# Stata (Level 1 – Data) Workshop

Quantitative and Computing Lab (QCL)

# Before We Begin

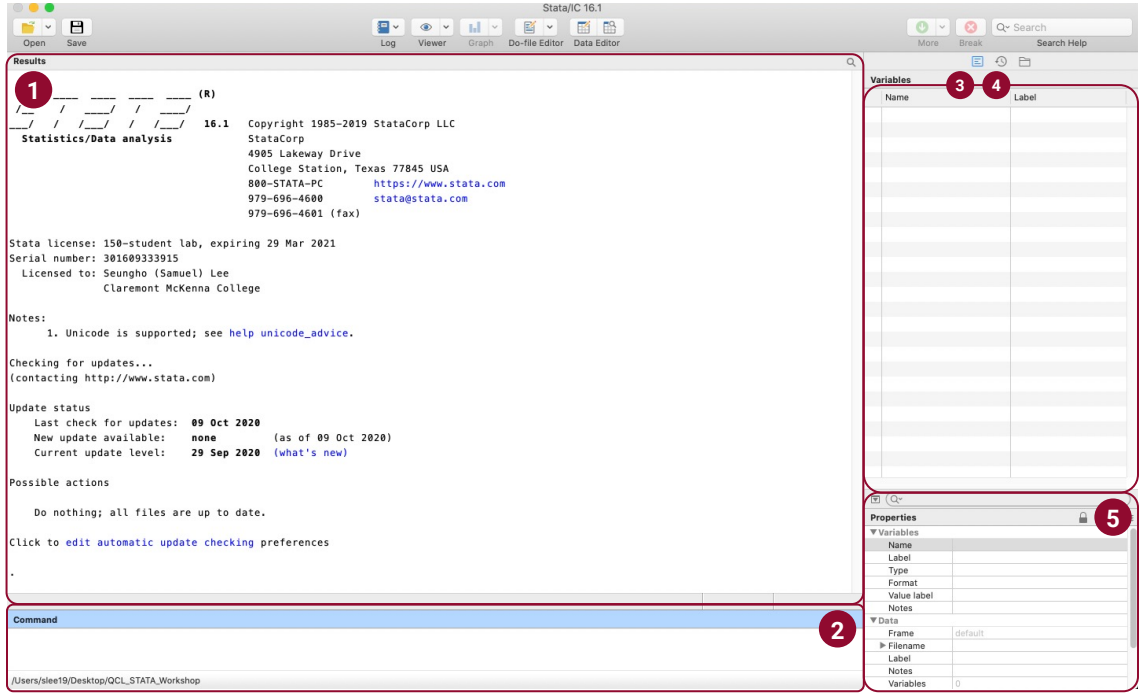
1. Sign-in Link
2. Retrieve Workshop file at (https://github.com/CMC-QCL/STATA-L1-Workshop/blob/students/Stata_Workshop_Files.zip)
   - After you have downloaded “Workshop_Files” compressed file, extract the folder on “Desktop”
3. Learning Objective: Ensure that all participants gain some level of confidence using Stata and statistical analysis
4. Tip: Open .do, PDF, and any other files that I am using throughout the workshop to make sure that you are following along.

# Workshop Agenda

| | | |
|---|---|---|
| 1 | User Interface: Console | 03:00 PM – 03:05 PM |
| 2 | Data Import | 03:05 PM – 03:10 PM |
| 3 | Define Data | 03:10 PM – 03:25 PM |
| 4 | Summary Statistics | 03:25 PM – 03:50 PM |
| 5 | Regression Analysis | 03:50 PM – 04:15 PM |
| 6 | Charts: Histogram and Scatter Plot | 04:15 PM – 04:20 PM |
| 7 | Hands-on Exercises | 04:20 PM – 04:50 PM |
| 8 | Q&A | 04:50 PM – 05:00 PM |

# 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)

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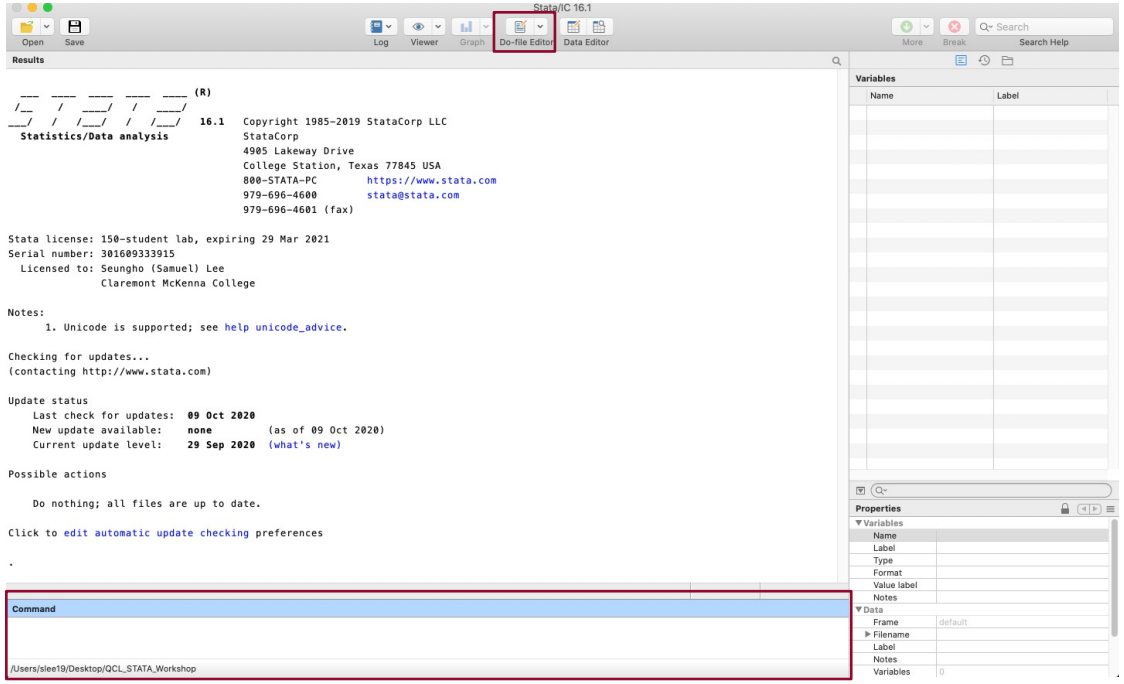
# Stata Console – How It Works

## 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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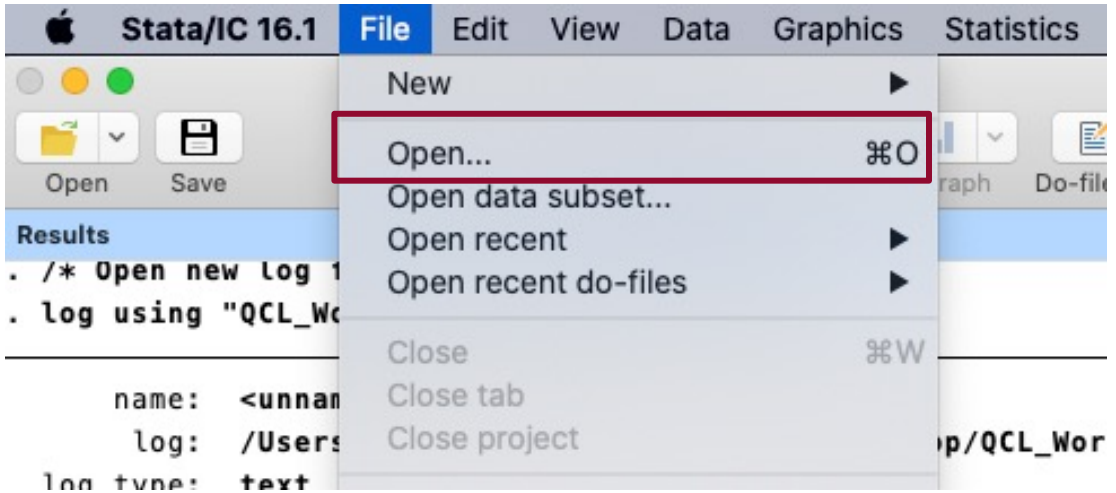
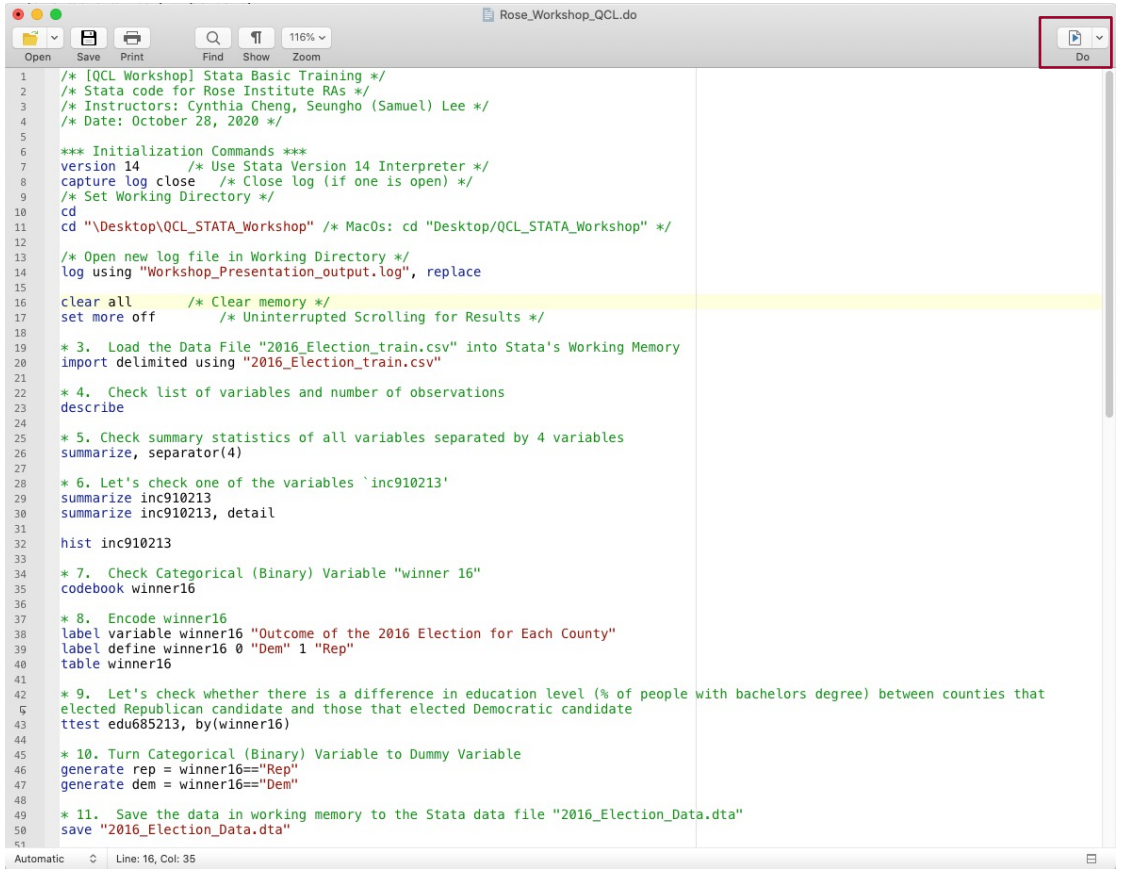
# Stata Console – Do-Files (Open)

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



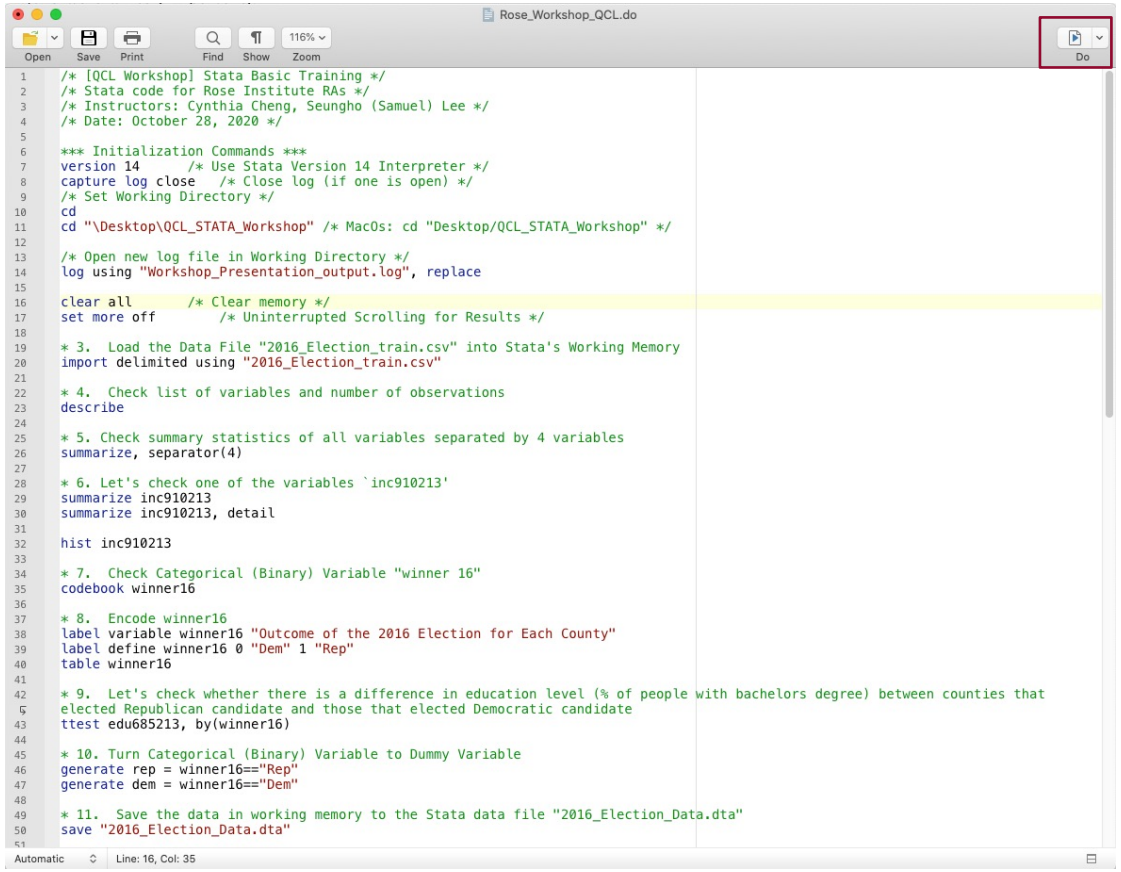
# Stata Console – Do-Files

- 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
```

| variable name | storage type | display format | value 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)

# 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*

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| 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!)

# 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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```

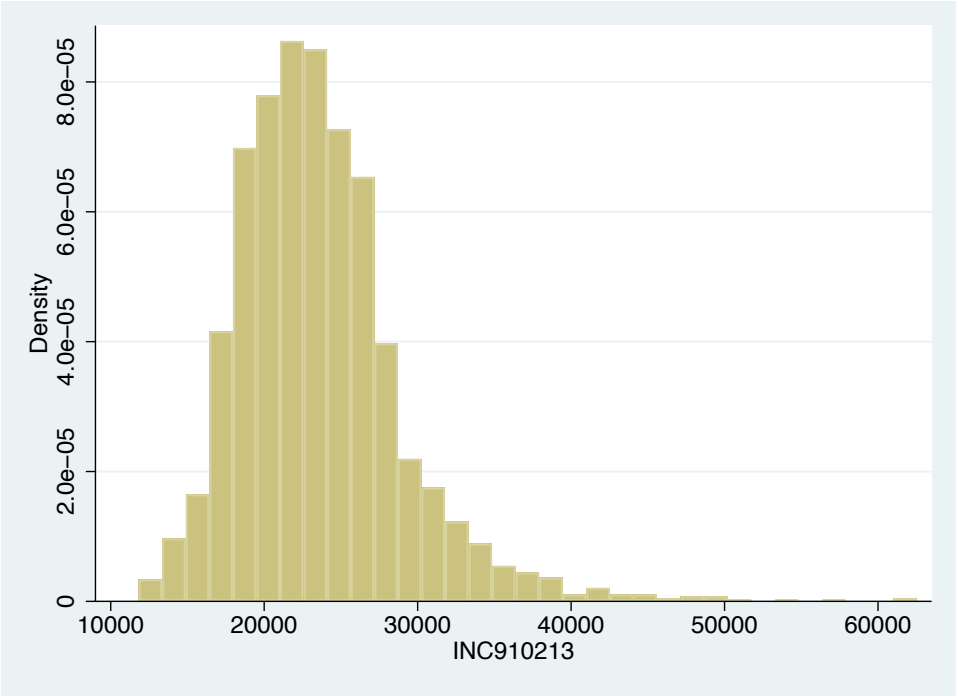


**Mean cannot be captured correctly, leading to wrong interpretation!**

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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

# 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**

# Categorical Data – Processing

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

- 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

```
. * 8.  Turn Categorical/Binary Variable "winner16"
. generate rep = winner16=="Rep"

.
. label variable winner16 "Outcome of the 2016 Elect

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

. label value rep winner16
```

1. Creates *rep* variable with 1 = “Rep” (all else are 0)
2. Set *winner16*‘s label with a description
3. Define numerical values to *winner16*’s string values
4. Assign *winner16* string values as *rep* labels

# Summary Statistics (cont.)

- 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 *without specifying by condition* produces the test on *whether the variable is statistically significantly different from 0*
- **Results**
  - We find the difference ***statistically significant*** almost at ***100% 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
```

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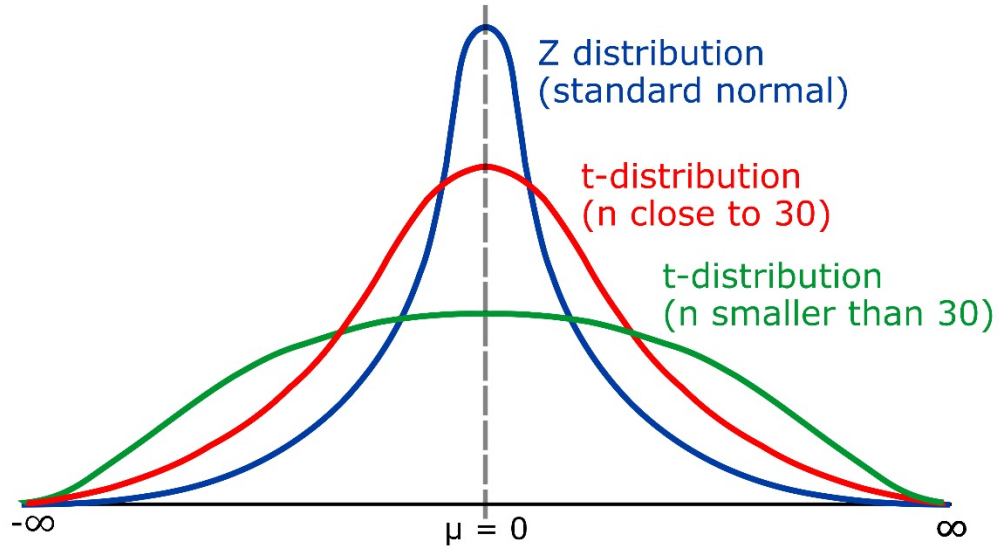
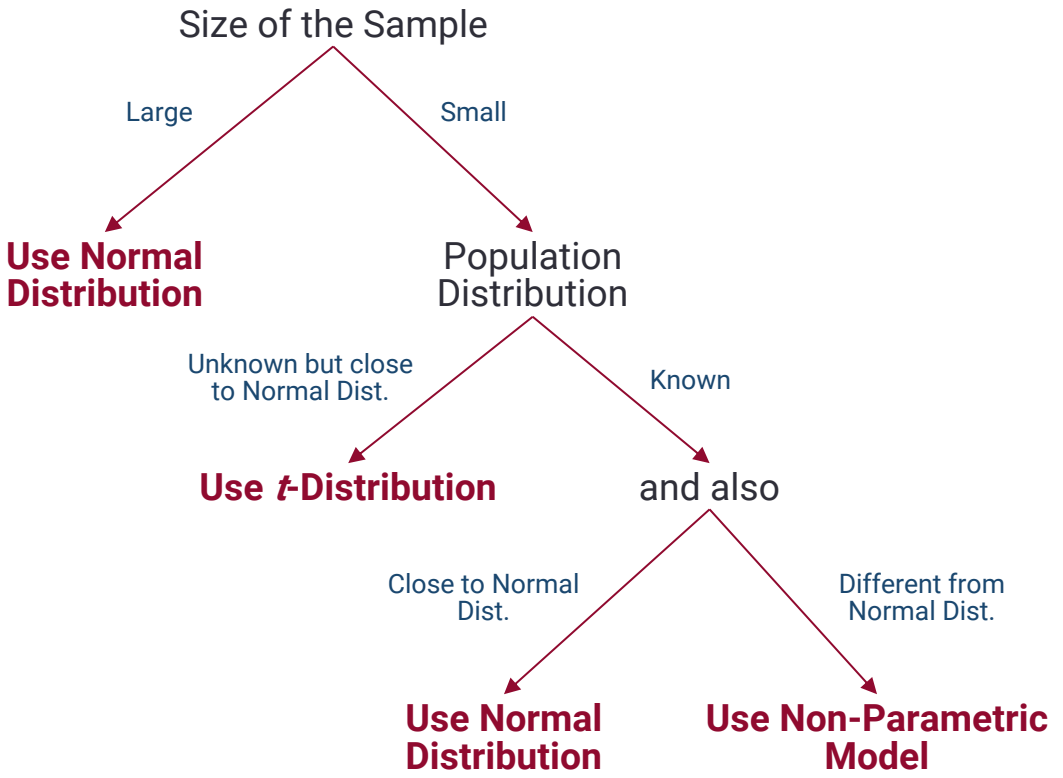
# Summary Statistics

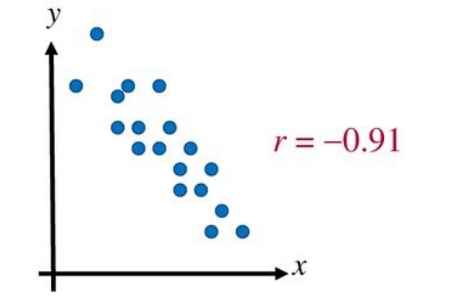



Source: "Student's t-distribution in Statistics," *GeeksforGeeks.org*.

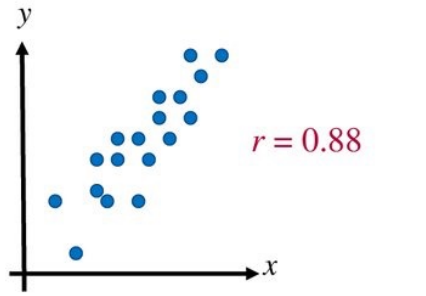


# Regression – Background

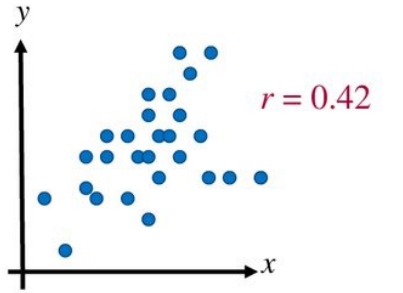
**Before jumping into analyzing *winner16*, let's take a look at how population size impacts the number of firms in counties**



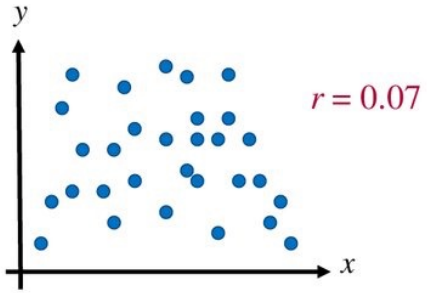
Strong negative correlation



Strong positive correlation



Weak positive correlation



Nonlinear Correlation

- **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
- Note that $\mathbf{Correlation \neq Causation}$

# 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, what would the regression look like?

# Regression – Background

## Regression Output

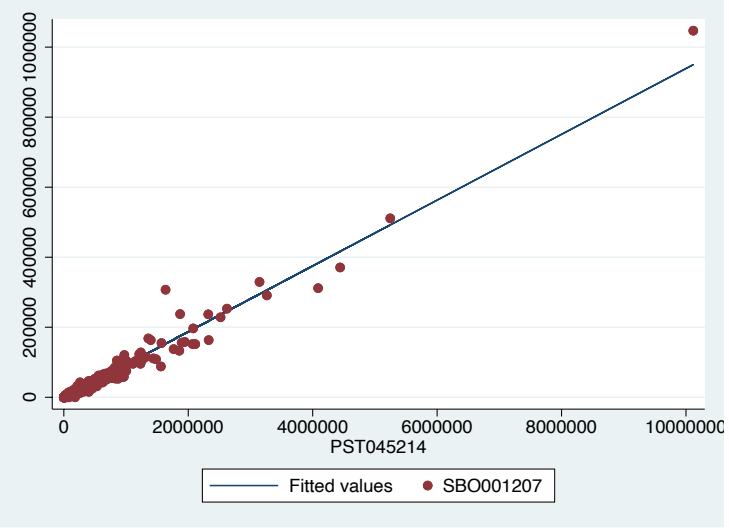
```
. reg sbo001207 pst045214
```

| Source | SS | df | MS | | |
|---|---|---|---|---|---|
| Model | 2.7093e+12 | 1 | 2.7093e+12 | Number of obs | = 2,489 |
| Residual | 8.6213e+10 | 2,487 | 34665466.3 | F(1, 2487) | = 78154.33 |
| | | | | Prob > F | = 0.0000 |
| | | | | 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



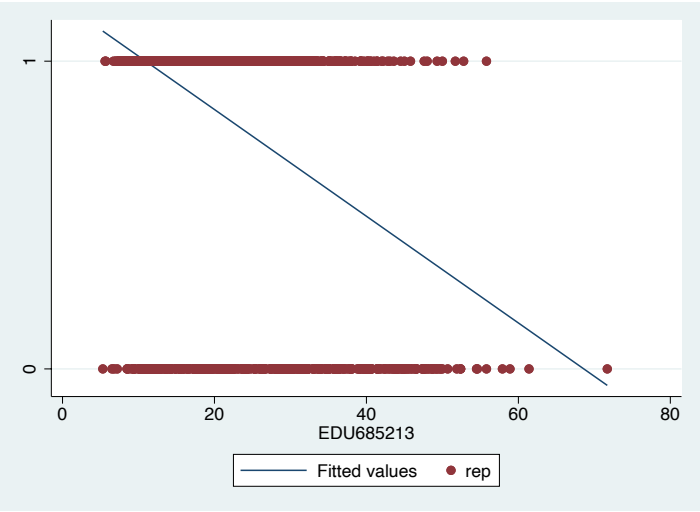

- Commands required to plot the regression:
  - **predict yhat** (right after running the regression)
  - **twoway scatter yhat y x, connect(l .) symbol(i 0)**
- We will now regress *Rep* binary variable on % of college educated to see the relationship

# Regression – Simple Regression

```
. reg rep edu685213
```

| Source | SS | df | MS | | |
|---|---|---|---|---|---|
| Model | 54.9822781 | 1 | 54.9822781 | Number of obs | = 2,489 |
| Residual | 265.611535 | 2,487 | .106799974 | F(1, 2487) | = 514.82 |
| | | | | Prob > F | = 0.0000 |
| | | | | 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, $\boldsymbol{Rep = \beta_0 + \beta_1 \cdot \text{edu685213} + \epsilon}$.
  - 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
- We can also see that coefficient of the % of college graduates is statistically significant (large *t*-statistics / low *p*-value)

# 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)
```

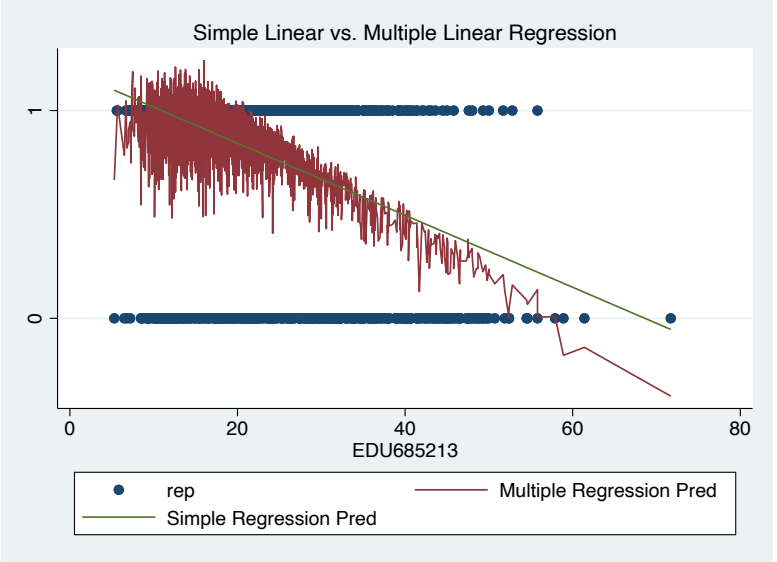
| | e~685213 | e~635213 |
|---|---|---|
| edu685213 | **1.0000** | |
| edu635213 | **0.5958** | **1.0000** |

# 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, $\boldsymbol{y = \beta_0 + \beta_1 \cdot \text{edu685213} + \beta_2 \cdot \text{edu635213} + \epsilon}$.
  - There is a recognizable improvement from the model
  - Also, notice that the coefficients have low *p*-values

# Regression – Multiple Regression

- Our final model exhibits relatively high performance with coefficients statistically significant
  - Adjusted R-Squared: 0.4324
  - Each coefficient represents a percentage point difference on selecting Trump by a unit change in the variable
    (e.g., having **1% higher proportion** of *Persons under 18 years* lead to **1.66 p.p increase** in chances of *selecting Trump*)
- BONUS: Instead of Linear Regression model, what can we use to address this *classification problem*?

```
. reg rep edu685213 age295214 rhi825214 inc910213 edu685_inc910
```

| Source | SS | df | MS | Number of obs | = | 2,489 |
|---|---|---|---|---|---|---|
| | | | | F(5, 2483) | = | 380.13 |
| Model | 139.003014 | 5 | 27.8006027 | Prob > F | = | 0.0000 |
| Residual | 181.590799 | 2,483 | .073133628 | R-squared | = | 0.4336 |
| | | | | Adj R-squared | = | 0.4324 |
| Total | 320.593813 | 2,488 | .128856034 | Root MSE | = | .27043 |

| rep | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| edu685213 | -.0124817 | .0020331 | -6.14 | 0.000 | -.0164685 | -.0084949 |
| age295214 | .0166106 | .0017648 | 9.41 | 0.000 | .0131499 | .0200713 |
| rhi825214 | .0092258 | .000322 | 28.65 | 0.000 | .0085945 | .0098572 |
| inc910213 | .0000142 | 2.61e-06 | 5.46 | 0.000 | 9.12e-06 | .0000193 |
| edu685_inc910 | -2.72e-07 | 6.99e-08 | -3.90 | 0.000 | -4.09e-07 | -1.35e-07 |
| _cons | -.1959171 | .0678765 | -2.89 | 0.004 | -.3290174 | -.0628168 |

# 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:

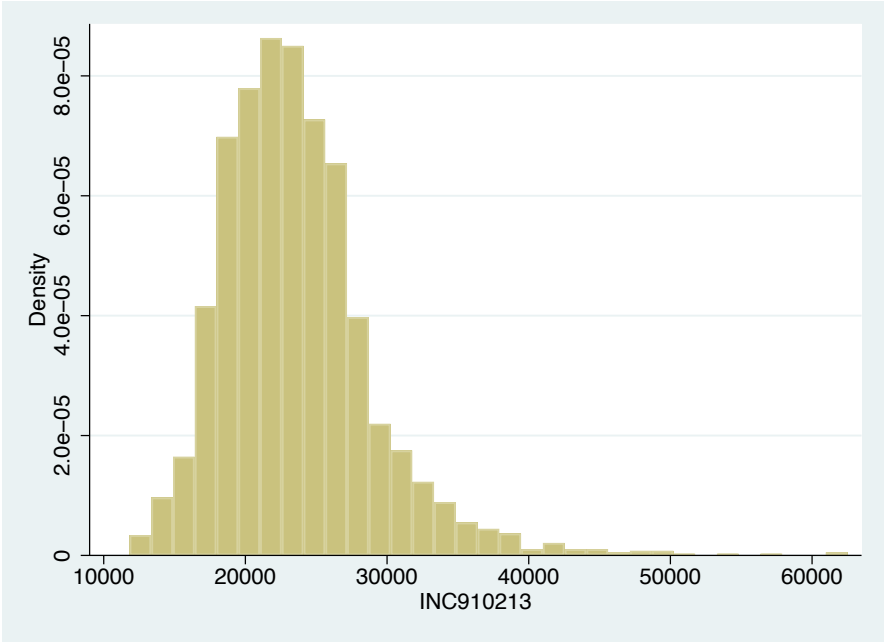
$$\log\left(\frac{p(X)}{1-p(X)}\right) = \beta_0 + \beta_{1X} + \cdots + \beta_x X_x$$

  - *Utilizes Maximum Likelihood Estimation (MLE)*
  - *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)
  - Can be used as a prediction model or as a model for Propensity Score Matching in experimental designs

```
. 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
------------------------------------------------------------------------------
```

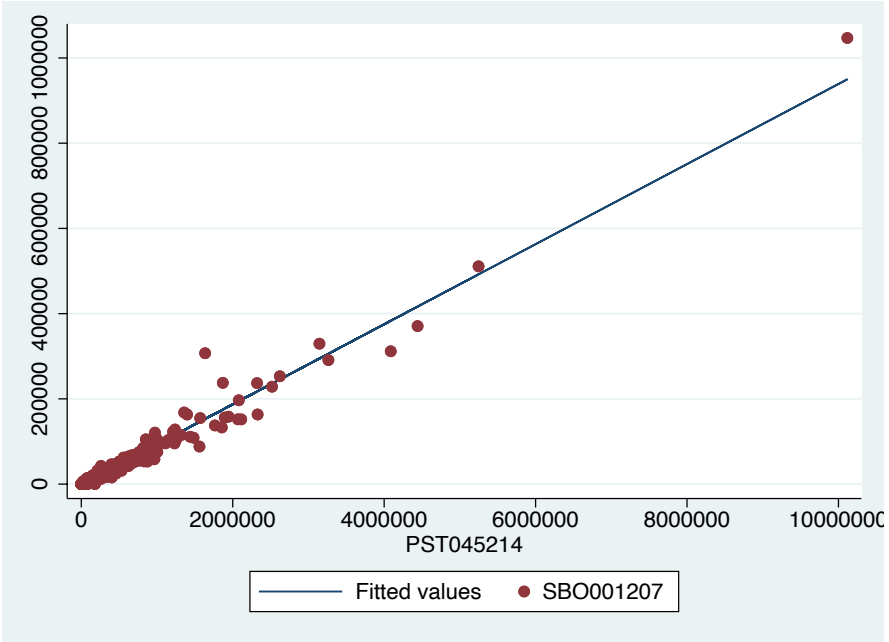
# Charts – Syntax and Examples

## Histogram of *INC910213*




Command: **hist inc910213**

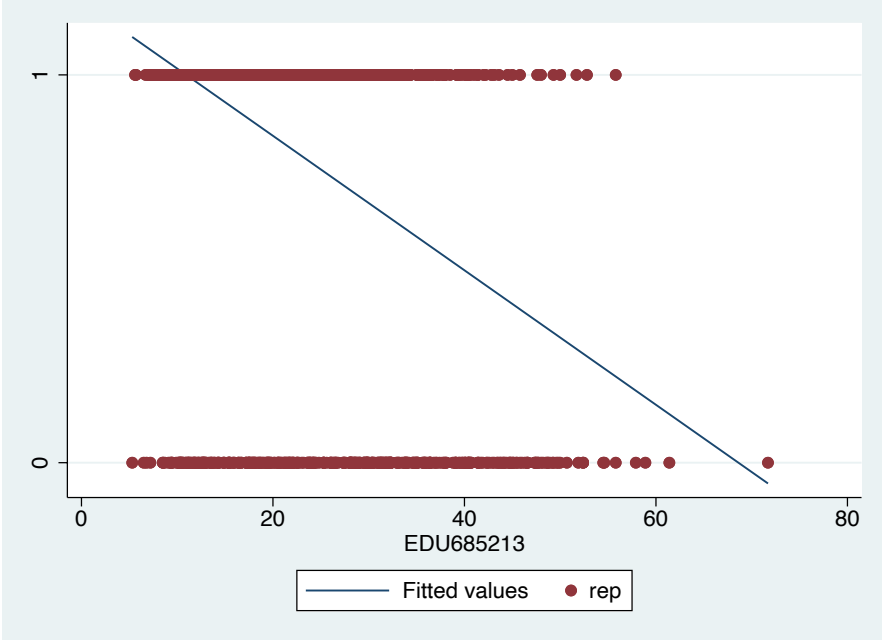
## Regression Plot of Simple Linear Regression




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

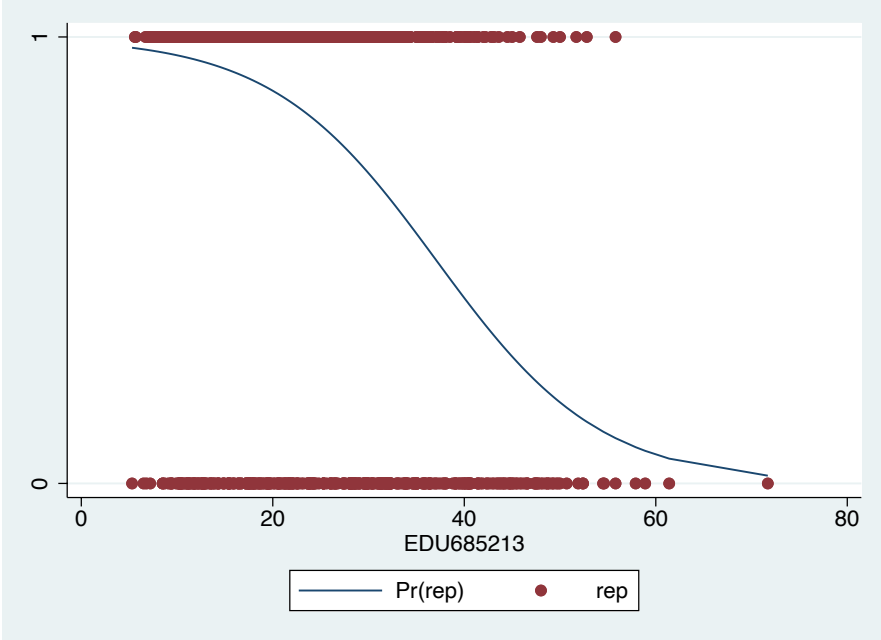
# Charts – Syntax and Examples

## 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)**

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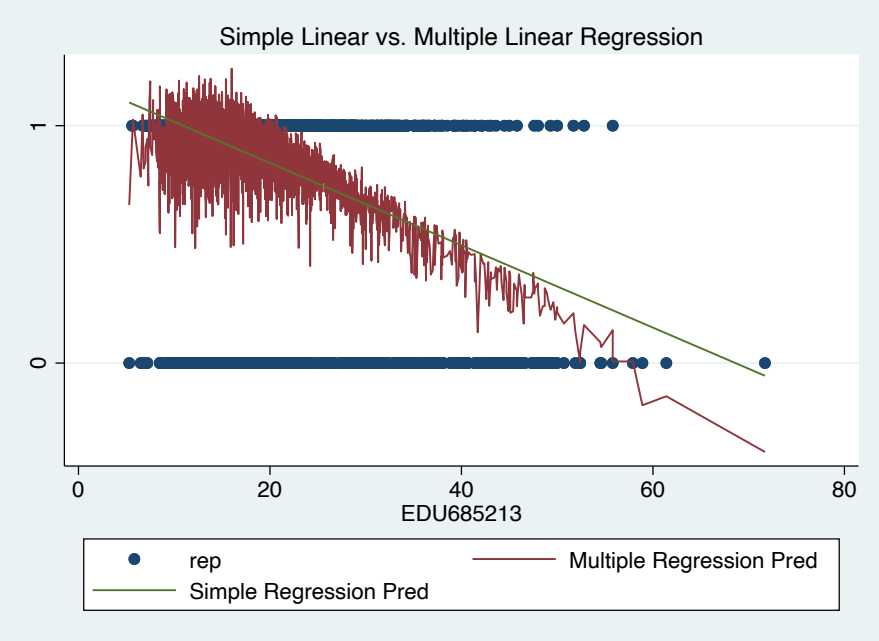
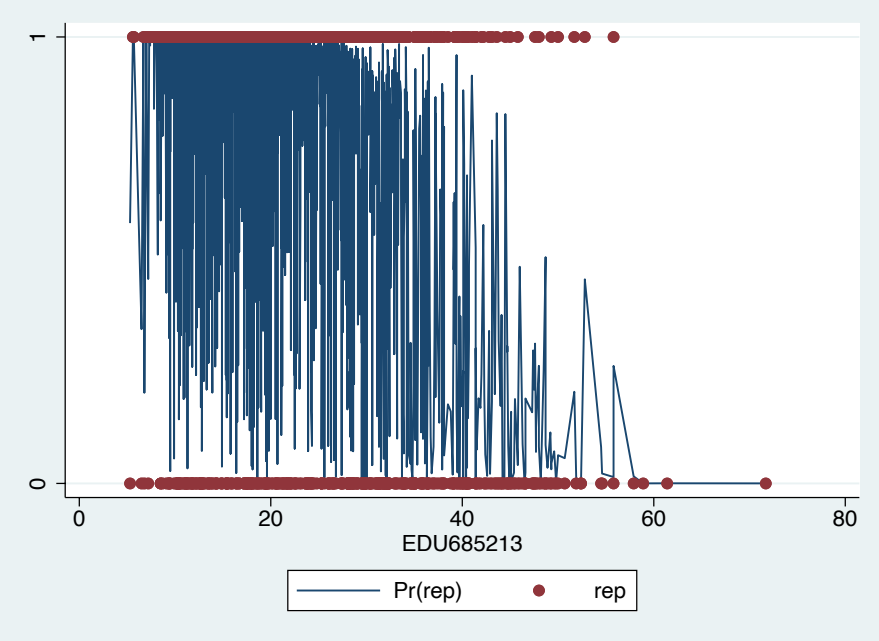
# Charts – Syntax and Examples

## 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. Plot the distribution of age variable with a normal distribution, with 25 bins (bars). How does the distribution look like compared to the normal distribution?
  2. Run summary statistics for age, weight and height variables. What can you imply about the variables?
  3. Graph a bar chart to plot mean age across 5 borrows of New York City. Note that a default value for a bar chart is mean.
  4. Use Logistic Regression to show how a probability of suspects found with a weapon is influenced by age, weight, height, and a dummy variable for Manhattan borough.

# 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/
  - Princeton DSS: https://www.princeton.edu/~otorres/Stata/StataTutorial.pdf
- Contact: theqcl@cmc.edu (with a title: “Re: QCL Stata Workshop”)
  - Feel free to contact me (slee19@students.cmc.edu) if you have any questions on PowerPoint and Stata materials

# Appendix

# Regression – Multiple Regression

```
. reg rep edu685213 edu635213 age295214
```

| Source | SS | df | MS | | |
|---|---|---|---|---|---|
| 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 |

| Number of obs | = | 2,489 |
|---|---|---|
| F(3, 2485) | = | 303.19 |

| 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 Adjusted $R^2$ that there is a lot of room to improve (73.29% of variation is still not explained)
  - Also, note that *age295214* has a relatively high *p*-value but within 95% Confidence Level
- Can adding *rhi825214* (White alone, Not Hispanic) help to increase our model's performance?

# Regression – Multiple Regression

- As expected, including race variable leads to better performance (42.69% of variation explained)
- We also see that a coefficient of the high school graduates is not statistically significant. Why?
- How should we proceed?

```
. reg rep edu635213 edu685213 age295214 rhi825214
```

| Source | SS | df | MS | | |
|---|---|---|---|---|---|
| Model | 136.867873 | 4 | 34.2169683 | Number of obs | = 2,489 |
| Residual | 183.72594 | 2,484 | .073963744 | F(4, 2484) | = 462.62 |
| | | | | Prob > F | = 0.0000 |
| | | | | R-squared | = 0.4269 |
| | | | | Adj R-squared | = 0.4260 |
| Total | 320.593813 | 2,488 | .128856034 | Root MSE | = .27196 |

| rep | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| edu635213 | .001145 | .001255 | 0.91 | 0.362 | -.001316 | .0036059 |
| edu685213 | -.0166986 | .0008822 | -18.93 | 0.000 | -.0184286 | -.0149686 |
| age295214 | .0176026 | .0017657 | 9.97 | 0.000 | .0141403 | .0210649 |
| rhi825214 | .009711 | .0003699 | 26.25 | 0.000 | .0089856 | .0104365 |
| _cons | -.0706276 | .093642 | -0.75 | 0.451 | -.254252 | .1129969 |

# Regression – Multiple Regression

- Is *edu635213* variable duplicitous in our model? Should we exclude them?
- What other variables do you think we can include in our model?
  (Hint: Think about how policies impact people based on their background)

```
. corr edu635213 edu685213 age295214 rhi825214
(obs=2,489)
```

| | e~635213 | e~685213 | a~295214 | r~825214 |
|---|---|---|---|---|
| edu635213 | 1.0000 | | | |
| edu685213 | 0.5958 | 1.0000 | | |
| age295214 | -0.2035 | -0.1214 | 1.0000 | |
| rhi825214 | 0.4768 | -0.0165 | -0.3200 | 1.0000 |

# Regression – Multiple Regression

- How about Income variable?
  - *INC910213*: Per Capita Income
- From checking the correlation table, what can we infer about the relationship between the level of education and per capital income level?
- If we assume that the impact of income on political leanings differ by the education level, we can use two methods:
  **1) Interaction Terms**
  2) Instrumental Variable (IV)

```
. corr edu685213 inc910213
(obs=2,489)
```

| | e~685213 | i~910213 |
|---|---|---|
| edu685213 | 1.0000 | |
| inc910213 | 0.7714 | 1.0000 |

# Regression – Multiple Regression

- *Let's try to make interaction term from the two variables:*

$$\mathbf{EDU685\_INC910} = \mathbf{EDU685213} \cdot \mathbf{INC910213}$$

- Use ***gen edu685_inc910 = edu685213 * inc910213*** command to generate the interaction variable
- Regress the following:
  ***reg* rep *edu685213 age295214 rhi825214 inc910213 edu685_inc910***

```
. corr edu685213 inc910213
(obs=2,489)
```

| | e~685213 | i~910213 |
|---|---|---|
| edu685213 | 1.0000 | |
| inc910213 | 0.7714 | 1.0000 |