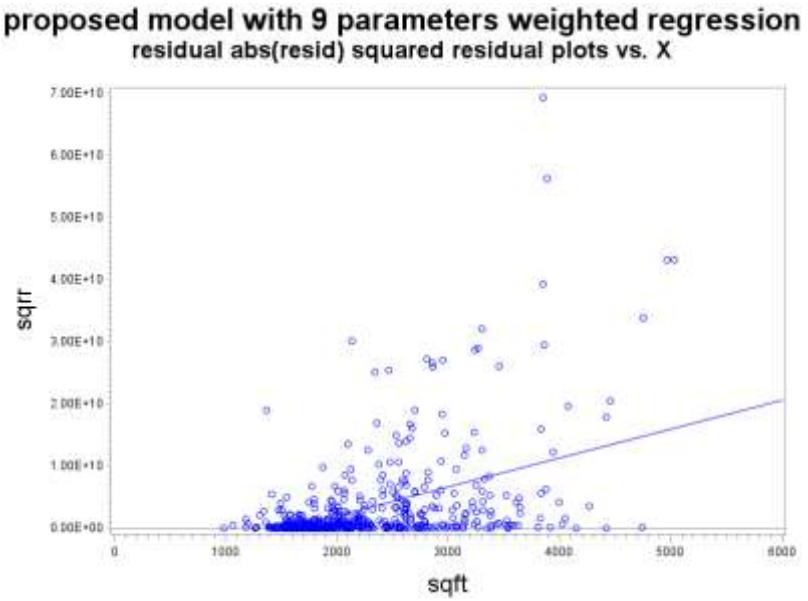
The root MSE is drastically reduced from 3303411517 to 0.03209

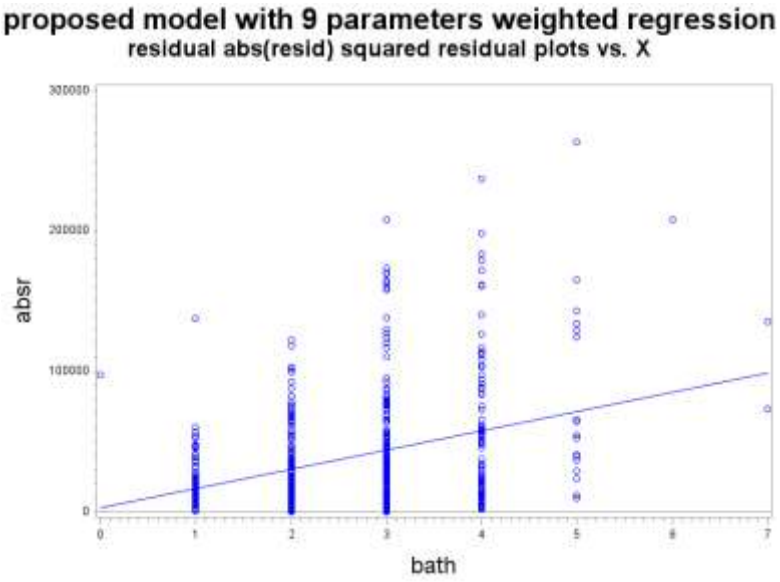
However, with this transformation, style1 now has too high a P-value so should be removed. However, since I did not ask for further model selection, no further actions will be performed.

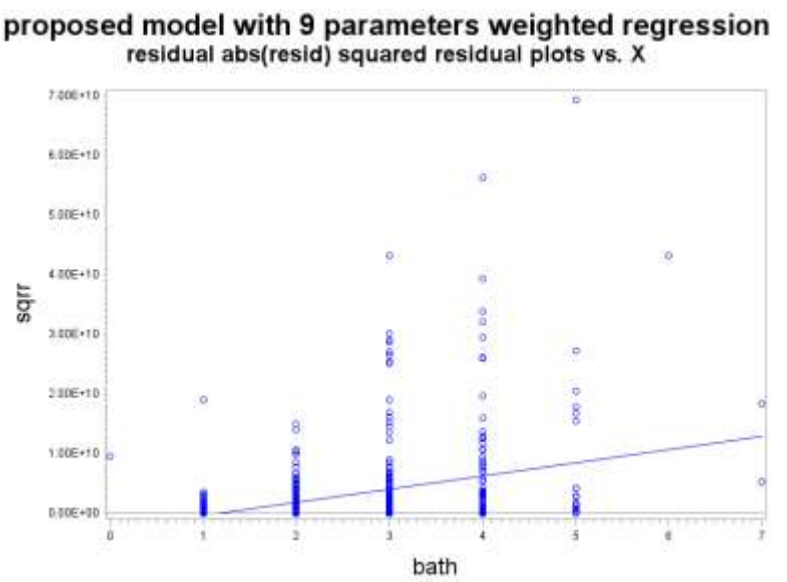
Weighted Least Squares

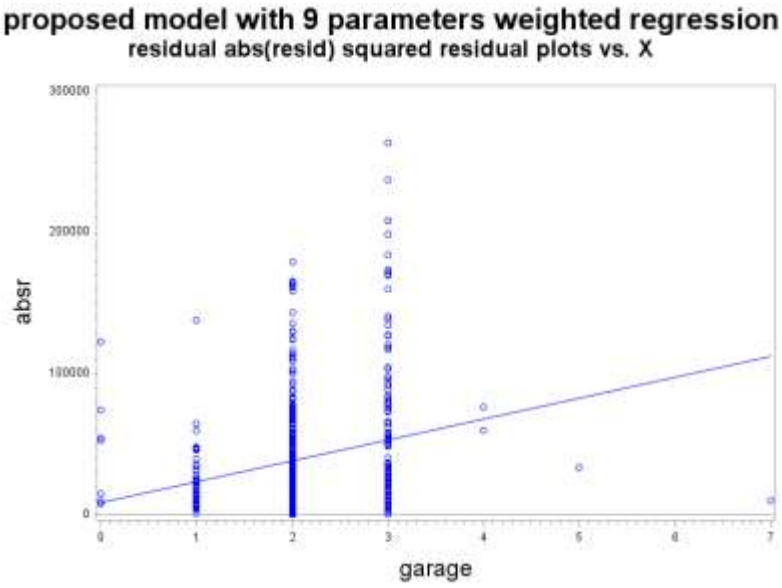
We first need to decide whether to use |resid| or resid^2 to form the weights: The plots for |resid| are in the left column and the plots for resid^2 are in the right column.

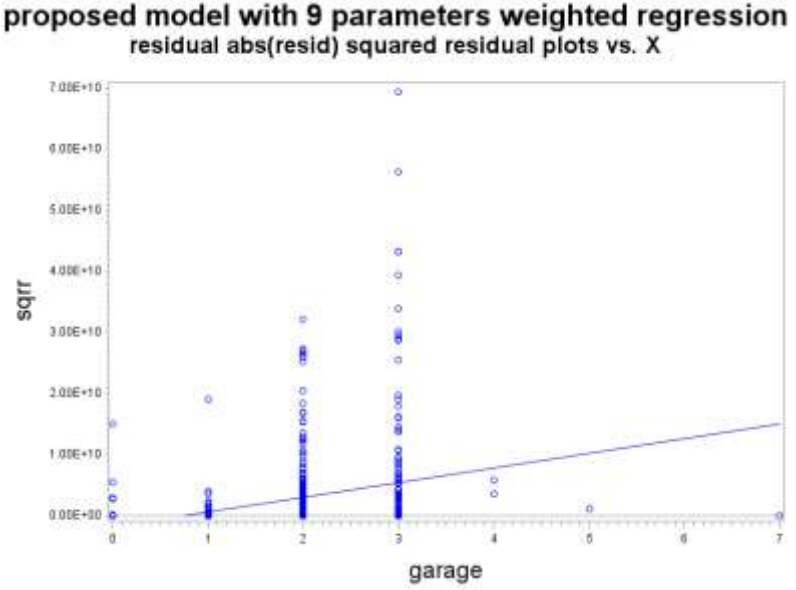


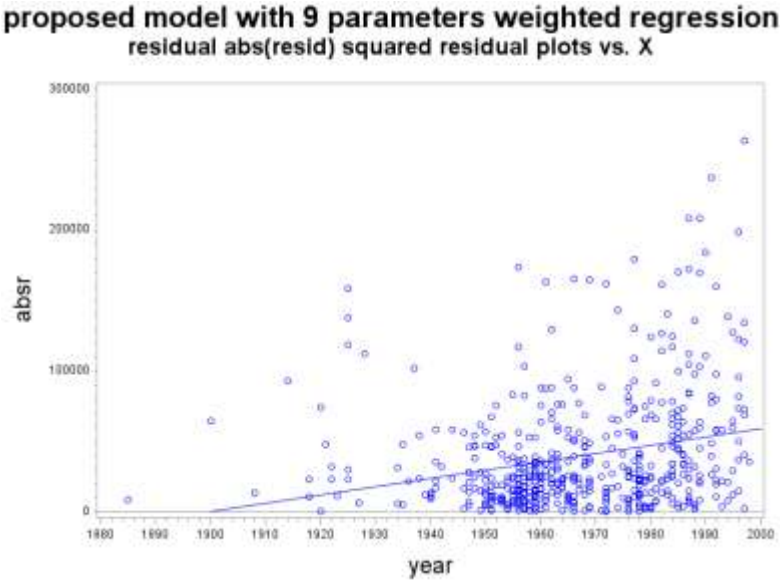


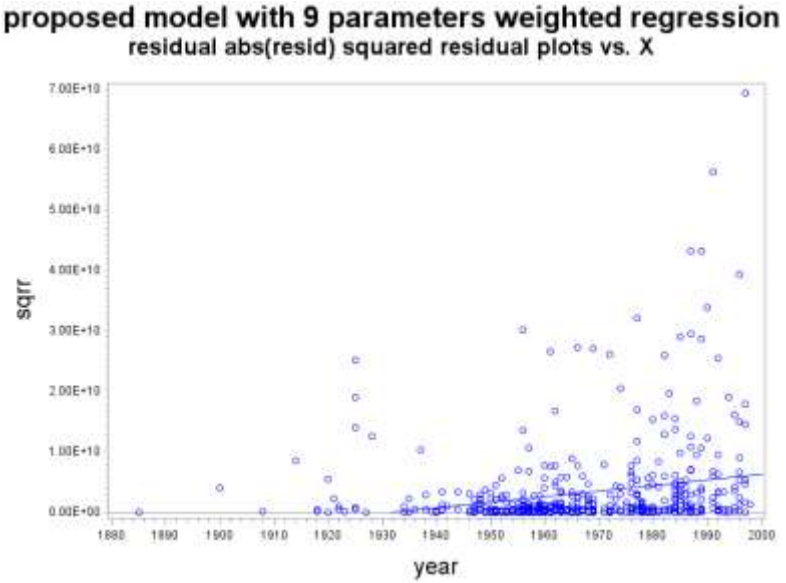

proposed model with 9 parameters weighted regression
residual abs(resid) squared residual plots vs. X
absr
bath

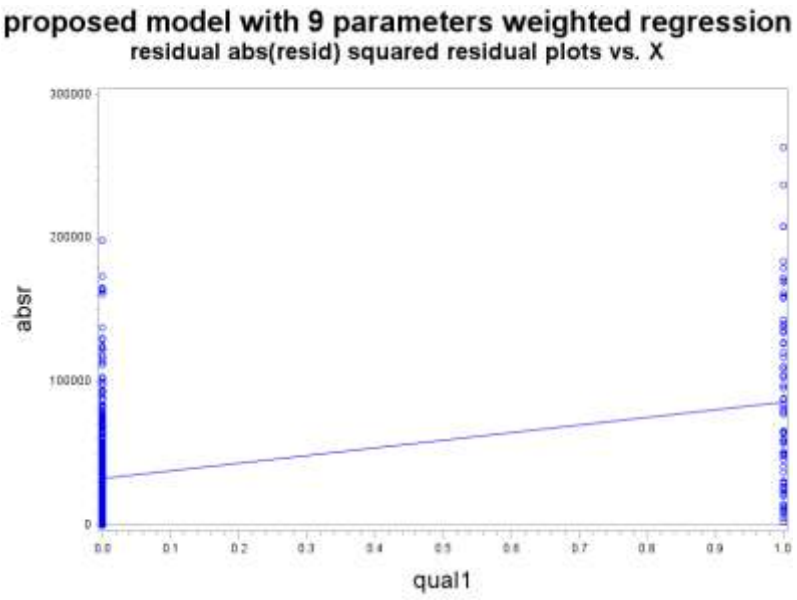

proposed model with 9 parameters weighted regression
residual abs(resid) squared residual plots vs. X
sqrr
bath

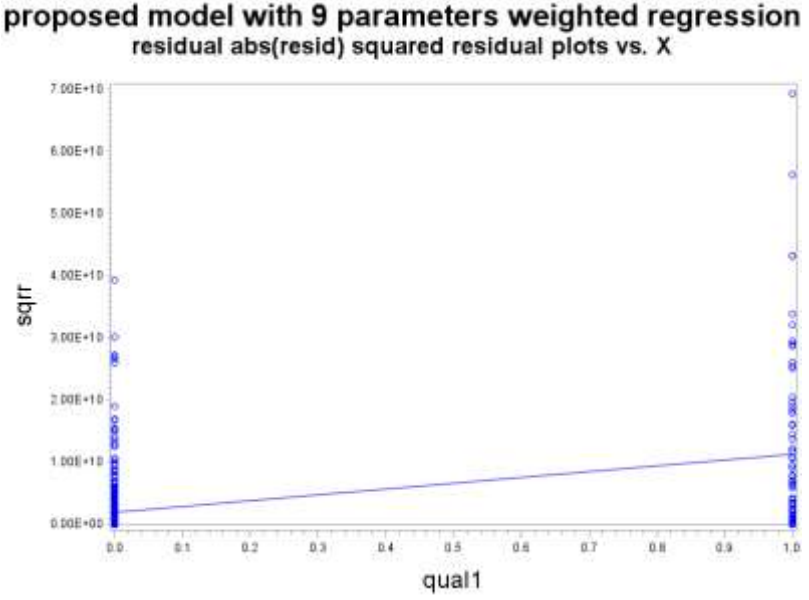

proposed model with 9 parameters weighted regression
residual abs(resid) squared residual plots vs. X
absr
garage

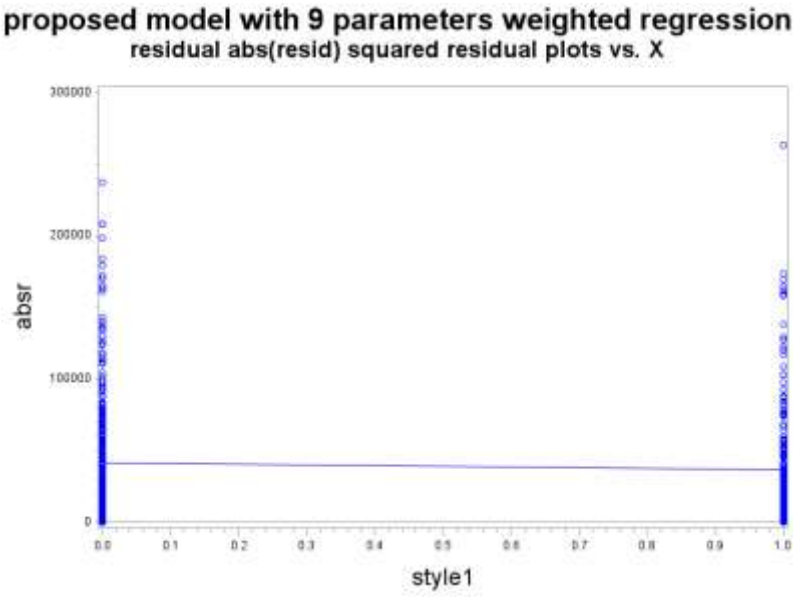

proposed model with 9 parameters weighted regression
residual abs(resid) squared residual plots vs. X
sqrr
garage

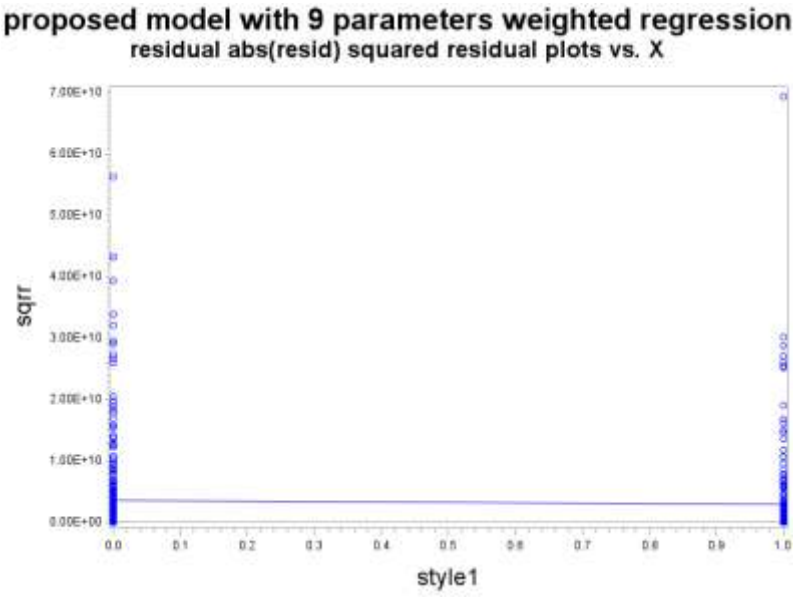

proposed model with 9 parameters weighted regression
residual abs(resid) squared residual plots vs. X
absr
year

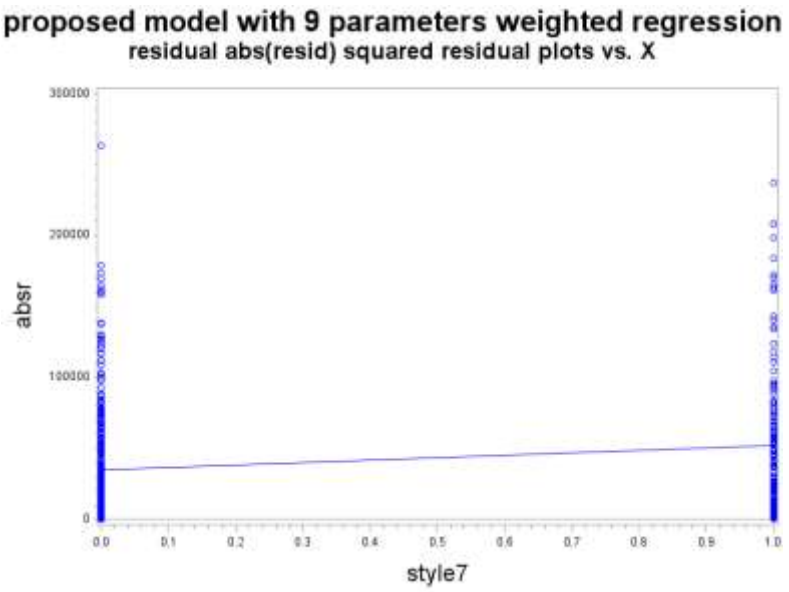

proposed model with 9 parameters weighted regression
residual abs(resid) squared residual plots vs. X
sqrr
year

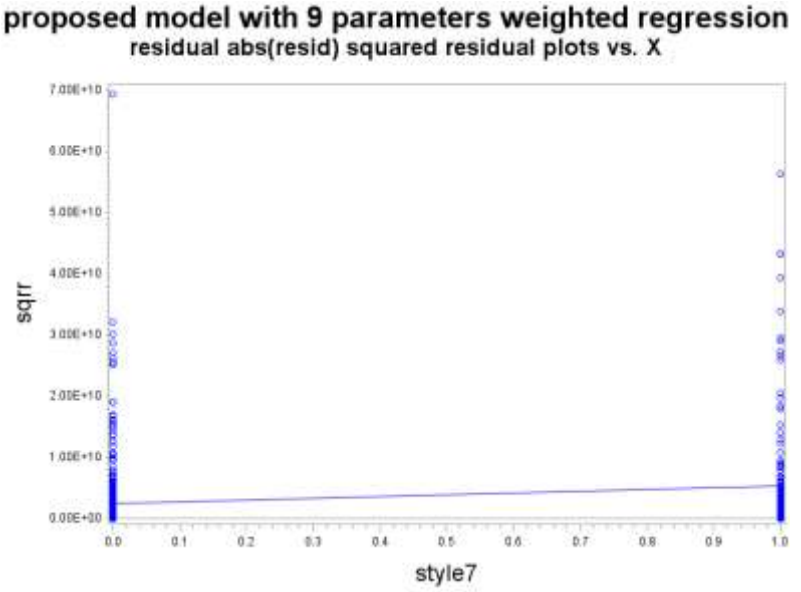

proposed model with 9 parameters weighted regression
residual abs(resid) squared residual plots vs. X
absr
qual1

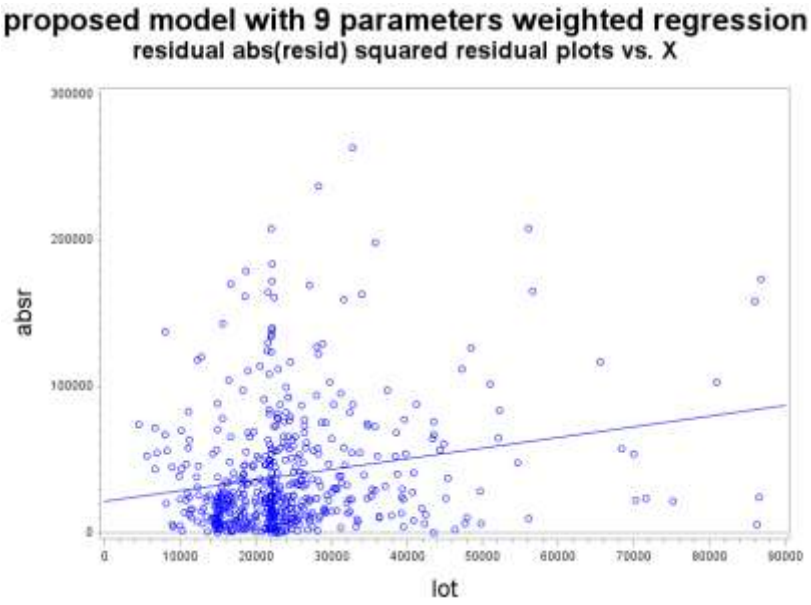

proposed model with 9 parameters weighted regression
residual abs(resid) squared residual plots vs. X
sqrr
qual1

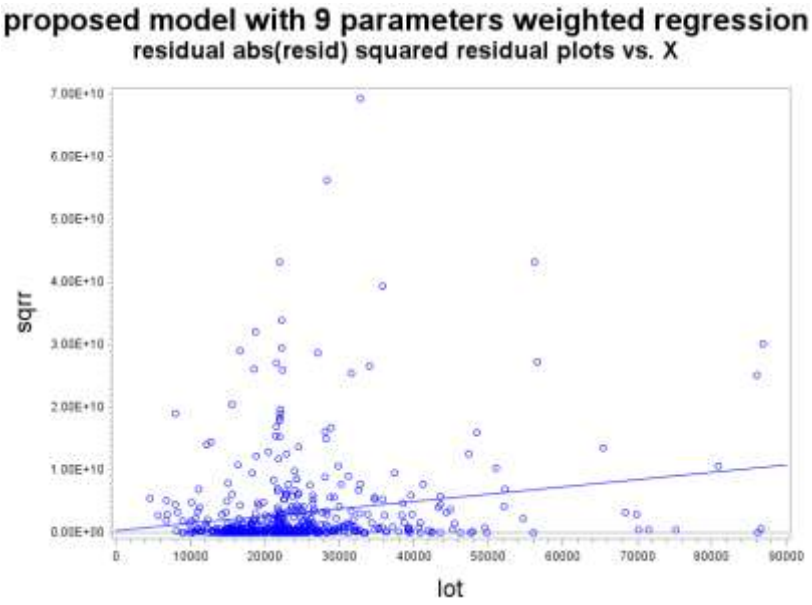

proposed model with 9 parameters weighted regression
residual abs(resid) squared residual plots vs. X
absr
style1

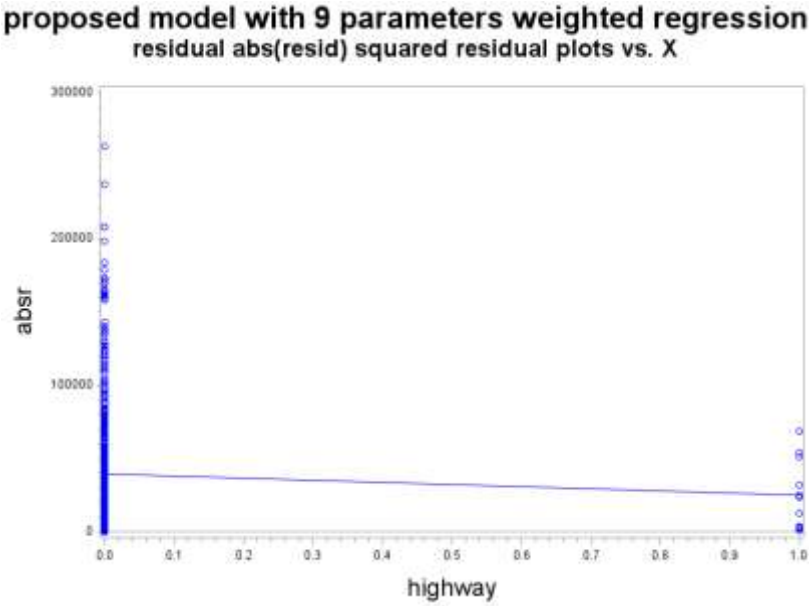

proposed model with 9 parameters weighted regression
residual abs(resid) squared residual plots vs. X
sqrr
style1

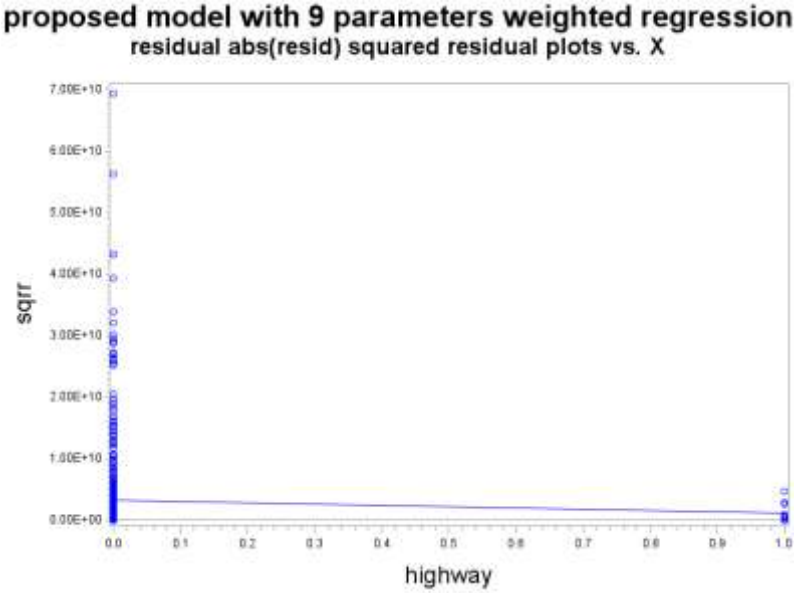

proposed model with 9 parameters weighted regression
residual abs(resid) squared residual plots vs. X
absr
style7


proposed model with 9 parameters weighted regression
residual abs(resid) squared residual plots vs. X
sqrr
style7









From the plots, I would choose to use |resid| for the plots, but I will run both of the methods to see which generates the smallest confidence intervals and generates and MSE closest to 1.

|resid|

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	9	4185.38845	465.04316	218.94	<.0001
Error	512	1087.51118	2.12405		
Corrected Total	521	5272.89963			

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	95% Confidence Limits	
Intercept	**1**	-752979	186304	-4.04	<.0001	-1118993	-386965
sqft	**1**	91.34065	5.37314	17.00	<.0001	80.78454	101.89676
bath	**1**	10107	2372.49490	4.26	<.0001	5446.30375	14768
garage	**1**	4213.24024	2608.30879	1.62	0.1069	-911.06437	9337.54484
year	**1**	389.67565	96.84848	4.02	<.0001	199.40634	579.94496
qual1	**1**	172119	15551	11.07	<.0001	141567	202672
style1	**1**	-7983.77329	3505.42517	-2.28	0.0232	-14871	-1096.98656
style7	**1**	-23863	5670.11571	-4.21	<.0001	-35002	-12723
lot	**1**	0.26115	0.19953	1.31	0.1912	-0.13084	0.65315
highway	**1**	-29805	3670.30441	-8.12	<.0001	-37016	-22594

resid^2

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	9	1629.06364	181.00707	172.22	<.0001
Error	442	464.56416	1.05105		
Corrected Total	451	2093.62780			

Parameter Estimates							
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**	**95% Confidence Limits**	
Intercept	**1**	-1695520	253735	-6.68	<.0001	-2194197	-1196842
sqft	**1**	100.67212	7.11372	14.15	<.0001	86.69121	114.65303
bath	**1**	13092	2655.51871	4.93	<.0001	7872.50663	18311
garage	**1**	-2875.78464	4110.07440	-0.70	0.4845	-10954	5201.93195
year	**1**	849.79353	129.63545	6.56	<.0001	595.01507	1104.57199
qual1	**1**	151917	14768	10.29	<.0001	122892	180942
style1	**1**	-112.19468	3574.49661	-0.03	0.9750	-7137.31583	6912.92647
style7	**1**	-26711	5695.29627	-4.69	<.0001	-37904	-15517
lot	**1**	1.31559	0.21642	6.08	<.0001	0.89025	1.74093
highway	**1**	-21302	16403	-1.30	0.1948	-53540	10937

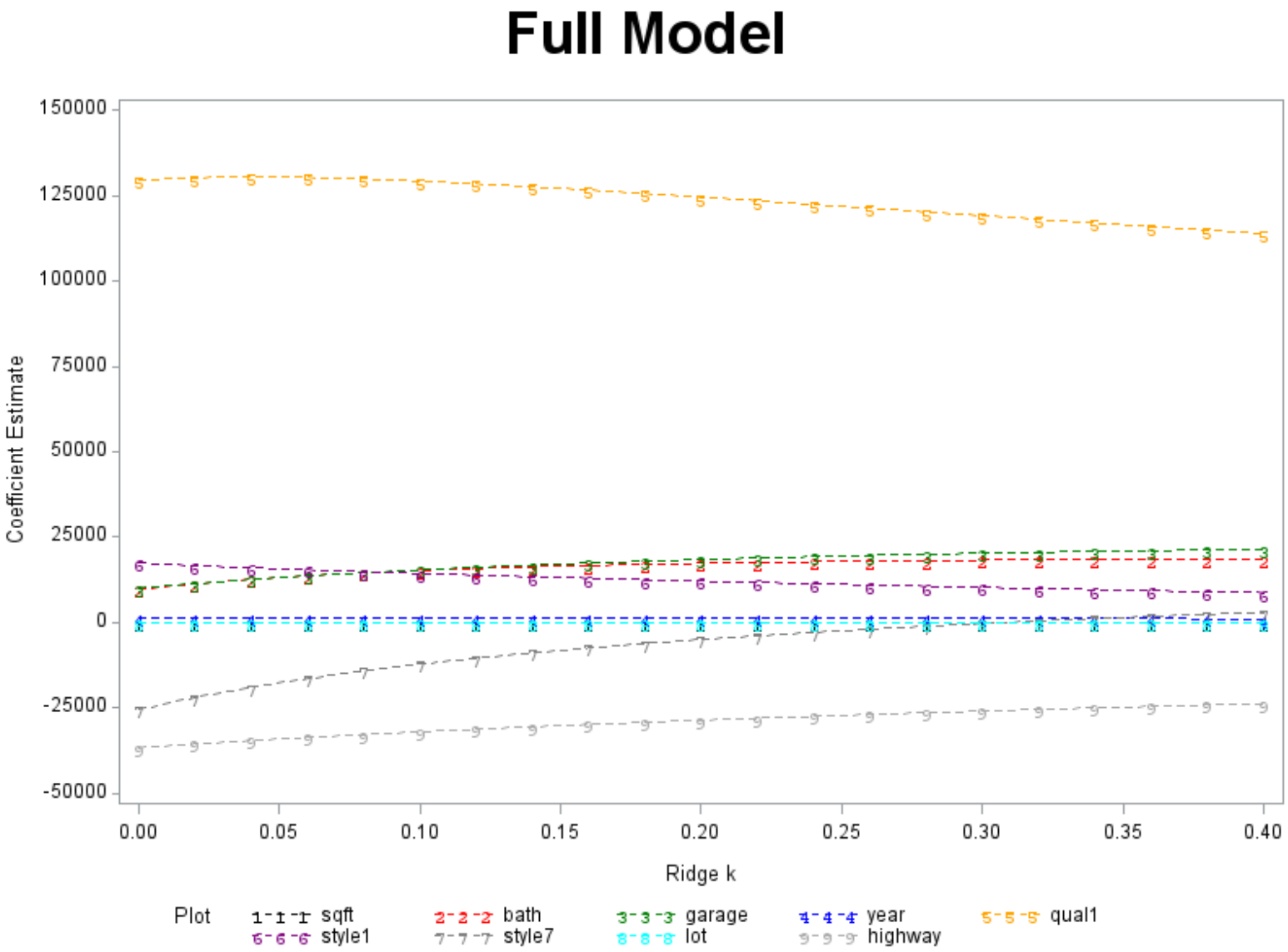
|resid| does have the more precise confidence intervals, however, the MSE is closer to 1 with the resid^2. Since both are close 1, they both should be ok.

Ridge Regression

This should not change much since the VIF factors state that there is no problem with multicollinearity in this model.

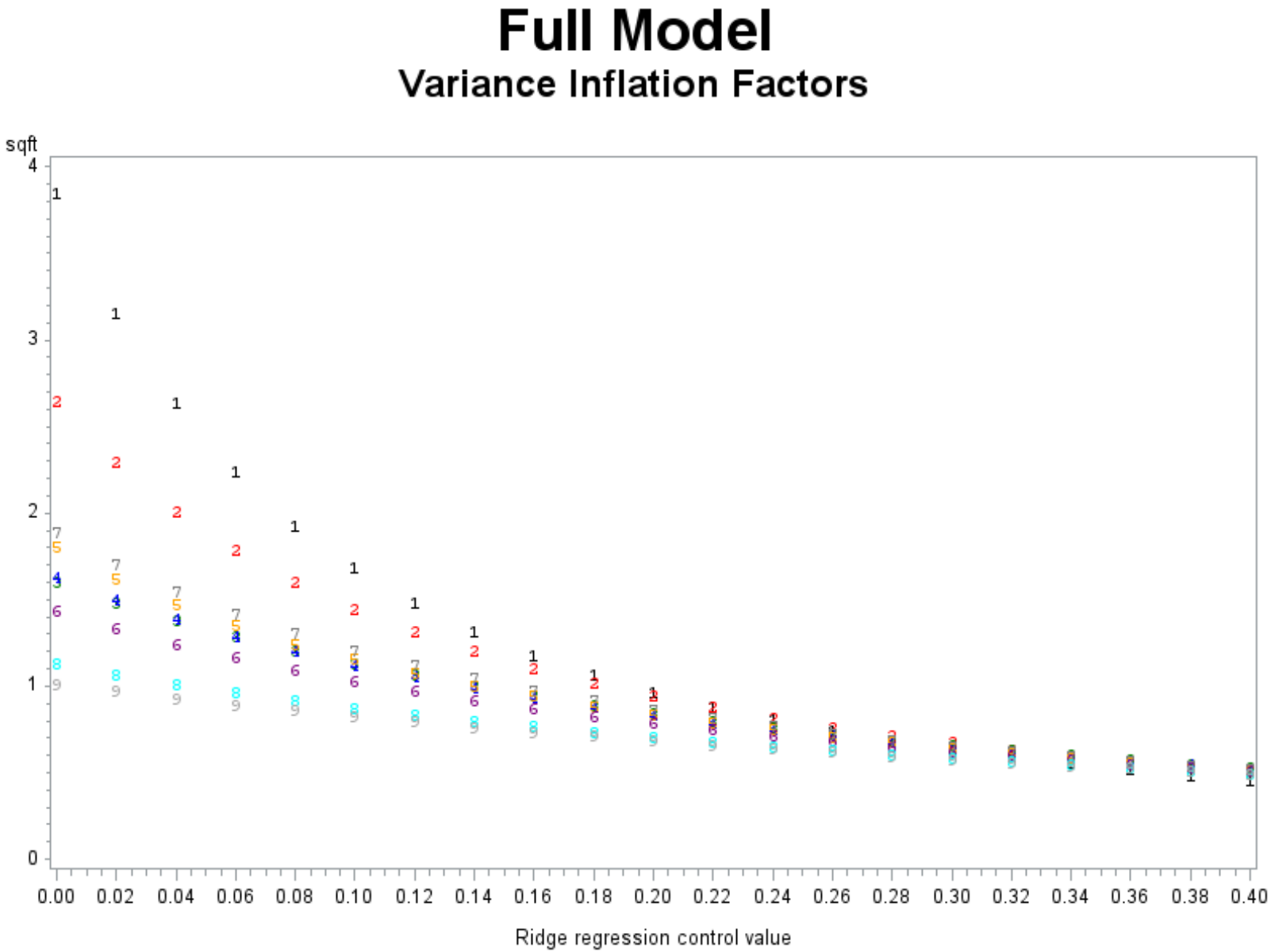
To determine the value of c:

1) Output from the ridge trace plot:



You can see when you increase the bias, the values of the parameters do change. However, because there is no extreme change at c close to 0, I would say that there is little problem with multicollinearity in this data set. I cannot determine a reasonable value of c from this plot.

2) from the VIF factor plot and printout.



In this plot, you are looking for the values when all of the VIF's are close to 1. It is hard to tell the value of c from this plot.

Obs	_RIDGE_	sqft	bath	garage	year	qual1	style1	style7	lot	highway
2	0.00	3.86618	2.66152	1.61809	1.64979	1.82010	1.44877	1.90843	1.14296	1.02976
4	0.02	3.16918	2.30823	1.50076	1.51831	1.63887	1.34976	1.72222	1.08257	0.98728
6	0.04	2.65140	2.02961	1.39684	1.40482	1.49075	1.26177	1.56712	1.02784	0.94749
8	0.06	2.25576	1.80448	1.30418	1.30563	1.36688	1.18309	1.43561	0.97797	0.91016
10	0.08	1.94630	1.61899	1.22106	1.21807	1.26141	1.11235	1.32256	0.93230	0.87507
12	0.10	1.69941	1.46371	1.14615	1.14016	1.17030	1.04844	1.22428	0.89031	0.84204
14	0.12	1.49909	1.33198	1.07833	1.07037	1.09066	0.99046	1.13802	0.85154	0.81091
16	0.14	1.33416	1.21896	1.01670	1.00750	1.02037	0.93766	1.06171	0.81563	0.78152
18	0.16	1.19664	1.12105	0.96050	0.95058	0.95782	0.88939	0.99375	0.78226	0.75374
20	0.18	1.08067	1.03552	0.90908	0.89882	0.90177	0.84513	0.93286	0.75117	0.72745
22	0.20	0.98190	0.96025	0.86190	0.85156	0.85125	0.80442	0.87802	0.72213	0.70254
24	0.22	0.89703	0.89359	0.81849	0.80827	0.80545	0.76687	0.82840	0.69495	0.67892
26	0.24	0.82351	0.83420	0.77844	0.76848	0.76375	0.73213	0.78330	0.66944	0.65650
28	0.26	0.75938	0.78102	0.74142	0.73180	0.72562	0.69993	0.74216	0.64545	0.63518
30	0.28	0.70306	0.73316	0.70711	0.69789	0.69063	0.67000	0.70450	0.62287	0.61491
32	0.30	0.65330	0.68992	0.67526	0.66647	0.65841	0.64213	0.66991	0.60156	0.59561
34	0.32	0.60911	0.65069	0.64561	0.63729	0.62865	0.61613	0.63806	0.58142	0.57722
36	0.34	0.56966	0.61498	0.61798	0.61013	0.60108	0.59181	0.60864	0.56236	0.55968
38	0.36	0.53428	0.58236	0.59217	0.58480	0.57548	0.56903	0.58140	0.54431	0.54295
40	0.38	0.50241	0.55246	0.56804	0.56112	0.55165	0.54766	0.55611	0.52717	0.52696
42	0.40	0.47359	0.52500	0.54542	0.53896	0.52942	0.52757	0.53259	0.51089	0.51167

I would say that a value of c = 0.18 would be the appropriate value.

Obs	_RIDGE_	_RMSE_	Intercept	sqft	bath	garage	year	qual1	style1	style7	lot	highway
3	0.00	57475.31	-2865456.83	101.272	9798.36	10055.76	1432.89	129560.55	17433.40	-25430.33	1.33104	-36593.72
5	0.02	57523.68	-2782942.38	95.572	11418.06	11441.16	1393.56	130340.20	16711.23	-21914.28	1.32268	-35523.53
7	0.04	57642.48	-2714299.12	90.839	12700.79	12643.47	1360.93	130564.40	16061.10	-18935.20	1.31313	-34540.19
9	0.06	57805.44	-2655965.60	86.834	13733.61	13697.50	1333.27	130399.89	15465.15	-16369.62	1.30279	-33628.17
11	0.08	57997.19	-2605492.93	83.391	14576.31	14628.85	1309.42	129959.05	14911.50	-14130.69	1.29192	-32776.42
13	0.10	58208.36	-2561143.99	80.392	15271.33	15456.94	1288.52	129319.82	14391.98	-12155.36	1.28072	-31976.72
15	0.12	58433.04	-2521653.92	77.749	15849.54	16196.91	1269.97	128537.45	13900.80	-10396.55	1.26932	-31222.77
17	0.14	58667.35	-2486080.96	75.397	16333.92	16860.84	1253.31	127651.92	13433.78	-8818.31	1.25781	-30509.57
19	0.16	58908.70	-2453710.41	73.286	16741.93	17458.53	1238.19	126692.58	12987.77	-7392.64	1.24626	-29833.10
21	0.18	59155.31	-2423990.67	71.378	17087.05	17998.07	1224.36	125681.28	12560.40	-6097.34	1.23473	-29190.00
23	0.20	59405.90	-2396489.79	69.641	17379.84	18486.20	1211.59	124634.42	12149.80	-4914.53	1.22326	-28577.43
25	0.22	59659.56	-2370865.01	68.050	17628.70	18928.64	1199.73	123564.48	11754.50	-3829.67	1.21187	-27992.99
27	0.24	59915.58	-2346841.22	66.586	17840.36	19330.25	1188.64	122480.97	11373.29	-2830.73	1.20059	-27434.56
29	0.26	60173.44	-2324195.24	65.232	18020.32	19695.22	1178.21	121391.17	11005.18	-1907.70	1.18944	-26900.29
31	0.28	60432.74	-2302744.34	63.974	18173.06	20027.17	1168.35	120300.71	10649.31	-1052.14	1.17842	-26388.54
33	0.30	60693.15	-2282337.54	62.801	18302.30	20329.26	1159.00	119213.91	10304.98	-256.89	1.16754	-25897.84
35	0.32	60954.39	-2262849.17	61.703	18411.14	20604.27	1150.08	118134.11	9971.55	484.18	1.15682	-25426.88
37	0.34	61216.25	-2244173.82	60.672	18502.20	20854.66	1141.55	117063.87	9648.47	1176.35	1.14625	-24974.43
39	0.36	61478.53	-2226222.51	59.701	18577.67	21082.58	1133.37	116005.12	9335.24	1824.19	1.13584	-24539.43
41	0.38	61741.09	-2208919.62	58.785	18639.43	21289.96	1125.50	114959.35	9031.41	2431.71	1.12559	-24120.86
43	0.40	62003.78	-2192200.54	57.917	18689.08	21478.53	1117.90	113927.65	8736.58	3002.40	1.11550	-23717.80

Therefore, the final parameters would be for c = 0.18:

Variable	Parameter Estimate Original	Parameter Estimate Ridge Regression
Intercept	-2865457	-2423990.67
sqft	101.27161	71.378
bath	9798.35842	17087.05
garage	10056	17998.07
year	1432.88644	1224.36
qual1	129561	125681.28
style1	17433	12560.40
style7	-25430	-6097.34
lot	1.33104	1.23473
highway	-36594	-29190.00

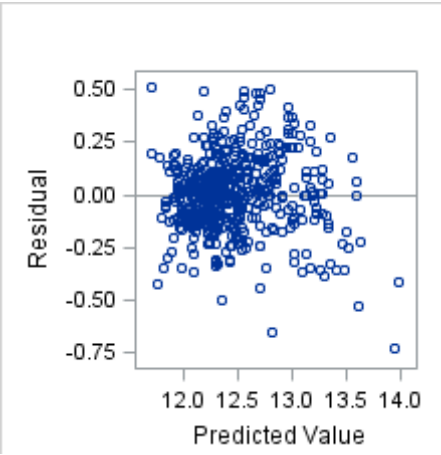
None of these changed dramatically. Therefore, in this model, there is not enough justification to say that multicollinearity affects the parameter estimates and this remedial action should NOT be performed.

(b) Did your remedial action, correct the problem? Explain your answer by displaying the appropriate plots or other SAS output.

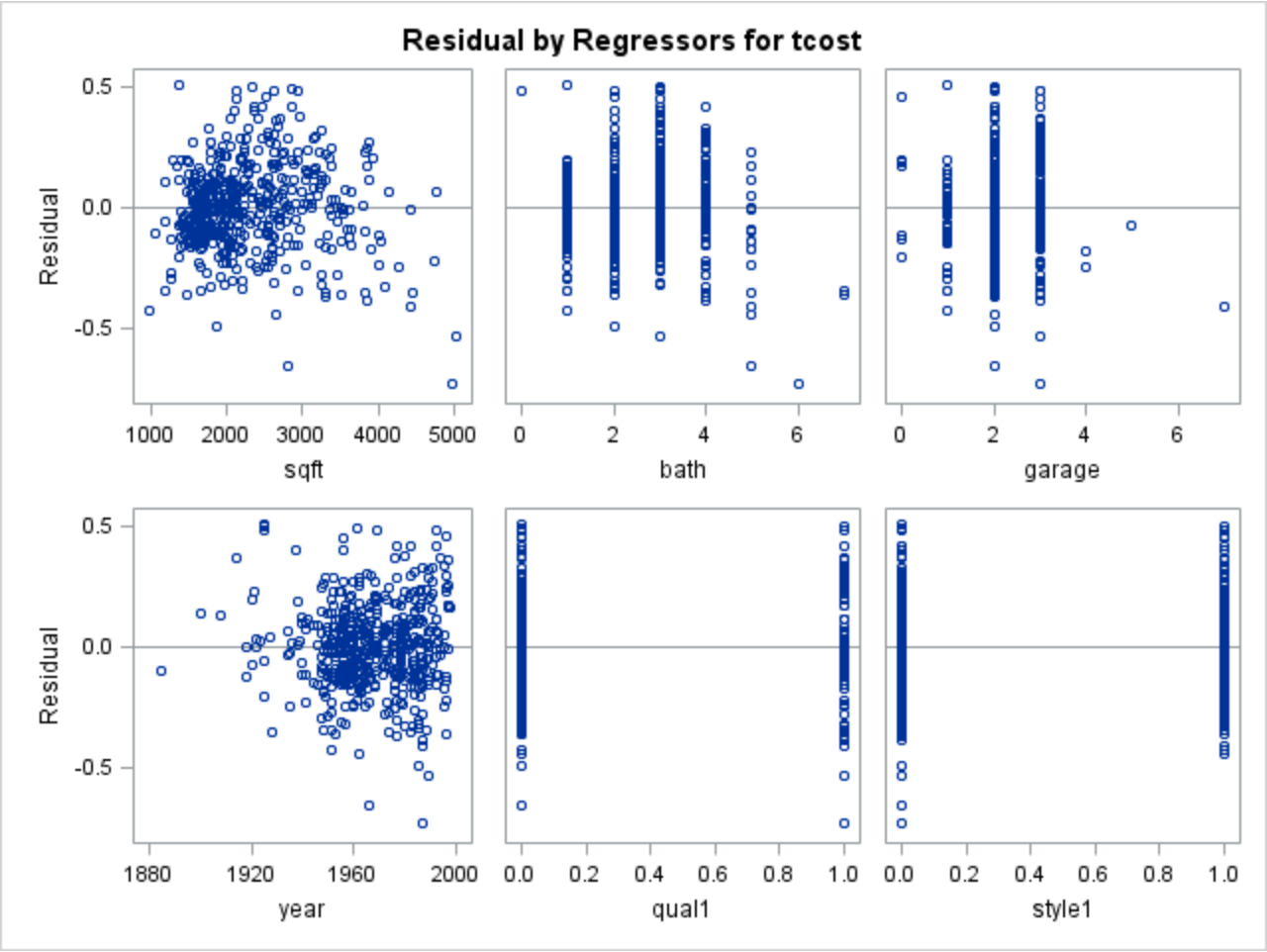
Note: The scatterplot is of the original data, so it will not change:

Y transformation

Residual Plots



In the original model, this plot might have been curved with a problem of constant variance. It looks like these problems have been corrected. There still is a problem with outliers which might have been increased.



sqft: corrected problem with constant variance. Made the outliers worse.

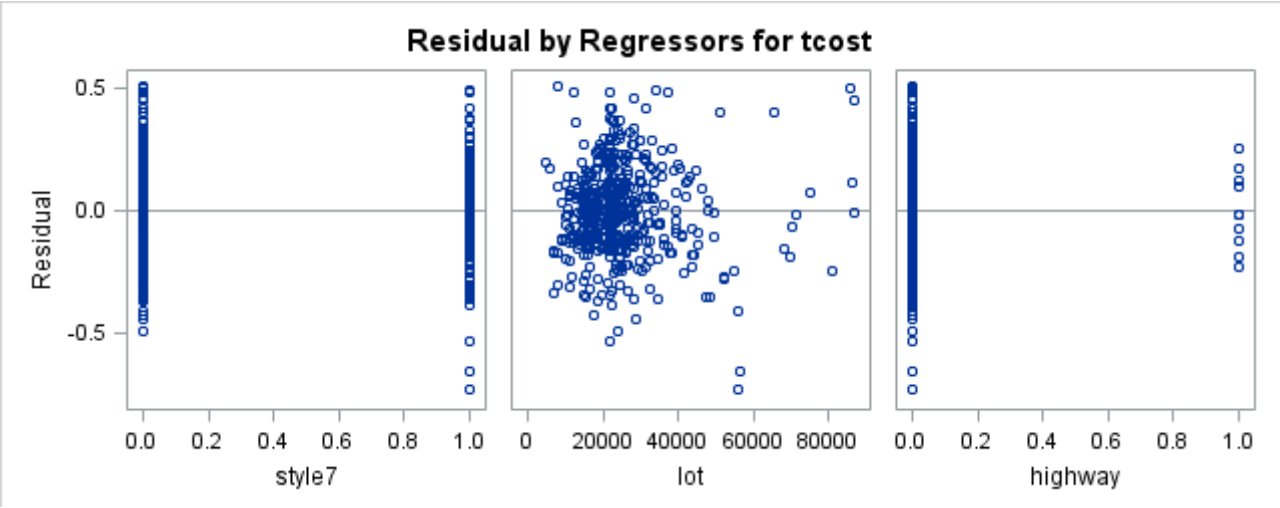
bath: corrected problem with constant variance. No change with outliers.

garage: partially corrected problem with constant variance. No change with outliers.

year: corrected problem with constant variance. Partially corrected problem with outliers..

qual1: looks ok

style1: looks ok

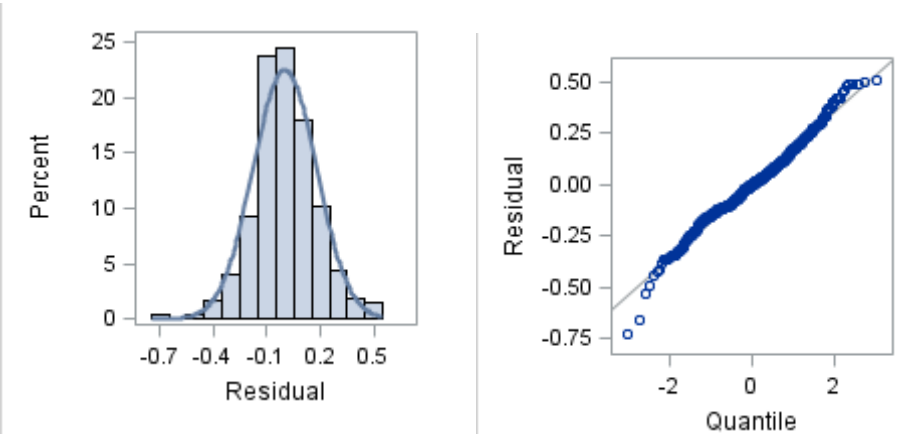


style7: looks ok, possibly increased a problem with outliers

lot: The variance is more constant then before. there is still a problem with outliers.

highway: It helped correct the problem with constant variance, but there is still a problem.

Normal Plots



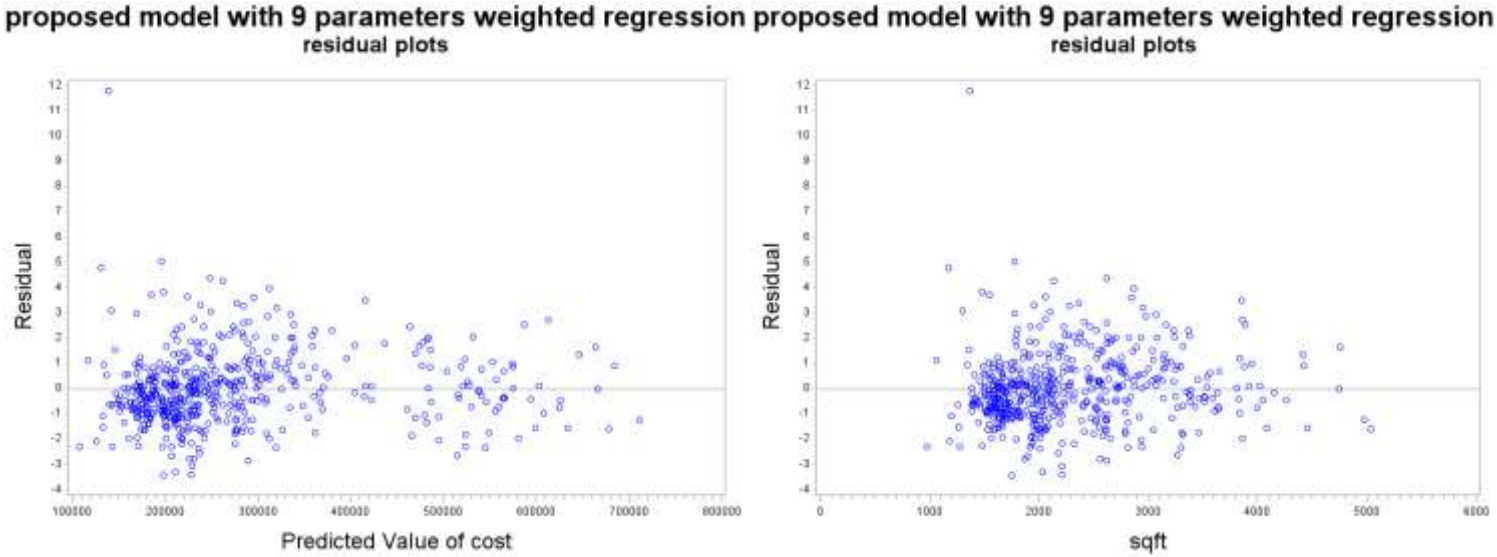
This is close to being corrected well enough for the assumption to be considered valid

Conclusion: It looks like this remedial action did correct most of the problems but there is still a problem with constant variance with the garage predictor. The problems with the outliers still remain.

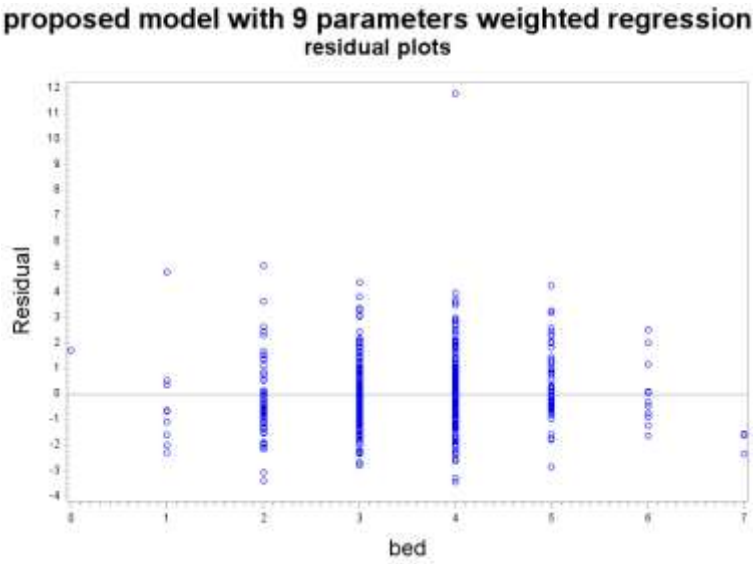
Weighted Least squares

|resid|

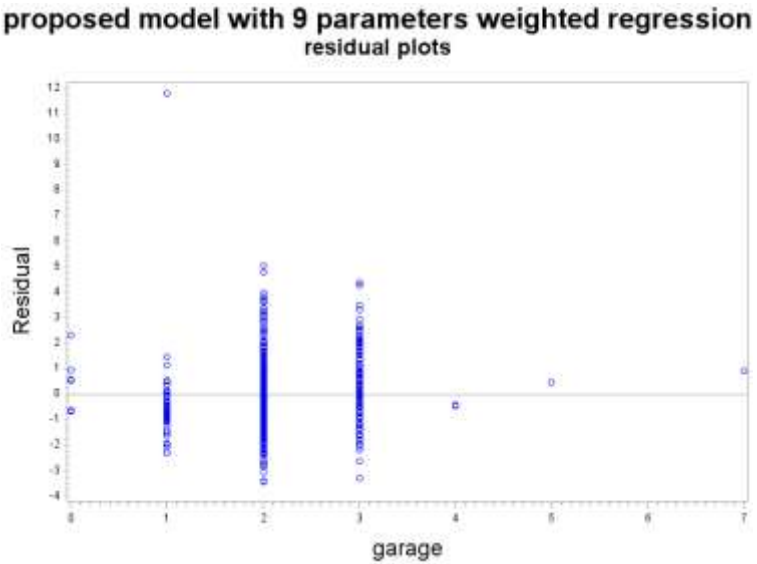
residual plots



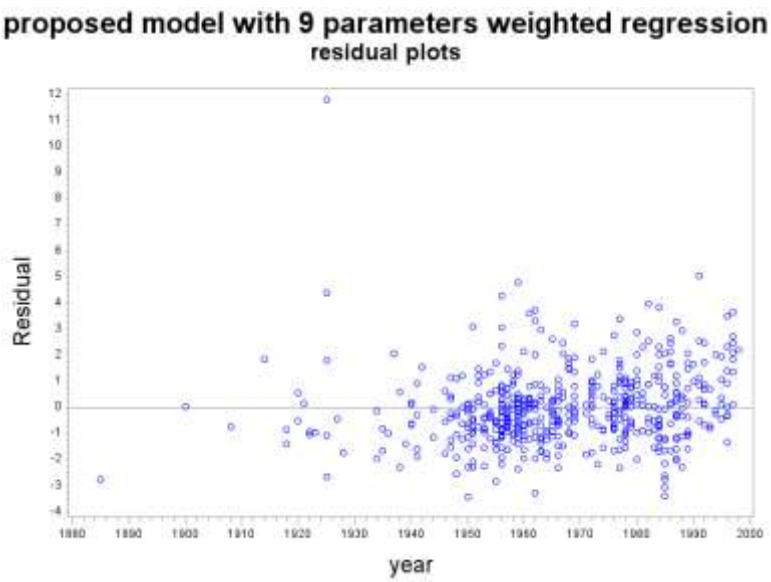
It looks like the problem with constant variance is corrected. However, there is one very bad outlier.



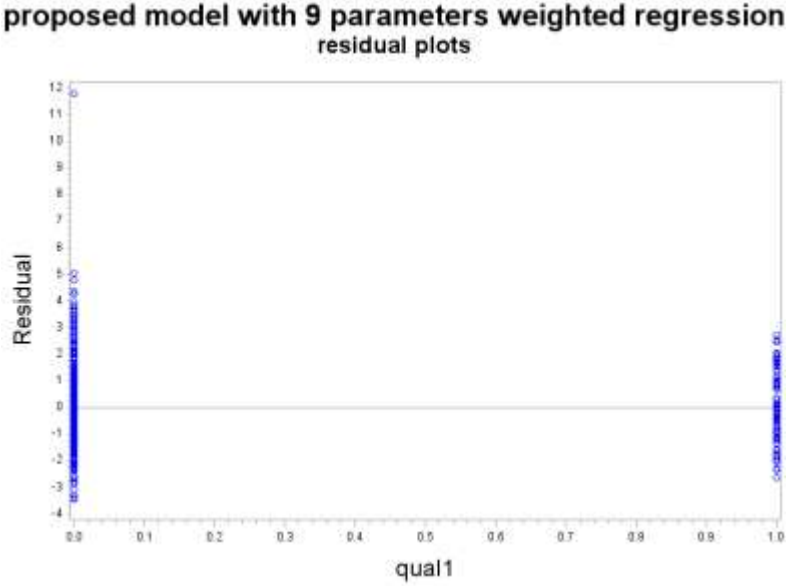
Constance variance: corrected, bad outlier



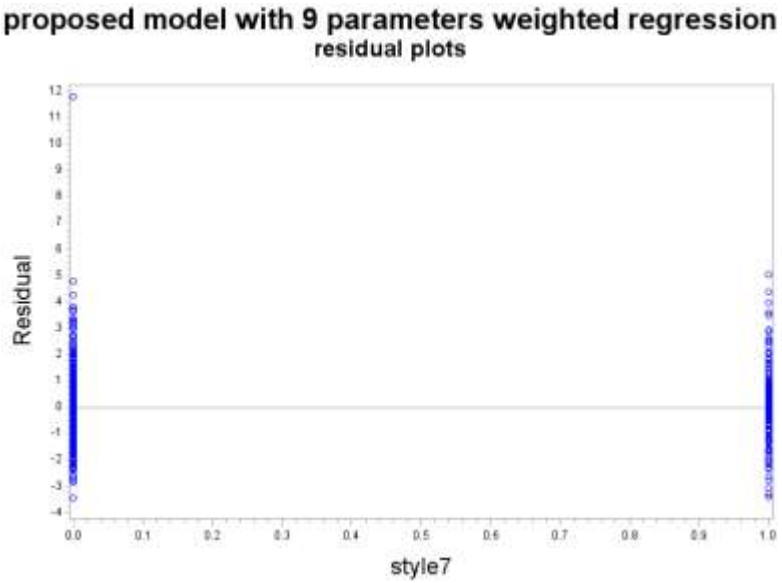
Constant variance better, bad outliers.



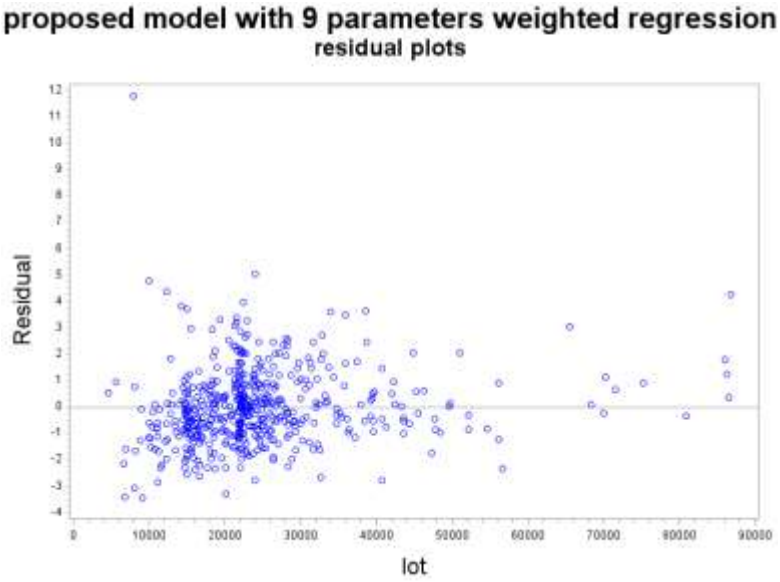
Constant variance better, bad outlier



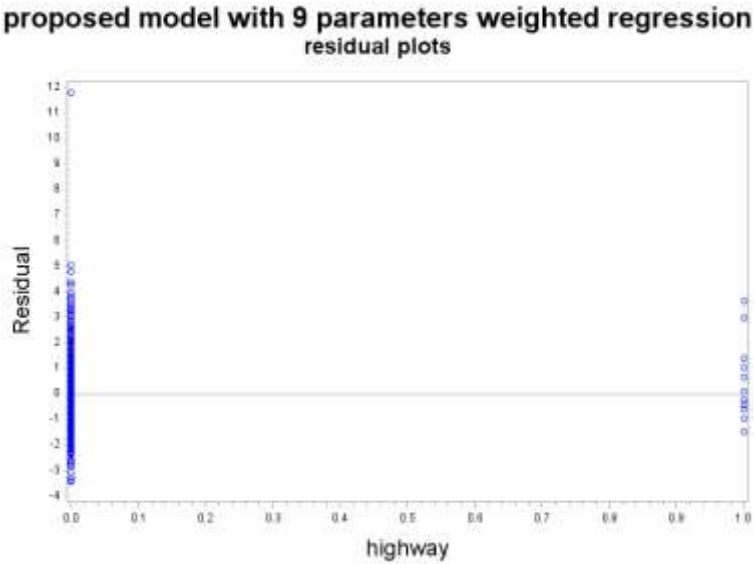
Constant variance better.



Corrected

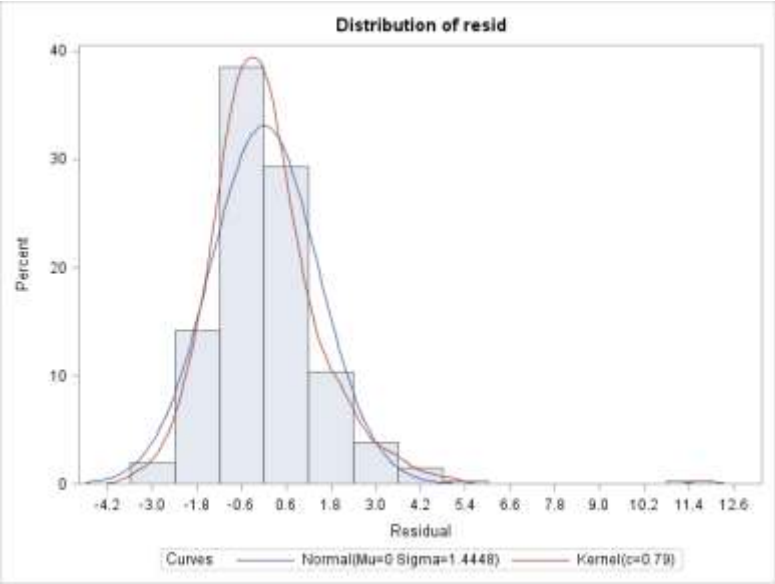


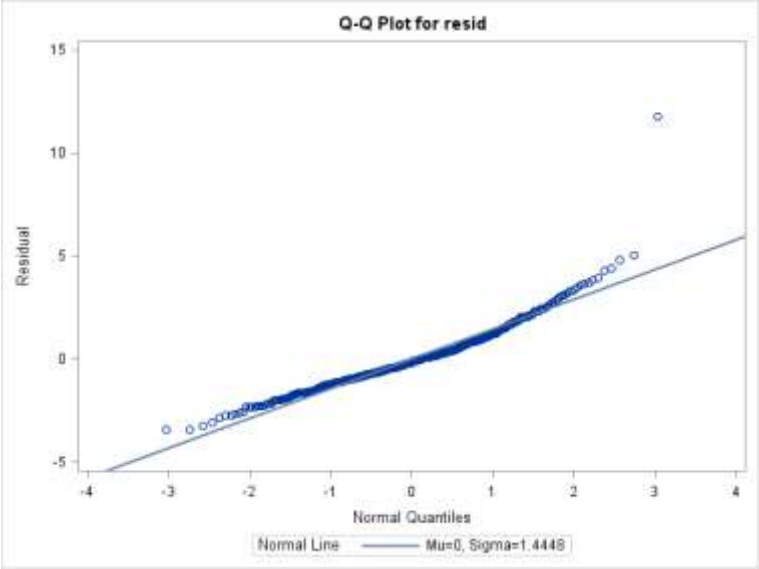
Constant variance corrected, bad outlier.



Constant variance better.

normality plots

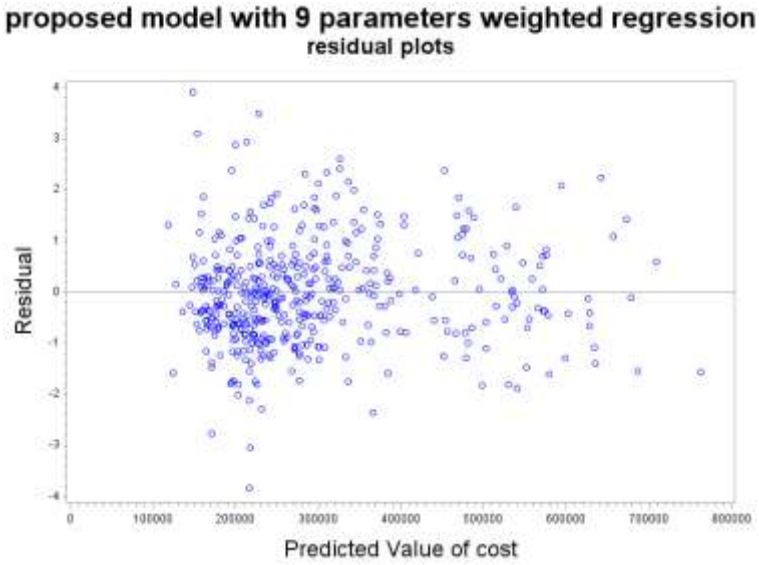


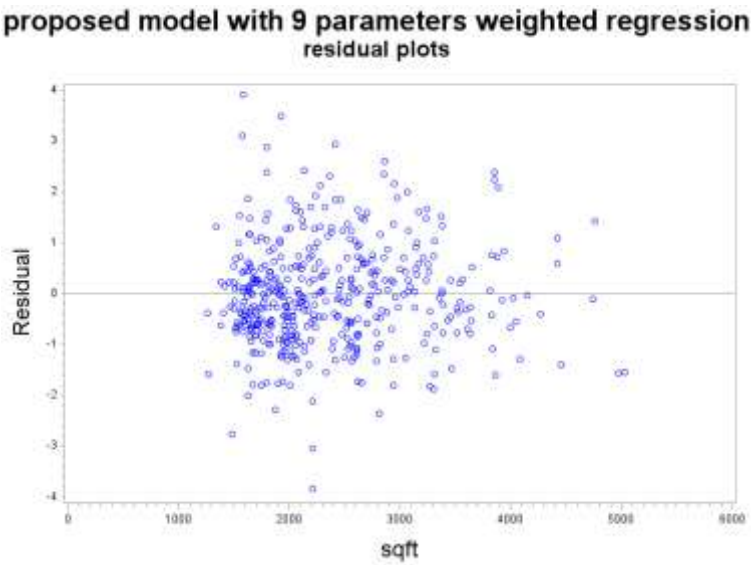


Now, the data looks slightly right skewed, but this is due to one outlier.

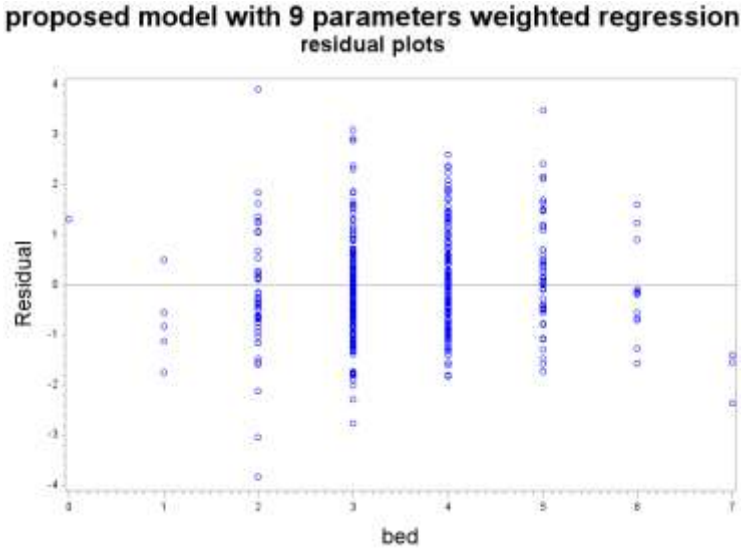
resid^2

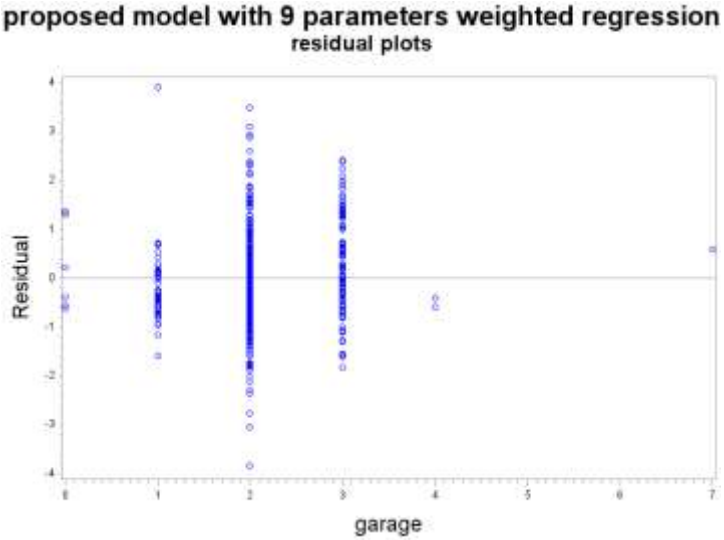
residual plots



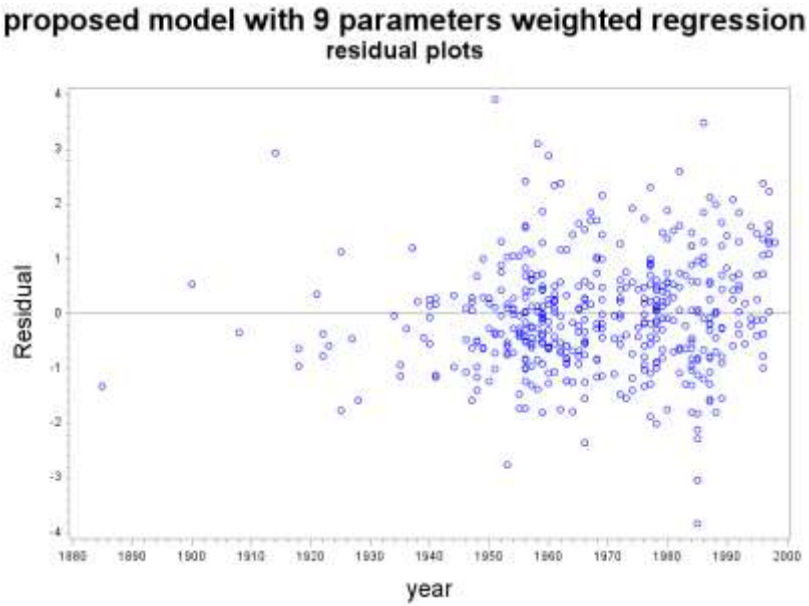


problems have been corrected.

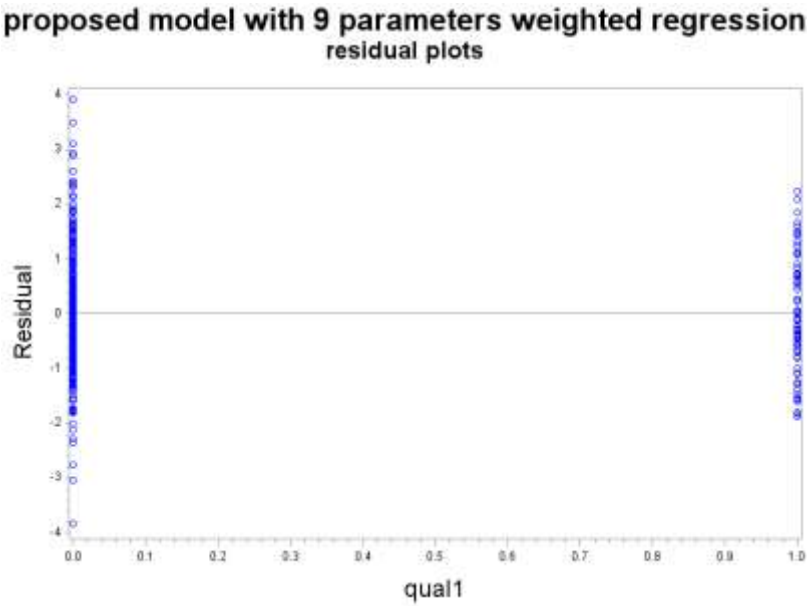




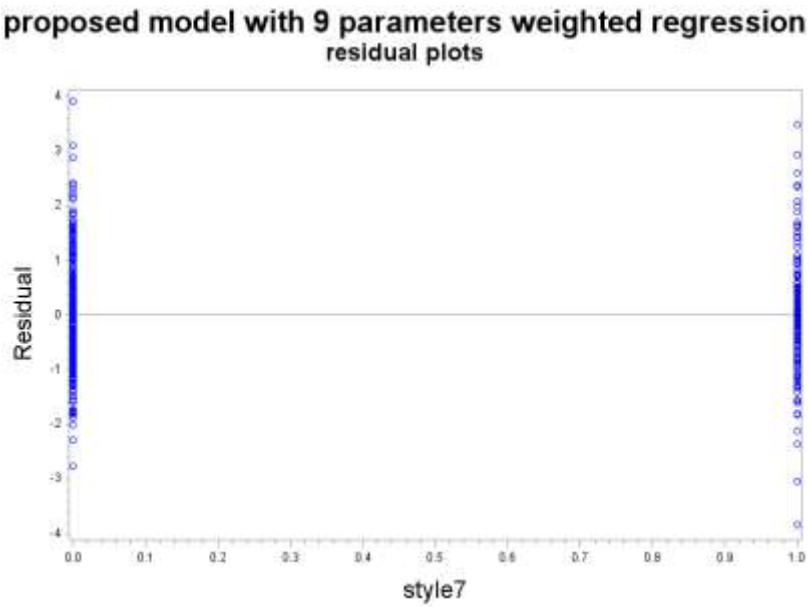
Constant variance seems to be mostly corrected, but there is still a problem with outliers.



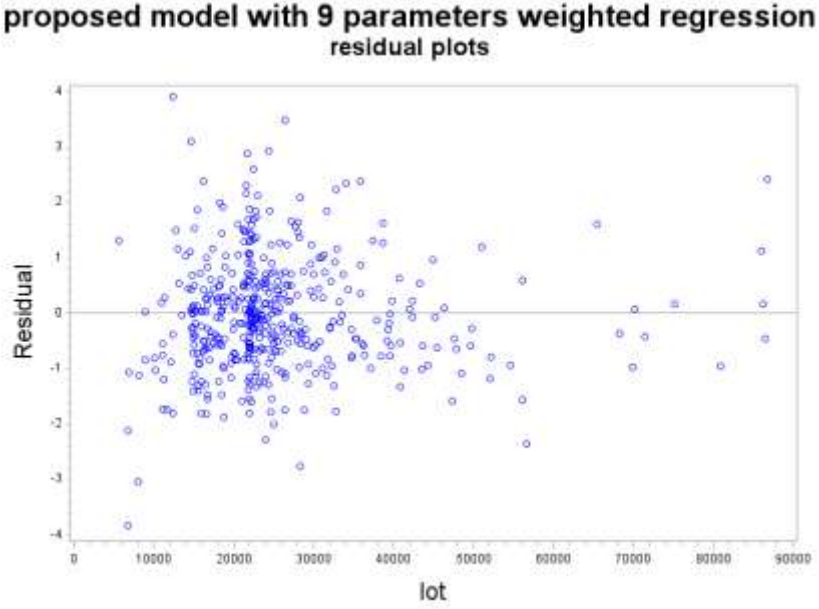
Constant variance is better, still outliers



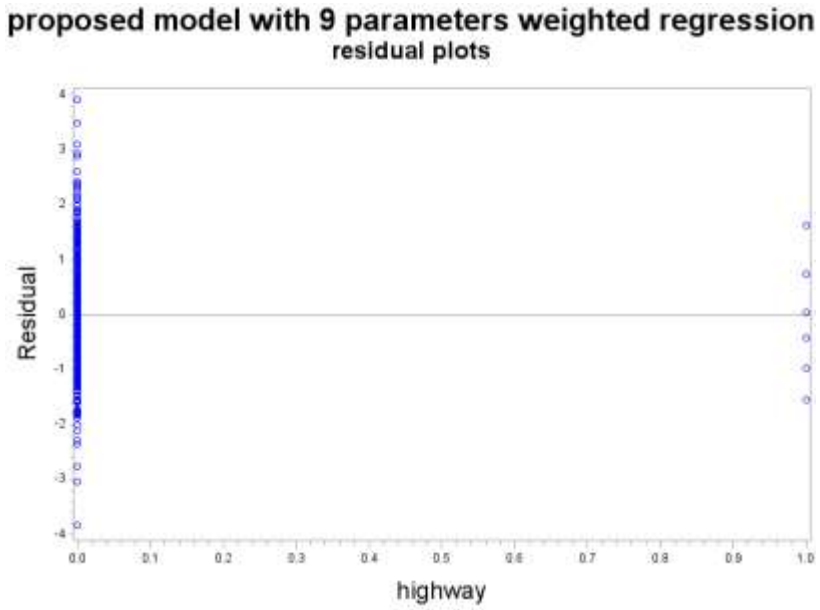
Constant variance better. No outliers



Constant variance corrected. No outliers

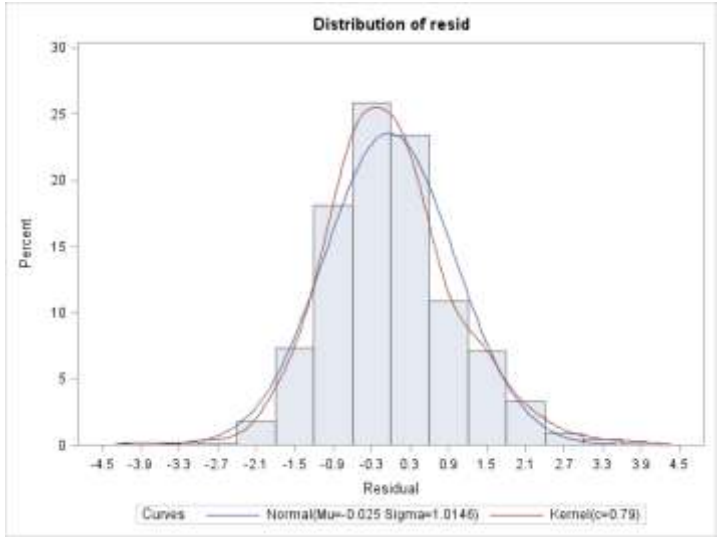


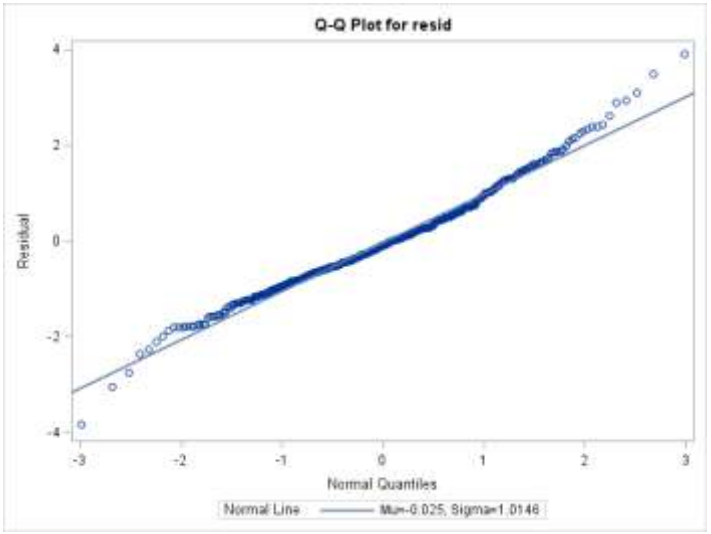
Constant variance corrected, still outliers.



Constant variance better, still a problem with highway = 1

normality plots





The normality is slightly improved, but still a problem with long tails.

Because |resid| plots have a very bad outliers and resid^2 plots don't have this problem, the better weighting system is with resid^2.

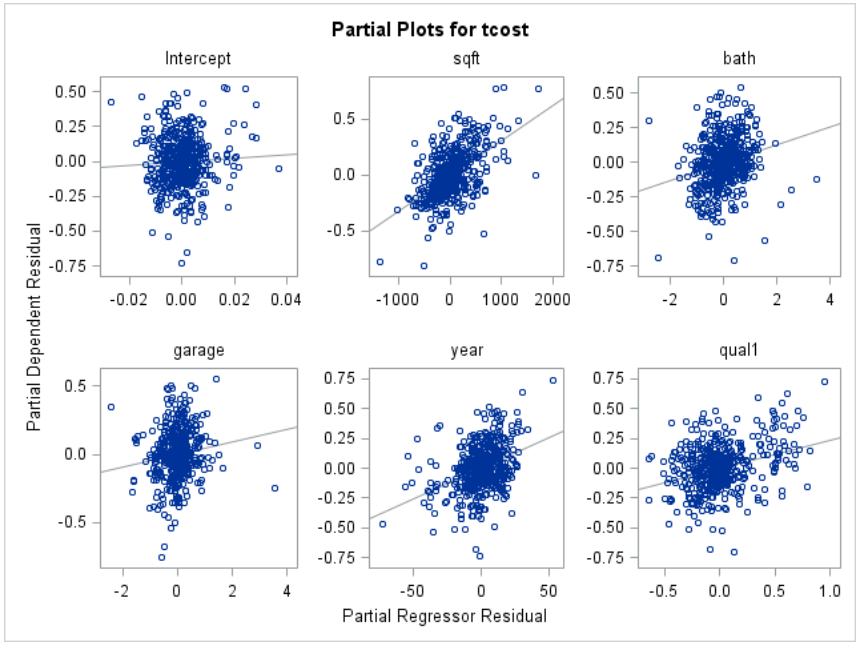
Ridge Regression

Since this method does not correct a problem with assumptions, no output is required.

(c) Regenerate any of the other parts (a) – (e) in question 6 that are required to be sure that all of the assumptions are met. Again, comments are necessary on all plots. If any assumptions are still not met, what would you do next to correct the problem? Please explain your answer. YOU DO NOT NEED TO PERFORM ANY MORE REMEDIAL ACTIONS!

Y transformations

I am not going to redo the outlier/influential points information because we didn't perform a full analysis of the points in the first place. The only additional plots required are for the partial regression plots.



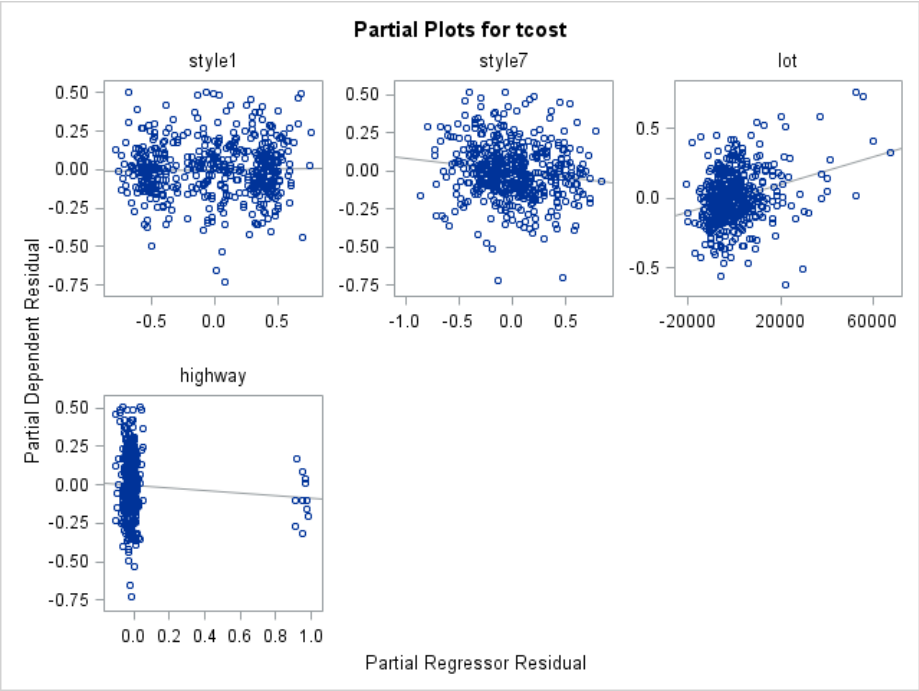
sqft: this is definitely significant, it does look linear and the problems with the outliers seems to be less.

bath: this is significant and again there is a problem with the outliers.

garage: this is significant and again there is a problem with the outliers.

year: this is significant and again there is a problem with the outliers. It looks like the curvature has been corrected.

qual1: this is significant and it looks like the problems with the outliers is less than before.



style1: this does not look significant

style7: this looks significant and there is a problem with outliers.

lot: this is significant and again there is a problem with the outliers.

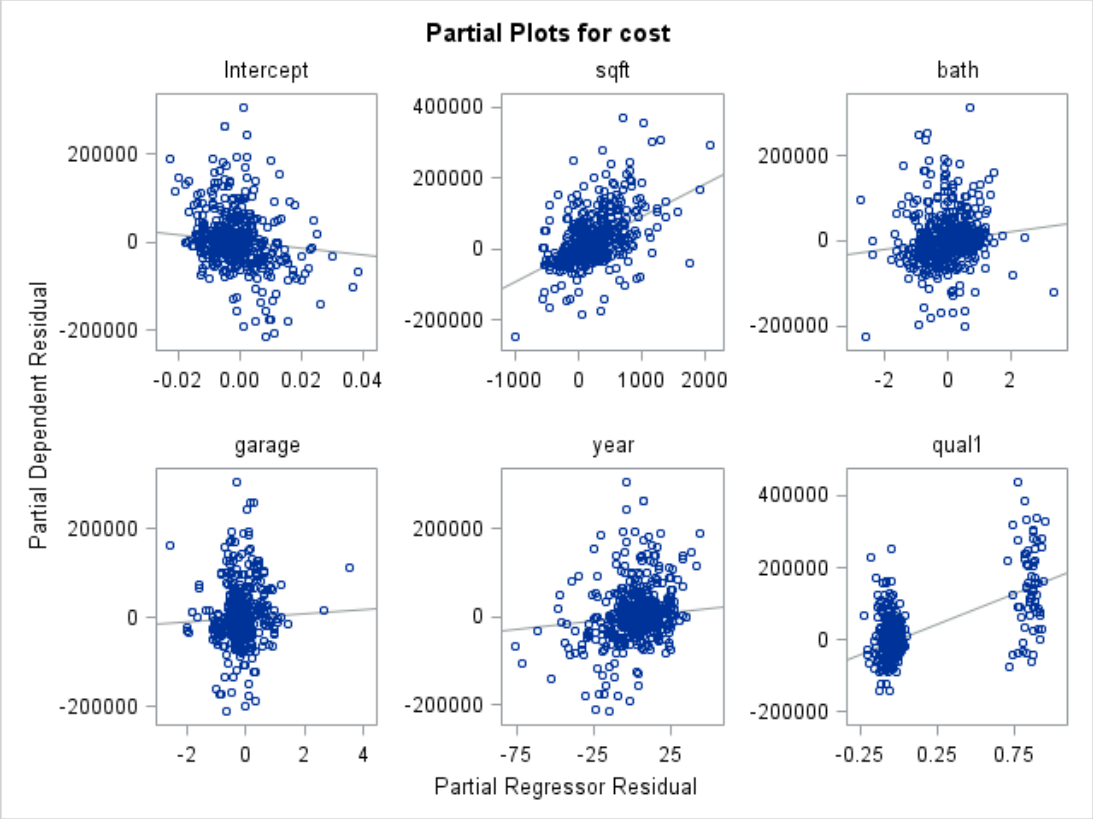
highway: this is hard to tell because of the small number of points at 1.

This method makes the assumptions more appropriate.

WLS

I am not going to redo the outlier/influential points information because we didn't perform a full analysis of the points in the first place. The only additional plots required are for the partial regression plots.

|resid|



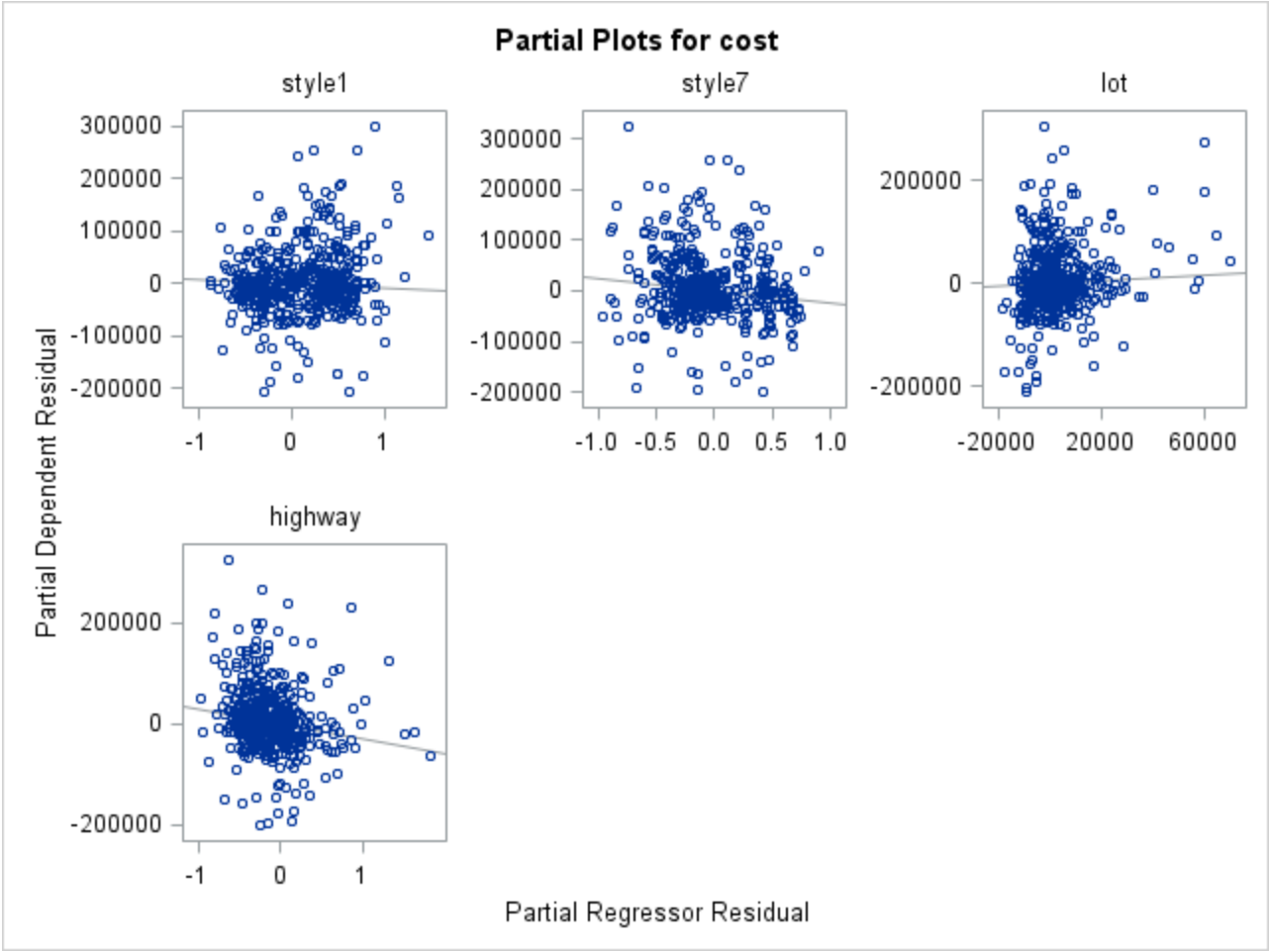
sqft: this is definitely significant, it does look linear and the problems with the outliers seems to be less.

bath: this is significant and again there is a problem with the outliers.

garage: this seems to make it more bunched up so there is more of a problem with outliers then before.

year: similar to garage, this seem to increase the problem with the outliers.

qual1: this separated this variable into two distinct groups.



style1: this does not look significant and made the outliers worse.

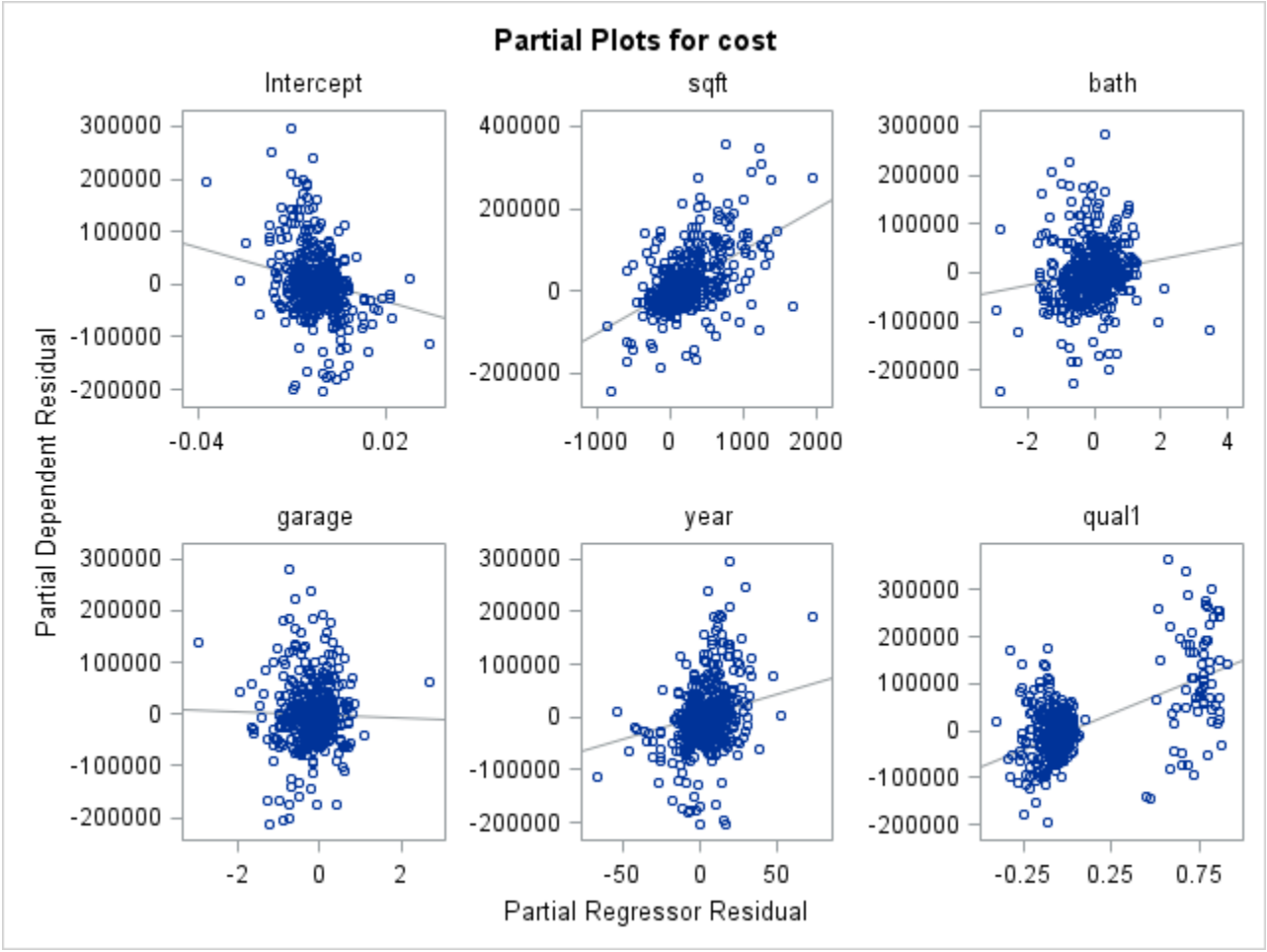
style7:this looks significant and increased the problem with outliers.

lot: this is less significant and increased the problem with outliers.

highway: this made this better and more linear though there is still a problem with outliers.

In general, this method made the outliers worse so I would not use this particular weighting scheme.

resid^2



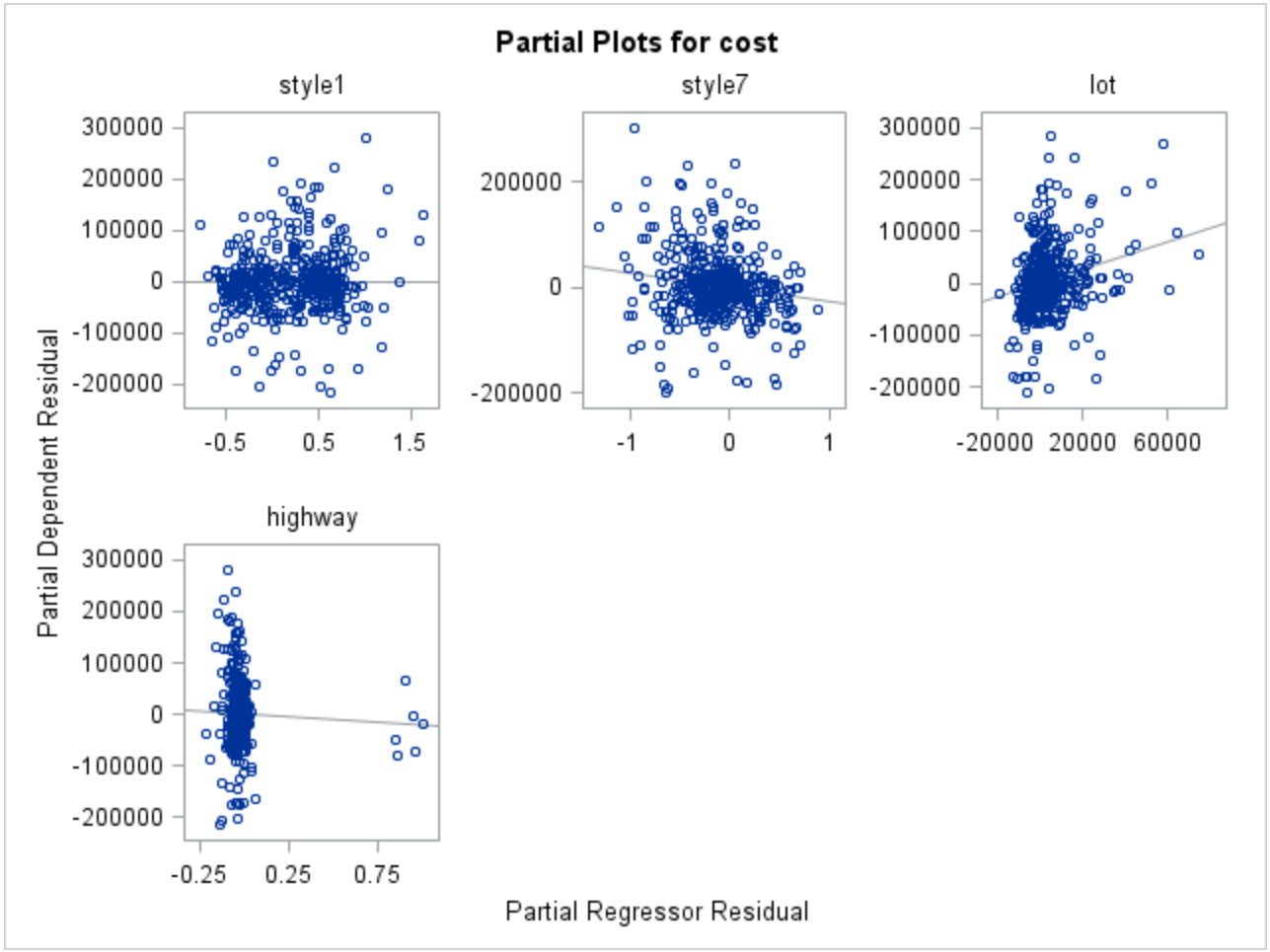
sqft: this is definitely significant, it looks like there is some curvature now and the variance is larger.

bath: this is significant and it looks like there is a serious problem with the outliers.

garage: this is more spread out but there are still outlier problems.

year: this looks a little more bunched up so it increases the problem with the outliers.

qual1: this separated this variable into two distinct groups.



style1: this does not look significant and made the outliers worse.

style7:this looks significant; the problems with the outliers is similar to before

lot: this is more bunched up so the problems with the outliers increases.

highway: improves the situation a little.

This method does help with the assumptions though there are still serious problems.

Ridge Regression

Since this method does not correct a problem with assumptions, no output is required.

Further remedial action: There is still a problem with constant variance, so performing a weighted regression with different weighting method or a non-parametric regression might be needed. In addition, the large number of outliers in this data set might be causing both the problem with constant variance and normality. I would look at the outliers/influential points in more detail and see if the points really do look influential. A possible remedial action for this is to rerun the analysis without the outlying points (one at a time) and see if the results change. In addition, robust regression might be performed or another method that is not as influenced by these points.

8. (13.5 pts.) Finally, we need to summarize our results using the specifics of the variables.

(a) Give the equation of the fitted regression using the selected explanatory variables.

Y transformation:

ln Y= 1.24883 + 0.00031482 sqft + 0.06331 bath + 0.04499 garage + 0.00513 year + 0.23533 qual1 + 0.01028 style1 - 0.08416 style7 + 0.00000490 lot - 0.08961 highway

Weighted Regression (using |resid|)

Y_i = -752979 + 91.34065 sqft + 10107 bath + 4213.24024 garage + 389.67565 year + 172119 qual1 – 7983.77329 style1 – 23863 style7+ 0.26115 lot – 29805 highway

(b) If there is a indicator variable left in the model (Air conditioning, Pool, Quality, Style, Adjacent to highway), give the equation with and without that variable and using the estimated regression coefficient explain how the variable predicts the final sales price. Does this make sense? Explain your answer.

I am just going to do the analysis for the Y transformation equation. The results are similar for the weighted least regression.

There are four indicator variables in the model, highway, qual1, style1 and style7.

Highway:

Highway = 0 (not adjacent to a highway)

ln Y= 1.24883 + 0.00031482 sqft + 0.06331 bath + 0.04499 garage + 0.00513 year + 0.23533 qual1 + 0.01028 style1 - 0.08416 style7 + 0.00000490 lot - 0.08961 highway

highway = 1 (adjacent to a highway)

ln Y= 1.24883 + 0.00031482 sqft + 0.06331 bath + 0.04499 garage + 0.00513 year + 0.23533 qual1 + 0.01028 style1 - 0.08416 style7 + 0.00000490 lot - 0.08961

= 1.15922 + 0.00031482 sqft + 0.06331 bath + 0.04499 garage + 0.00513 year + 0.23533 qual1 + 0.01028 style1 - 0.08416 style7 + 0.00000490 lot

Because there are no interaction terms, this has the effect of decreasing the intercept. The coefficient is negative which means being adjacent to the highway decreased the cost. This makes sense because the area around the house is more congested, etc. To me, I want to be close to the main roads, but not on them; again this is personal preference.

Qual1

Qual1 = 0 (low or medium quality)

ln Y= 1.24883 + 0.00031482 sqft + 0.06331 bath + 0.04499 garage + 0.00513 year + 0.01028 style1 - 0.08416 style7 + 0.00000490 lot - 0.08961 highway

qual1 = 1 (high quality)

ln Y= 1.48416 + 0.00031482 sqft + 0.06331 bath + 0.04499 garage + 0.00513 year + 0.01028 style1 - 0.08416 style7 + 0.00000490 lot - 0.08961 highway

Because there are no interaction terms, this has the effect of increasing the intercept. The coefficient is positive which means that if the quality of the house is high the house costs more. This makes sense.

Style1

Style1 = 0 (all styles except 1)

ln Y= 1.24883 + 0.00031482 sqft + 0.06331 bath + 0.04499 garage + 0.00513 year + 0.23533 qual1 - 0.08416 style7 + 0.00000490 lot - 0.08961 highway

style1 = 1 (style 1)

ln Y= 1.25911 + 0.00031482 sqft + 0.06331 bath + 0.04499 garage + 0.00513 year + 0.23533 qual1 - 0.08416 style7 + 0.00000490 lot - 0.08961 highway

This data implies that if the house has style 1, it costs more. Since I don't know what that style is, I can't state if it makes sense or not.

Style7

Style7 = 0 (all styles except 7)

ln Y= 1.24883 + 0.00031482 sqft + 0.06331 bath + 0.04499 garage + 0.00513 year + 0.23533 qual1 + 0.01028 style1 + 0.00000490 lot - 0.08961 highway

style7 = 1 (style 7)

ln Y= 1.16467 + 0.00031482 sqft + 0.06331 bath + 0.04499 garage + 0.00513 year + 0.23533 qual1 + 0.01028 style1 + 0.00000490 lot - 0.08961 highway

This data implies that if the house has style 7, it costs less. Again, I can't state if it makes sense or not.

(c) For the continuous variables, explain how each variable predicts the final sales price. Does this make sense? Explain your answer.

sqft: this has a positive slope which makes sense, the larger the square feet, the sales price is higher.

bath: again, this has a positive slope which makes sense, the more bathrooms, the sales price is higher.

garage: this makes sense for the same reason as before.

year: the newer the house, the higher the sales price.

lot: the larger the lot, the higher the sales price.

(d) To me (having recently bought a house), all of the predictor variables are important in the sales price. Can you think of a reason why not all of the predictors are in the final model. (Possible reasons: multicollinearity, all houses have it, very few houses have it, variety of preferences.) There should be one statement per predictor variable NOT in the final model.

number of bedrooms: A reason why this might not be included is because this is related to the number of bathrooms and size of the house. There was a pairwise correlation in this study.

air conditioning: Maybe an equal number of people wanted it or didn't want it. I did check the data, not all of the houses had air conditioning. However, most of them did include it.

Pool: Again, this might be a non-issue because of different preferences of the buyers. If you don't want a pool and the house has a pool, it might lower the price. If you want a pool and the house doesn't have a pool it could lower the price, etc.

quality: A reason why low quality is the only one that is included is that most people cannot determine the difference between medium and high quality when buying a house.

style: Since we don't know what the individual styles are, it is hard to answer this part. However, this could go back to personal preference. For example, when I bought a house, I wanted a 'split design' one story. However, if there are young kids, it might be preferable to not have the split design with more than one story.

(e) **Though we are not including any interaction terms in this model, can you think any of the possible interaction terms might have been important in this model? Why or why not? (You just need to include one possibility.) Rerun your chosen model given in part a) including your chosen interaction term (remember that both of the first order terms need to be included if they are not already there). Is this interaction term important? Please comment.**

I can think of a couple of obvious interactions that might be relevant in this study.

1) number of bedrooms/number of bathrooms – think about this situation, if there are two bedrooms then there might be little difference between the price of 1 and 2 bathrooms, however, if there are 3 bedrooms, I would expect the price to be much lower for 1 bathroom versus 2 bathrooms.

2) square feet/lot size: I would hope that the lot size is a certain percentage larger than the square feet of the house.

3) pool/square feet/lot size: If there is a pool, the lot size should be even larger.

4) bedrooms/garage: If there are more bedrooms, there might need to be a larger garage.

I am sure there are other interaction terms that might have been important in this model. This part is going to be graded on if the reason makes sense.

Results using the Y-transformed data.

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	11	81.56512	7.41501	243.70	<.0001
Error	510	15.51780	0.03043		
Corrected Total	521	97.08292			

Root MSE	0.17443	**R-Square**	0.8402
Dependent Mean	12.43463	**Adj R-Sq**	0.8367
Coeff Var	1.40280		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	**1**	1.17299	1.08649	1.08	0.2808
sqft	**1**	0.00032702	0.00002191	14.92	<.0001
bed	**1**	0.09630	0.01975	4.88	<.0001
bath	**1**	0.17982	0.02473	7.27	<.0001
garage	**1**	0.03334	0.01502	2.22	0.0269
year	**1**	0.00500	0.00055727	8.97	<.0001
qual1	**1**	0.25353	0.03112	8.15	<.0001
style1	**1**	0.02323	0.01894	1.23	0.2205
style7	**1**	-0.07115	0.02420	-2.94	0.0034
lot	**1**	0.00000503	6.999645E-7	7.19	<.0001
highway	**1**	-0.10695	0.05404	-1.98	0.0483
bedbath	**1**	-0.03453	0.00632	-5.46	<.0001

In this model, the interaction term IS important because the interaction term has a P-value of <0.0001. See my explanation above concerning why this is relevant. Remember that even though bed was originally not significant, it still needs to be included in the model because we added the interaction term. Since bed is now significant, this means that this is not an appropriate method of adding interaction terms. The preferred method is to include all of the interaction terms in the original model and then perform the model selection and continue the project from there. I did not use this method in this project because of the complexity of the full model even if you only include pairwise interactions.

Note: To perform this step with the weighted regression, the following steps are required: 1) Generate the new weights using the different model (you may use the same methodology either |resid| or $resid^2$ as before, 2) run the regression.

Instead of adding the interaction term AFTER remedial actions were performed as was stated in the project, this should really be added before the remedial actions were performed in step 7. The following is the output from the model of

$Y= \beta_0 + \beta_1$ sqft $+ \beta_2$ bed $+ \beta_3$ bath $+ \beta_4$ garage $+ \beta_5$ year $+ \beta_6$ qual1 $+ \beta_7$ style1 $+ \beta_8$ style7 $+ \beta_8$ lot $+ \beta_9$ highway $+ \beta_{10}$ bed*bath

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	11	8.247384E12	7.497622E11	229.86	<.0001
Error	510	1.663528E12	3261819101		
Corrected Total	521	9.910912E12			

Root MSE	57112	**R-Square**	0.8322
Dependent Mean	277894	**Adj R-Sq**	0.8285
Coeff Var	20.55183		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	**1**	-2853418	355734	-8.02	<.0001
sqft	**1**	105.79513	7.17443	14.75	<.0001
bed	**1**	9727.78050	6465.37974	1.50	0.1330
bath	**1**	29338	8095.37168	3.62	0.0003
garage	**1**	8448.32919	4917.26528	1.72	0.0864
year	**1**	1405.39805	182.45805	7.70	<.0001
qual1	**1**	129928	10190	12.75	<.0001
style1	**1**	18349	6200.29441	2.96	0.0032
style7	**1**	-24326	7923.78392	-3.07	0.0023
lot	**1**	1.36095	0.22918	5.94	<.0001
highway	**1**	-38701	17694	-2.19	0.0292
bedbath	**1**	-5266.53432	2069.92765	-2.54	0.0112

This time the interaction term is still significant (and style1), but bed, garage are not significant. Remember, bed is required to be in the model. Again, you can see that adding additional terms does change which factors are significant. Please keep this in mind when you are doing model selection in your future career. It is a very complicated process to figure out which predictor variables are significant and the answer is not necessarily unique. Therefore, you need to be very careful when you report your conclusions.