FP2 EDA

March 26, 2021

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1 Introduction

The goal of my final project is to accurately predict county-level unemployment rates in the United States using historical data. The unemployment rate measures the number of unemployed workers as a percentage of the labor force and is typically used to evaluate the health of the labor market. This statistic is especially important during recessions to determine the economic condition of a given area. This problem is important because high levels of unemployment can seriously damage a nation's economic growth and financial development. Being able to predict the unemployment rate will allow us to understand the factors that are associated with high and low levels of unemployment. This allows us to more efficiently and effectively implement policies to reduce the unemployment rate.

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2 Data Wrangling and Cleaning

The data set used for this project came from the 2019 American Community Survey (5-year estimates) and was retrieved from Social Explorer.

Link to the downloaded report

The data used to classify counties as metro or nonmetro came from the US Department of Agriculture Economic Research Reserve. The data set used was the 2013 Rural-Urban Continuum Codes.

[1]:
```
# import tools
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import os
from scipy.stats import binned_statistic

# change directory
os.chdir('C:/Users/hubst/ECON_490/Final Project')

# increase size of figures
```

```
sns.set(rc = {'axes.titlesize': 20,
              'axes.labelsize': 15,
              'xtick.labelsize': 10,
              'ytick.labelsize': 10,
              'figure.figsize': (10, 5)})
```

[2]:
```
# load in data
data = pd.read_csv('final_project.csv')

# load in metro classification table
codes = pd.read_excel('ruralurbancodes2013.xlsx', engine = 'openpyxl')
```

[3]:
```
# print head of codes
codes.head()
```

[3]:
```
     FIPS State     County_Name  Population_2010  RUCC_2013  \
0  1001.0    AL  Autauga County          54571.0        2.0
1  1003.0    AL  Baldwin County         182265.0        3.0
2  1005.0    AL  Barbour County          27457.0        6.0
3  1007.0    AL     Bibb County          22915.0        1.0
4  1009.0    AL   Blount County          57322.0        1.0

                                         Description
0  Metro - Counties in metro areas of 250,000 to …
1  Metro - Counties in metro areas of fewer than …
2  Nonmetro - Urban population of 2,500 to 19,999…
3  Metro - Counties in metro areas of 1 million p…
4  Metro - Counties in metro areas of 1 million p…
```

[4]:
```
# setting metro status as a categorical feature with metro being 1 and nonmetro␣
↪being 0
codes['Metro Status'] = (codes['RUCC_2013'] <= 3)*1
```

[5]:
```
# trimming codes table by selecting only variables that are needed
codes = codes[['FIPS', 'Metro Status']]
```

[6]:
```
# dropping nan values from codes
codes.dropna(inplace = True)

# changing FIPS to int to remove the decimal place
codes['FIPS'] = codes['FIPS'].astype(int)
```

[7]:
```
# print head of data to see what I'm working with
data.head()
```

[7]:
```
       FIPS Geographic Identifier      Area Name           Qualifying Name  \
0  Geo_FIPS             Geo_GEOID       Geo_NAME                 Geo_QName
```

```
1    01001         05000US01001  Autauga County  Autauga County, Alabama
2    01003         05000US01003  Baldwin County  Baldwin County, Alabama
3    01005         05000US01005  Barbour County  Barbour County, Alabama
4    01007         05000US01007     Bibb County     Bibb County, Alabama

  State Postal Abbreviation Summary Level Geographic Component  \
0               Geo_STUSAB    Geo_SUMLEV          Geo_GEOCOMP
1                       al           050                   00
2                       al           050                   00
3                       al           050                   00
4                       al           050                   00

  File identification Logical Record Number      US  …  \
0         Geo_FILEID          Geo_LOGRECNO  Geo_US  …
1              ACSSF               0000013     NaN  …
2              ACSSF               0000014     NaN  …
3              ACSSF               0000015     NaN  …
4              ACSSF               0000016     NaN  …

  Average Commute to Work (In Min) Total Population:.2  \
0                     SE_A09003_001       SE_A06001_001
1                                24               55380
2                                27              212830
3                                22               25361
4                                30               22493

  Total Population: Native Born Total Population: Foreign Born  \
0                 SE_A06001_002                  SE_A06001_003
1                         54081                           1299
2                        204906                           7924
3                         24672                            689
4                         22153                            340

  Total Population: Foreign Born: Naturalized Citizen  \
0                                      SE_A06001_004
1                                                750
2                                               3650
3                                                335
4                                                140

  Total Population: Foreign Born: Not a Citizen  \
0                                 SE_A06001_005
1                                           549
2                                          4274
3                                           354
4                                           200
```

```
  % Total Population: Native Born % Total Population: Foreign Born  \
0               PCT_SE_A06001_002               PCT_SE_A06001_003
1                           97.65                            2.35
2                           96.28                            3.72
3                           97.28                            2.72
4                           98.49                            1.51

  % Total Population: Foreign Born: Naturalized Citizen  \
0                                  PCT_SE_A06001_004
1                                               1.35
2                                               1.71
3                                               1.32
4                                               0.62

  % Total Population: Foreign Born: Not a Citizen
0                               PCT_SE_A06001_005
1                                            0.99
2                                            2.01
3                                             1.4
4                                            0.89

[5 rows x 193 columns]
```

[8]:
```python
# drop first row
data = data.drop(index = 0)
```

[9]:
```python
# set fips column in data as int to match the data type in the codes table
data['FIPS'] = data['FIPS'].astype(int)
```

[10]:
```python
# merging data and codes via an inner join
data = data.set_index('FIPS').join(codes.set_index('FIPS'), how = 'inner')
```

[11]:
```python
# dropping nan values within these features so they don't get dropped
data.dropna(subset = ['Average Gross Rent for Renter-Occupied Housing Units'],␣
 ↪inplace = True)
data.dropna(subset = ['Average Commute to Work (In Min)'], inplace = True)

# drop all columns with nan values
data = data.dropna(axis = 'columns')

# rename geographic identifier for county
data.rename(columns = {'Qualifying Name': 'County'}, inplace = True)

# append county to the index
data.set_index(['County'], append = True, inplace = True)

# drop unnecessary geographic columns
```

```
data = data.drop(columns = ['Geographic Identifier', 'Area Name', 'State Postal␣
↪Abbreviation',
                            'Summary Level','Geographic Component', 'File␣
↪identification',
                            'Logical Record Number', 'State (FIPS Code)',␣
↪'County of current residence'])

# drop duplicated columns
data = data.drop(columns = ['Total Population:', 'Total Population:.1', 'Total␣
↪Population:.2',
                            'Total Employed Civilian Population 16 Years and␣
↪Over'])
```

[12]:
```
# changing all data values to numeric
data = data.apply(pd.to_numeric)
```

[13]:
```
# creating features

# percentage of population that is living in poverty
data['Poverty Level'] = (data['Population Under 18 Years of Age for Whom␣
↪Poverty Status Is Determined: Living in Poverty'] +
                         data['Population Age 18 to 64 for Whom Poverty Status ␣
↪Is Determined: Living in Poverty'] +
                         data['Population Age 65 and Over for Whom Poverty ␣
↪Status Is Determined: Living in Poverty'])*100/data['Total Population']

# percentage of adults with at least a bachelor's degree
data["Bachelor's or more"] = (data["Population 25 Years and Over: Bachelor's␣
↪Degree"] +
                              data["Population 25 Years and Over: Master's␣
↪Degree"] +
                              data["Population 25 Years and Over: Professional␣
↪School Degree"] +
                              data["Population 25 Years and Over: Doctorate␣
↪Degree"])*100/data['Population 25 Years and Over:']
```

[14]:
```
# renaming features
data.rename(columns = {'Median Household Income (In 2019 Inflation Adjusted␣
↪Dollars)': 'Median Household Income',
                       'Average Gross Rent for Renter-Occupied Housing Units':␣
↪'Average Rent',
                       'Median Age:': 'Median Age',
                       'Average Commute to Work (In Min)': 'Average Commute␣
↪Time',
                       '% Population 16 Years and Over: in Labor Force:␣
↪Civilian: Unemployed': 'Unemployment Rate',
```

```
                        '% Total Population: Female': 'Female',
                        '% Total Population: Foreign Born': 'Immigrant',
                        '% Total Population: Black or African American Alone':␣
↪'African American',
                        '% Total Population: Hispanic or Latino': 'Hispanic',
                        '% Female Population 16 Years and Over: in Labor Force':␣
↪'Female Labor Force Participation Rate',
                        '% Employed Civilian Population 16 Years and Over:␣
↪Manufacturing': 'Manufacturing',
                        '% Employed Civilian Population 16 Years and Over:␣
↪Agriculture, Forestry, Fishing and Hunting, and Mining': 'Agriculture and␣
↪Mining'}, inplace = True)
```

[15]:
```
# reordering features and dropping columns that are unnecessary
data = data[['Unemployment Rate', 'Female Labor Force Participation Rate',␣
↪'Female', 'African American', 'Hispanic',
             "Bachelor's or more", 'Manufacturing', 'Agriculture and Mining',␣
↪'Immigrant', 'Poverty Level', 'Median Age',
             'Average Household Size', 'Median Household Income', 'Average␣
↪Rent', 'Average Commute Time', 'Metro Status']]
```

[16]:
```
# check out head of data to make sure everything looks correct
data.head()
```

[16]:
```
                              Unemployment Rate  \
FIPS County
1001 Autauga County, Alabama               2.13
1003 Baldwin County, Alabama               2.45
1005 Barbour County, Alabama               4.11
1007 Bibb County, Alabama                  3.56
1009 Blount County, Alabama                1.66

                              Female Labor Force Participation Rate  Female  \
FIPS County
1001 Autauga County, Alabama                                  51.51   51.37
1003 Baldwin County, Alabama                                  52.82   51.37
1005 Barbour County, Alabama                                  44.66   47.08
1007 Bibb County, Alabama                                     49.60   45.98
1009 Blount County, Alabama                                   44.18   50.60

                              African American  Hispanic  Bachelor's or more  \
FIPS County
1001 Autauga County, Alabama             19.03      2.83           26.571574
1003 Baldwin County, Alabama              9.26      4.56           31.862460
1005 Barbour County, Alabama             47.58      4.36           11.578713
1007 Bibb County, Alabama                22.29      2.57           10.378525
1009 Blount County, Alabama               1.61      9.26           13.093413
```

```
                            Manufacturing  Agriculture and Mining  \
FIPS County
1001 Autauga County, Alabama        12.95                    0.87
1003 Baldwin County, Alabama         9.25                    1.21
1005 Barbour County, Alabama        23.05                    5.72
1007 Bibb County, Alabama           16.90                    3.86
1009 Blount County, Alabama         17.16                    2.08

                            Immigrant  Poverty Level  Median Age  \
FIPS County
1001 Autauga County, Alabama      2.35      15.059588        38.2
1003 Baldwin County, Alabama      3.72      10.197810        43.0
1005 Barbour County, Alabama      2.72      27.108553        40.4
1007 Bibb County, Alabama         1.51      16.627395        40.9
1009 Blount County, Alabama       4.54      13.416896        40.7

                            Average Household Size  Median Household Income  \
FIPS County
1001 Autauga County, Alabama                  2.56                    58731
1003 Baldwin County, Alabama                  2.59                    58320
1005 Barbour County, Alabama                  2.41                    32525
1007 Bibb County, Alabama                     2.99                    47542
1009 Blount County, Alabama                   2.74                    49358

                            Average Rent  Average Commute Time  Metro Status
FIPS County
1001 Autauga County, Alabama  980.419948                    24             1
1003 Baldwin County, Alabama  941.294799                    27             1
1005 Barbour County, Alabama  546.168582                    22             0
1007 Bibb County, Alabama     560.294952                    30             1
1009 Blount County, Alabama   555.809222                    34             1
```

[17]:
```python
# check out shape of the data
data.shape
```

[17]: (3216, 16)

[18]:
```python
# check out data type to make sure everything looks correct
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 3216 entries, (1001, 'Autauga County, Alabama') to (72153, 'Yauco
Municipio, Puerto Rico')
Data columns (total 16 columns):
 #   Column                                Non-Null Count  Dtype
---  ------                                --------------  -----
 0   Unemployment Rate                     3216 non-null   float64
```

```
 1   Female Labor Force Participation Rate  3216 non-null   float64
 2   Female                                 3216 non-null   float64
 3   African American                       3216 non-null   float64
 4   Hispanic                               3216 non-null   float64
 5   Bachelor's or more                     3216 non-null   float64
 6   Manufacturing                          3216 non-null   float64
 7   Agriculture and Mining                 3216 non-null   float64
 8   Immigrant                              3216 non-null   float64
 9   Poverty Level                          3216 non-null   float64
 10  Median Age                             3216 non-null   float64
 11  Average Household Size                 3216 non-null   float64
 12  Median Household Income                3216 non-null   int64
 13  Average Rent                           3216 non-null   float64
 14  Average Commute Time                   3216 non-null   int64
 15  Metro Status                           3216 non-null   int32
dtypes: float64(13), int32(1), int64(2)
memory usage: 772.4+ KB
```

[19]:
```
# check out descriptive statistics of the data
data.describe()
```

[19]:
```
       Unemployment Rate  Female Labor Force Participation Rate       Female  \
count        3216.000000                            3216.000000  3216.000000
mean            3.078759                              53.656878    49.964471
std             1.554574                               7.565923     2.346874
min             0.000000                              18.110000    27.280000
25%             2.190000                              48.880000    49.430000
50%             2.880000                              54.100000    50.390000
75%             3.680000                              59.022500    51.170000
max            15.560000                              77.580000    57.190000

       African American     Hispanic  Bachelor's or more  Manufacturing  \
count       3216.000000  3216.000000         3216.000000    3216.000000
mean           9.159356    11.571688           21.985656      12.249238
std           14.622991    19.385061            9.491006       7.092657
min            0.000000     0.000000            1.047120       0.000000
25%            0.727500     2.260000           15.424850       6.847500
50%            2.395000     4.380000           19.629423      11.330000
75%           10.282500    10.392500           25.958667      16.560000
max           87.230000    99.980000           77.557411      47.530000

       Agriculture and Mining    Immigrant  Poverty Level   Median Age  \
count             3216.000000  3216.000000    3216.000000  3216.000000
mean                 6.427453     4.686807      15.302330    41.437158
std                  7.188999     5.697437       7.838040     5.337611
min                  0.000000     0.000000       2.355808    22.300000
25%                  1.650000     1.330000      10.402349    38.300000
```

```
50%                  3.915000     2.675000      13.808197    41.300000
75%                  8.272500     5.590000      18.142045    44.500000
max                 59.640000    53.720000      64.493827    67.400000

       Average Household Size  Median Household Income  Average Rent  \
count             3216.000000              3216.000000   3216.000000
mean                 2.521210             52652.674440    700.829105
std                  0.275519             14981.141925    267.697479
min                  1.410000             12441.000000     84.057971
25%                  2.350000             43539.250000    534.910945
50%                  2.480000             51493.000000    648.983460
75%                  2.640000             59519.250000    813.529932
max                  4.140000            142299.000000   2301.892381

       Average Commute Time  Metro Status
count           3216.000000   3216.000000
mean              23.964552      0.384017
std                5.900364      0.486438
min                5.000000      0.000000
25%               20.000000      0.000000
50%               24.000000      0.000000
75%               28.000000      1.000000
max               53.000000      1.000000
```

[20]:

```python
# creating pickle
data.to_pickle('final_project.pkl')
```

---

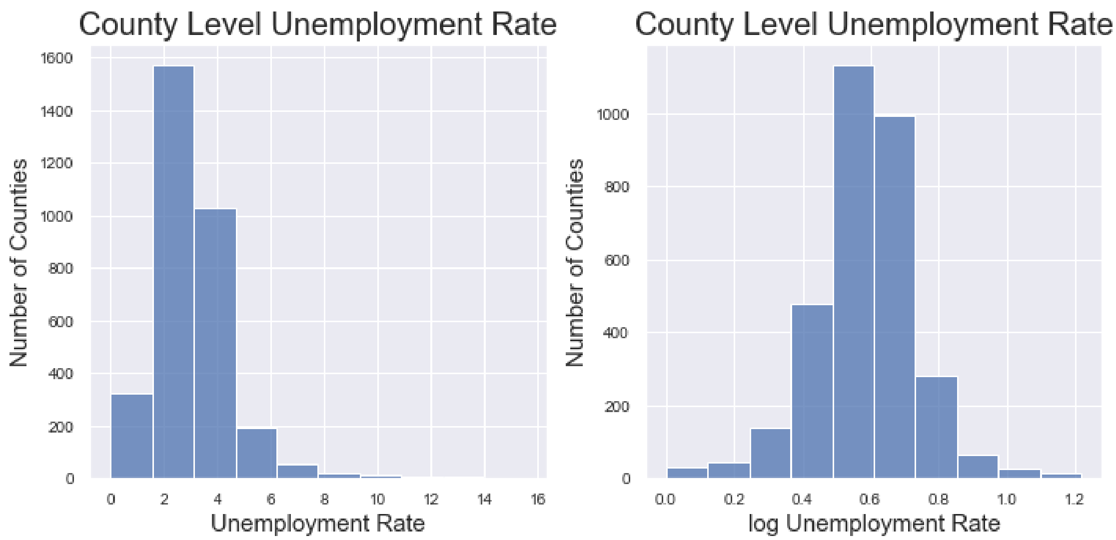
3 Label Figure

[21]:

```python
# transforming data with log(y + 1)
data['log Unemployment Rate'] = np.log10(data['Unemployment Rate'] + 1)
```

[22]:

```python
plt.subplot(1, 2, 1)
sns.histplot(data = data, x = 'Unemployment Rate', bins = 10)
plt.title('County Level Unemployment Rate')
plt.ylabel('Number of Counties')
plt.xlabel('Unemployment Rate')

plt.subplot(1, 2, 2)
sns.histplot(data = data, x = 'log Unemployment Rate', bins = 10)
plt.title('County Level Unemployment Rate')
plt.ylabel('Number of Counties')
plt.xlabel('log Unemployment Rate')

plt.tight_layout()
```



A log transformation is appropriate for the label. However, because some of the values of the label are equal to 0, I used `log(y + 1)` to transform the data.

[23]:
```
data.drop(columns = 'Unemployment Rate', inplace = True)
```

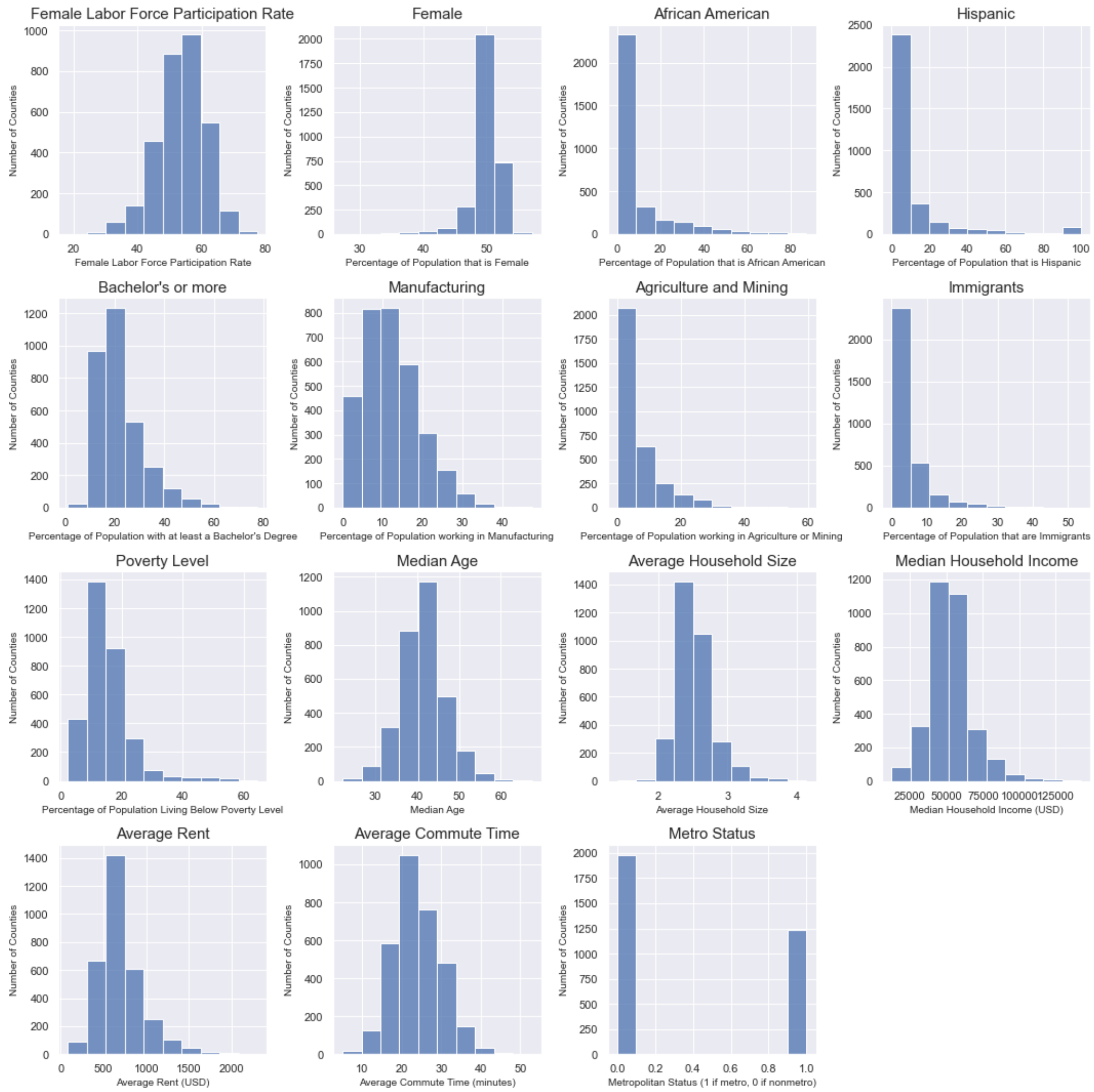
---

4 Feature Transformations

[24]:
```
sns.set(rc = {'axes.titlesize': 15,
              'axes.labelsize': 10,
              'figure.figsize': (15, 15)})

plt.subplot(4, 4, 1)
sns.histplot(data = data, x = 'Female Labor Force Participation Rate', bins =␣
 ↪10)
plt.title('Female Labor Force Participation Rate')
plt.ylabel('Number of Counties')
plt.xlabel('Female Labor Force Participation Rate')

plt.subplot(4, 4, 2)
sns.histplot(data = data, x = 'Female', bins = 10)
plt.title('Female')
plt.ylabel('Number of Counties')
plt.xlabel('Percentage of Population that is Female')

plt.subplot(4, 4, 3)
sns.histplot(data = data, x = 'African American', bins = 10)
plt.title('African American')
```

```python
plt.ylabel('Number of Counties')
plt.xlabel('Percentage of Population that is African American')

plt.subplot(4, 4, 4)
sns.histplot(data = data, x = 'Hispanic', bins = 10)
plt.title('Hispanic')
plt.ylabel('Number of Counties')
plt.xlabel('Percentage of Population that is Hispanic')

plt.subplot(4, 4, 5)
sns.histplot(data = data, x = "Bachelor's or more", bins = 10)
plt.title("Bachelor's or more")
plt.ylabel('Number of Counties')
plt.xlabel("Percentage of Population with at least a Bachelor's Degree")

plt.subplot(4, 4, 6)
sns.histplot(data = data, x = 'Manufacturing', bins = 10)
plt.title('Manufacturing')
plt.ylabel('Number of Counties')
plt.xlabel('Percentage of Population working in Manufacturing')

plt.subplot(4, 4, 7)
sns.histplot(data = data, x = 'Agriculture and Mining', bins = 10)
plt.title('Agriculture and Mining')
plt.ylabel('Number of Counties')
plt.xlabel('Percentage of Population working in Agriculture or Mining')

plt.subplot(4, 4, 8)
sns.histplot(data = data, x = 'Immigrant', bins = 10)
plt.title('Immigrants')
plt.ylabel('Number of Counties')
plt.xlabel('Percentage of Population that are Immigrants')

plt.subplot(4, 4, 9)
sns.histplot(data = data, x = 'Poverty Level', bins = 10)
plt.title('Poverty Level')
plt.ylabel('Number of Counties')
plt.xlabel('Percentage of Population Living Below Poverty Level')

plt.subplot(4, 4, 10)
sns.histplot(data = data, x = 'Median Age', bins = 10)
plt.title('Median Age')
plt.ylabel('Number of Counties')
plt.xlabel('Median Age')

plt.subplot(4, 4, 11)
sns.histplot(data = data, x = 'Average Household Size', bins = 10)
```

```
plt.title('Average Household Size')
plt.ylabel('Number of Counties')
plt.xlabel('Average Household Size')

plt.subplot(4, 4, 12)
sns.histplot(data = data, x = 'Median Household Income', bins = 10)
plt.title('Median Household Income')
plt.ylabel('Number of Counties')
plt.xlabel('Median Household Income (USD)')

plt.subplot(4, 4, 13)
sns.histplot(data = data, x = 'Average Rent', bins = 10)
plt.title('Average Rent')
plt.ylabel('Number of Counties')
plt.xlabel('Average Rent (USD)')

plt.subplot(4, 4, 14)
sns.histplot(data = data, x = 'Average Commute Time', bins = 10)
plt.title('Average Commute Time')
plt.ylabel('Number of Counties')
plt.xlabel('Average Commute Time (minutes)')

plt.subplot(4, 4, 15)
sns.histplot(data = data, x = 'Metro Status', bins = 10)
plt.title('Metro Status')
plt.ylabel('Number of Counties')
plt.xlabel('Metropolitan Status (1 if metro, 0 if nonmetro)')

plt.tight_layout()
```



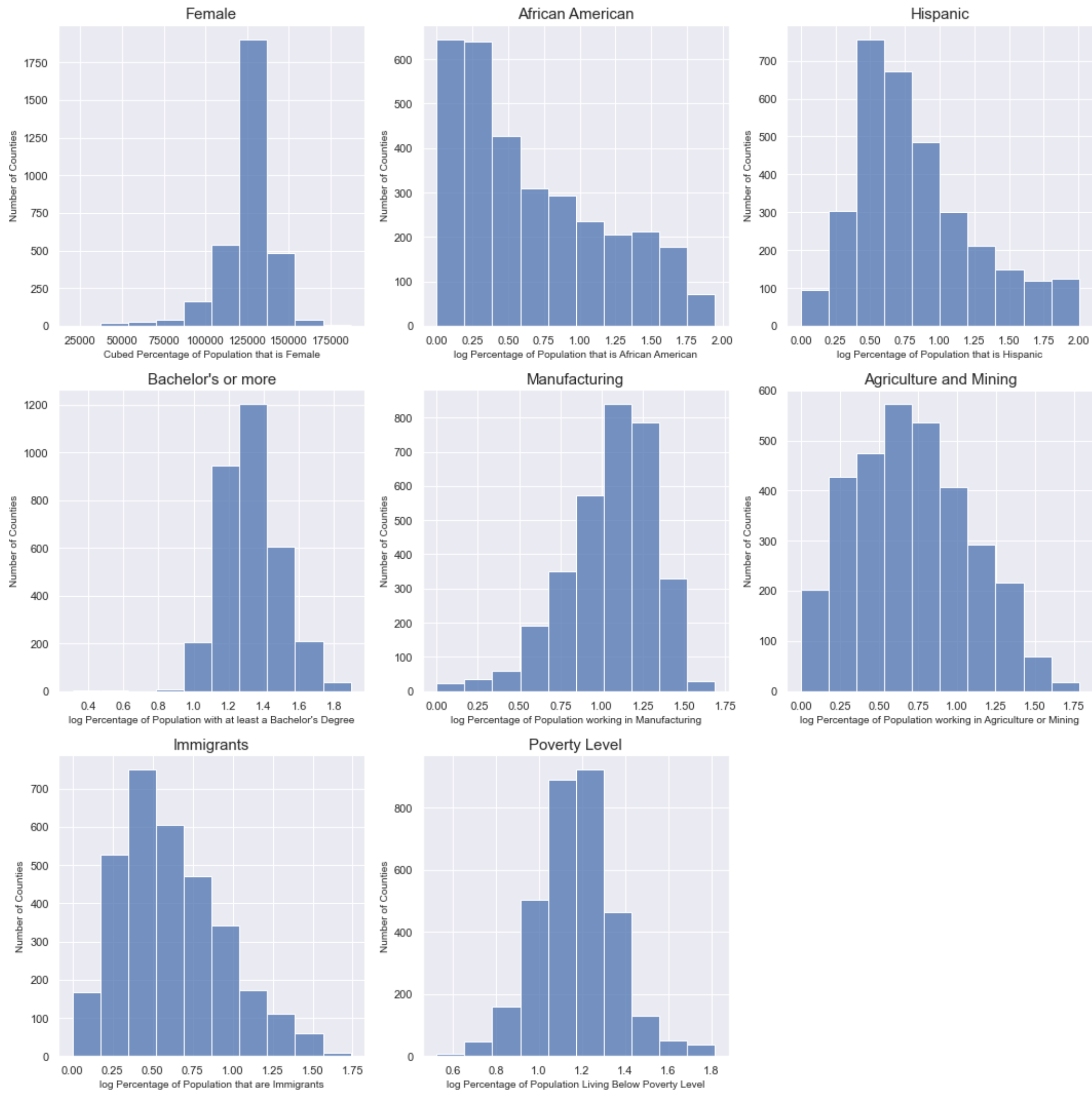
The features that need transformations are `Female`, `African American`, `Hispanic`, `Bachelor's or more`, `Manufacturing`, `Agriculture and Mining`, `Immigrants` and `Poverty Level`.

[25]:
```
data['cube Female'] = np.power(data['Female'], 3)
data = data.drop(columns = 'Female')

data['log African American'] = np.log10(data['African American'] + 1)
data = data.drop(columns = 'African American')

data['log Hispanic'] = np.log10(data['Hispanic'] + 1)
data = data.drop(columns = 'Hispanic')

data["log Bachelor's or more"] = np.log10(data["Bachelor's or more"] + 1)
```

```
data = data.drop(columns = "Bachelor's or more")

data['log Agriculture and Mining'] = np.log10(data['Agriculture and Mining'] +␣
 ↪1)
data = data.drop(columns = 'Agriculture and Mining')

data['log Poverty Level'] = np.log10(data['Poverty Level'] + 1)
data = data.drop(columns = 'Poverty Level')

data['log Immigrant'] = np.log10(data['Immigrant'] + 1)
data = data.drop(columns = 'Immigrant')

data['log Manufacturing'] = np.log10(data['Manufacturing'] + 1)
data = data.drop(columns = 'Manufacturing')
```

[26]:
```
# checking the transformed features
plt.subplot(3, 3, 1)
sns.histplot(data = data, x = 'cube Female', bins = 10)
plt.title('Female')
plt.ylabel('Number of Counties')
plt.xlabel('Cubed Percentage of Population that is Female')

plt.subplot(3, 3, 2)
sns.histplot(data = data, x = 'log African American', bins = 10)
plt.title('African American')
plt.ylabel('Number of Counties')
plt.xlabel('log Percentage of Population that is African American')

plt.subplot(3, 3, 3)
sns.histplot(data = data, x = 'log Hispanic', bins = 10)
plt.title('Hispanic')
plt.ylabel('Number of Counties')
plt.xlabel('log Percentage of Population that is Hispanic')

plt.subplot(3, 3, 4)
sns.histplot(data = data, x = "log Bachelor's or more", bins = 10)
plt.title("Bachelor's or more")
plt.ylabel('Number of Counties')
plt.xlabel("log Percentage of Population with at least a Bachelor's Degree")

plt.subplot(3, 3, 5)
sns.histplot(data = data, x = 'log Manufacturing', bins = 10)
plt.title('Manufacturing')
plt.ylabel('Number of Counties')
plt.xlabel('log Percentage of Population working in Manufacturing')

plt.subplot(3, 3, 6)
```

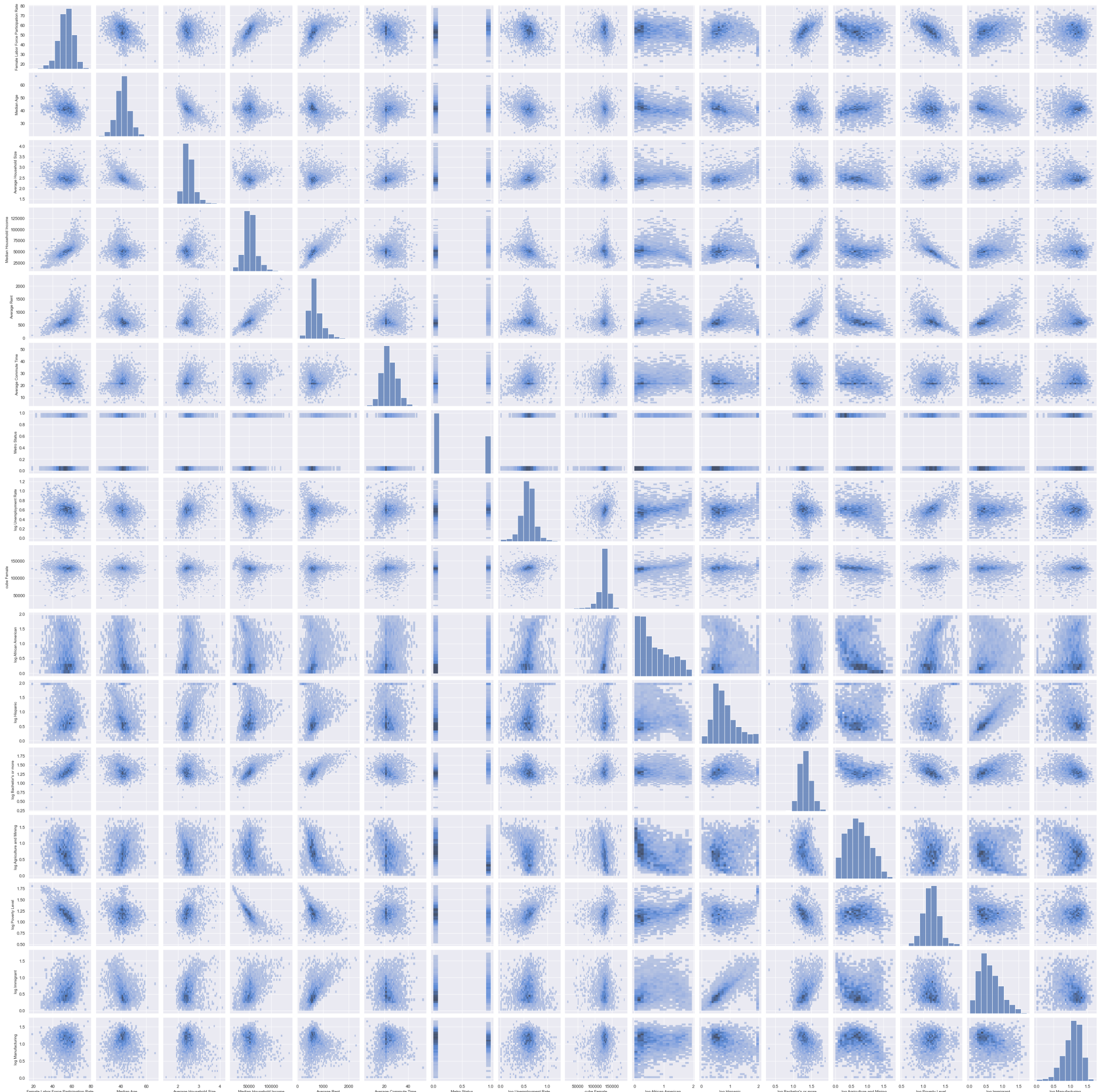
```python
sns.histplot(data = data, x = 'log Agriculture and Mining', bins = 10)
plt.title('Agriculture and Mining')
plt.ylabel('Number of Counties')
plt.xlabel('log Percentage of Population working in Agriculture or Mining')

plt.subplot(3, 3, 7)
sns.histplot(data = data, x = 'log Immigrant', bins = 10)
plt.title('Immigrants')
plt.ylabel('Number of Counties')
plt.xlabel('log Percentage of Population that are Immigrants')

plt.subplot(3, 3, 8)
sns.histplot(data = data, x = 'log Poverty Level', bins = 10)
plt.title('Poverty Level')
plt.ylabel('Number of Counties')
plt.xlabel('log Percentage of Population Living Below Poverty Level')

plt.tight_layout()
```



---

5 Feature vs Label Figures

[27]:
```
sns.set(rc = {'axes.labelsize': 10,})
sns.pairplot(data = data, kind = 'hist',
             diag_kws = {'bins': 10})
plt.show()
```



A lot of the features seem to have a very weak or nonexistent relationship.

It looks like there is a linear relationship between `Average Rent` and `Median Household Income`.

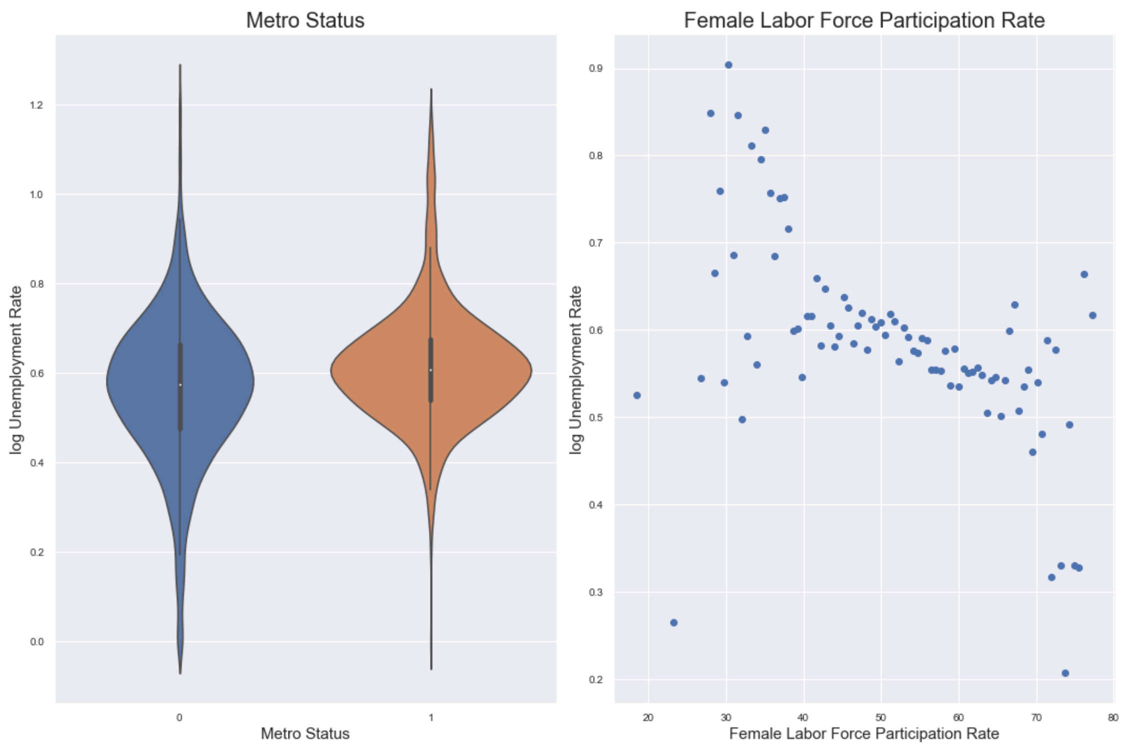
It looks like there is a linear relationship between `Hispanic` and `Immigrant`.

It looks like there is a linear relationship between `Median Household Income` and `Poverty Level`.

It looks like there is a quadratic relationship between `Median Household Income` and `Bachelor's or more`.

[28]:
```
sns.set(rc = {'axes.titlesize': 20,
              'axes.labelsize': 15,
              'xtick.labelsize': 10,
              'ytick.labelsize': 10,
```

```
                'figure.figsize': (15, 10)})

plt.subplot(1, 2, 1)
sns.violinplot(data = data, x = 'Metro Status', y = 'log Unemployment Rate')
plt.title('Metro Status')
plt.ylabel('log Unemployment Rate')
plt.xlabel('Metro Status')

plt.subplot(1, 2, 2)
n = 100
bin_mean, bin_edge, _ = binned_statistic(data['Female Labor Force Participation␣
 ↪Rate'], data['log Unemployment Rate'], bins = n)
x = np.average([bin_edge[:-1], bin_edge[1:]], axis = 0)
plt.scatter(x, bin_mean, label = '%d bins' % n)
plt.title('Female Labor Force Participation Rate')
plt.ylabel('log Unemployment Rate')
plt.xlabel('Female Labor Force Participation Rate')

plt.tight_layout()
```



It looks like `Unemployment Rate` is normally distributed for both metro and nonmetro.

It looks like there is a weak linear relationship between the `Unemployment Rate` and `Female Labor Force Participation Rate`.

[29]:
```python
# updating pickle with transformed features and label
data.to_pickle('final_project.pkl')
```