

Top Kaggle STAT E-104 Project

Jeff Collier*

4 MAE 2015

The Challenge

Given some data on home sales, we're to demonstrate our ability at modeling using linear regression. Building on that, use the model to estimate the prices of houses represented by a smaller set of data as part of a challenge.

The only real trick to cooking is to pick good ingredients and make sure you don't screw them up. One mantra from the TV series Top Chef is if it didn't work, don't serve it. I have a feeling those may be conflicting goals modeling these data. Still, they are the guidelines that will inform my actions. That said, let's take a look at what we have in the pantry.

The Data

The data is described in Table 1. I renamed some of the original variables because \LaTeX sucks at random underscores. One of the first steps to a regression analysis is to look at each variable. I'll break the data up into groups and get a taste of each of them individually.

salesprice, pl

Let's start with a taste of what we are trying to predict, *salesprice*. Some strong hints and ex-

*but on Kaggle they call me Maurice

ploratory regressions indicated that transforming *salesprice* might be a good idea. Stata's reports via detailed summary that the skewness of *saleprice* is > 0.97 ; this is greater than our 0.8 rule of thumb for requiring transform. Regression estimates are really the mean of a normal distribution. If the actual underlying data is skewed, our estimate are more likely to be more off. It was nigh on impossible to get exploratory regressions of *salesprice* to pass Stata's *sktest*.

We see from Figure 1 that *salesprice* is skewed towards larger values and has a few outliers. We will leave outliers in the mix for now: removing them would restrict the range of values we could predict for.

Given that it is likely we'll need to eventually transform *salesprice* we will use $pl = \ln(\text{salesprice})$ as our dependent variable going forward. We see from Figure 2* that a natural log transform gives us a roughly normal fit.

This will force us to adjust our interpretations of the coefficients[†]. Using the log means coefficients represent the percentage change in our dependent variable based on change in the predictor. But this is better than restricting the range of values our model can reasonably predict for.

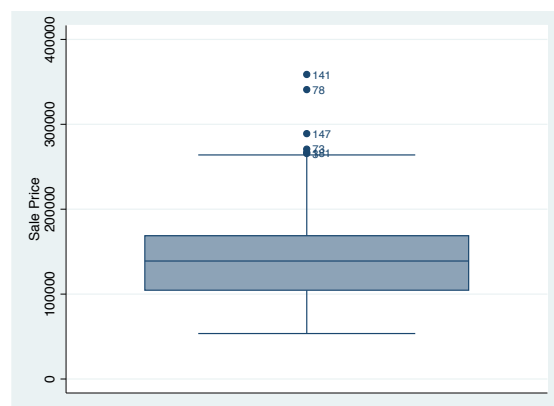


Figure 1: salesprice

*This plot gives us a line that, if the distribution were normal, the scattered points would fall on or near.

[†]I learned what I know of this from "<http://www.biostathandbook.com/transformation.html>" but all misunderstanding are my own.

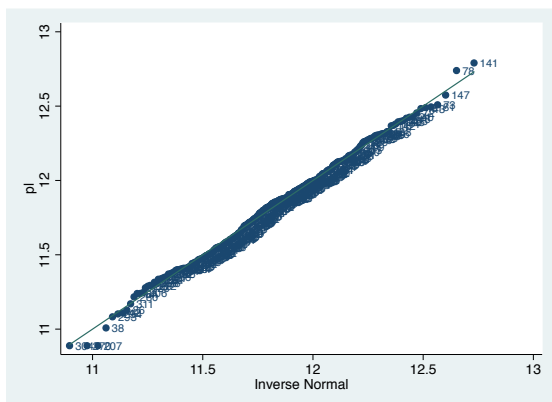


Figure 2: Transformed Sales Price

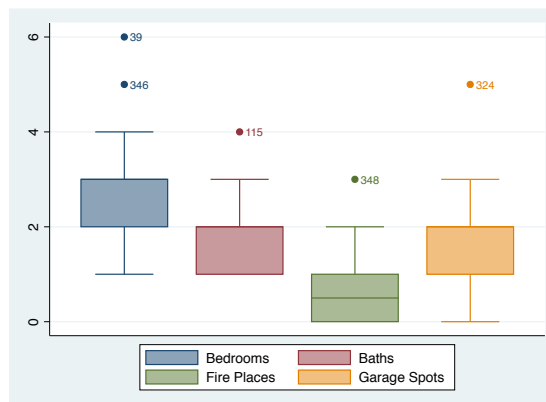


Figure 4: Bedrooms, baths, fire places, garage spots

Month Sold

Month sold would seem to be a better predictor of volume of sales, not price. Examining sales price by month in Figure 3 shows a more uniform distribution of sales price. Both the middle 50% of the price of homes sold and the remaining data all overlap to some degree, many to a large degree. I plan on ignoring this variable.

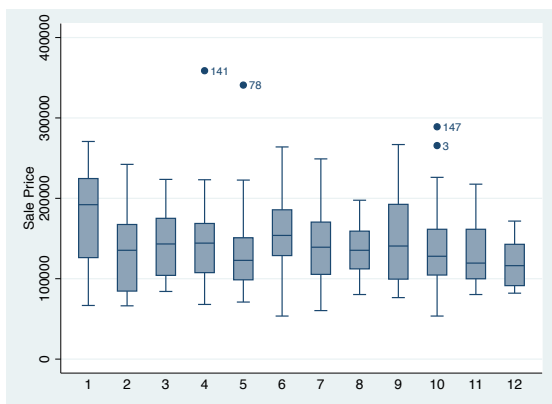


Figure 3: Sales price by month sold

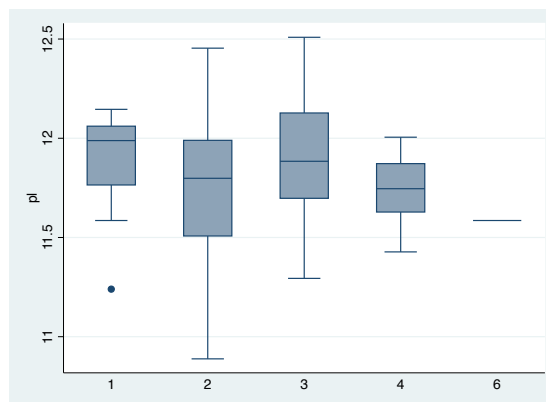


Figure 5: Variance of pl over bedrooms

The Counts

Baths, bedrooms, fire places and garage spots: these counts would all seem likely predictors of sales price, worth the trouble of mining. I expect that the sale price would increase as these values increase. But Figure 4 shows that there isn't much variance in these data. Also, the distribution fire places is skewed, so I added an indicator variable, fpp, if it has one or more. Bed rooms is also a curiosity: observe the variance of pl over each value in Figure 5. This explains why this variable had a negative coefficient in exploratory regressions.

Age

Age is a continuous variable that negatively affects the price of the house, as seen in Figure 6. Transforming by ln only seems to have traded one curve for another (Figure 7), but exploratory regressions using the two different variables show that while *age* doesn't pass Stata's *ovtest* and *hettest* for linearity and heteroscedasticity, *aget* is suitable for regression on its own.

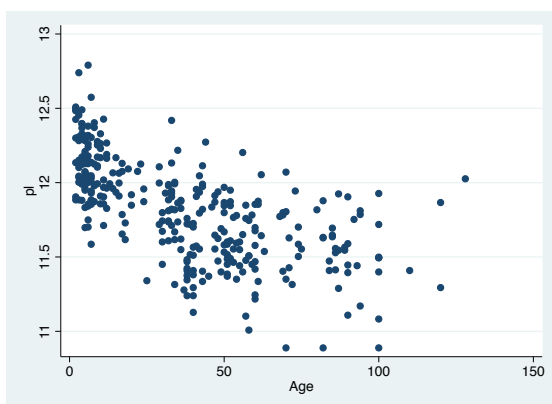


Figure 6: Curvy scatter of Age

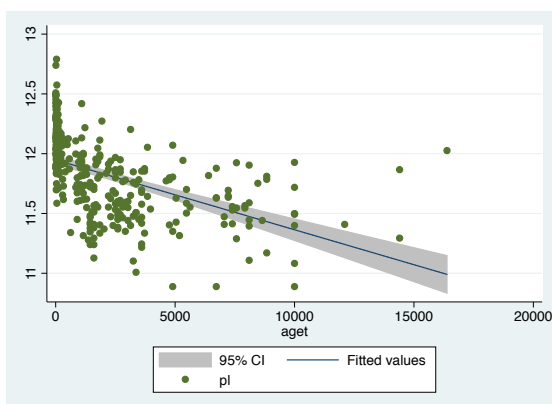


Figure 7: Curvy scatter of transformed Age

Central Air Conditioning

While most homes have this, there is clearly a differential in the Figure 8. This was confirmed by a two sample t-test. Given $H_0 : \mu_{cac=1} = \mu_{cac=0}$; $H_a : \mu_{cac=1} > \mu_{cac=0}$ resulted in $p < 0.0001$ which means we reject the null hypothesis; homes with central air sell for more.

This could be a useful indicator variable but only five of 319 homes in modeling data don't have it. While the three "outliers" shown on this graph represent price outliers, they were culled since they won't help stata with this variable.

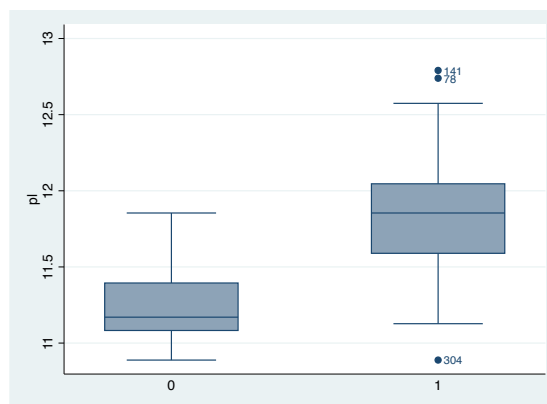


Figure 8: Central Air

Condition

I had high hopes for this but it has some serious trouble (Figure 9). Note the scores for *condition* = 5: We see nice, similar-ish variances for the other conditions, gradually creeping up in price. Perhaps someone thought the scale was 1-5, or there was some other data error. I will introduce a hack, recoding 1=3, 2=4, 3=6, 4=7 and 5=5,8,9 and call it *recond*, then break that up into *bar1-5*.

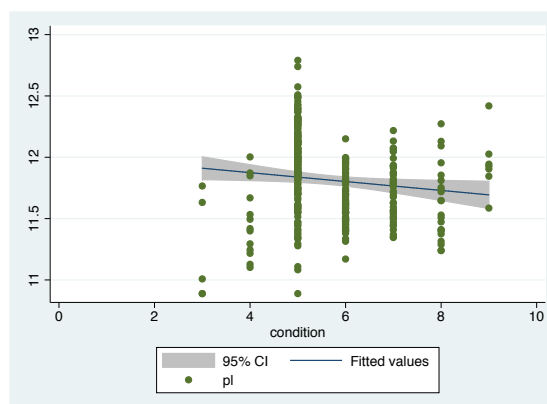


Figure 9: Condition

Basement Square Feet

I had high hopes for this one. A continuous variable with not many outliers (Figure 10), exploratory regressions show it loves to generate heteroscedasticity. It also failed Stata's `ovtest`, so I tried a number of transforms, partitioning the basement sizes using `ttest ...`, `by()`, etc., all to no avail. We'll see how it affects heteroscedasticity in the multiple regression model: if we see heteroscedasticity in that model, we'll pull basement and see what improvements we get.

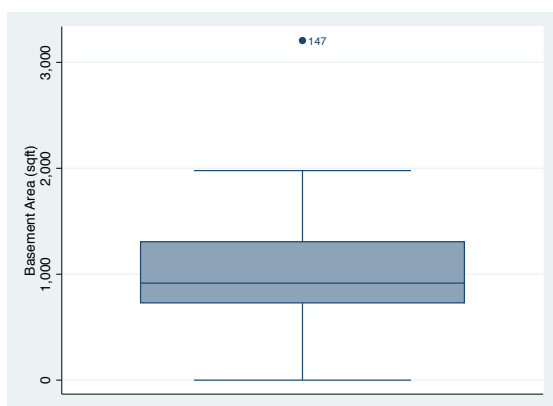


Figure 10: Basement Square Feet

Lot Size

Another continuous variable with high hopes, the box plot (Figure 11) shows some problems. Attempts at transformations (\ln , etc.) did not help. Attempts at dealing with outliers resulted in exacerbated skewness, and while not terrific at nearly 0.77, it is less than 0.8. I was able to remove four worst from these diagrams by selecting `lotSize > 19000`. One off the cuff test was a `ttest` of lot sizes between our modeling building set of data and our kaggle data: Stata says the μ of lot size in the Kaggle data is smaller. This supports the decision to model without the larger lots, hopefully trading overall accuracy of the model for a model that will guess better at the unknown observations I have in front of me.

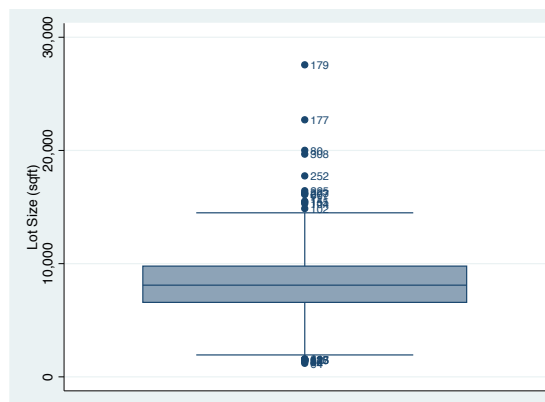


Figure 11: lotSize Box

Living Area

A continuous variable that looks good (Figure 12), exploratory regressions show it failed Stata's `ovtest`. You can see that it doesn't fit well to the normal distribution shown in Figure 13. I eventually transformed this using square root, which seems to generate a better model even though it still doesn't quite pass the `ovtest`. `sktest` reports both are not normally distributed; we'll serve up the less doctored one in the final dish and experiment with the transformed if it doesn't work well.

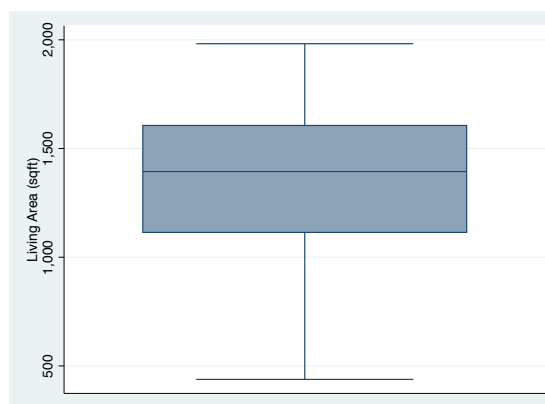


Figure 12: Living Area

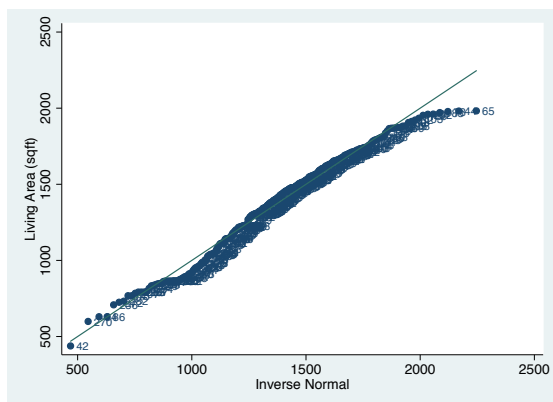


Figure 13: Living Area, normal distribution?

Deck

Everyone loves a deck, no? Alas, another continuous variable but no real correlation with price (Stata reports a correlation < 0.27). The variation on this variable is particularly screwy, in particular note the variance on “no deck” spans all prices (Figure 14).

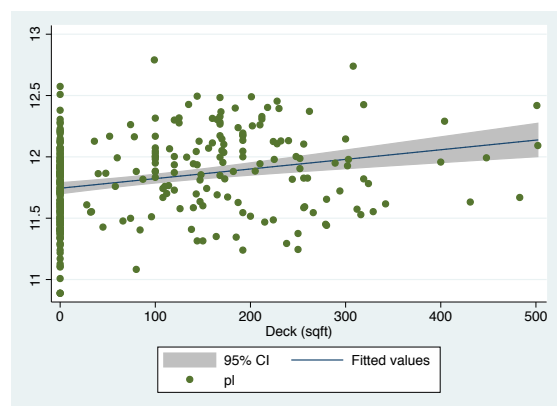


Figure 14: deck scatter

Miscellaneous

A scatter plot of *distFire*, the distance to the fire department, shows an amorphous blob. Stata reports a correlation between *distFire*, *pl* of -0.0559 ; we can safely ignore this variable. Likewise, Stata’s *ttest* fails to reject the null hypothesis that there’s no difference for prices by *smoker*; the correlation with price is 0.0572 . Pass.

Recap

This feels like the junk food challenge on Top Chef, since much of the data is skewed or has strange associations with our dependent variable. We’ll cobble together some recipes and see what we can serve up.

Kitchen Sink

Now throw it all into one large regression. After the first iteration, work to exclude residuals with an absolute value > 2 and influential observations via Cook’s Distance, then rerun. We get a pretty good run, all things considered, with Listing 1. The p-value (Prob $> F$) is < 0.0001 , so we need at least some of our variables in the model. Each variable is confirmed by its respective p-value < 0.05 . $r^2 = 0.8814$, $r^2_{adjusted} = 0.8765$: This model accounts for 88.14% of the variability in *pl*, and $r^2_{adjusted}$ being close to r^2 tells us that this isn’t just because we tossed a lot of ingredients into the blender. $s_e = 0.10754$, still within spitting distance of what I was able to achieve with some questionable experiments.

Looking to the residuals, we observe that 3.2% of our standardized residuals are greater than two standard deviations from our prediction, we’d expect up to 5%. H_0 : Residuals are normally distributed; H_a : Residuals are not normally distributed, Stata’s Skewness/Kurtosis test reports a p-value of 0.1282. We fail to reject the null hypothesis, our residuals look to be normally distributed, confirming one assumption of regression. We also test H_0 : The model fits a straight line; H_a : The model fits some other line. Stata’s Ramsey Reset test reports a p-value of 0.2675, we fail to reject the null hypothesis and confirm another assumption of regression.

Finally we test for heteroscedasticity. H_0 : Variance is constant across predicted values; H_a : variance is not constant, Stata’s Breusch-Pagan / Cook-Weisberg test reports a p-value of

0.3771, again we fail to reject and this model looks good.

There are some troubles. First, there are a lot of variables. And a lot of this data is past its sell-by date. We also had to cull a lot of observations—nearly 70 of 320. The MAE score for modeled data was roughly 12,000, but non-modeled data rolled in over 20,000. Finally, there are a lot of variables in this model to explain and some of them (*br*) have nonintuitive explanations to make. I pass.

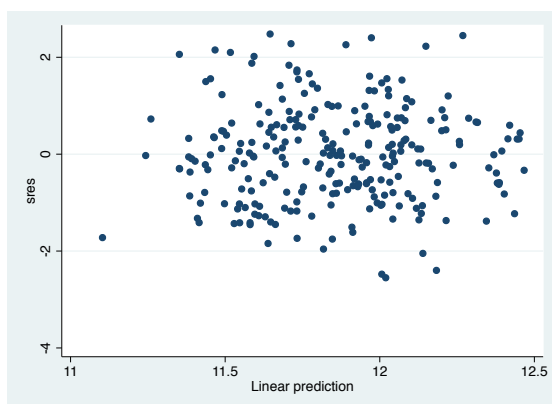


Figure 15: Residuals vs. Fit for Candidate

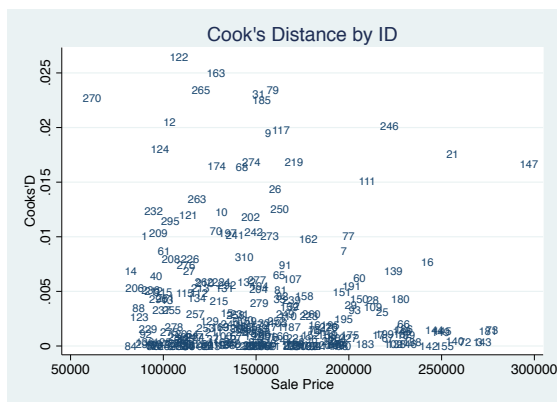


Figure 16: Cooks Distance for Candidate

1 Good Knife Work?

So I decided to make my own regression choices and attempt to find a more parsimonious model. One thing I was hoping to not lose so many

observations to outliers in predictor variables. There was some initial success as I had 18 more observations to start, but 10 came back out after looking at Cook's Distance and large residuals (> 2.5). Still, I removed less than 20% but still a lot.

1a Technical Analysis

Technically, the model is sound, noted in Listing 2. The p-value ($\text{Prob} > F$) is < 0.0001 , so we need at least some of our variables in the model. Each variable is confirmed by its respective p-value < 0.05 . $r^2 = 0.8367$, $r^2_{\text{adjusted}} = 0.8327$: This model accounts for 83.67% of the variability in *pl*, and r^2_{adjusted} being close to r^2 reassures us again. $s_e = 0.12475$, still within spitting distance of our sink model and what I was able to achieve with some questionable experiments.

5.4% of our standardized residuals (Figure 15) were greater than two, casting some niggling doubt on the predictive power of our model.

H_0 : Residuals are normally distributed; H_a : Residuals are not normally distributed, Stata's Skewness/Kurtosis test reports a p-value of 0.5008. We fail to reject the null hypothesis, our residuals look to be normally distributed, confirming one assumption of regression. We also test H_0 : The model fits a straight line; H_a : The model fits some other line. Stata's Ramsey Reset test reports a p-value of 0.5875, we fail to reject the null hypothesis and confirm another assumption of regression.

Finally we test for heteroscedasticity. H_0 : Variance is constant across predicted values; H_a : variance is not constant, Stata's Breusch-Pagan / Cook-Weisberg test reports a p-value of 0.2974, again we fail to reject and this model looks good.

1b Interpretation

Our model predicts the natural log (x) of *salesprice*:

$$x = 11.01223 - 0.1221579 \times aget + 0.0205386 \times sqftt + 0.1141497 \times bar4 + 0.0000216 \times lotsize + 0.0466525 \times fpp + 0.1355746 \times garage$$

Finally, $salesprice = e^x$.

It can be interpreted as follows: The sale price of a brand new house on an infinitesimally small lot with no living space, panned for its condition, no fireplace, no garage would be $e^{11.01223} = \$60,610.90$, on average. For every 1% increase in age, while all other variables remaining the same, the price of the house decreases 12.2%, on average. As square feet increase by squares (1, 4, 9, 16, 25, ...), while all other variables remaining the same, the price of the house increases 2.05%, on average. For each unit increase in condition, while all other variables remaining the same, the price of the house increases 11.41%, on average. For each additional square foot in the size of the lot, while all other variables remaining the same, the price of the house increases 0.0022%, on average. Fireplaces will add 4.66% to the price of the house, on average, all other variables remaining the same. Each additional garage space adds 13.56% to the price of the house, on average, all other variables remaining the same.

Creating the the CI for this estimate is a little more difficult. It's still $\pm 1.96 \times 0.12475$ but this is to the natural log, the actual CI will be asymmetric because you adding/subtracting to the exponent of e. The lower bound will be closer to the estimate than the upper bound.

1c Notes and Caveats

I did predict for a 100 year 200 sqft house on a 500 sqft lot with nothing and got a prediction \$42,844.

I would like to research and understand better the idea of a percentage increase for things like

“if fireplaces” and garage spots. This seems to run a counter to what I’ve seen.

This model predicts meh for observations from the model, with a MAE of 14,224, and less than meh for observations not from the model, a MAE of 28036 from the model data that I dropped, and 17,269 for the Kaggle data.

The model seems rotated counter-clockwise. I found the median sale price and counted the large residuals (> 2 , < 2) by price greater and price less than. I see that for prices less than the median, gross underestimates outnumber the overestimates 15-4. For prices greater, the overestimates win 13-5[‡]

Armed with this knowledge and some healthy skepticism with regard to overfitting, I would prefer this model to the stepwise model shown earlier.

[‡]Using all modeling building data, whether I actually included it in my regression model or not.

Listing 1: Stepwise Multiple Regression, Kitchen Sink

```
. stepwise , pr(0.05) : regress pl aget bar2 bar3 bar4 basement baths br cac recond
    deck distFire fp garage lotSiz
> e monthSold smoker sqftt if model
    begin with full model
p = 0.8812 >= 0.0500 removing monthSold
p = 0.8667 >= 0.0500 removing bar2
p = 0.1947 >= 0.0500 removing deck
p = 0.1711 >= 0.0500 removing distFire
p = 0.2234 >= 0.0500 removing baths
p = 0.0698 >= 0.0500 removing cac
p = 0.0734 >= 0.0500 removing smoker
```

Source	SS	df	MS	Number of obs =	250
Model	20.5458051	10	2.05458051	F(10, 239) =	177.66
Residual	2.76395908	239	.011564682	Prob > F =	0.0000
				R-squared =	0.8814
				Adj R-squared =	0.8765
Total	23.3097642	249	.093613511	Root MSE =	.10754

	pl	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
aget		-.1058091	.0094444	-11.20	0.000	-.1244141 -.0872041
lotSize		.0000131	2.45e-06	5.32	0.000	8.22e-06 .0000179
bar3		.0695827	.029167	2.39	0.018	.0121255 .1270399
bar4		.1370819	.0247909	5.53	0.000	.0882453 .1859184
basement		.0001652	.0000215	7.67	0.000	.0001227 .0002076
garage		.0908664	.0150552	6.04	0.000	.0612085 .1205242
br		-.0603909	.0134081	-4.50	0.000	-.086804 -.0339778
fp		.0285014	.0128621	2.22	0.028	.0031639 .053839
recond		.0359796	.0130071	2.77	0.006	.0103564 .0616029
sqftt		.027752	.0023803	11.66	0.000	.023063 .032441
_cons		10.67145	.1089018	97.99	0.000	10.45692 10.88598

Skewness/Kurtosis tests for Normality

Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
sres	250	0.7106	0.0471	4.11	0.1282

Ramsey RESET test using powers of the fitted values of pl

Ho: model has no omitted variables

F(3, 236) = 1.32

Prob > F = 0.2675

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Ho: Constant variance

Variables: fitted values of pl

chi2(1) = 0.78

Prob > chi2 = 0.3771

Listing 2: Manual Multiple Regression

```
. regress pl aget sqftt bar4 lotSize fpp garage if model
```

Source	SS	df	MS	Number of obs = 258		
Model	20.007548	6	3.33459133	F(6, 251)	=	214.27
Residual	3.9062121	251	.015562598	Prob > F	=	0.0000
				R-squared	=	0.8367
				Adj R-squared	=	0.8327
Total	23.9137601	257	.09304965	Root MSE	=	.12475

pl	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
aget	-.1221579	.0096961	-12.60	0.000	-.141254	-.1030619
sqftt	.0205386	.0023146	8.87	0.000	.0159801	.0250972
bar4	.1141497	.0249036	4.58	0.000	.065103	.1631965
lotSize	.0000216	2.61e-06	8.27	0.000	.0000165	.0000268
fpp	.0466525	.0175641	2.66	0.008	.0120608	.0812443
garage	.1355746	.0166735	8.13	0.000	.1027369	.1684123
_cons	11.01223	.0885233	124.40	0.000	10.83789	11.18657

Skewness/Kurtosis tests for Normality

Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
sres	258	0.2688	0.6997	1.38	0.5008

Ramsey RESET test using powers of the fitted values of pl

Ho: model has no omitted variables

F(3, 248) = 0.64

Prob > F = 0.5875

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Ho: Constant variance

Variables: fitted values of pl

chi2(1) = 1.09

Prob > chi2 = 0.2974

Table 1: Data Description

Variable	Original	Description
ID		data driven observation ID
salesprice		Selling price in dollars
pl	new transform	natural log of salesprice
sqft	live_area_sqft	Square footage of living space
sqftt	new transform	\sqrt{sqft}
basement	bsmt_sf	Square footage of basement
lotSize	lot_sq_ft	Size of lot in square feet
lotSizet	new transform	ln of lotSize
deck	deck_sf	Size of deck in square feet
dp	new dummy	<i>deck</i> > 50 square feet?
age		Age of the house in years
aget	new transform	natural log of age
distFire		Distance from the closest fire station
baths		Count of bathrooms
bedrooms		Count of bedrooms
fp	fireplaces	Count of fireplaces
fpp		Has one or more fireplaces
garage	garage_cars	Count of spaces in garage
condition		Rated conditon 1-10
recond	recode	Recoded condition, 1-5
barn	recode	Indicators for recode
cac		Boolean, central air
smoker		Boolean, previous owner smoked
monthSold	month_sold	Month of year sold 1-12