Stata (Level 1 – Data) Workshop

Quantitative and Computing Lab (QCL)

Claremont McKenna College

Before We Begin

1. Sign-in Link
2. Retrieve Workshop file at (GitHub URL)
    - Make sure to unzip the file on “Desktop” folder on your Windows/MacOS!

Workshop Agenda

1	User Interface: Console	04:00 PM – 04:05 PM
2	Data Import	04:05 PM – 04:10 PM
3	Define Data	04:10 PM – 04:25 PM
4	Summary Statistics	04:25 PM – 04:35 PM
5	Regression Analysis	04:35 PM – 04:50 PM
6	Charts: Histogram and Scatter Plot	04:50 PM – 05:05 PM
7	Hands-on Exercises	05:05 PM – 05:25 PM
8	Q&A	05:25 PM – 05:30 PM

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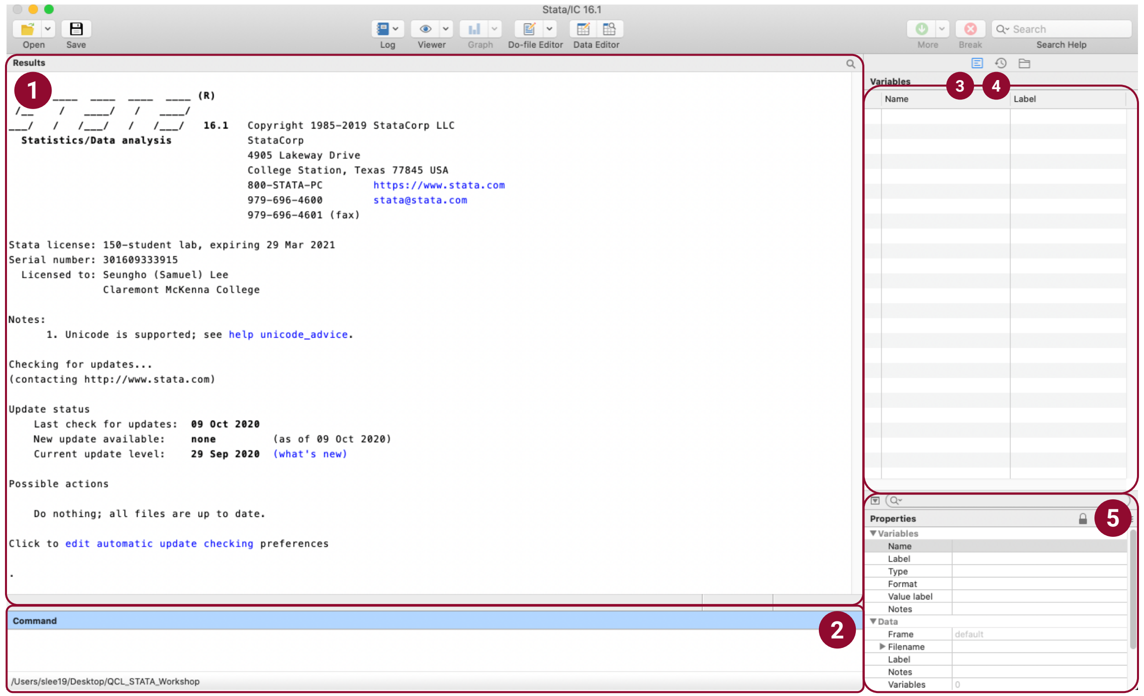
Stata Console – Main Window

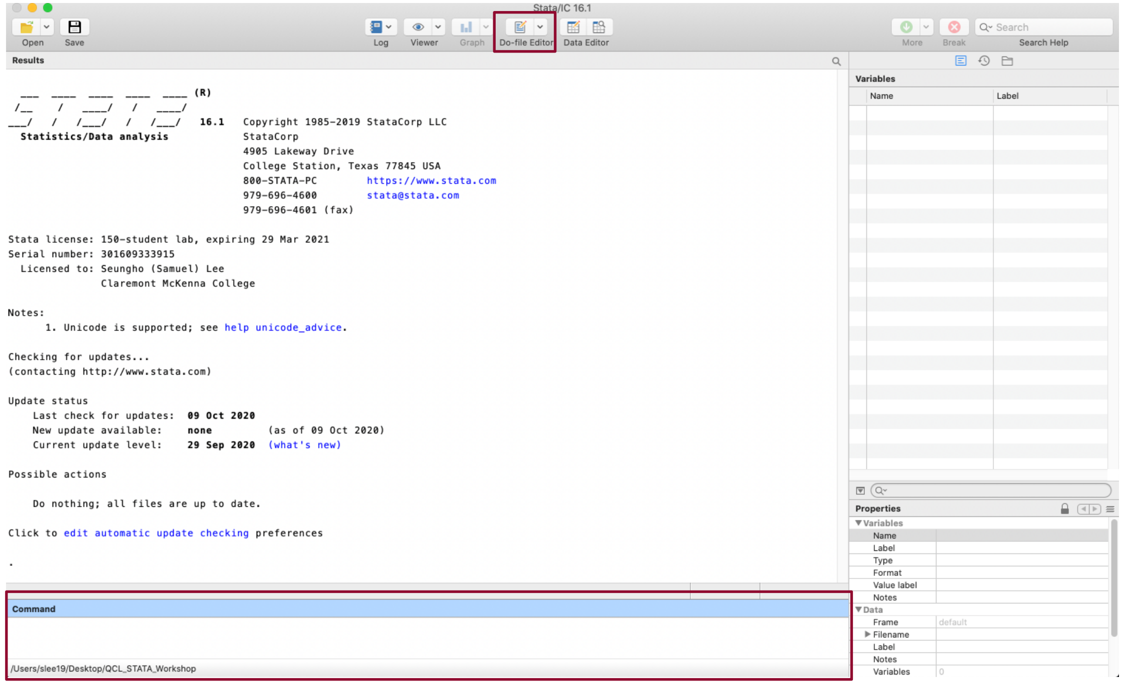
Stata window largely consists of command history, command line, output window, variable list, and data format.



1. **Results**: displays commands and resulting outputs from current session
2. **Command Line**: a window where a user enters a command
3. **Variable List**: lists all variables specified in active session
4. **Command History**: shows every command performed in active session
5. **Data Format**: detailed description of highlighted variable (e.g., type)

Stata Console – How It Works

While Stata is truly "interactive," users can also run a program as a "batch" mode (running commands listed on a file)



1. **Interactive Use**: typing Stata commands *directly* on the Command window to produce results.
2. **Batch Mode**: All commands are compiled in a file (called *Do-Files*), which Stata reads and executes.

During this workshop, we are going to use Do-File ".do" to import and explore data and conduct relevant analysis

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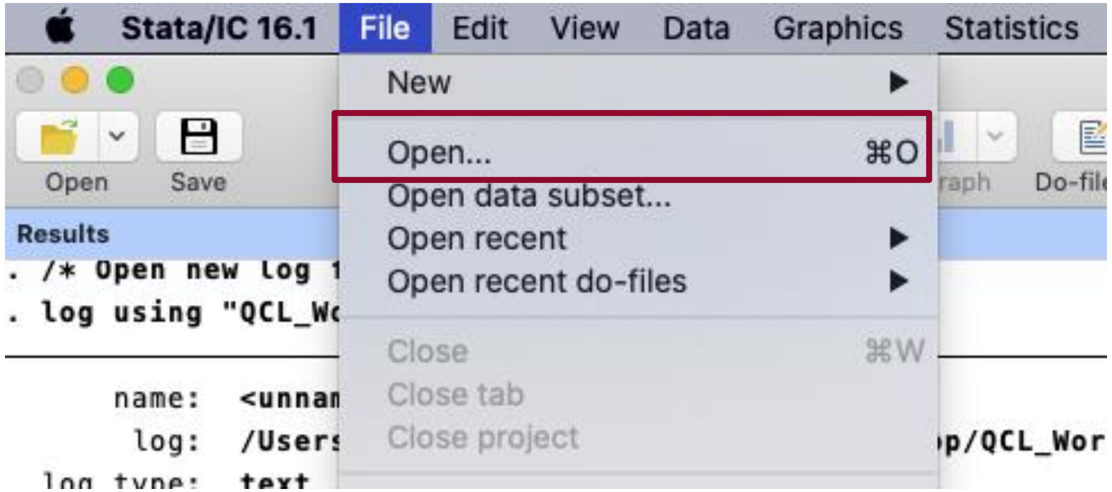
Stata Console – Do-Files (Open)

1. Press “File” on a top menu bar
2. Select “Open…”
3. Go to “QCL_Workshop” folder we downloaded on “Desktop” folder
4. Open “Rose_Workshop_QCL.do” file



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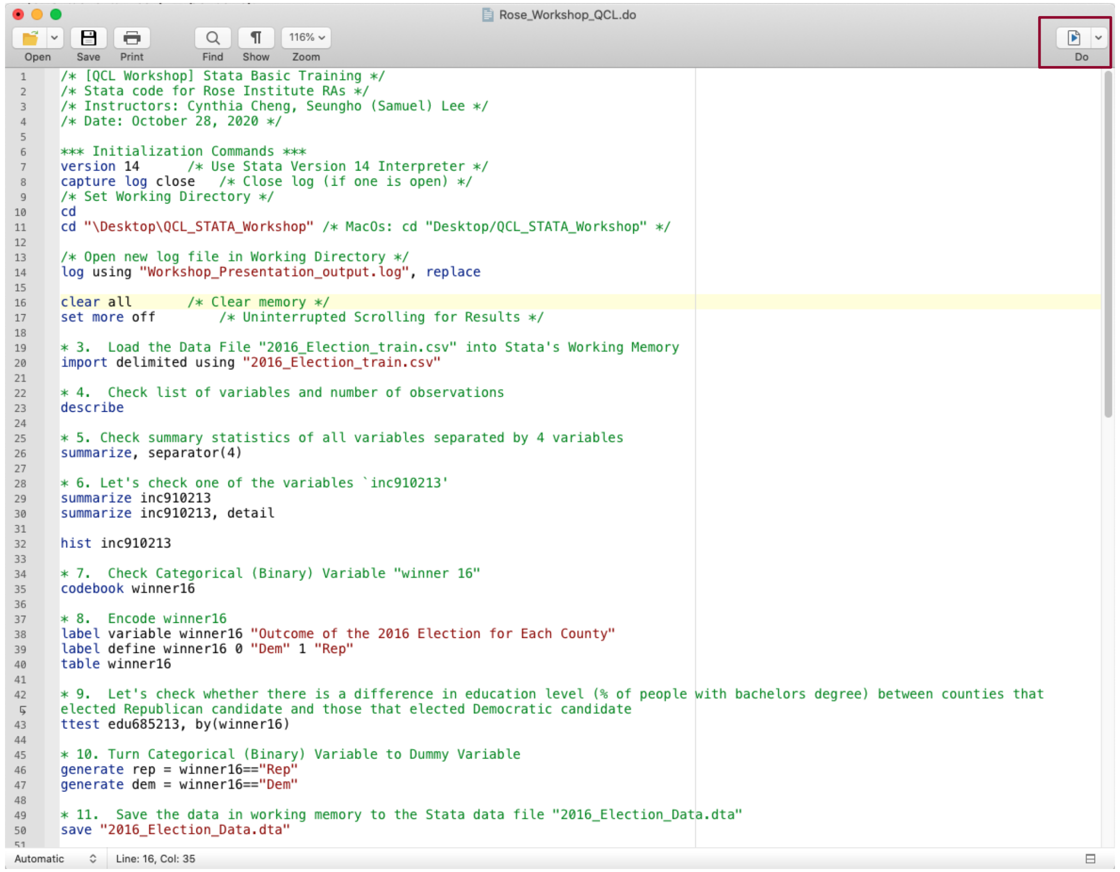
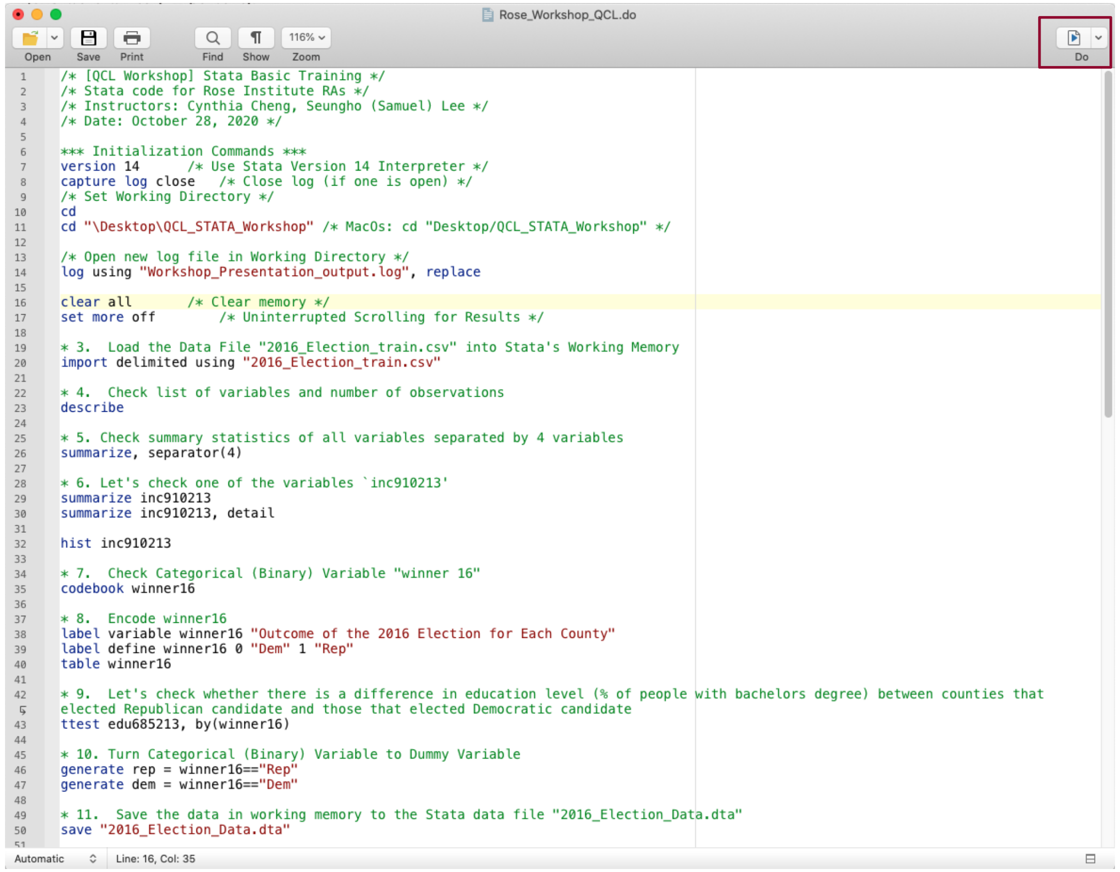
Stata Console – Do-Files

- Think of it as a set of *instructions* for Stata to conduct without manual input
- It is a good practice to compile *Do-File* since doing so allows others to ***reproduce***
- **Comment:**
  - **/* [INSERT COMMENT] */**: comments a specified section
  - *****: comments a whole line
- Press **boxed icon** shown on the screenshot to execute the file



Data Import

- **Setting Working Directory**:
  - *"cd"* command sets which folder you are going to be working on
  - Make sure to include data files in the folder
- **Importing Data**
  - Run *import delimited using "filename.csv"* command to import data files
  - You can also import Excel files (and many others) as well as direct URL link!



Define data

Whenever you use *import* function, it outputs a message that indicates the numbers of variables and observations in the dataset. For more details, use *describe*

```
. * 3.  Load the Data File "2016_Election_train.csv" into Stata's Working Memory
. import delimited using "2016_Election_train.csv"
(52 vars, 2,489 obs)

.
. * 4.  Check list of variables and number of observations
. describe

Contains data
  obs:         2,489
 vars:            52
------------------------------------------------------------------------------------
              storage   display    value
variable name   type    format     label      variable label
------------------------------------------------------------------------------------
pst045214       long    %12.0g                PST045214
pst040210       long    %12.0g                PST040210
pst120214       float   %9.0g                 PST120214
pop010210       long    %12.0g                POP010210
age135214       float   %9.0g                 AGE135214
age295214       float   %9.0g                 AGE295214
age775214       float   %9.0g                 AGE775214
sex255214       float   %9.0g                 SEX255214
rhi125214       float   %9.0g                 RHI125214
rhi225214       float   %9.0g                 RHI225214
```

- Data: Sampled 2016 Presidential Election Data by Counties (ECON122)
- ***describe* function can be used see a more detailed information of the imported data:**
  - Observations, Variables
  - Variable Name, Storage Type (e.g., long, float), Display format, value label, variable label
  - On Stata, you can label values and variables, which are helpful references
    (we will look at these functions during the Hands-on Exercise)

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Define data

Whenever you use *import* function, it outputs a message that indicates the numbers of variables and observations in the dataset. For more details, use *describe*

```
. * 3.  Load the Data File "2016_Election_train.csv" into Stata's Working Memory
. import delimited using "2016_Election_train.csv"
(52 vars, 2,489 obs)

.
. * 4.  Check list of variables and number of observations
. describe

Contains data
  obs:         2,489
 vars:            52
----------------------------------------------------------------------------------
              storage   display    value
variable name   type    format     label      variable label
----------------------------------------------------------------------------------
pst045214       long    %12.0g                PST045214
pst040210       long    %12.0g                PST040210
pst120214       float   %9.0g                 PST120214
pop010210       long    %12.0g                POP010210
age135214       float   %9.0g                 AGE135214
age295214       float   %9.0g                 AGE295214
age775214       float   %9.0g                 AGE775214
sex255214       float   %9.0g                 SEX255214
rhi125214       float   %9.0g                 RHI125214
rhi225214       float   %9.0g                 RHI225214
```

- **Common Storage Types**
  - byte: integer values between -127 and 100
  - int: integer values between -32,767 and 32,740
  - long: integer values between -2,147,483,647 and 2,147,483,620
  - float: real numbers (i.e., numbers with decimal points) with about 8 digits of accuracy
  - double: real numbers (i.e., numbers with decimal points) with about 16 digits of accuracy
  - str3: string values with a maximum length of 3
- What does having string values imply about the variable? (winner16 is a string variable!)

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Summary Statistics

- ***summarize*** function can be used see a more detailed information of the imported data:
  - Observations: number of observations in the variable
  - Mean: Mean (Average) Value of the variable
  - Standard Deviation
  - Min
  - Max

```
. summarize inc910213
```

Variable	Obs	Mean	Std. Dev.	Min	Max
inc910213	2,489	23558.73	5382.698	11818	62498

Summary Statistics

- Including *detail* option in ***summarize*** allows users to check more specific statistics:
  - **Percentiles**: a value of the variable at a given percentile (50th Percentile = Median)
  - **Smallest/Largest**: 4 lowest/highest values
  - **Skewness**: degree of distortion in our distribution (from normal) and direction
    - **Positive**: skewed to the right
    - **Negative**: skewed to the left
    - **Zero**: Normal
  - **Kurtosis**: how “fat” the tails are in the distribution, which shows whether there are *extreme outliers* in the data
    - **High deviation from 3** indicates that there is *high kurtosis*

```
. summarize inc910213, detail

                          INC910213
-------------------------------------------------------------
      Percentiles      Smallest
 1%        13954          11818
 5%        16540          12042
10%        17842          12113       Obs               2,489
25%        19929          12177       Sum of Wgt.       2,489

50%        22888                      Mean           23558.73
                        Largest       Std. Dev.      5382.698
75%        26187          54608
90%        29905          56791       Variance       2.90e+07
95%        33170          62018       Skewness       1.437638
99%        42210          62498       Kurtosis       7.982021
```

Mean cannot be captured correctly, leading to wrong interpretation!

Summary Statistics

```
. summarize inc910213, detail

                          INC910213
-------------------------------------------------------------
      Percentiles      Smallest
 1%        13954          11818
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10%        17842          12113       Obs               2,489
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```

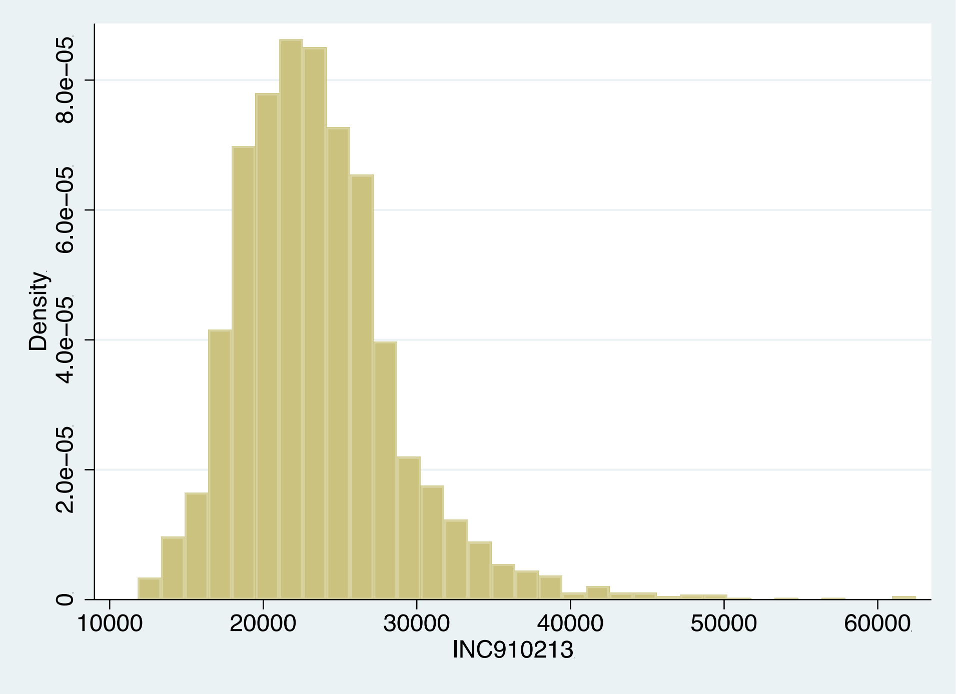

Mean cannot be captured correctly, leading to wrong interpretation!

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Summary Statistics

Summarize function can be used to see more detailed information about each variable. This can be done with all at once or on an individual basis

```
. summarize, separator(4)
```

Variable	Obs	Mean	Std. Dev.	Min	Max
pst045214	2,489	105939.7	351141.8	262	1.01e+07
pst040210	2,489	102615.3	337237.6	286	9818664
pst120214	2,489	.4666131	4.212294	-17	72.9
pop010210	2,489	102609.2	337229.8	286	9818605
age135214	2,489	5.88188	1.166596	1.5	12.2
age295214	2,489	22.52294	3.291917	7.4	37.5
age775214	2,489	17.66199	4.405271	4.1	52.9
sex255214	2,489	49.99574	2.167879	30.2	56.8
rhi125214	2,489	85.68112	15.331	12.8	99.3
rhi225214	2,489	9.123423	14.22124	0	84.1
rhi325214	2,489	1.916191	5.948727	0	82.2
rhi425214	2,489	1.322981	2.427037	0	42.4
rhi525214	2,489	.0992768	.3537572	0	12.7
rhi625214	2,489	1.849538	1.278885	0	29.4
rhi725214	2,489	9.007553	13.41946	.2	95.2
rhi825214	2,489	77.68726	19.34094	3.1	98.6
pop715213	2,489	86.40723	4.401603	50.8	99.8
pop645213	2,489	4.461511	5.482427	0	47.8
pop815213	2,489	9.077139	11.31973	0	94.2
edu635213	2,489	84.56774	6.806949	54	99

- For a summary statistics output for all variables, following values are produced for each variable:
  - Observations
  - Mean
  - Standard Deviation
  - Min
  - Max
- What can we know about *winner16* variable?

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Summary Statistics

Summarize function can be used to see more detailed information about each variable. This can be done with all at once or on an individual basis

```
. summarize winner16

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
    winner16 |          0
```

- Why does *winner16* have 0 observation?
  - As we mentioned before, it is stored as a *string* type, which needs to be recoded
  - Let's try ***codebook*** function to check what string inputs are recorded in the variable

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Summary Statistics

```
. codebook winner16

--------------------------------------------------------------------------------
winner16                                                            (unlabeled)
--------------------------------------------------------------------------------

                  type:  string (str3)

         unique values:  2                        missing "":  0/2,489

            tabulation:  Freq.  Value
                           378  "Dem"
                         2,111  "Rep"
```

- **We can see that there are 378 occurrences of “Dem” and 2,111 occurrences of “Rep”**
  - As we can see from a boxed corner, our binary variable is not labeled
  - By labeling / encoding our data, we are able to assess statistical significance of differences between different groups (or *string* values), which is done with *t*-test
- Let’s **label** *winner16* variable and run ***t*-test**

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Summary Statistics

Labeling is useful in analyzing variables from different observations based on their *string* values

```
1 label variable winner16 "Outcome of the 2016 Election for Each County"

2 label define winner16 0 "Dem" 1 "Rep"

3 table winner16
```

Outcome of the 2016 Election for Each County	Freq.
Dem	378
Rep	2,111

- **Descriptions of Executed Commands**

  1. Sets *variable label* as "Outcome of the 2016 Election for Each County"
  2. Sets *value label* as 0 for "Dem" and 1 for "Rep" values
  3. Shows encoded result of *winner16*

- We will now run a *t*-test to check whether there is **a difference in education level** between counties that elected Republican candidate and those that elected Democratic candidate

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Summary Statistics

- This is *t*-test of % of county residents with bachelor's degree (*edu685213*) on two *string* groups
    - Shows *t*-test result on ***difference between the two groups*** with summary statistics of each group and a complete dataset
    - Running *t*-test <u>*without specifying by condition*</u> produces the test on *whether the variable is statistically significantly different from 0*
- **Results**
    - We find the difference ***statistically significant*** at almost ***0% confidence level***
    - We also find that the counties that elected a democratic candidate have ***higher proportion of college educated residents***

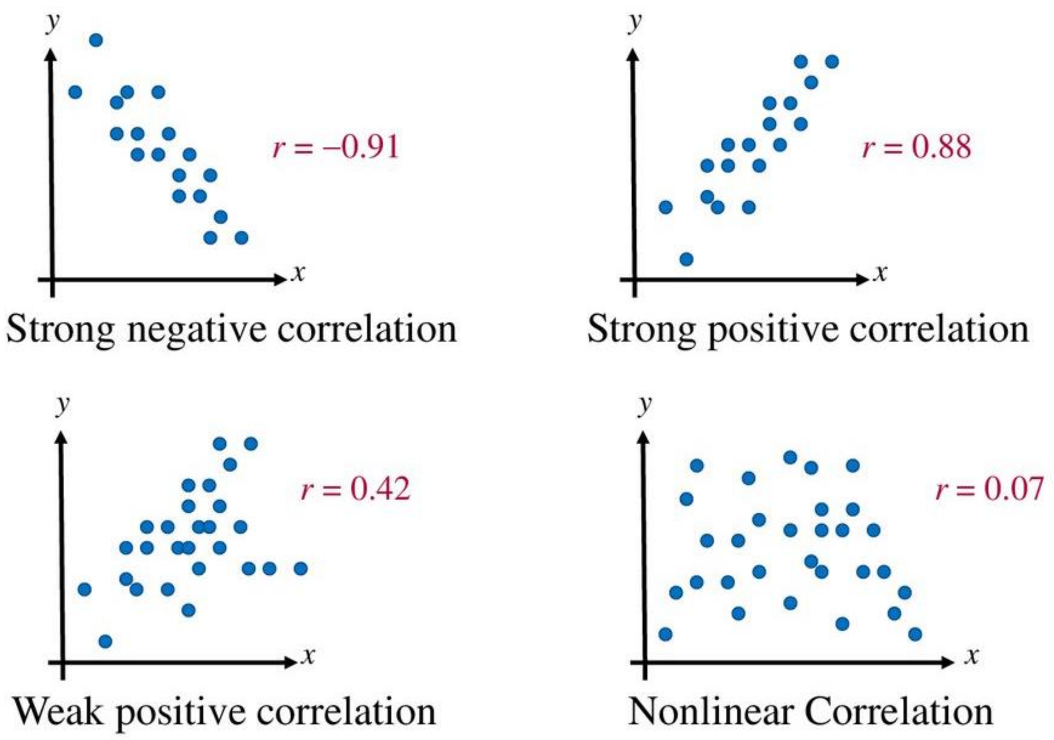
```
. ttest edu685213, by(winner16)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
     Dem |     378    28.08862    .6283082    12.21571     26.8532    29.32405
     Rep |   2,111     18.1973    .1462483    6.719467    17.91049    18.48411
---------+--------------------------------------------------------------------
combined |   2,489    19.69948    .1718544    8.573794    19.36249    20.03647
---------+--------------------------------------------------------------------
    diff |            9.891324    .4359419                9.036478    10.74617
------------------------------------------------------------------------------
    diff = mean(Dem) - mean(Rep)                                  t =  22.6895
Ho: diff = 0                                     degrees of freedom =     2487

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

Regression – Background

Before jumping into analyzing *winner16*, let's take a look at how population size impacts the number of firms in counties



- **Correlation Analysis**: evaluates the strength of relationship between two numerical variables
  - If the coefficient is **close to ±1**, a relationship between the two are **strongly correlated**
  - **Strongly Positive**: two variables move along the same direction
  - **Strongly Negative**: two variables move along the opposite direction

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Regression – Background

Before jumping into analyzing *winner16*, let's take a look at how population size impacts the number of firms in counties

```
. corr sbo001207 pst045214
(obs=2,489)

             | s~001207 p~045214
-------------+------------------
   sbo001207 |   1.0000
   pst045214 |   0.9845   1.0000
```

- **Correlation Analysis**: evaluates the strength of relationship between two numerical variables
  - If the coefficient is **close to ±1**, a relationship between the two are **strongly correlated**
  - **Strongly Positive**: two variables move along the same direction
  - **Strongly Negative**: two variables move along the opposite direction
- If the two variables have corr. coefficient of 0.9845, how would the regression look like?

Regression – Background

Regression Output

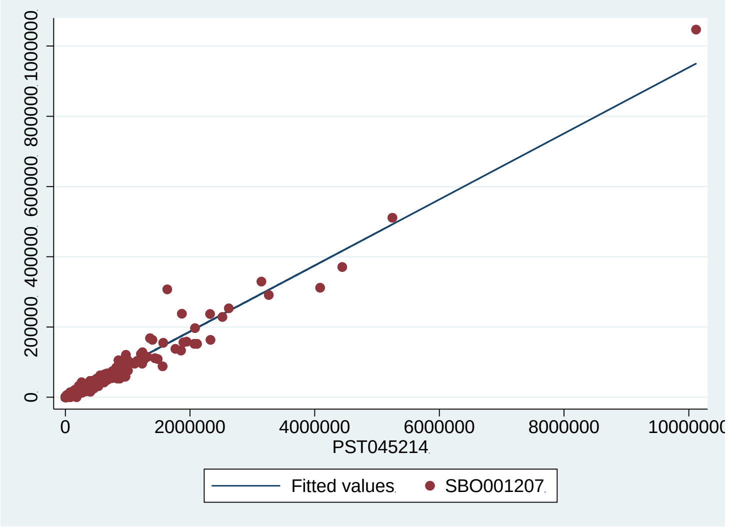
```
. reg sbo001207 pst045214

      Source |       SS           df       MS      Number of obs   =     2,489
-------------+----------------------------------   F(1, 2487)      =  78154.33
       Model |  2.7093e+12         1  2.7093e+12   Prob > F        =    0.0000
    Residual |  8.6213e+10     2,487  34665466.3   R-squared       =    0.9692
-------------+----------------------------------   Adj R-squared   =    0.9691
       Total |  2.7955e+12     2,488  1.1236e+09   Root MSE        =    5887.7

------------------------------------------------------------------------------
   sbo001207 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   pst045214 |   .0939761   .0003362   279.56   0.000     .0933169    .0946353
       _cons |  -849.4545   123.2708    -6.89   0.000    -1091.179   -607.7304
------------------------------------------------------------------------------
```

- **R^2 value** is 0.9692, meaning that **96.92%** of variation is explained
  - This is squared value of correlation coefficient that we saw earlier

Regression Plot



- Commands required to plot the regression:
  - **predict yhat** (right after running the regression)
  - **twoway scatter yhat y x, connect(l .) symbol(i 0)**

Regression – Background (Categorical)

We will be creating dummy variables from a binary variable *winner16* to analyze how certain variables impact the election outcome

- Categorical Variables
  - **Binary**, Nominal, Ordinal
  - Can be used for classifying different categories, **predicting categorical events**, or explaining differences among categorical values
- Numerical Variables
  - Continuous (infinite interval) or Discrete (finite)
  - Take on any value within a finite or infinite interval
  - Can be used for finding relationships and identifying characteristics

```
* 10. Turn Categorical (Binary) Variable to Dummy Variable
generate rep = winner16=="Rep"

generate dem = winner16=="Dem"
```

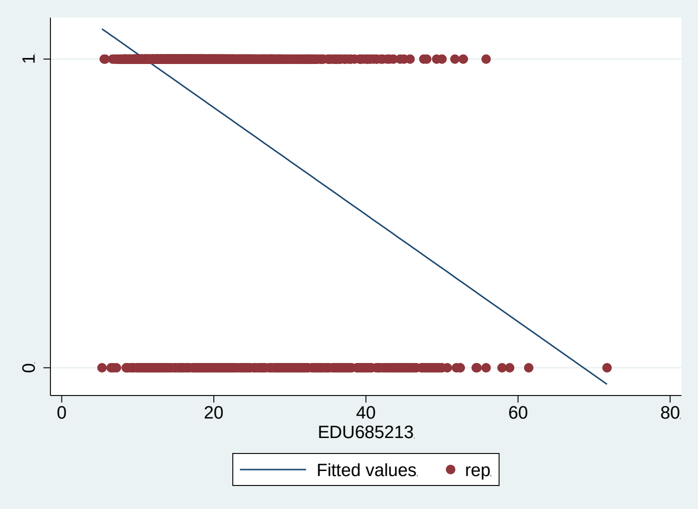
1. Creates *rep* variable with 1 = "Rep" (all else are 0)
2. Creates *dem* variable with 1 = "Dem" (all else are 0)

Regression – Simple Regression

```
. reg rep edu685213

      Source |       SS           df       MS      Number of obs   =     2,489
-------------+----------------------------------   F(1, 2487)      =    514.82
       Model |  54.9822781         1  54.9822781   Prob > F        =    0.0000
    Residual |  265.611535     2,487  .106799974   R-squared       =    0.1715
-------------+----------------------------------   Adj R-squared   =    0.1712
       Total |  320.593813     2,488  .128856034   Root MSE        =     .3268

------------------------------------------------------------------------------
         rep |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   edu685213 |  -.0173386   .0007642   -22.69   0.000     -.018837   -.0158401
       _cons |   1.189692   .0164171    72.47   0.000       1.1575    1.221885
------------------------------------------------------------------------------
```



- This is a simple linear regression model, $\boldsymbol{y} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} \cdot \mathbf{edu685213} + \boldsymbol{\epsilon}$.
  - We can see from R^2 that there is a lot of room to improve (82.85% of variation is still not explained)
  - Let's try to add more explanatory (independent) variables

Regression – Multiple Regression

- Take a look at a correlation between % of residents with bachelor's degree and those with high school diploma (***edu635213***)
- **Rules of Thumb**:
  No linear relationship = 0
  Perfect linear relationship = ±1
  Weak linear relationship = | 0 – 0.3 |
  Moderate linear relationship = |0.3 – 0.7|
  Strong linear relationship = |0.7 – 1.0|
- Generally, adding two or more variables with *R* < 0.7 does not increase a presence of *Multicollinearity*

```
. corr edu685213 edu635213
(obs=2,489)
```

	e~685213	e~635213
edu685213	1.0000	
edu635213	0.5958	1.0000

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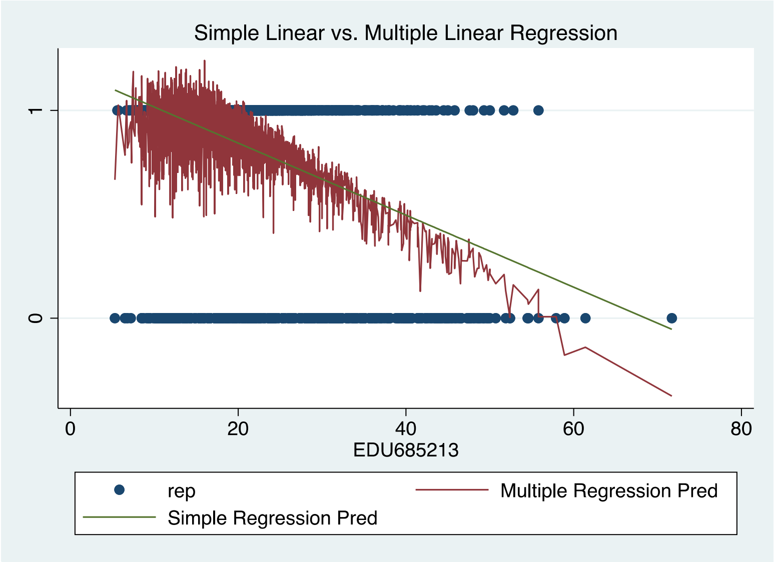
Regression – Multiple Regression

```
.   reg rep edu685213 edu635213

      Source |       SS           df       MS      Number of obs   =     2,489
-------------+----------------------------------   F(2, 2486)      =    451.47
       Model |  85.4182128         2  42.7091064   Prob > F        =    0.0000
    Residual |  235.1756       2,486       .0946   R-squared       =    0.2664
-------------+----------------------------------   Adj R-squared   =    0.2658
       Total |  320.593813     2,488  .128856034   Root MSE        =    .30757

------------------------------------------------------------------------------
         rep |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   edu685213 |  -.0269097   .0008955   -30.05   0.000    -.0286657   -.0251536
   edu635213 |   .0202324    .001128    17.94   0.000     .0180205    .0224443
       _cons |  -.3327694   .0862735    -3.86   0.000    -.5019448    -.163594
------------------------------------------------------------------------------
```



- This is a multiple linear regression model, $y = \beta_0 + \beta_1 \cdot \mathbf{edu685213} + \beta_2 \cdot \mathbf{edu635213} + \epsilon$.
  - We can see from R^2 that there is a lot of room to improve (82.85% of variation is still not explained)
  - Let's try to add more explanatory (independent) variables

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Regression – Multiple Regression


```
. reg rep edu685213 edu635213 age295214

      Source |       SS           df       MS      Number of obs   =     2,489
-------------+----------------------------------   F(3, 2485)      =    303.19
       Model |  85.9024426         3  28.6341475   Prob > F        =    0.0000
    Residual |   234.69137     2,485  .094443207   R-squared       =    0.2679
-------------+----------------------------------   Adj R-squared   =    0.2671
       Total |  320.593813     2,488  .128856034   Root MSE        =    .30732

------------------------------------------------------------------------------
         rep |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   edu685213 |  -.0269092   .0008948   -30.07   0.000    -.0286638   -.0251546
   edu635213 |   .0206581   .0011426    18.08   0.000     .0184175    .0228986
   age295214 |   .0043285   .0019116     2.26   0.024       .00058     .008077
       _cons |  -.4662677   .1044352    -4.46   0.000    -.6710568   -.2614787
------------------------------------------------------------------------------
```

- Let's try to add more explanatory variable: *age295214* (persons under 18 years)
  - We can see from R^2 that there is a lot of room to improve (82.85% of variation is still not explained)
  - Also, note that *age295214* is not statistically significant at 99% confidence
- Let's try to add **interaction variable** of *age295214* and another with *strongest correlation*

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Regression – Multiple Regression

- From the correlation coefficients, we can see that *age295214* is weakly correlated with *edu685213 with second highest value.*
- *Let's try to make interaction term from the two variables:*

$$AGE295\_EDU685 = \mathrm{AGE295214} \cdot \mathrm{EDU685213}$$

- Use **gen** ***age295_edu685 = age295214 * edu685213*** command to generate the interaction variable

```
. corr edu635213 edu685213 age295214
(obs=2,489)

             | e~635213 e~685213 a~295214
-------------+---------------------------
   edu635213 |   1.0000
   edu685213 |   0.5958   1.0000
   age295214 |  -0.2035  -0.1214   1.0000
```

Regression – Multiple Regression

- We see that there is **a very slight improvement in *R^2***, which is pretty common in variable selection process:
  - Depending on what kinds of variables are being included, interaction variables could *drastically help to better fit* or *does not have much impact* in the model
- Let's include one more variable: *rhi825214*
  - Definition: "White alone, not Hispanic"

```
. gen age295_edu635 = age295214 * edu635213

.

.

. reg rep edu685213 edu635213 age295214 age295_edu635
```

Source	SS	df	MS
Model	86.595906	4	21.6489765
Residual	233.997907	2,484	.094202056
Total	320.593813	2,488	.128856034

Number of obs	=	2,489
F(4, 2484)	=	229.81
Prob > F	=	0.0000
R-squared	=	0.2701
Adj R-squared	=	0.2689
Root MSE	=	.30692

rep	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
edu685213	-.0264762	.0009078	-29.17	0.000	-.0282563	-.0246961
edu635213	.0064699	.0053524	1.21	0.227	-.0040257	.0169655
age295214	-.0451726	.0183442	-2.46	0.014	-.0811441	-.0092012
age295_edu635	.0005926	.0002184	2.71	0.007	.0001643	.001021
_cons	.7138551	.4472872	1.60	0.111	-.1632391	1.590949

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Regression – Multiple Regression

```
. reg rep edu635213 edu685213 age295214 rhi825214 edu635_685

      Source |       SS           df       MS      Number of obs   =     2,489
-------------+----------------------------------   F(5, 2483)      =    376.54
       Model |  138.256344         5  27.6512688   Prob > F        =    0.0000
    Residual |  182.337469     2,483  .073434341   R-squared       =    0.4313
-------------+----------------------------------   Adj R-squared   =    0.4301
       Total |  320.593813     2,488  .128856034   Root MSE        =    .27099

------------------------------------------------------------------------------
         rep |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   edu635213 |    .007472   .0019186     3.89   0.000     .0037098    .0112342
   edu685213 |   .0290921   .0105674     2.75   0.006     .0083703    .0498138
   age295214 |   .0176986   .0017595    10.06   0.000     .0142485    .0211488
   rhi825214 |   .0100813   .0003783    26.65   0.000     .0093394    .0108231
  edu635_685 |  -.0005053   .0001162    -4.35   0.000    -.0007332   -.0002774
       _cons |  -.6792475   .1682171    -4.04   0.000    -1.009108   -.3493873
------------------------------------------------------------------------------
```

- Taking a similar approach, we end up with $y = \textbf{edu635213} + \textbf{edu685213} + \textbf{age295214} + \textbf{rhi825214} + \textbf{edu635\_685}$
  - **Interaction Variable:** $\text{edu635\_685} = \text{edu635213} \cdot \text{edu685213}$
  - Final R^2 value is 0.4301, which is a significant improvement from a simple linear model we constructed
  - *p*-values also suggest that all variables that we use have statistical significance

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Regression – Logistic Regression

- **Logistic Regression**: a binary classification model, with a $0 \leq h_{\theta(x)} \leq 1$ range, that outputs probability of an observation to be either of the binary values, using:

$$\log\left(\frac{p(X)}{1-p(X)}\right) = \beta_0 + \beta_{1X} + \cdots + \beta_x X_x$$

  - *Good for analyzing binary variables since it is bound between 0 and 1*
  - *Coefficients:* the expected change in log odds for one-unit increase in one of the independent variables (all held constant)
- *We can see that Pseudo R2 is 0.5396, which is an improve from the previous model. Therefore, logistic regression can better capture binary values*

```
. logit rep edu635213 edu685213 age295214 rhi825214

Iteration 0:   log likelihood = -1060.1549
Iteration 1:   log likelihood = -613.33484
Iteration 2:   log likelihood = -497.25696
Iteration 3:   log likelihood = -488.21436
Iteration 4:   log likelihood = -488.11949
Iteration 5:   log likelihood = -488.11942
Iteration 6:   log likelihood = -488.11942

Logistic regression                             Number of obs     =      2,489
                                                LR chi2(4)        =    1144.07
                                                Prob > chi2       =     0.0000
Log likelihood = -488.11942                     Pseudo R2         =     0.5396
```

rep	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
edu635213	-.0726455	.0223479	-3.25	0.001	-.1164466	-.0288445
edu685213	-.1565054	.0132512	-11.81	0.000	-.1824772	-.1305336
age295214	.2281572	.0251916	9.06	0.000	.1787825	.2775319
rhi825214	.1311172	.0077747	16.86	0.000	.1158791	.1463552
_cons	-2.670578	1.508954	-1.77	0.077	-5.628074	.2869181

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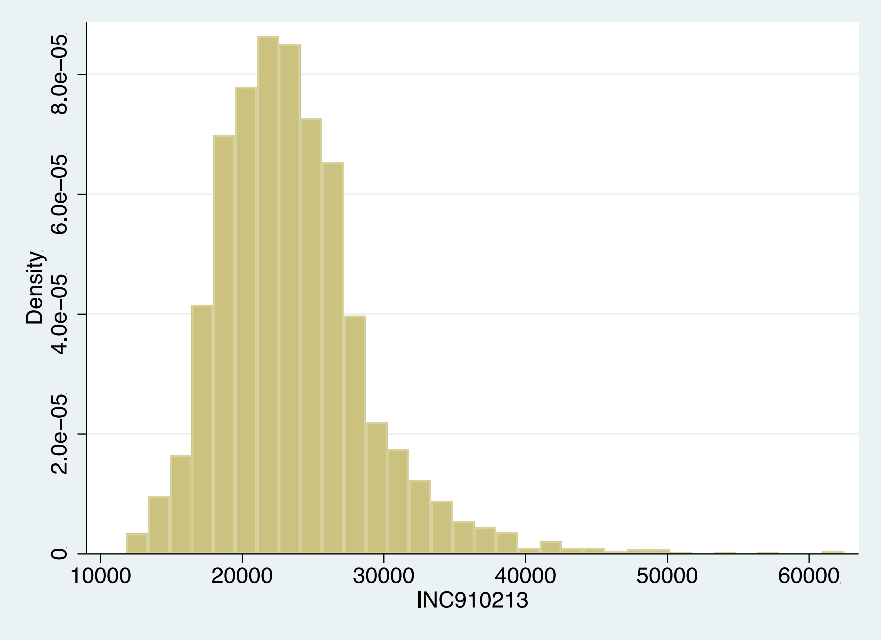
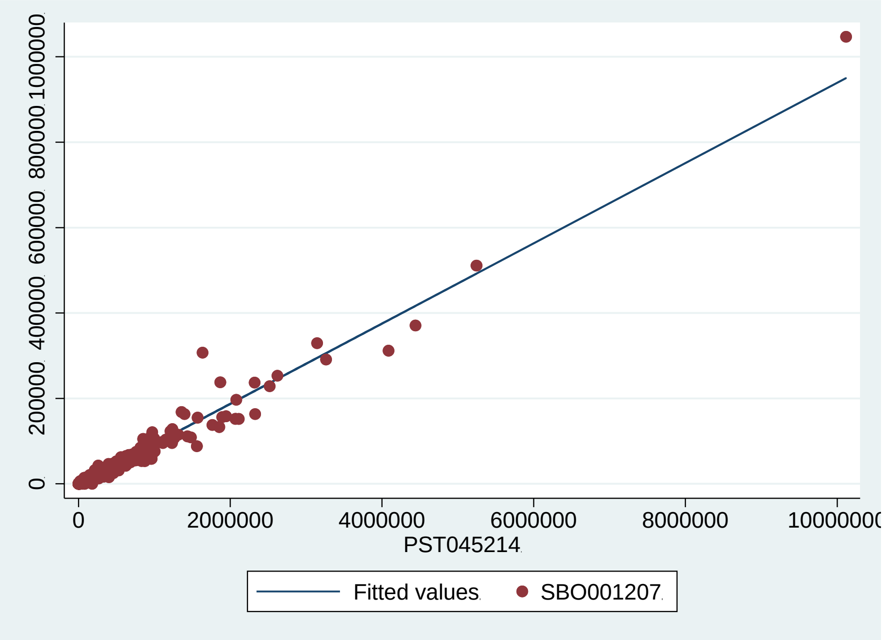
Charts – Syntax and Examples

Histogram of *INC910213*



Command: **hist ubc819213**

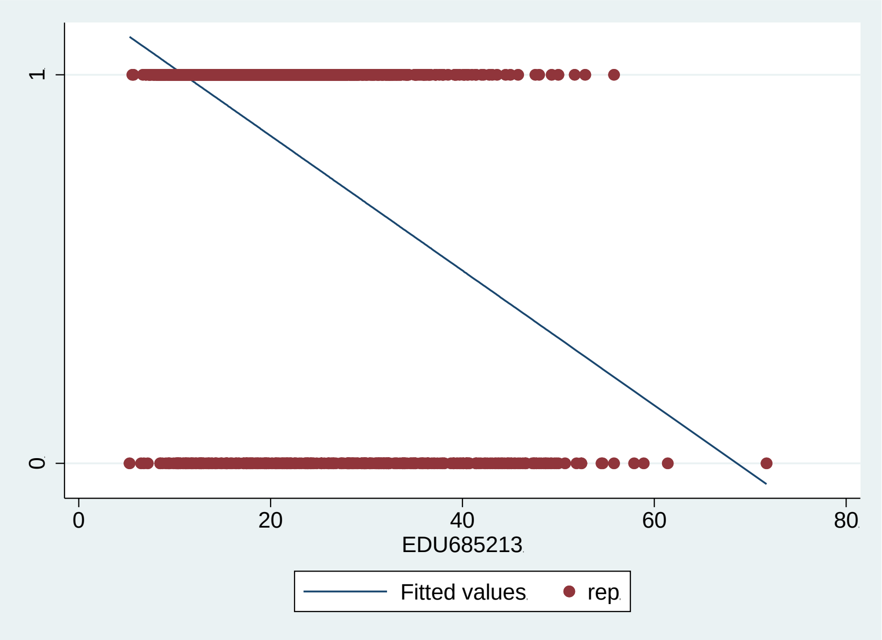
Regression Plot of Simple Linear Regression



twoway scatter yhat_ex sbo001207 pst045214, connect(l .) symbol(i 0)

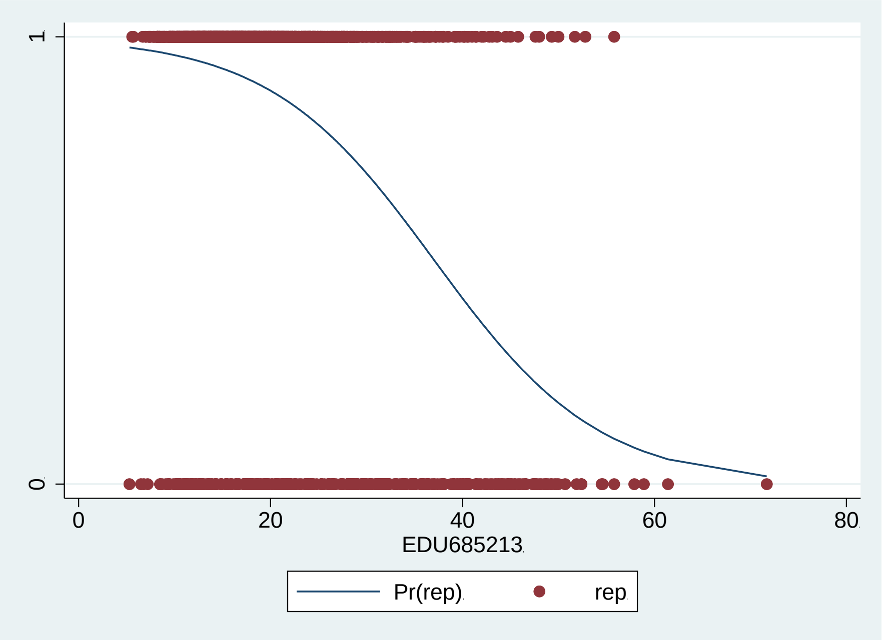
Charts – Syntax and Examples

Simple Linear Regression Plot



twoway scatter yhat_linear rep edu685213, connect(l .) symbol(i 0) sort ylabel(0 1)

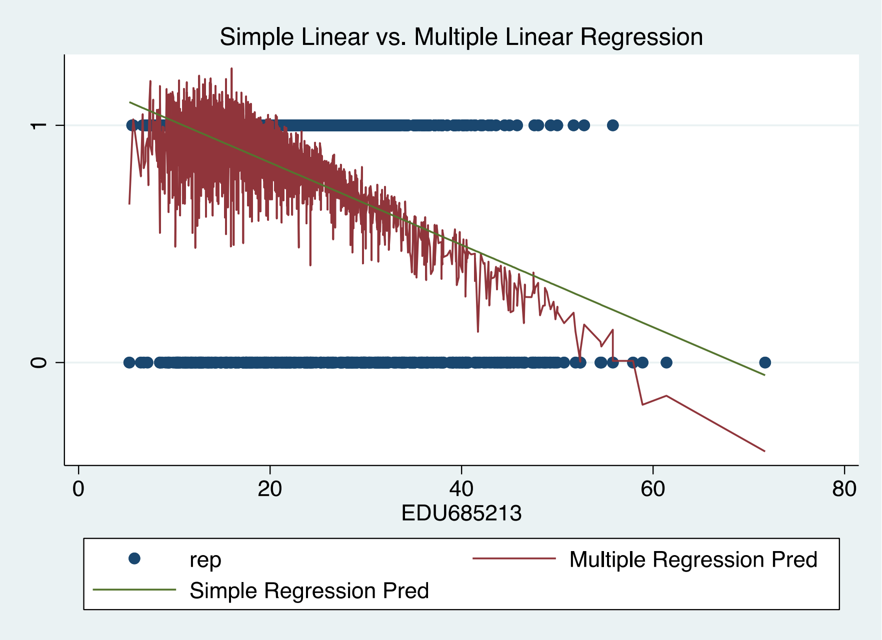
Regression Plot of Simple Logistic Regression (Logit)



twoway scatter yhat_logit rep edu685213, connect(l i) msymbol(i 0) sort ylabel(0 1)

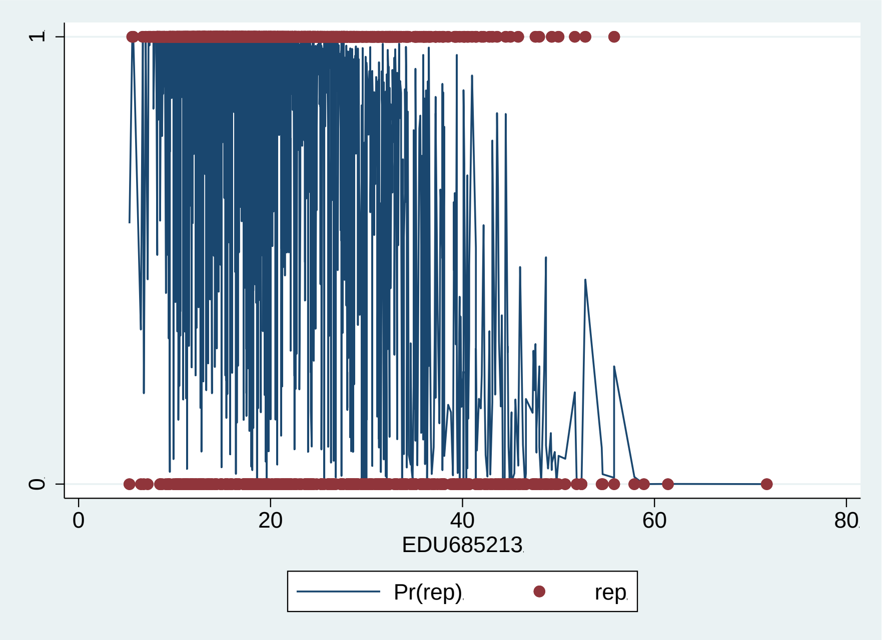
Charts – Syntax and Examples

Simple Linear vs. Multiple Linear Regression Plot



twoway scatter rep MLR yhat_linear edu685213, connect(. l -) msymbol(. i i) sort ylabel(0 1)

Regression Plot of Multiple Logistic Regression (Logit)



twoway scatter yhat_all rep edu685213, connect(l i) msymbol(i 0) sort ylabel(0 1)

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Hands-on Exercise

- Using the sqf-2019.xlsx (NYCLU's 2019 NYC Stop-and-Frisk Dataset), generate the following output:

    1. Histogram plot using the age variable, divide the ranges into 5 groups.
    2. Summary statistics for age, weight and height variables.
    3. Correlation using age, weight and height variables.
    4. Scatter plot using age and weight variables.
    5. Simple regression equation using age and weight variables.
    6. Multiple regression equation using age, weight and height variables.

Summary / Q&A

- Key Takeaways:
  - User Interface (Do-File)
  - Data Import and Exploration
  - Summary Statistics
  - Regression Analysis
- Tips:
  - Stata/R Useful Packages: https://geocenter.github.io/StataTraining/portfolio/06_resource/
  - Internet Guide to Stata: http://wlm.userweb.mwn.de/Stata/
  - UCLA IDRE Guide: https://stats.idre.ucla.edu/stata/
- Contact: qcl@cmc.edu (with a title: “Re: Rose Institute Stata Workshop”)
  - Feel free to contact me (slee19@students.cmc.edu) if you have any questions on PowerPoint and Stata materials