```
  ___  ____  ____  ____  ____ (R)
 /__    /   ____/   /   ____/
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Notes:
      1.  Unicode is supported; see help unicode_advice.
```

Functional Form Misspecification (Using Stata)

Let us say our model's functional form is not correct, what will happen then?

The assumption of a "0" conditional mean will be violated, and the estimates will be inconsistent. This assumption is only broken when we have problems related to:

- Improper model specification: When the regression model itself is flawed.
- Endogeneity: When one or more regressors are correlated with the error term.
- Measurement errors: When the behavior of one or more regressors cannot be accurately measured.

To check the functional form of the regression, we use various measures.

Let us try to cover them using Stata.

Data Set & Graph Matrix

Download dataset for working with this tutorial - https://bit.ly/46qOnsx

Upload the dataset and use describe - to get variables details.

```
. use "C:\Users\ASUS\Desktop\hprice2a.dta",clear(Housing price data for Boston-area
communities)

. describe

Contains data from C:\Users\filepath.dta
  obs:          506                   Housing price data for Boston-area
  communities
 vars:           13                   5 Oct 2004 09:50
 size:       26,312
----------------------------------------------------------------------------------
              storage   display    value
variable name   type    format     label      variable label
----------------------------------------------------------------------------------
price           float   %9.0g                 median housing price, $
crime           float   %9.0g                 crimes committed per capita
nox             float   %9.0g                 nitrous oxide, parts per 100m
rooms           float   %9.0g                 avg number of rooms per house
dist            float   %9.0g                 weighted dist. to 5 employ centers
radial          float   %9.0g                 accessibiliy index to radial hghwys
proptax         float   %9.0g                 property tax per $1000
stratio         float   %9.0g                 average student-teacher ratio
lowstat         float   %9.0g                 % of people 'lower status'
lprice          float   %9.0g                 log(price)
lnox            float   %9.0g                 log(nox)
lproptax        float   %9.0g                 log(proptax)
ldist           float   %9.0g                 log(dist)
----------------------------------------------------------------------------------
Sorted by:
```

Let's do graph matrix to find the relationship b/w lprice and causal factors.

```
. graph matrix lprice lnox ldist rooms stratio, ms(0h) msize(tiny)name(scatter_matrix)
title("Scatterplot Matrix of Variables")

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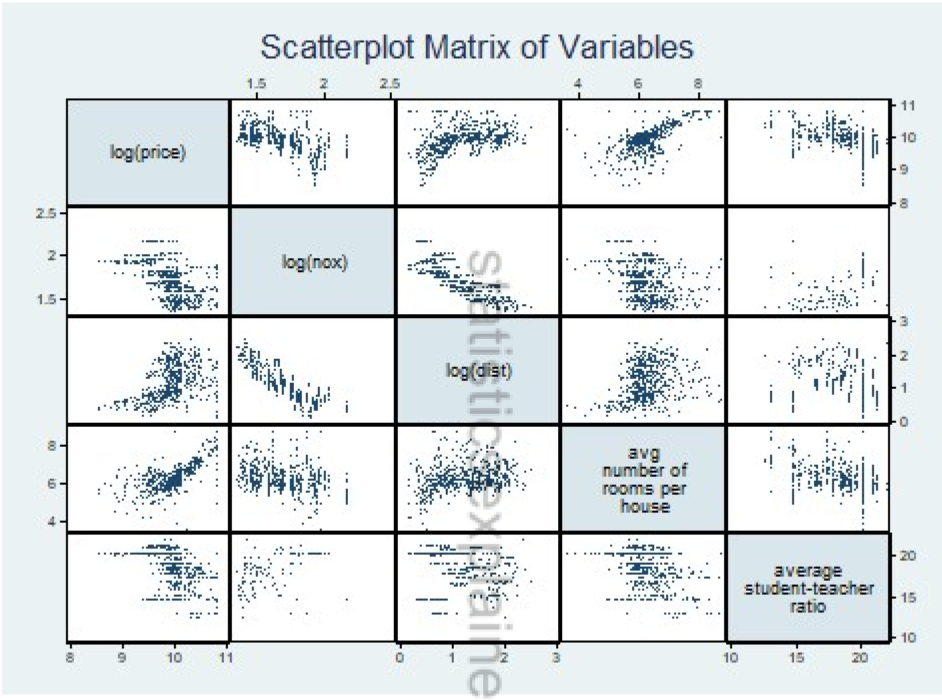

Here,

- We use ms(Oh) to focus on the lines or other graphical elements connecting the points rather than the points themselves.
- We use Msize(tiny) to set the size of the markers to "tiny".
- We use name(scatter_matrix) to specify a prefix for the name of the graph.
- We use title(scatterplot matrix of variable) to add a title to the graph matrix.

Note: The graphs below the main diagonal can be used to determine if there is a high intercorrelation between the regressors or if there is a problem of collinearity.

The scatter points between lnox and ldist appear to be linear. Let us explore this relationship further.

Using the correlated command to check relationship between lnox and ldist

corr lnox ldist(obs=506)

	lnox	ldist
lnox	**1.0000**	
ldist	**-0.8607**	**1.0000**

Note: The two variables have a simple correlation of -0.86

Added Variable Plot

The added variable plots are used to assess the relationship between an independent variable and the response variable while controlling for other variables in the model.

Note: In an added variable plot, the residuals of the response variable are plotted on the y-axis, while the residuals of the independent variable are plotted on the x-axis. This allows us to examine whether there is a linear association or not.

Added variable plots are useful for model validation in regression analysis. They help in detecting potential issues such as non-linearity or outliers.

Let us generate a new variable room^2 and create an added variable plot of it.

```
. gen room2 = room^2

. regress lprice lnox ldist rooms room2 stratio lproptax

      Source |       SS           df       MS      Number of obs   =       506
-------------+----------------------------------   F(6, 499)       =    138.41
       Model |  52.8357813         6  8.80596356   Prob > F        =    0.0000
    Residual |  31.7464896       499  .06362022   R-squared       =    0.6247
-------------+----------------------------------   Adj R-squared   =    0.6202
       Total |  84.5822709       505  .167489645   Root MSE        =    .25223

------------------------------------------------------------------------------
      lprice |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        lnox |  -.6615694   .1201606    -5.51   0.000    -.8976524   -.4254864
       ldist |   -.095087   .0421435    -2.26   0.024    -.1778875   -.0122864
       rooms |  -.5625662   .1610315    -3.49   0.001    -.8789496   -.2461829
       room2 |   .0634347   .0124621     5.09   0.000     .0389501    .0879193
     stratio |  -.0362928   .0060699    -5.98   0.000    -.0482185   -.0243671
    lproptax |  -.2211125   .0410202    -5.39   0.000     -.301706   -.1405189
       _cons |   14.15454   .5693846    24.86   0.000     13.03585    15.27323
------------------------------------------------------------------------------

. avplots, ms(0h) msize(small) col(3)

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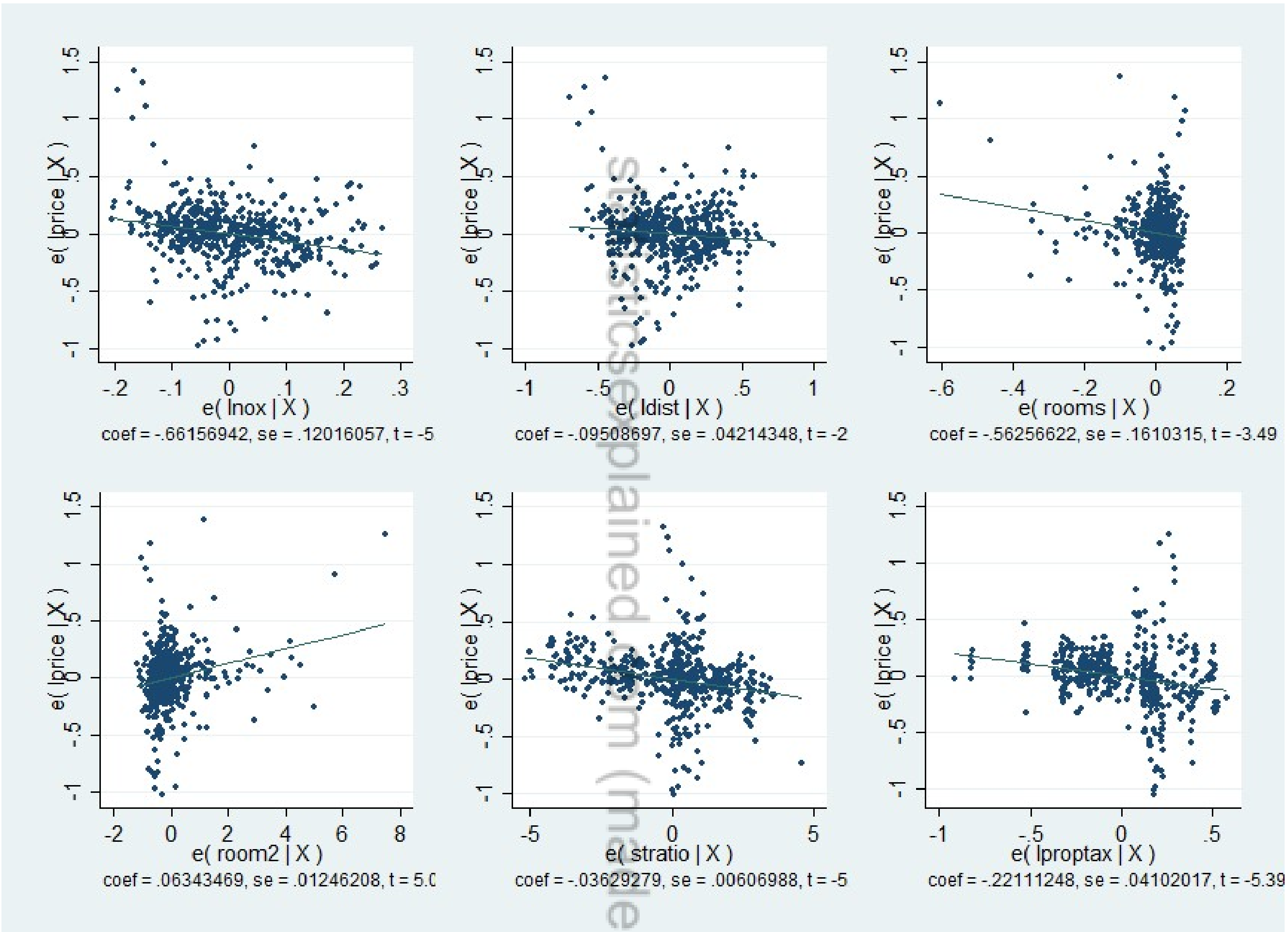
(note:  named style 0h not found in class symbol, default attributes used)
(note:  named style 0h not found in class symbol, default attributes used)
```

Note: Here, we use col(3) to arrange the plots in three columns.



Note: Here, we use col(3) to arrange the plots in three columns. Also, in each pane several observations are far from the straight linking the dependent & the independent variables. Thus, we shall now do Ramsey's RESET.

Ramsey's RESET (Regression Equation Specification Error Test)

Ramsey RESET is used to detect potential functional form misspecification. They help determine if the inclusion of additional powers improves the model's fit.

The RESET test statistic, typically an F-statistic, is used to make an inference about the correctness of the model specification. If the p-value associated with the RESET test is below a pre-defined significance level (e.g., 0.05), it suggests that the null hypothesis of correct specification is rejected, indicating a potential misspecification.

Let's proceed to use the Ramsey RESET test.

To do Ramsey we need regression results - here will run regression quietly.

```
. quietly regress lprice lnox ldist rooms stratio
```

Note: Using quietly will suppress the regression result. Next, we will use the command estat ovtest for Ramsey.

```
. estat ovtest, rhs

Ramsey RESET test using powers of the independent
       variablesHo: model has no omitted variables
              F(12, 489) =      11.79
                Prob > F =       0.0000
```

Note: estat ovtest command is used to perform the overidentification test. We write "rhs" to specify that the test should be performed on the right-hand side (exogenous) variables only. Here, we have p-value = 0, means there is specification error.

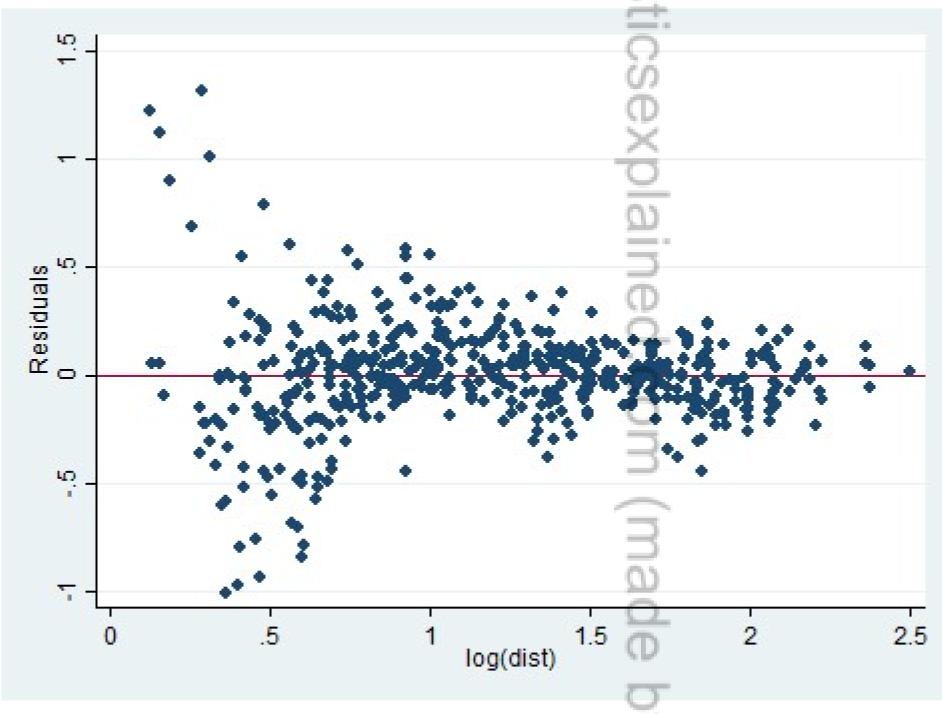
Residual-versus-fitted-plot

It is used to access the specification of the model.

Let us graph the residuals versus the predicted values for ldist

```
. quietly regress lprice lnox ldist rooms stratio

. rvpplot ldist, ms(0h) yline(0)
(note:  named style 0h not found in class symbol, default attributes used)
```



Note: In this graph, the residuals appear much more variable for low levels versus high levels of log of distance (ldist), it seems there is constant variance issue.

Interaction Terms

To address the issue of specification we sometime introduce interaction terms. For example, we have lproptax and stratio - we can use their interaction. The notion here is, people like to pay lower property tax and prefer schools with low student teacher ratio - so interaction can be - lproptax*stratio.

```
. gen interaction = lproptax*stratio

. regress lprice lnox ldist stratio lproptax interaction

      Source |       SS           df       MS      Number of obs   =       506
-------------+----------------------------------   F(5, 500)       =     84.47
       Model |  38.7301562         5  7.74603123   Prob > F        =    0.0000
    Residual |  45.8521148       500  .09170423   R-squared       =    0.4579
-------------+----------------------------------   Adj R-squared   =    0.4525
       Total |  84.5822709       505  .167489645   Root MSE        =    .30283

------------------------------------------------------------------------------
      lprice |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        lnox |  -.9041103   .1441253    -6.27   0.000    -1.187276   -.6209444
       ldist |  -.1430541   .0501831    -2.85   0.005    -.2416499   -.0444583
     stratio |  -.4388722   .1538321    -2.85   0.005    -.7411093   -.1366351
    lproptax |   -1.48103   .5163117    -2.87   0.004    -2.495438   -.4666219
 interaction |   .0641648    .026406     2.43   0.015     .0122843    .1160452
       _cons |   21.47905   2.952307     7.28   0.000      15.6786    27.27951
------------------------------------------------------------------------------
```

Note: Here the interaction term is coming out to be significant, however we have not included rooms in the regression model.

Outliers

Sometimes the presence of unusual points can change the entire results because they can change the actual coefficient values.

We can address the problem of outliers by identifying influential data. Let us try this.

```
. quietly regress lprice lnox ldist rooms room2 stratio lproptax
```

Let us generate a new variable "town" with unique identifier for each obs.

```
. generate town = _n
```

Let us use the predict command to calculate the leverage values and store them in the variable "lev" for the observations in the sample.

```
. predict double lev if e(sample), leverage
```

Note: We use "double" to specify the data type (it is optional). The unusual data point is a problem for least-square regression fit because it alters the estimated coefficients by a sizable amount.

Sometime the data points with large residuals have an unusual leverage, we can identify these unusual points using leverage.

Also "if e(sample)" this condition ensures that the residuals are only calculated for observations that were part of the estimation sample.

Let us use predict command to calculate the residuals and store them in the variable "eps" for the observations in the sample.

```
. predict double eps if e(sample), res
```

Create a variable "eps2" that contains the squared residuals.

```
. generate double eps2 = eps^2
```

Get summary statistics.

```
. summarize price lprice
```

Variable	Obs	Mean	Std. Dev.	Min	Max
price	506	22511.51	9208.856	5000	50001
lprice	506	9.941057	.409255	8.517193	10.8198

Let us use sort the dataset in descending order based on the variable lev to produce the descending-sort order.

```
. gsort -lev
```

Let us list down the top 5 observations in terms of lev along with the variable's town, price, lprice lev and eps2.

```
. list town price lprice lev eps2 in 1/5
```

	town	price	lprice	lev	eps2
1.	366	27499	10.2219	.17039262	.61813718
2.	368	23100	10.04759	.11272637	.30022048
3.	365	21900	9.994242	.10947853	.33088957
4.	258	50001	10.8198	.08036068	.06047061
5.	226	50001	10.8198	.0799096	.03382768

Let us also get the town with largest squared errors.

```
. gsort -eps2
. list town price lprice lev eps2 in 1/5
```

	town	price	lprice	lev	eps2
1.	369	50001	10.8198	.02250047	1.7181195
2.	373	50001	10.8198	.01609848	1.4894088
3.	372	50001	10.8198	.02056901	1.2421055
4.	370	50001	10.8198	.0172083	1.0224558
5.	406	5000	8.517193	.00854955	1.0063662

Note: Both the results differ, thus a large value of leverage does not imply a large, squared residual and vice-versa.

DFITS (Difference in Fits)

DFITS values assess how much the predicted values change when a particular observation is removed from the analysis.

Note: Here, we will create a cutoff value to compare with DFITS statistics absolute value. The cut off value = 1 if it is large and 0 otherwise.

Let us find DFITS for our dataset.

```
. predict double dfits if e(sample), dfits
```

Let us sort the calculated DFITS statistics in descending order and check the results.

```
. gsort -dfits
```

Create a cut off value based on the degrees of freedom (e(df_m)), the number of observations (e(N)), and a multiplication factor of 2.

It uses the formula 2 * sqrt ((df_m + 1) / N).

```
. quietly generate cutoff = abs(dfits) > 2*sqrt((e(df_m)+1)/e(N)) & e(sample)

. list town price lprice dfits if cutoff
```

	town	price	lprice	dfits
1.	366	27499	10.2219	1.5679033
2.	368	23100	10.04759	.82559867
3.	369	50001	10.8198	.8196735
4.	372	50001	10.8198	.65967704
5.	373	50001	10.8198	.63873964
6.	371	50001	10.8198	.55639311
7.	370	50001	10.8198	.54354054
8.	361	24999	10.12659	.32184327
9.	359	22700	10.03012	.31516743
10.	408	27901	10.23642	.31281326
11.	367	21900	9.994242	.31060611
12.	360	22600	10.02571	.28892457
13.	363	20800	9.942708	.27393758
14.	358	21700	9.985067	.24312885
490.	386	7200	8.881836	-.23838749
491.	388	7400	8.909235	-.25909393
492.	491	8100	8.999619	-.26584795
493.	400	6300	8.748305	-.28782824
494.	416	7200	8.881836	-.29288953
495.	402	7200	8.881836	-.29595696
496.	381	10400	9.249561	-.29668364
497.	258	50001	10.8198	-.30053391
498.	385	8800	9.082507	-.302916
499.	420	8400	9.035987	-.30843965
500.	490	7000	8.853665	-.3142718
501.	401	5600	8.630522	-.33273658
502.	417	7500	8.922658	-.34950136
503.	399	5000	8.517193	-.36618139
504.	406	5000	8.517193	-.37661853
505.	415	7012	8.855378	-.43879798
506.	365	21900	9.994242	-.85150064

Note: Above are the observations that satisfy the cutoff criterion. Most of the observations associated with large positive DFITS are those which have a top-coded value of $50,001 for median housing price.

DFBETA (Deletion Residuals or change-in-estimate statistics)

It assesses how much the estimated coefficients change when a particular observation is removed from the analysis.

Like DFITS Statistics, let us follow the same steps to generate DFBETA.

```
. quietly regress lprice lnox ldist rooms room2 stratio lproptax
```

Calculate the DFBETA statistic for the variable lnox and store the values it in the variable _dfbeta_1.

```
. dfbeta lnox
                          _dfbeta_1:  dfbeta(lnox)
```

Create a binary variable named dfcut based on a condition involving the absolute value of _dfbeta_1 and a threshold value.

Note: The above condition checks if the absolute value of _dfbeta_1 is greater than 2/sqrt(e(N)) and if the observation is part of the sample.

```
. quietly generate dfcut = abs(_dfbeta_1) > 2/sqrt(e(N)) & e(sample)

. sort _dfbeta_

. summarize lnox
```

Variable	Obs	Mean	Std. Dev.	Min	Max
lnox	506	1.693091	.2014102	1.348073	2.164472

	town	price	lprice	lnox	_dfbeta_1
1.	369	50001	10.8198	1.842136	-.4316933
2.	372	50001	10.8198	1.842136	-.4257791
3.	373	50001	10.8198	1.899118	-.3631822
4.	371	50001	10.8198	1.842136	-.2938702
5.	370	50001	10.8198	1.842136	-.2841335
6.	365	21900	9.994242	1.971299	-.2107066
7.	408	27901	10.23642	1.885553	-.1728729
8.	368	23100	10.04759	1.842136	-.1309522
9.	11	15000	9.615806	1.656321	-.1172723
10.	410	27499	10.2219	1.786747	-.1117743
11.	413	17900	9.792556	1.786747	-.0959273
12.	437	9600	9.169518	2.00148	-.0955826
13.	146	13800	9.532424	2.164472	-.0914387
490.	154	19400	9.873029	2.164472	.0910494
491.	463	19500	9.87817	1.964311	.0941472
492.	464	20200	9.913438	1.964311	.0974507
493.	427	10200	9.230143	1.764731	.1007114
494.	406	5000	8.517193	1.93586	.1024767
495.	151	21500	9.975808	2.164472	.1047597
496.	152	19600	9.883285	2.164472	.1120427
497.	460	20000	9.903487	1.964311	.1142668
498.	160	23300	10.05621	2.164472	.1165014
499.	491	8100	8.999619	1.806648	.1222368
500.	362	19900	9.898475	2.04122	.1376445
501.	363	20800	9.942708	2.04122	.1707894
502.	490	7000	8.853665	1.806648	.1791869
503.	358	21700	9.985067	2.04122	.1827834
504.	360	22600	10.02571	2.04122	.2209745
505.	361	24999	10.12659	2.04122	.2422512
506.	359	22700	10.03012	2.04122	.2483543

Note: Just like DFITS we have similar patterns for the DFBETA for lnox. The sample here, exhibiting large values for $50,001 of median housing price which confirm outliers.

PS - The problem of this type - removing the bottom and top observations from the sample can be done using censoring (coding extreme value) with Tobit model.