

## Diagnosing and Fixing Common Problems With Regression

### Introduction

There are three ways to get a good intuitive grasp of whether there might be some issues with your model fit:

1. Plot the data
2. Plot the data
3. Plot the data

### Collinearity

The test to use for collinearity in Stata is `vif`. The results of the VIF (Variance Inflation Factor) test states whether inflation has been increased because the covariate is correlated with the other regressors. The rule of thumb with VIF's is that 10 is large, while 20 is unacceptable.

Stata's `vif` command can be run after a regression to check for collinearity.

```
. estat vif
```

Variable	VIF	1/VIF
iq	52.76	0.018955
test3	52.24	0.019143
s	1.60	0.623911
kww	1.31	0.761735
med	1.18	0.848345
expr	1.15	0.867604
tenure	1.10	0.907839
rns	1.06	0.944157
smsa	1.05	0.948668
Mean VIF	12.61	

It looks like there's a big problem with the `iq` variable and the `test3` variable. I first do an F test to see if they both belong in the model.

```
. test test3 iq  
( 1) test3 = 0
```

```
( 2)  iq = 0

      F( 2, 748) = 6.65
      Prob > F = 0.0014
```

They are jointly significant, so I need to choose one to eliminate. In this case I drop test3, re-run the model, and ask again for variance inflation factors.

```
. local controls kww iq expr tenure rns smsa med

.
. reg `y' `x' `controls'

      Source |      SS      df      MS      Number of obs = 758
-----+-----+-----+-----+-----+-----+-----+
      Model | 50.6098566      8  6.32623207      F( 8, 749) = 53.43
      Residual | 88.6762933     749  .118392915      Prob > F      = 0.0000
-----+-----+-----+-----+-----+
      Total | 139.28615     757  .183997556      R-squared      = 0.3634
                                           Adj R-squared = 0.3566
                                           Root MSE     = .34408

-----+-----+-----+-----+-----+
      lw |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----+-----+-----+-----+-----+
      s |   .0878976   .0070921    12.39   0.000    .0739749    .1018203
      kww |   .0030669   .0019596     1.57   0.118   -.0007801    .0069139
      iq |   .0028559   .0011028     2.59   0.010    .000691    .0050208
      expr |   .0386396   .0063668     6.07   0.000    .0261407    .0511385
      tenure |   .0322462   .0078371     4.11   0.000    .0168608    .0476315
      rns |  -.0720075   .0289852    -2.48   0.013   -.1289095   -.0151055
      smsa |   .1302547   .0281144     4.63   0.000    .0750623    .1854471
      med |   .0055788   .004952     1.13   0.260   -.0041427    .0153004
      _cons |   3.840349   .1126832    34.08   0.000    3.619136    4.061561
-----+-----+-----+-----+-----+

. eststo full_model_a, title("Model 2:No Test 3")

.
. estat vif

      Variable |      VIF      1/VIF
-----+-----+-----+
      s |      1.60    0.624254
      iq |      1.44    0.693400
      kww |      1.31    0.763785
      med |      1.18    0.848802
      expr |      1.15    0.870279
      tenure |      1.10    0.909065
      rns |      1.06    0.945150
      smsa |      1.05    0.949180
-----+-----+-----+
      Mean VIF |      1.24
```

Much better! All vifs are now in an acceptable range.

Remember that as a practical matter, collinearity does not bias your estimates, it just makes them inefficient. It's usually just not that serious a problem— but it's worth checking to see if you're dealing with an extreme case.

## Quick Exercise

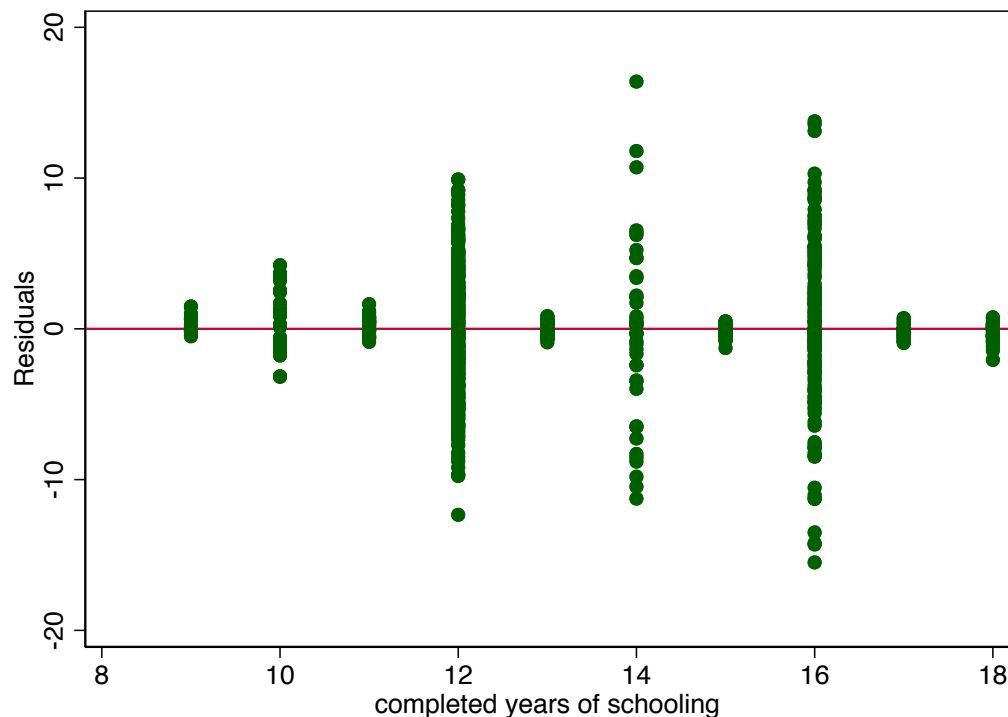
What happens to VIFs when a variable of your choice is removed?

# Heteroskedasticity

Heteroskedasticity implies that the error terms are not identically distributed, but instead may be related in some way to the regressors or another factor. In this situation, our estimates are unbiased, but our distributional assumptions about our *variance* estimates no longer hold, and standard tests of significance don't work.

Figure 1 shows the residuals for a regression of log wages on various covariates plotted against years of experience. This shows a highly heteroskedastic pattern in the residuals.

Figure 1: Residuals Plotted Against Years of Experience



There are several ways of attempting to diagnose heteroskedastic results. The Breusch-Pagan command as an omnibus test looks at whether the variance of the squared residuals is related to any of the regressors. We get this by regressing the square of the residuals on the covariates and conducting an F test (or an LM test of the form  $nR^2$ ). If significant, then the covariates predict the residuals, which indicates a violation. In Stata we get this result by using the `hettest` command. Another option is the White test. The White test follows the same basic form as the BP test, but instead uses the test statistic  $nR^2$  from the regression of the square of the residuals on the covariates, their squares, and their cross-products. Like the BP test, this test statistic has been shown to be distributed  $\chi^2$  with degrees of freedom equal to the number of regressors in the auxiliary regression.

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: fitted values of lw_het
```

```

        chi2(1)      =      4.69
        Prob > chi2   =      0.0304

.
. estat hettest s expr

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: s expr

        chi2(2)      =      21.50
        Prob > chi2   =      0.0000

.
. /*White Test */
.
. estat imtest, white

White's test for Ho: homoskedasticity
against Ha: unrestricted heteroskedasticity

        chi2(42)      =      87.39
        Prob > chi2   =      0.0000

Cameron & Trivedi's decomposition of IM-test

```

Source	chi2	df	p
Heteroskedasticity	87.39	42	0.0000
Skewness	7.80	8	0.4534
Kurtosis	15.12	1	0.0001
Total	110.31	51	0.0000

In the first BP test above, the squared residuals are regressed on the predicted values from the regression. In the second test, the squared residuals are regressed on all of the covariates. And in the last, the squared residuals are regressed on a specified subset of the covariates. This last can help to identify the source of the non iid error terms.

You can correct for heteroskedasticity in a number of ways. The most straightforward is to use robust standard errors, which take into account possible non iid errors. If you suspect the errors in clusters (such as schools) are correlated, you can calculate clustered standard errors, with clustering at the group level. (N.B. My example below is artificial, and honestly, incorrect).

```

. /*Robust s.e.'s*/
. reg lw_het `x' `controls', robust

```

Linear regression

```

Number of obs =      758
F( 8, 749) =      2.37
Prob > F      =      0.0158
R-squared     =      0.0202
Root MSE     =      3.9241

```

	lw_het	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
s		.2513847	.0746952	3.37	0.001	.1047479 .3980215
kww		-.0103424	.0237815	-0.43	0.664	-.0570288 .036344
iq		-.0189512	.01152	-1.65	0.100	-.0415666 .0036642
expr		-.0359087	.0682226	-0.53	0.599	-.169839 .0980215

```

      tenure | .1580198 .0947811 1.67 0.096 -.0280485 .3440881
      rns | .3126439 .3020458 1.04 0.301 -.2803131 .9056009
      smsa | .3692457 .3106519 1.19 0.235 -.2406063 .9790977
      med | -.028291 .0568756 -0.50 0.619 -.1399456 .0833635
      _cons | 4.345555 1.177585 3.69 0.000 2.033796 6.657315
-----+-----

. eststo full_model_robust, title("Model 2: Robust SE")

.
. /*Clustered se.`s*/
. reg `y' `x' `controls', cluster(med)

Linear regression                               Number of obs =      758
                                              F(   8,   18) =   126.22
                                              Prob > F      =    0.0000
                                              R-squared     =    0.3634
                                              Root MSE     =    .34408

                               (Std. Err. adjusted for 19 clusters in med)
-----+-----
      |               Robust
      |               Std. Err.
      |               t      P>|t|      [95% Conf. Interval]
-----+-----
      s | .0878976 .0090694   9.69  0.000   .0688436   .1069516
      kww | .0030669 .0017164   1.79  0.091  -.0005391   .0066729
      iq | .0028559 .0008181   3.49  0.003   .001137   .0045747
      expr | .0386396 .0068981   5.60  0.000   .0241472   .053132
      tenure | .0322462 .0049196   6.55  0.000   .0219105   .0425818
      rns | -.0720075 .0236252  -3.05  0.007  -.1216422  -.0223729
      smsa | .1302547 .0144499   8.98  0.000   .0997935   .1607159
      med | .0055788 .003547   1.57  0.133  -.0018732   .0130309
      _cons | 3.840349 .1197726  32.06  0.000   3.588716   4.091982
-----+-----

. eststo full_model_cluster, title("Model 2: Cluster SE")

.

```

Angrist and Pischke suggest that we should assume that there IS heteroskedasticity in the residuals, unless we can specifically prove that there's none. Basically, you should always use robust standard errors (or other appropriate variance estimation technique).

## Quick Exercise

Is there heteroskedasticity when we don't use the (made up) log wage variable, but rather the real one?

## Data Scaling

The results of regression are invariant to linear transforms, but sensitive to non-linear transforms. Changing the latter changes the functional form of the regression model.

Results can be scaled in any number of ways. The most common is standardized coefficients, which scales each coefficient as follows:

$$\hat{\beta}_j^s = \hat{\beta}_j \frac{SD(x_j)}{SD(y)}$$

In the results below I show the standardized coefficients for the independent variables in the model, then transform the years of schooling variable and re-run the model. While the coefficient estimates change, the t-statistic and standardized coefficient does not.

```
.
. /*Data Scaling*/
.
. reg `y' `x' `controls'
```

Source	SS	df	MS	Number of obs =	758
Model	50.6098566	8	6.32623207	F( 8, 749) =	53.43
Residual	88.6762933	749	.118392915	Prob > F =	0.0000
				R-squared =	0.3634
				Adj R-squared =	0.3566
Total	139.28615	757	.183997556	Root MSE =	.34408

```
-----+-----
```

lw	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
s	.0878976	.0070921	12.39	0.000	.0739749 .1018203
kww	.0030669	.0019596	1.57	0.118	-.0007801 .0069139
iq	.0028559	.0011028	2.59	0.010	.000691 .0050208
expr	.0386396	.0063668	6.07	0.000	.0261407 .0511385
tenure	.0322462	.0078371	4.11	0.000	.0168608 .0476315
rns	-.0720075	.0289852	-2.48	0.013	-.1289095 -.0151055
smsa	.1302547	.0281144	4.63	0.000	.0750623 .1854471
med	.0055788	.004952	1.13	0.260	-.0041427 .0153004
_cons	3.840349	.1126832	34.08	0.000	3.619136 4.061561

```
-----+-----
```

```
.
. reg `y' `x' `controls', beta
```

Source	SS	df	MS	Number of obs =	758
Model	50.6098566	8	6.32623207	F( 8, 749) =	53.43
Residual	88.6762933	749	.118392915	Prob > F =	0.0000
				R-squared =	0.3634
				Adj R-squared =	0.3566
Total	139.28615	757	.183997556	Root MSE =	.34408

```
-----+-----
```

lw	Coef.	Std. Err.	t	P> t	Beta
s	.0878976	.0070921	12.39	0.000	.4573323
kww	.0030669	.0019596	1.57	0.118	.0522099
iq	.0028559	.0011028	2.59	0.010	.0906704
expr	.0386396	.0063668	6.07	0.000	.1896665
tenure	.0322462	.0078371	4.11	0.000	.1258147
rns	-.0720075	.0289852	-2.48	0.013	-.0745005
smsa	.1302547	.0281144	4.63	0.000	.1386435
med	.0055788	.004952	1.13	0.260	.0356506
_cons	3.840349	.1126832	34.08	0.000	.

```
-----+-----
```

```
. eststo full_model_beta, title("Model 2: Standardized Coefficients")
.
. gen expr_new=1+2*s
.
. local x expr_new
.
. reg `y' `x' `controls', beta
```

Source	SS	df	MS	Number of obs =	758
Model	50.6098566	8	6.32623207	F( 8, 749) =	53.43
Residual	88.6762933	749	.118392915	Prob > F =	0.0000
				R-squared =	0.3634
				Adj R-squared =	0.3566

Total		139.28615	757	.183997556	Root MSE	=	.34408
-----							
lw		Coef.	Std. Err.	t	P> t	Beta	
-----							
expr_new		.0439488	.003546	12.39	0.000	.4573323	
kww		.0030669	.0019596	1.57	0.118	.0522099	
iq		.0028559	.0011028	2.59	0.010	.0906704	
expr		.0386396	.0063668	6.07	0.000	.1896665	
tenure		.0322462	.0078371	4.11	0.000	.1258147	
rns		-.0720075	.0289852	-2.48	0.013	-.0745005	
smsa		.1302547	.0281144	4.63	0.000	.1386435	
med		.0055788	.004952	1.13	0.260	.0356506	
_cons		3.7964	.1134835	33.45	0.000	.	

Rescaling on Z scores can make sense in many applications, but it is not a way to compare coefficients.

## Quick Exercise

Rescale the parental education variable using both a linear and a non-linear transform and check to see what difference it makes in the results.

## Functional Form

In checking on functional form, your best bet is almost always using graphical approaches. Below I plot the wages as a function of years of schooling, then plot the a line based on local linear regression.

Next I plot both a lowess line and a linear fit to see what the results of a simple regression might look like.

## Quick Exercise

Using a similar approach to the one I use in the do file, check on the functional form of the relationship between wages and kww scores.

## The log transformation

We covered this previously. Remember that the log transformation is a good idea when the dependent variable is on some kind of exponential scale.

Figure 2: Wages as a function of schooling

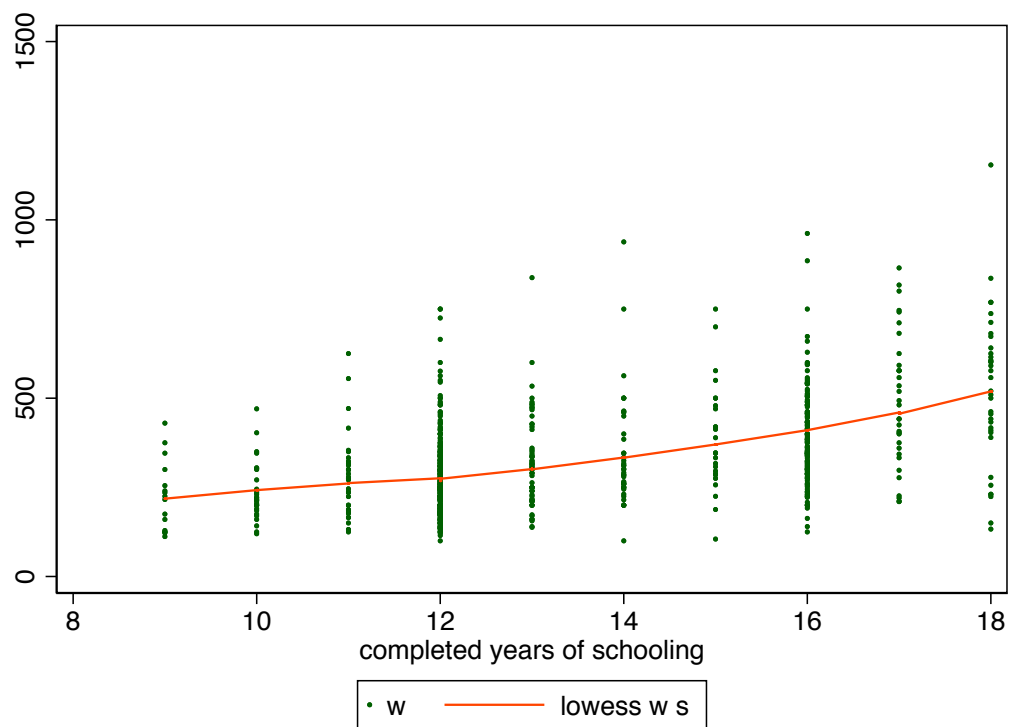


Figure 3: Wages as a function of schooling, linear fit to data

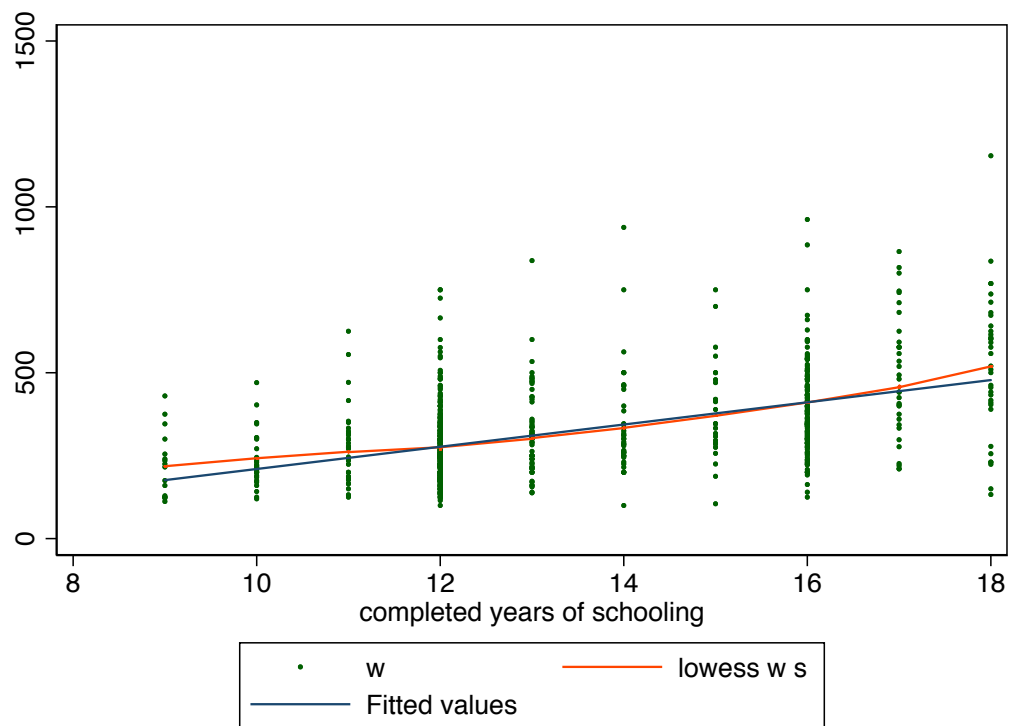
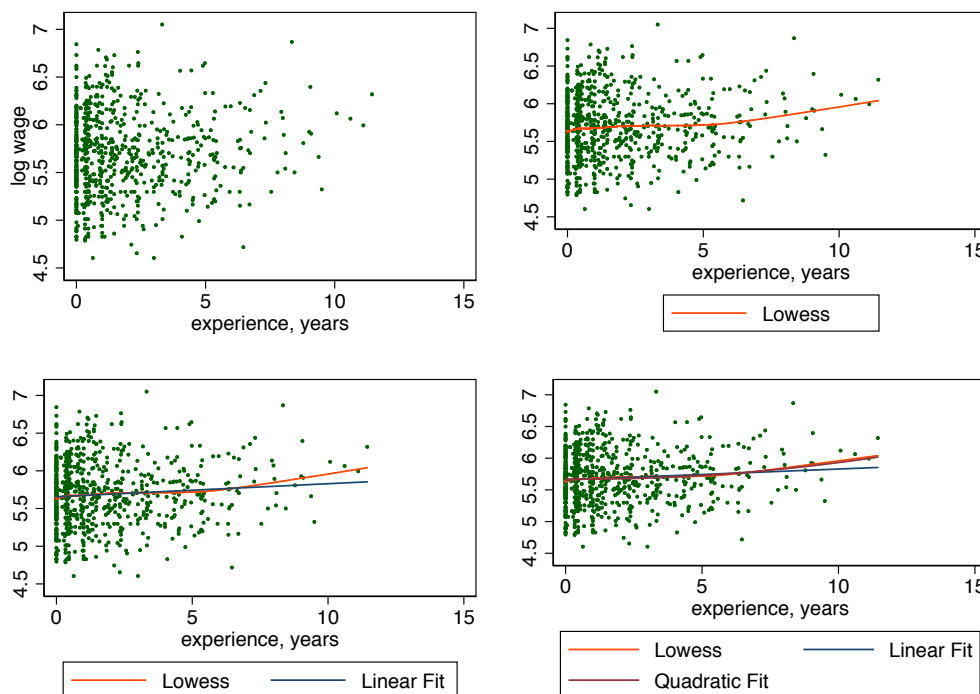




Figure 4: Wages as a function of schooling, multiple functional forms



## Influential Observations

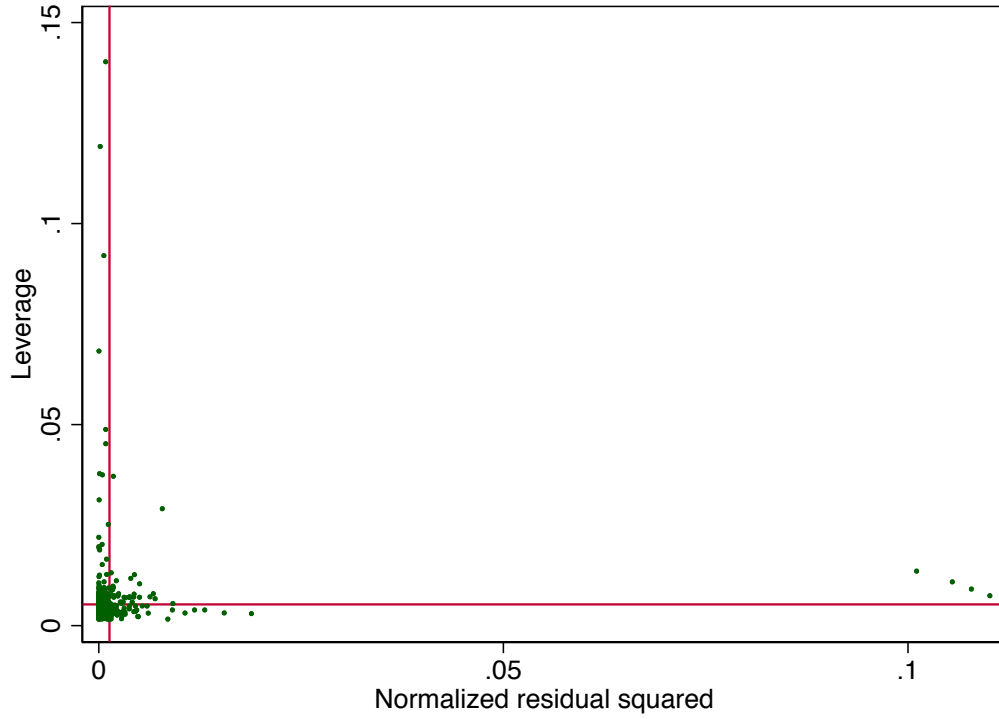
Regression is quite sensitive to outliers. A data point can “pull” the regression line quite far away given its distance from that line. We test for influential measures using several different measures including leverage, dfits, cooks D, or dfbeta.

- Leverage is measured in the scale of the dv and is the basic measure of influence from a residual.
- The dfits statistic compares the standardized residual for every observation on the scale of the standard error of the regression.
- Cook’s d combines information regarding leverage—how influential the observation is on the results— and the size of the residual—how far off the prediction the actual result is.
- Dfbetas are calculated for every unit AND every coefficient, and state how far the coefficient would move should that case be excluded.

A leverage plot is a good place to begin examining the data for influential observations.

The leverage plot shows the leverage of each observation on the y axis and the square of the residual on the x axis. The red lines on each axis are the cutoff points for “large” leverage or residual stats.

Figure 5: Leverage Plot



For each of the measures leverage, dfits, cooks' D and dfbeta, the procedure is the same. Calculate the measure, then look for observations that exceed a given rule of thumb. Here's that procedure applied to leverage.

For DFits, the measure is given by:

$$DFITS_j = r_j \sqrt{\frac{h_j}{1 - h_j}}$$

Where  $r_j$  is a studentized residual:

$$r_j = \frac{\epsilon_j}{s_{(j)}} \sqrt{1 - h_j}$$

The rule of thumb cutoff for dfits is  $|DFITS_j| > 2\sqrt{k/N}$ .

For Cook's D, the calculation is:

$$D_i = \frac{\sum_{i=1}^n (\hat{y}_i - \hat{y}_{i(w)})^2}{pMSE}$$

Where  $\hat{y}_i$  is the prediction with observation  $i$  and  $\hat{y}_{i(w)}$  is the prediction *without* observation  $i$ .

The rule of thumb for cooks D is to investigate values over  $4/n$ .

Last, the calculation for DFBETA is given by:

$$DFBETA_j = \frac{r_j v_j}{\sqrt{v^2(1 - h_j)}}$$

This tells you how much a regression coefficient would change if unit  $j$  was excluded. The cutoff suggested for DFBETA is  $2/\sqrt{n}$ .

```
. /* Leverage and outliers */
.
. predict lev if e(sample), leverage
.
. predict resid if e(sample), resid
.
. gen resid2=resid^2
.
. gsort -lev
.
. list w_influence s lev resid2 in 1/10
```

	w_infl~e	s	lev	resid2
1.	555.0176	11	.1402453	16845.92
2.	401.0154	12	.1191845	3480.702
3.	430.0924	9	.0920351	12456.28
4.	454.8647	12	.0682902	395.947
5.	204.9979	10	.0488069	16943.56
6.	288.0114	12	.045244	17041.28
7.	367.9695	12	.037804	1923.356
8.	375.0278	9	.0375033	8861.435
9.	600.0421	12	.0371506	35667.26
10.	332.9526	11	.0312744	839.5032

## Quick Exercise

Run the same regression without the schooling variable. Check for outliers using both graphical and tabular methods.