Texas_Stats_EDA_orosco

February 3, 2023

[1]:
```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
import math
import numpy as np
from sklearn.preprocessing import MinMaxScaler
import statsmodels.stats.api as sms
import statsmodels.formula.api as smf
from scipy.stats import shapiro, normaltest, ttest_ind, ttest_rel
```

[2]:
```python
def Compute_Cohend(mean1, mean2,ser1,ser2, var1, title):
    """Compute cohens'd to see the effect size"""

    diff = mean1 - mean2
    n1, n2, = len(ser1), len(ser2)

    pooled_var = (n1 * var1 + n2) / (n1 + n2)
    d = diff / math.sqrt(pooled_var)
    print(f'{title} = {d}  \n')
    return d


def Hist_Plot(subtitle, xlab1, xlab2, ser1, ser2):
    """Plot histogram using matplotlin ploty plots two small plots
        side by side for comparison"""

    # Main Title
    fig = plt.figure(figsize=(10,10))
    title = fig.suptitle(subtitle, fontsize=14, fontweight="bold")

    fig.subplots_adjust(top=0.88, wspace=0.3)

    # Histogram 1
    ax1 = ax1 = fig.add_subplot(1,2,1)
    ax1.set_xlabel(xlab1)
    ax1.set_ylabel("Frequency")
```

```
    freq1, bins1, patches1 = ax1.hist(ser1, bins=10, color='darksalmon', ␣
↪edgecolor='darkred', linewidth=1)


    # Histogram 2
    ax2 = ax2 = fig.add_subplot(1,2,2)
    ax2.set_xlabel(xlab2)
    ax2.set_ylabel("Frequency")

    freq2, bins2, patches2 = ax2.hist(ser2, bins=10, color='green',␣
↪edgecolor='darkblue', linewidth=1)


    return





def Sns_Kde(subtitle, xlab1, xlab2, ser1, mean1, ser2, mean2):
    """Plot KDE using seaborn- plot side by side for
        comparison"""

    # Main Title
    fig = plt.figure(figsize=(10,10))
    title = fig.suptitle(subtitle, \
                     fontsize=14, fontweight="bold")
    fig.subplots_adjust(top=0.88, wspace=0.3)

     # KDE 1
    ax1 = fig.add_subplot(1,2,1)
    ax1.set_xlabel(xlab1)
    ax1.set_ylabel("Density")
    sns.kdeplot(ser1, shade=True,  color='darksalmon' )
    plt.axvline(x=mean1, color="black", linestyle="--")

    # KDE 2
    ax2 = ax2 = fig.add_subplot(1,2,2)
    ax2.set_xlabel(xlab2)
    ax2.set_ylabel("Density")
    sns.kdeplot(ser2, shade=True,  color = 'green')
    plt.axvline(x=mean2, color="black", linestyle="--")
    return


def Cdf_Plot(subtitle, data):
```

```python
    """Plot the CDF plots"""

    fig = plt.figure(figsize=(10,10))
    title = fig.suptitle(subtitle,\
                         fontsize=14, fontweight="bold")
    kwargs1 = {'cumulative': True}
    kwargs = {'cumulative': True, 'density': True}
    sns.distplot(data, hist_kws=kwargs, kde_kws=kwargs1)
    return


def Pmf_plot(subtitle, data, xlab):
    """Plot a PMF"""

    fig = plt.figure(figsize=(10,10))
    title = fig.suptitle(subtitle, \
                     fontsize=14, fontweight="bold")

    fig.subplots_adjust(top=0.88, wspace=0.3)
    ax1 = fig.add_subplot(1,1,1)
    ax1.set_xlabel(xlab)
    probs=data.value_counts(normalize=True)
    sns.barplot(probs.index, probs.values)
    return


def Heatmap_Plot(subtitle, xlab1, xlab2, data1, data2):
    """Plot a heatmap or Correlation Map"""
    fig = plt.figure(figsize=(13,13))
    title = fig.suptitle(subtitle, \
                         fontsize=14, fontweight="bold")
    fig.subplots_adjust(top=0.88, wspace=0.3)
    # Heatmap1
    ax1 = fig.add_subplot(1,2,1)
    ax1.set_xlabel(xlab1)
    sns.heatmap(
            data1,
            vmin=-1, vmax=1, center=0,
            cmap=sns.diverging_palette(20, 220, n=220),
            square=True)

    ax1.set_xticklabels(
        ax1.get_xticklabels(),
        rotation=45,
        horizontalalignment='right')

    #Heatmap2
```

```python
    ax2 = fig.add_subplot(1,2,2)
    ax2.set_xlabel(xlab2)
    sns.heatmap(
            data2,
            vmin=-1, vmax=1, center=0,
            cmap=sns.diverging_palette(20, 220, n=220),
            square=True)

    ax2.set_xticklabels(
        ax2.get_xticklabels(),
        rotation=45,
        horizontalalignment='right')
    return


def sns_Scatter(subtitle, xlab, ylab, x_val, y_val, data):
    "Scatter plots for variables"
    fig = plt.figure(figsize=(10,10))
    title = fig.suptitle(subtitle, \
                         fontsize=14, fontweight="bold")
    fig.subplots_adjust(top=0.88, wspace=0.3)
    # Scatter Plots
    ax1 = fig.add_subplot(1,1,1)
    ax1.set_xlabel(xlab)
    ax1.set_xlabel(ylab)
    sns.scatterplot(x = x_val, y = y_val, data=data)
    return


def sns_Lmplot(subtitle, x_val, y_val, data):
    """Plot a rgeression line with the obs"""
    fig = plt.figure(figsize=(10,10))
    title = fig.suptitle(subtitle, \
                         fontsize=14, fontweight="bold")
    fig.subplots_adjust(top=0.88, wspace=0.3)

    # Scatter Plots
    ax1 = fig.add_subplot(1,4,1)
    sns.lmplot(x=x_val, y=y_val, data=data)

    return
```

[3]:
```python
# Set context to `"paper"`
sns.set(rc={"font.size":15,"axes.labelsize":10})
#fig, ax = plt.subplots(figsize=(10,10))
sns.set(color_codes=True)
```

[4]:
```
# ==============================================================================
# Using pg. 29 of your text as an example, compare two scenarios in your data␣
 ↪using a
# PMF. Reminder, this isn't comparing two variables against each other
#  - it is the same variable, but a different scenario. Almost like a filter.
#  The example in the book is first babies compared to all other babies, it
#  is still the same variable, but breaking the data out based on criteria
#  we are exploring (Chapter 3).
# ==============================================================================
```

0.1 Read in Dataset

[5]:
```
# ==============================================================================
# Read csv file and drop first row which has texas cumulative dats
# ==============================================================================
tx_data = pd.read_csv("~/tx_household.csv", sep = ",")
tx = pd.DataFrame(tx_data)
tx = tx.drop(tx.index[0])



# Create subsets

# RURAL
rural = tx[tx['Population'] <= 50000]  # rural communiy

# URBAN
urban = tx[tx['Population'] > 50000]

# rename variables for ease
# Rural

s_percent = rural.percent_single
grad = rural.Grad_Rate
maths = rural.Math
read = rural.Read

# Urban

s_percent1 = urban.percent_single
grad1 = urban.Grad_Rate
maths1 = urban.Math
read1 = urban.Read
```

[6]:
```
rural.describe()
```

[6]:

	nbr_sing_household	nbr_household	percent_single	Rural
count	186.000000	186.000000	186.000000	186.000000
mean	1122.634409	3468.086022	31.521505	7986.478495
std	1049.116656	3022.640709	10.032492	7027.797094
min	0.000000	61.000000	1.000000	82.000000
25%	321.000000	1044.000000	25.250000	2954.000000
50%	768.000000	2715.000000	32.000000	4983.500000
75%	1685.000000	5078.250000	37.000000	11931.250000
max	4875.000000	14001.000000	65.000000	31172.000000

\

	Population	Math	Read	Grad_Rate	poor_health
count	186.000000	186.000000	186.000000	186.000000	186.000000
mean	14770.026882	2.941398	2.785484	94.392473	3064.365591
std	12605.944718	0.279684	0.237678	5.939492	2673.077929
min	152.000000	2.100000	2.000000	62.000000	23.000000
25%	4470.000000	2.700000	2.700000	93.000000	857.250000
50%	10989.000000	2.900000	2.800000	96.000000	2335.500000
75%	21421.000000	3.100000	2.900000	98.000000	4372.750000
max	49728.000000	4.000000	3.400000	100.000000	14489.000000

\

	poor_sleep	Cost_Burden	Uninsured_health	Physicians	food_Insecure
count	186.000000	186.000000	186.000000	186.000000	186.000000
mean	4692.655914	496.537634	2444.564516	5.317204	2178.870968
std	4040.692191	505.374179	2083.528517	6.139057	2018.025879
min	50.000000	0.000000	27.000000	0.000000	10.000000
25%	1418.500000	120.000000	812.750000	1.000000	572.500000
50%	3414.500000	336.000000	1827.500000	3.000000	1490.000000
75%	6814.750000	656.750000	3549.000000	8.000000	3105.000000
max	16987.000000	2451.000000	9222.000000	38.000000	9970.000000

\

	Life_Expectancy
count	186.000000
mean	77.393548
std	2.376930
min	71.900000
25%	75.800000
50%	77.300000
75%	78.975000
max	89.700000

[7]:
```
urban.describe()
```

[7]:

	nbr_sing_household	nbr_household	percent_single	Rural
count	68.000000	6.800000e+01	68.000000	68.000000
mean	31809.117647	9.693757e+04	31.264706	34735.838235
std	68062.434466	1.882317e+05	6.571348	18480.051069
min	2392.000000	9.762000e+03	17.000000	5022.000000

\

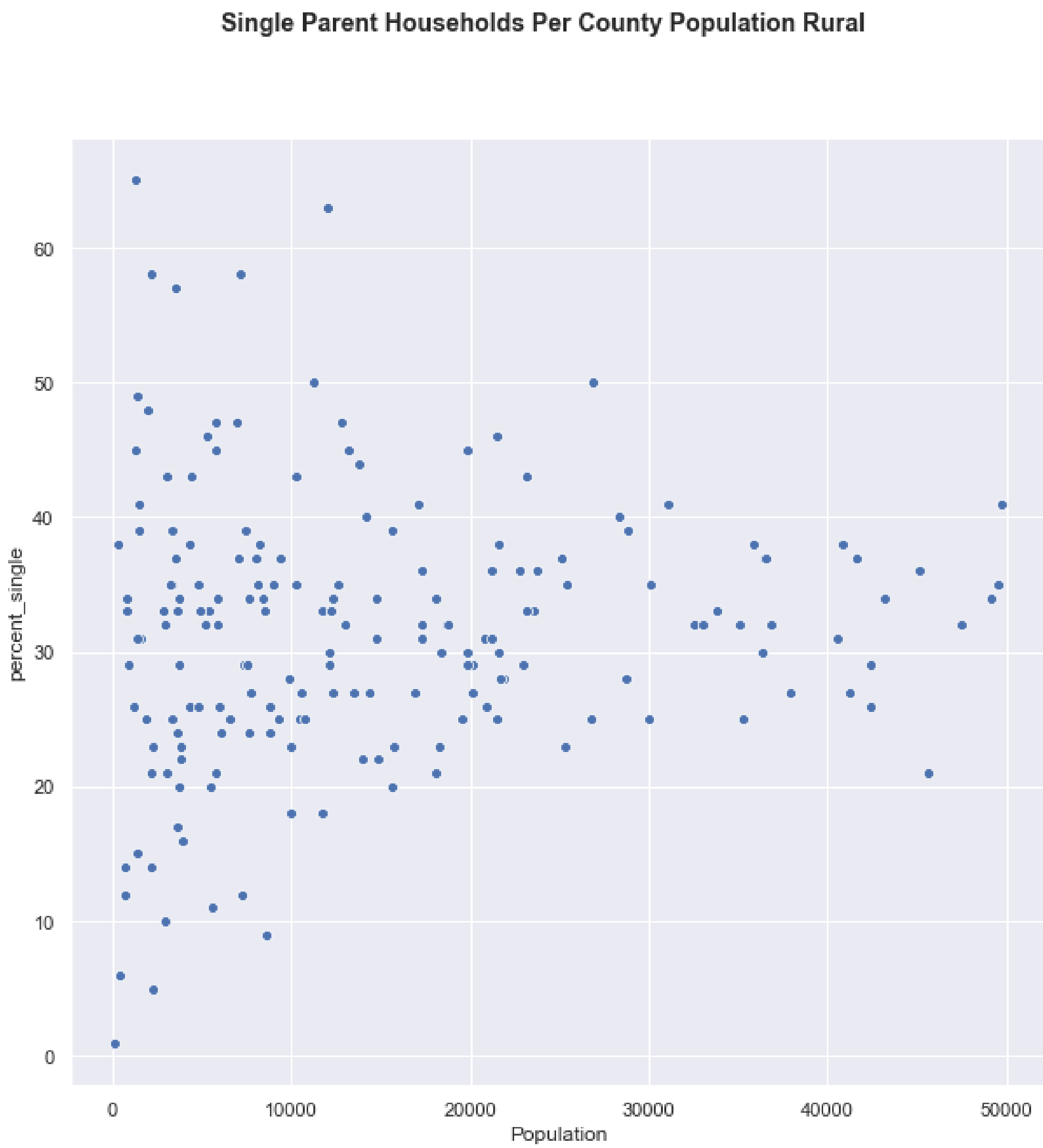
```
25%          5136.750000   1.750350e+04       26.750000   19776.500000
50%          9656.500000   3.161000e+04       32.000000   32598.000000
75%         25979.750000   8.180650e+04       37.000000   47476.750000
max        445154.000000   1.231476e+06       44.000000  103571.000000

         Population       Math       Read  Grad_Rate    poor_health  \
count  6.800000e+01  68.000000  68.000000  68.000000      68.000000
mean   3.816856e+05   3.085294   2.894118  91.926471   74733.455882
std    7.236031e+05   0.197948   0.176941   4.341113  141018.568160
min    5.003100e+04   2.600000   2.500000  75.000000    8414.000000
25%    6.795200e+04   3.000000   2.800000  90.000000   14305.500000
50%    1.330275e+05   3.100000   2.900000  93.000000   23471.000000
75%    3.150315e+05   3.200000   3.000000  95.000000   68266.000000
max    4.698619e+06   3.600000   3.400000  97.000000  885812.000000

         poor_sleep    Cost_Burden  Uninsured_health   Physicians  \
count  6.800000e+01      68.000000         68.000000    68.000000
mean   1.260119e+05   16881.529412      62499.058824   239.191176
std    2.434585e+05   36246.466308     135041.924584   462.947283
min    1.508600e+04    1182.000000       6687.000000     6.000000
25%    2.276400e+04    2361.000000      11253.500000    23.750000
50%    4.166000e+04    4829.500000      18019.500000    74.000000
75%    1.077918e+05   14472.000000      41986.500000   232.500000
max    1.593969e+06  240521.000000     908742.000000  2742.000000

       food_Insecure  Life_Expectancy
count      68.000000        68.000000
mean    54094.852941        78.020588
std    110360.809809         2.294286
min      4210.000000        73.300000
25%     10707.500000        76.200000
50%     17410.000000        78.300000
75%     47455.000000        79.425000
max    739120.000000        83.000000
```

0.1.1 Is there a significant statistical difference between rural single parent

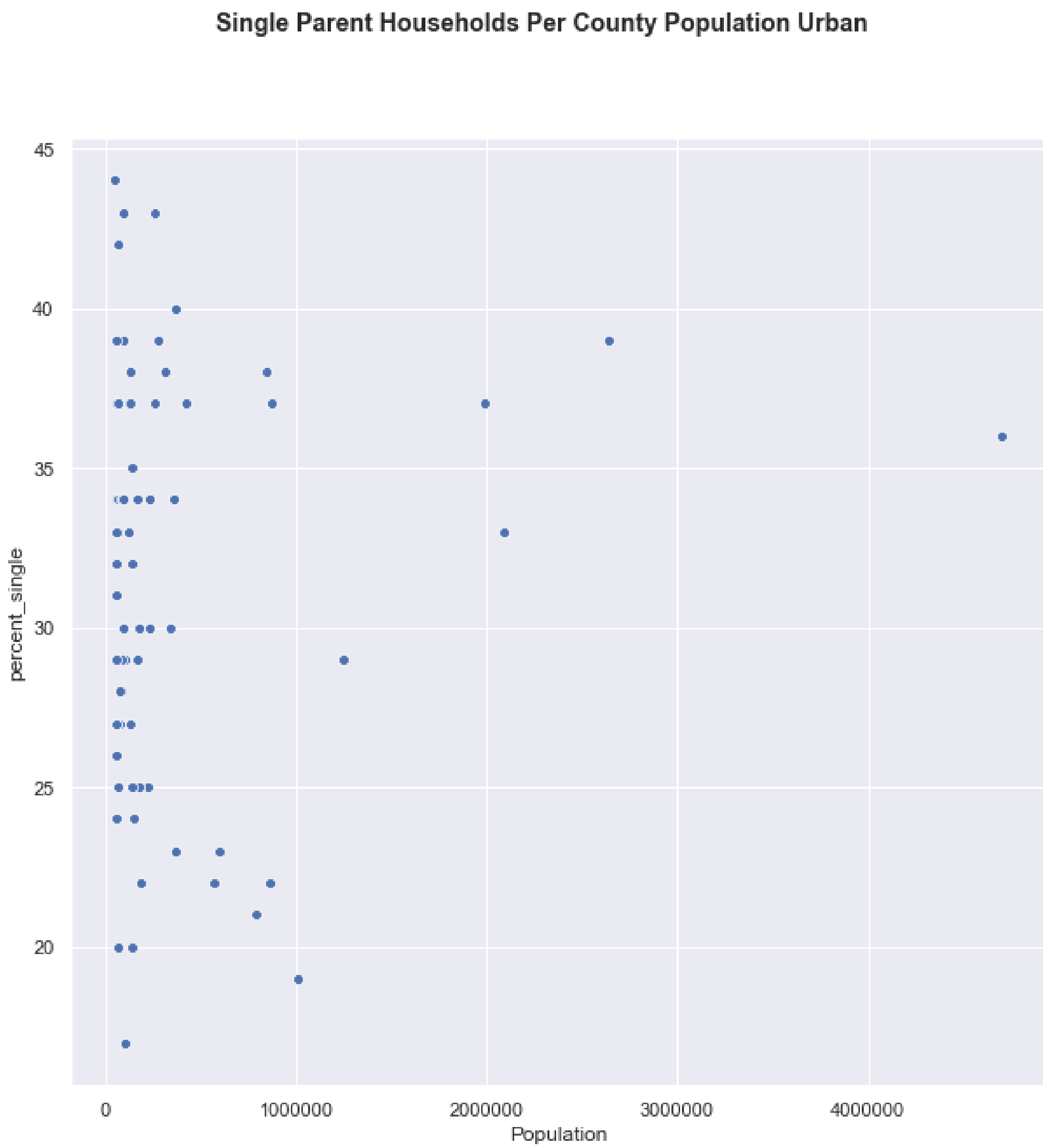
0.1.2 households and urban single parent households?

[8]:
```
# ============================================================================
# 1. Is there a significant statistical difference between rural single parent
#    households and urban single parent households?
#    look for counties that are considered rural 0 - 50K
#    or nbr of households > 50k
#     % single is based upon # hseholds
#    Look at the normal distribution for the precent single
#    In texas rural population is > than urban plus urban areas also
```

```python
#   rural populations. Did not count these as I couldn't tell from
#   the numbers if the rural was counted seperately from the urban.
# ============================================================================

# ============================================================================
# Create two scatter plots comparing two variables and provide your analysis
#  on correlation and causation. Remember, covariance, Pearson’s correlation,
#  and Non- Linear Relationships should also be considered during your analysis
#  (Chapter 7).
# ============================================================================
subtitle = 'Single Parent Households Per County Population Rural'
x_val = 'Population'
y_val = 'percent_single'
xlab = 'Population'
ylab = 'Single Parent Household'
data = rural
sns_Scatter(subtitle, xlab, ylab, x_val, y_val, data)
```




```
[9]: subtitle = 'Single Parent Households Per County Population Urban'
x_val = 'Population'
y_val = 'percent_single'
xlab = 'Population'
ylab = 'Single Parent Household'
data = urban
sns_Scatter(subtitle, xlab, ylab, x_val, y_val, data)
```



[10]:
```
# ==========================================================================
# Include the other descriptive characteristics about the variables: Mean,
#  Mode, Spread, and Tails (Chapter 2)
# ==========================================================================
# Compute Mean, Variance and Std.

rs_mean = s_percent.mean()
rs_var = s_percent.var()
rs_std = s_percent.std()
rs_mode = s_percent.mode()
```

```
print(f'Rural:  Mean = {rs_mean}  Var = {rs_var}  Std = {rs_std}  Mode =␣
↪{rs_mode} \n')

us_mean = s_percent1.mean()
us_var = s_percent1.var()
us_std = s_percent1.std()
us_mode = s_percent1.mode()
print(f'Urban:  Mean = {us_mean}  Var = {us_var}  Std = {us_std} Mode =␣
↪{us_mode} \n')

# Set values for plotting PDF and Cohen's d
mean1 = rs_mean
mean2 = us_mean
var1 = rs_var
ser1 = s_percent
ser2 = s_percent1

# ============================================================================
#  Cohen's d
#
#  What is the difference between single households in rural and urban
#  couldn't derive the precentage of singles on rural area within urban␣
↪counties.
# ============================================================================
ser1 = s_percent
ser2 = s_percent1
title = 'Cohens d for Single Parent Households Rural vs Urban'
cohen_d = Compute_Cohend(mean1, mean2, ser1, ser2, var1, title)
```

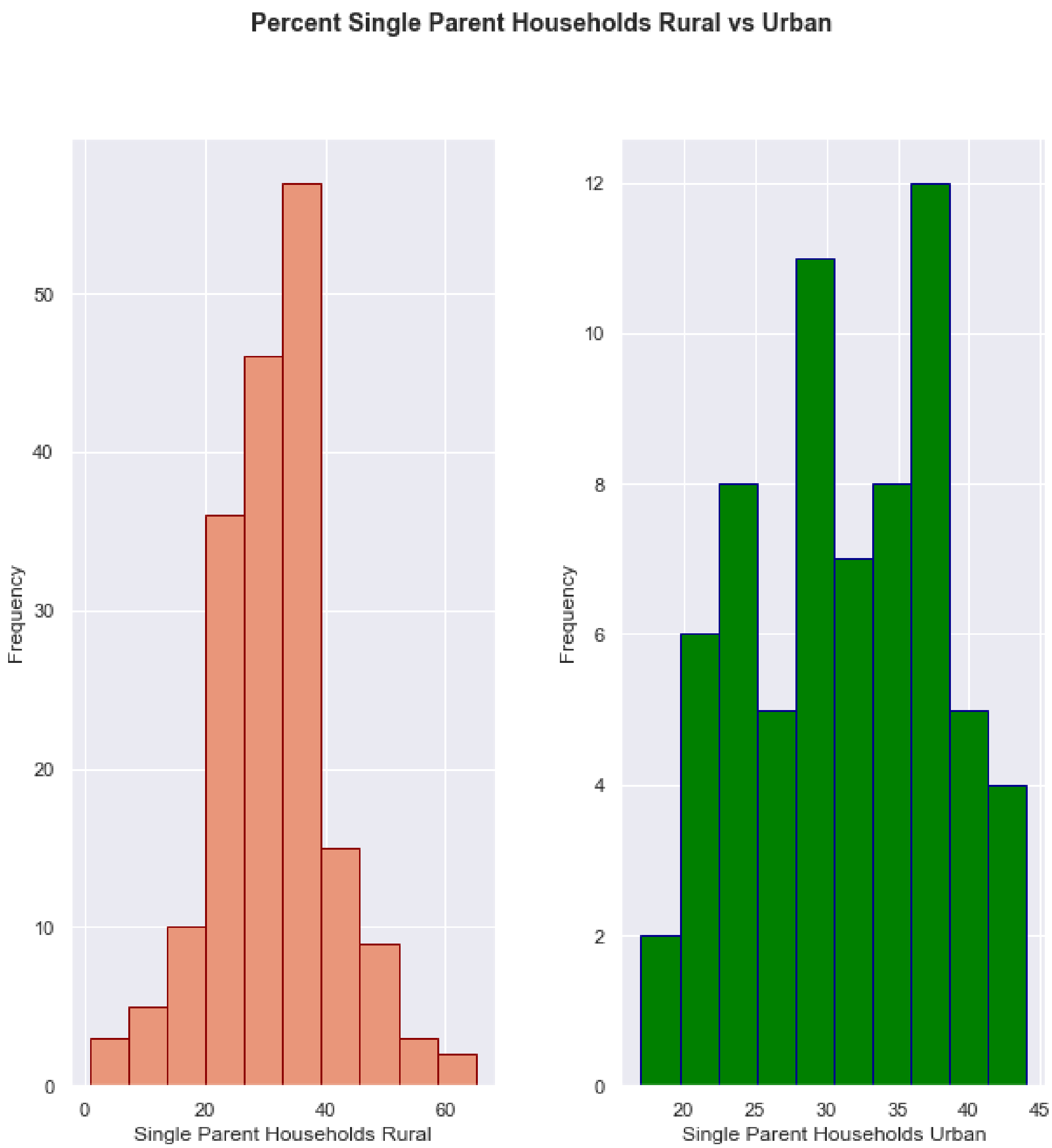
```
Rural:  Mean = 31.521505376344088  Var = 100.65088637024125  Std =
10.032491533524524  Mode = 0    32
dtype: int64

Urban:  Mean = 31.264705882352942  Var = 43.18261633011412  Std =
6.571348136426354 Mode = 0    37
dtype: int64

Cohens d for Single Parent Households Rural vs Urban = 0.029857843619705685
```

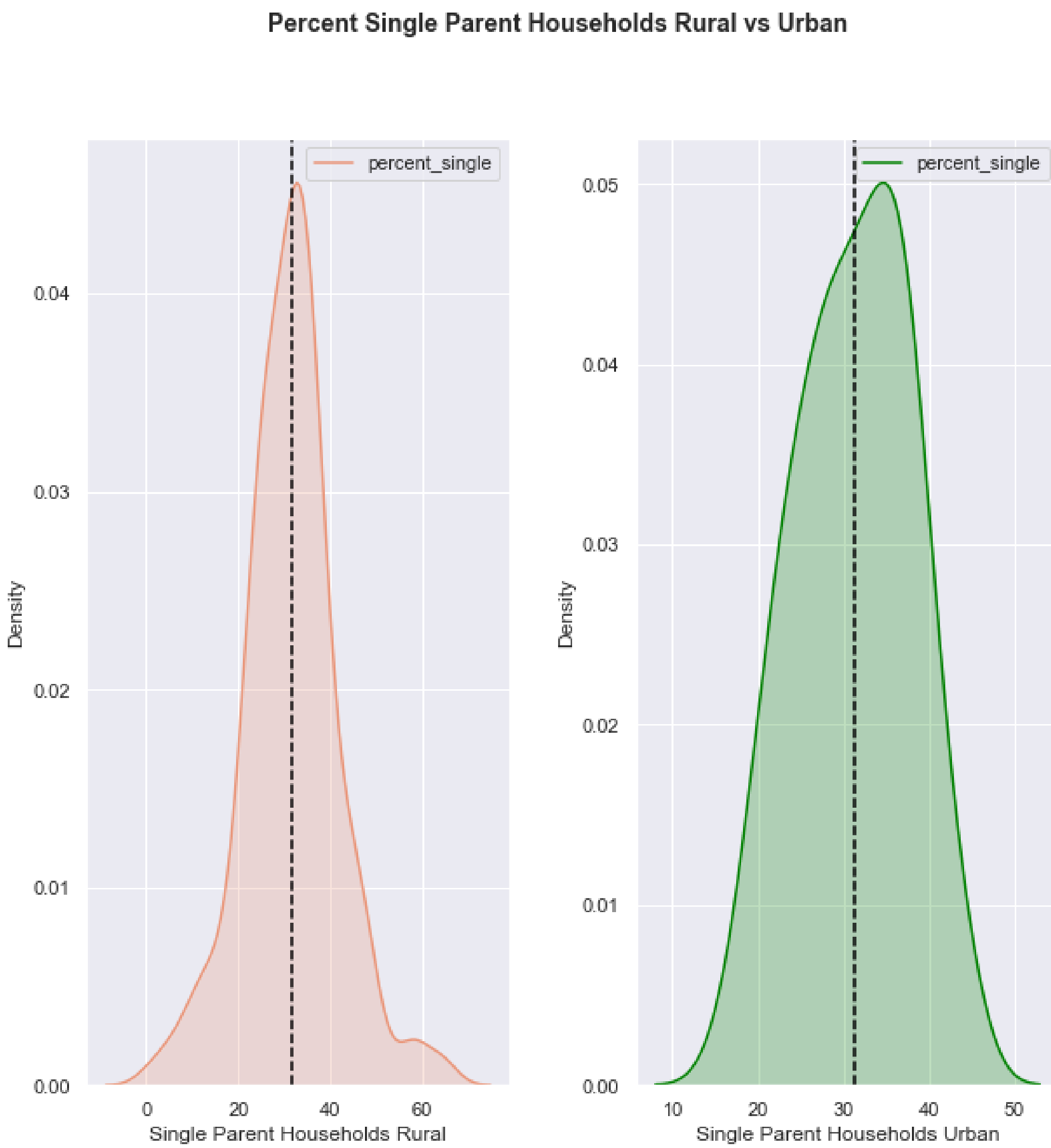
[11]:
```
# ============================================================================
# Include a histogram of each of the 5 variables - in your summary and
# analysis, identify any outliers and explain the reasoning for them being
# outliers and how you believe they should be handled (Chapter 2).
# ============================================================================

# ============================================================================
```

```
# Plot 1 analytical distribution and provide your analysis on how it applies
#  to the dataset you have chosen (Chapter 5).
# ==============================================================================
```

0.2 Histograms and PDFs

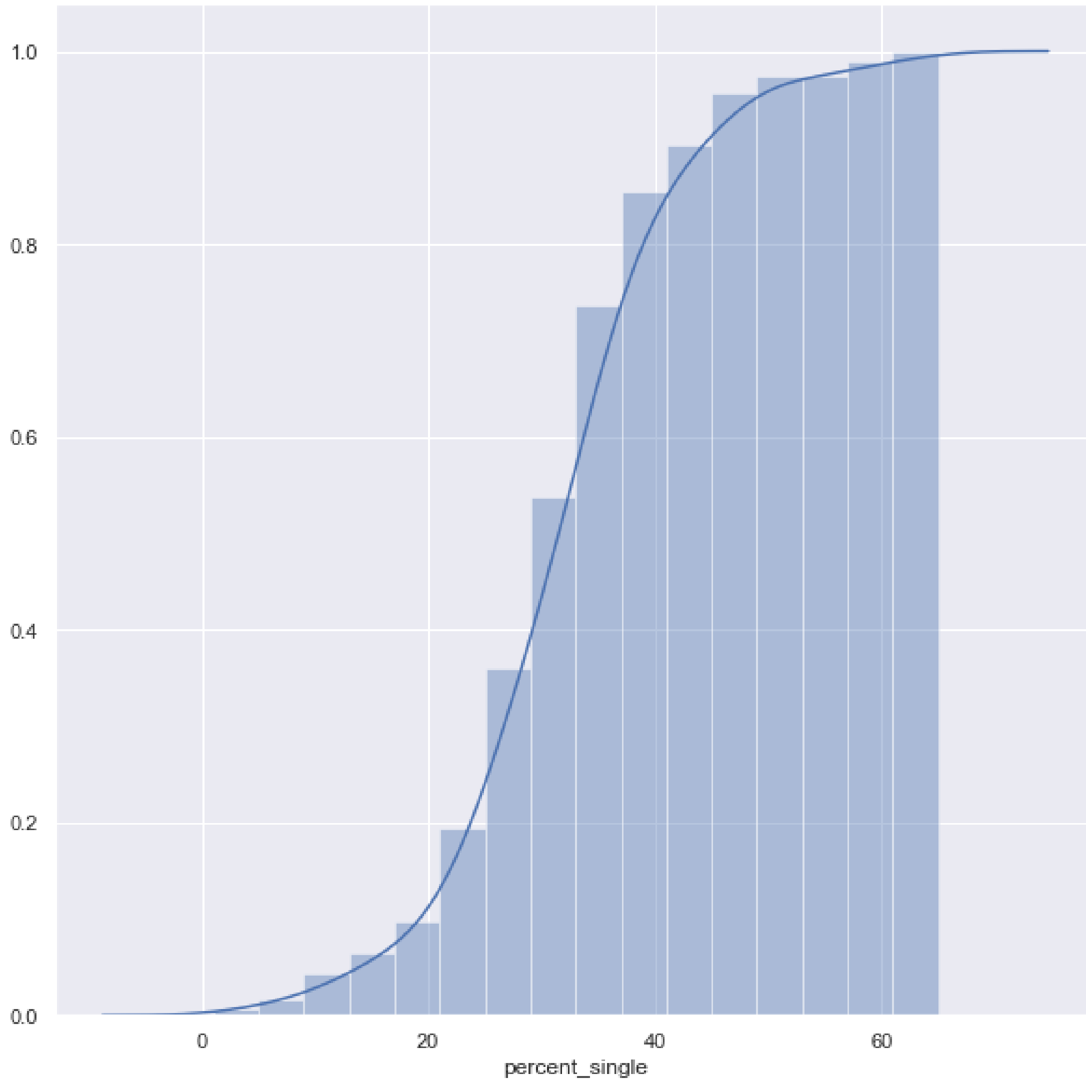
[12]:
```
# Histogram and PDFs Single parent households rural vs urban
# ==============================================================================
# plot side by side for comparison
subtitle = "Percent Single Parent Households Rural vs Urban"
xlab1 = "Single Parent Households Rural"
xlab2 = "Single Parent Households Urban"
binz = 10

Hist_Plot(subtitle, xlab1, xlab2, ser1, ser2)

# KDE/PDFs
Sns_Kde(subtitle,xlab1, xlab2, ser1, mean1, ser2, mean2)
```

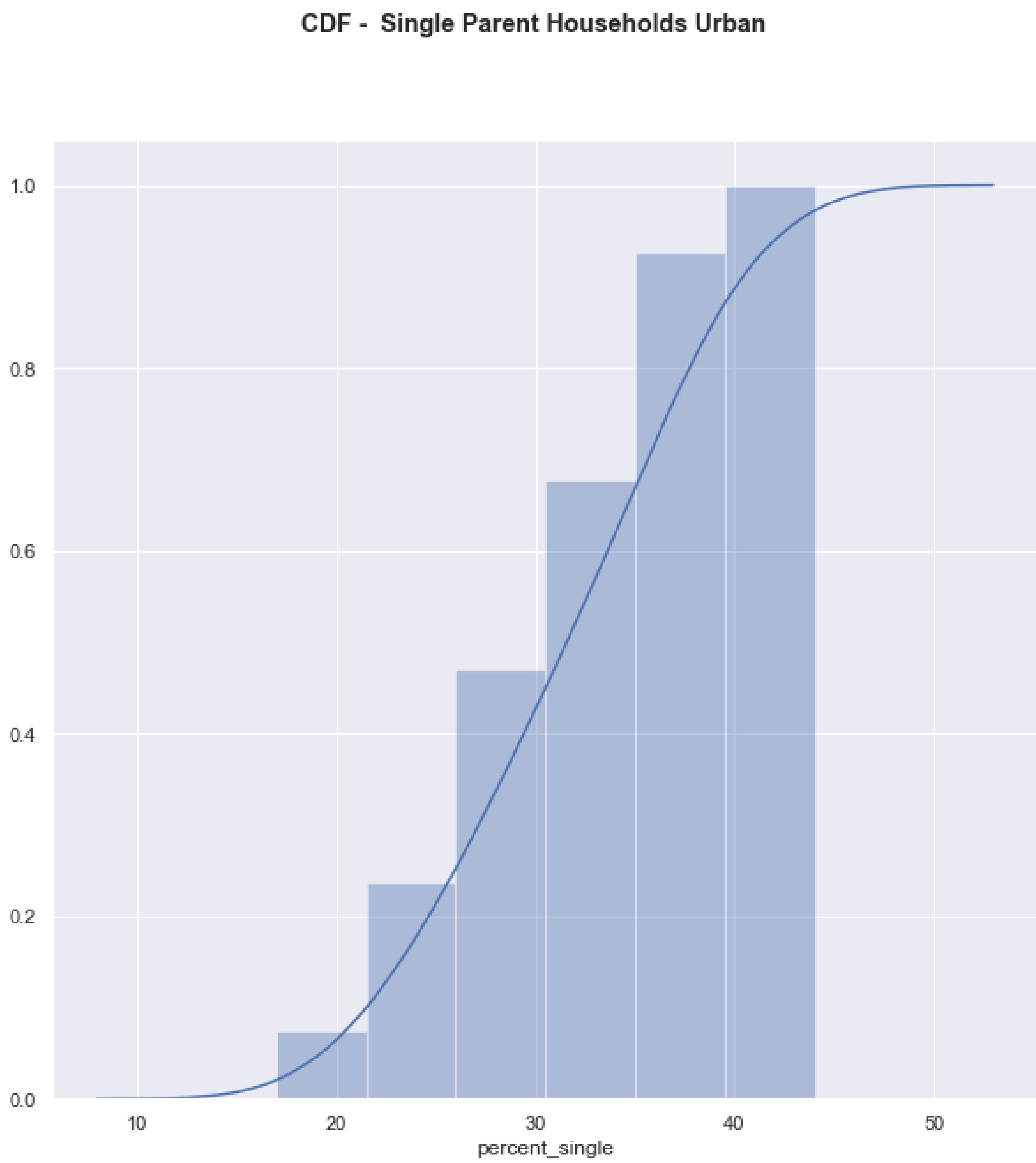

Percent Single Parent Households Rural vs Urban
Frequency
0
10
20
30
40
50
0
20
40
60
Single Parent Households Rural
Frequency
0
2
4
6
8
10
12
20
25
30
35
40
45
Single Parent Households Urban



[13]:
```
# ==============================================================================
# Create 1 CDF with one of your variables, using page 41-44 as your guide,
# what does
# this tell you about your variable and how does
#  it address the question you are trying to answer (Chapter 4).
# ==============================================================================

subtitle = " CDF -  Single Parent Households Rural"
Cdf_Plot(subtitle,ser1)
subtitle = " CDF -  Single Parent Households Urban"
Cdf_Plot(subtitle, ser2)
```

CDF - Single Parent Households Rural





0.3 Is the high school grduation rate and average math/reading scores

0.4 better in urban schools than rural schools?

[ ]:

```

```

[14]:

```
# ==========================================================================
#  2.Is the high school grduation rate and average math/reading scores
#     better in urban schools than rural schools?
#
```

```
#  There is a myth that the best schools are in suburban areas and urban and
#  rural schools are lacking in quality education.  Do the high school
#  graduation rates and 3rd grade reading/math scores reflect this?
# ============================================================================
```

[15]:

```
# ============================================================================
# # Compute Stats
# ============================================================================

# Graduation Rate
rg_mean = grad.mean()
rg_var = grad.var()
rg_std = grad.std()
rg_mode = grad.mode()
print(f'Rural - Grad_Rate:  Mean = {rg_mean}  Var = {rg_var}  Std = {rg_std} ␣
↪Mode = {rg_mode} \n')

ug_mean = grad1.mean()
ug_var = grad1.var()
ug_std = grad1.std()
ug_mode = grad.mode()
print(f'Urban - Grad_Rate:  Mean = {ug_mean}  Var = {ug_var}  Std = {ug_std}␣
↪Mode = {ug_mode} \n')

# Cohen's d
mean1 = rg_mean
mean2 = ug_mean
var1 = rg_var
ser1 = grad
ser2 = grad1
title = 'Cohens d for High School Graduation Rates Rural vs Urban'
Compute_Cohend(mean1, mean2,ser1,ser2, var1, title)

# 3rd Grade Average Reading Scores
rr_mean = read.mean()
rr_var = read.var()
rr_std = read.std()
rr_mode = read.mode()
print('Rural - 3rd Grade Average Reading Scores')
print(f'Mean = {rr_mean}  Var = {rr_var}  Std = {rr_std} Mode = {rr_mode}\n')

ur_mean = read1.mean()
ur_var = read1.var()
ur_std = read1.std()
ur_mode = read1.mode()
print('Urban - 3rd Grade Average Reading Scores')
print(f'Mean = {ur_mean}  Var = {ur_var}  Std = {ur_std} Mode = {ur_mode} \n')
```

```python
# Cohen's d
mean1 = rr_mean
mean2 = ur_mean
var1 = rr_var
ser1 = read
ser2 = read1
title = 'Cohens d for 3rd Grade Reading Levels Rural vs Urban'
Compute_Cohend(mean1, mean2,ser1,ser2, var1, title)

# 3rd Grade Average Math Scores
rm_mean = maths.mean()
rm_var = maths.var()
rm_std = maths.std()
rm_mode = maths.mode()
print('Rural - 3rd Grade Average Math Scores')
print(f'Mean = {rm_mean}  Var = {rm_var}  Std = {rm_std} Mode = {rm_mode} \n')

um_mean = maths1.mean()
um_var = maths1.var()
um_std = maths1.std()
um_mode = maths1.mode()
print('Urban - 3rd Grade Average Math Scores')
print(f'Mean = {um_mean}  Var = {um_var}  Std = {um_std} Mode = {um_mode}\n')

# Cohen's d
mean1 = rm_mean
mean2 = um_mean
var1 = rm_var
ser1 = maths
ser2 = maths1
title = 'Cohens d for 3rd Grade Math Levels Rural vs Urban'
Compute_Cohend(mean1, mean2,ser1,ser2, var1, title)
```

```
Rural - Grad_Rate:  Mean = 94.39247311827957  Var = 35.27756466143565  Std =
5.939491953141754  Mode = 0    98
dtype: int64

Urban - Grad_Rate:  Mean = 91.92647058823529  Var = 18.845258999122024  Std =
4.341112645292912 Mode = 0    98
dtype: int64

Cohens d for High School Graduation Rates Rural vs Urban = 0.4826872508130733

Rural - 3rd Grade Average Reading Scores
Mean = 2.7854838709677425  Var = 0.056490845684394046  Std = 0.23767802945243813
Mode = 0    2.7
```

```
dtype: float64

Urban - 3rd Grade Average Reading Scores
Mean = 2.894117647058824  Var = 0.031308165057067586  Std = 0.17694113444043358
Mode = 0    2.9
dtype: float64

Cohens d for 3rd Grade Reading Levels Rural vs Urban = -0.19540097249671604

Rural - 3rd Grade Average Math Scores
Mean = 2.9413978494623647  Var = 0.07822290031967445  Std = 0.2796835717729492
Mode = 0    3.0
dtype: float64

Urban - 3rd Grade Average Math Scores
Mean = 3.0852941176470585  Var = 0.03918349429323968  Std = 0.19794821113927674
Mode = 0    3.0
dtype: float64

Cohens d for 3rd Grade Math Levels Rural vs Urban = -0.2524115783211429
```

[15]:

```
-0.2524115783211429
```

[16]:

```python
# Descriptive Statistics

hs_df_rural = rural[['Grad_Rate', 'Math', 'Read']]
hs_df_rural.describe()
```

[16]:

	Grad_Rate	Math	Read
count	186.000000	186.000000	186.000000
mean	94.392473	2.941398	2.785484
std	5.939492	0.279684	0.237678
min	62.000000	2.100000	2.000000
25%	93.000000	2.700000	2.700000
50%	96.000000	2.900000	2.800000
75%	98.000000	3.100000	2.900000
max	100.000000	4.000000	3.400000

[17]:

```python
hs_df_urban = urban[['Grad_Rate', 'Math', 'Read']]
hs_df_urban.describe()
```

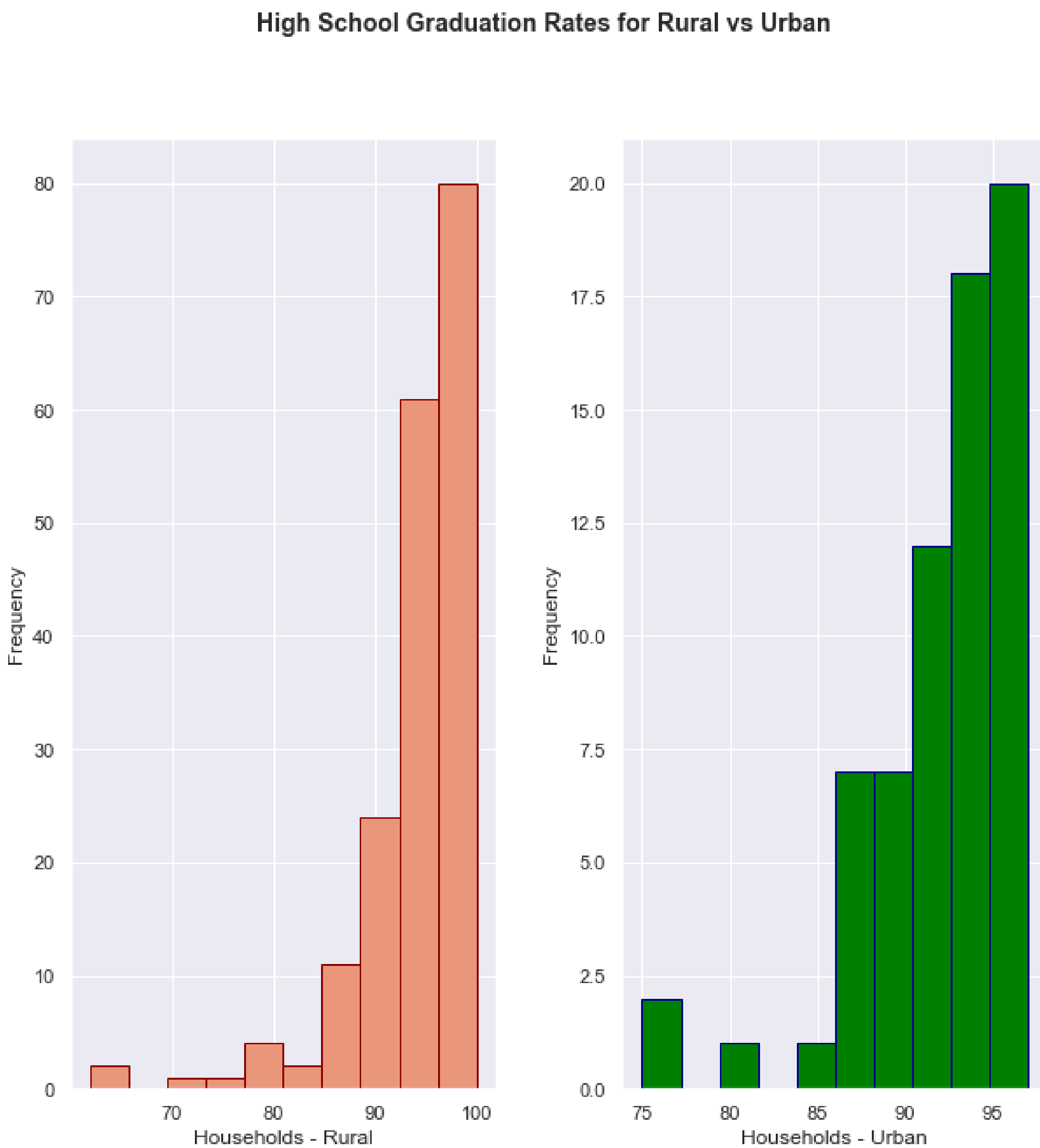
[17]:

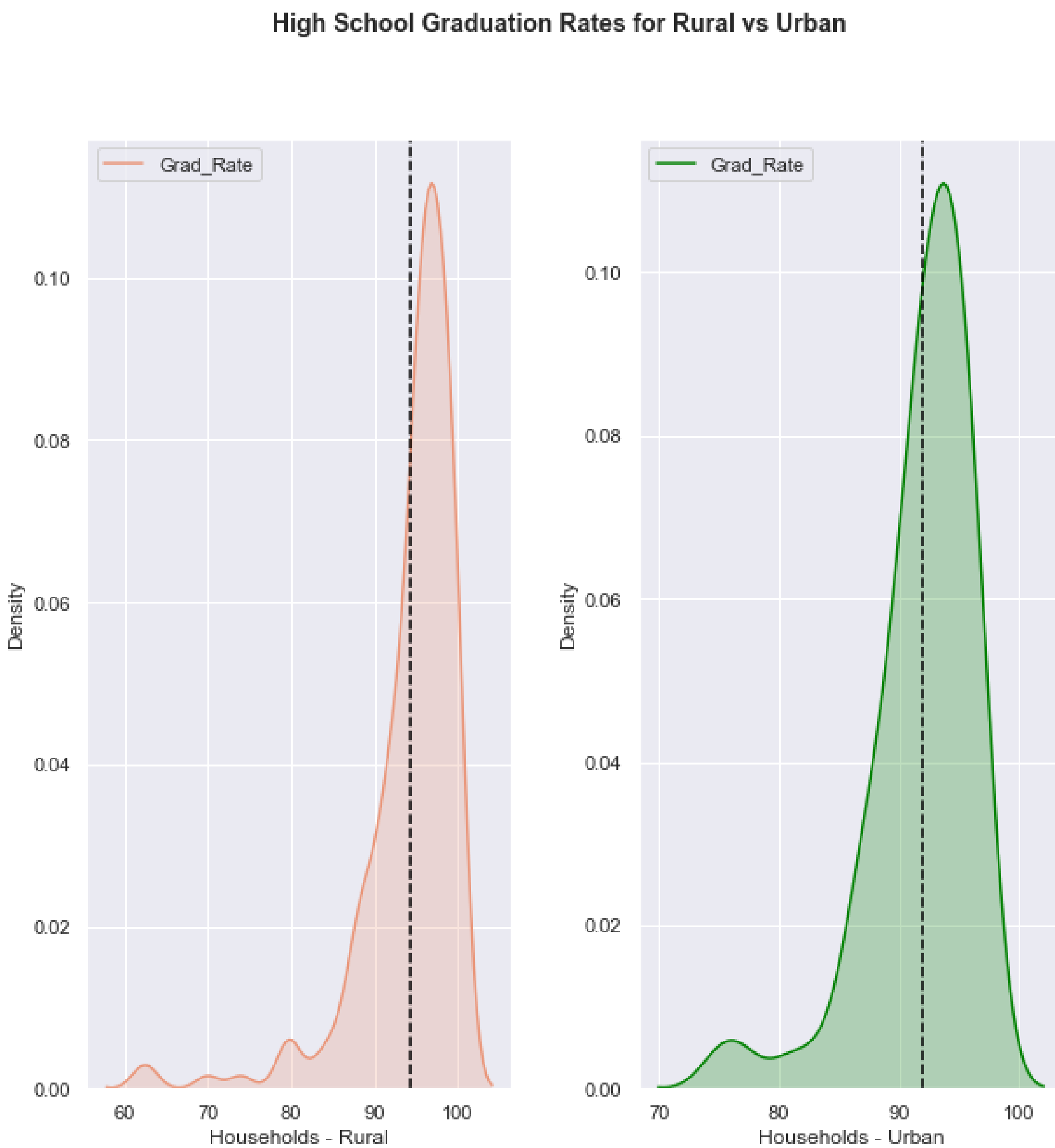
	Grad_Rate	Math	Read
count	68.000000	68.000000	68.000000
mean	91.926471	3.085294	2.894118
std	4.341113	0.197948	0.176941
min	75.000000	2.600000	2.500000

```
25%     90.000000   3.000000   2.800000
50%     93.000000   3.100000   2.900000
75%     95.000000   3.200000   3.000000
max     97.000000   3.600000   3.400000
```

0.4.1 Histograms and PDFs

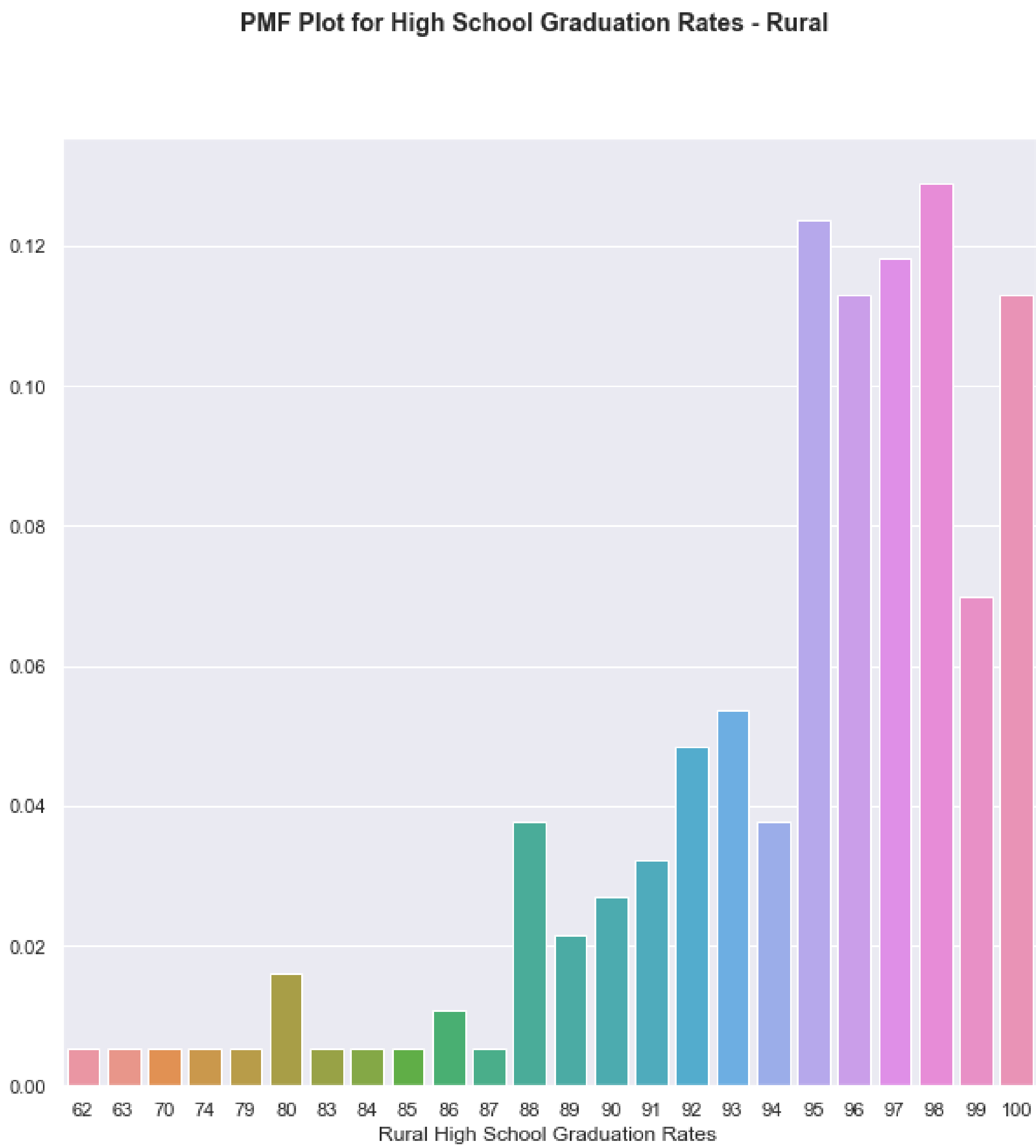
[18]:
```
# ==============================================================================
# Include a histogram of each of the 5 variables - in your summary and
# analysis, identify any outliers and explain the reasoning for them being
# outliers and how you believe they should be handled (Chapter 2).
# ==============================================================================
# Histogram for distribution - Placed these histograms and KDEs here because␣
↪they
# use the raw data not the normalized data. Did this so I could compare the
# actual vlues and not the normalized values.
# ==============================================================================

# ==============================================================================
# # Graduation Rates Rural vs Urban
# ==============================================================================
subtitle = "High School Graduation Rates for Rural vs Urban"
xlab1 = "Households - Rural"
xlab2 = "Households - Urban"
mean1 = rg_mean
mean2 = ug_mean
ser1 = grad
ser2 = grad1
Hist_Plot(subtitle, xlab1, xlab2, ser1, ser2)

# KDE/PDF
Sns_Kde(subtitle,xlab1, xlab2, ser1, mean1, ser2, mean2)
```

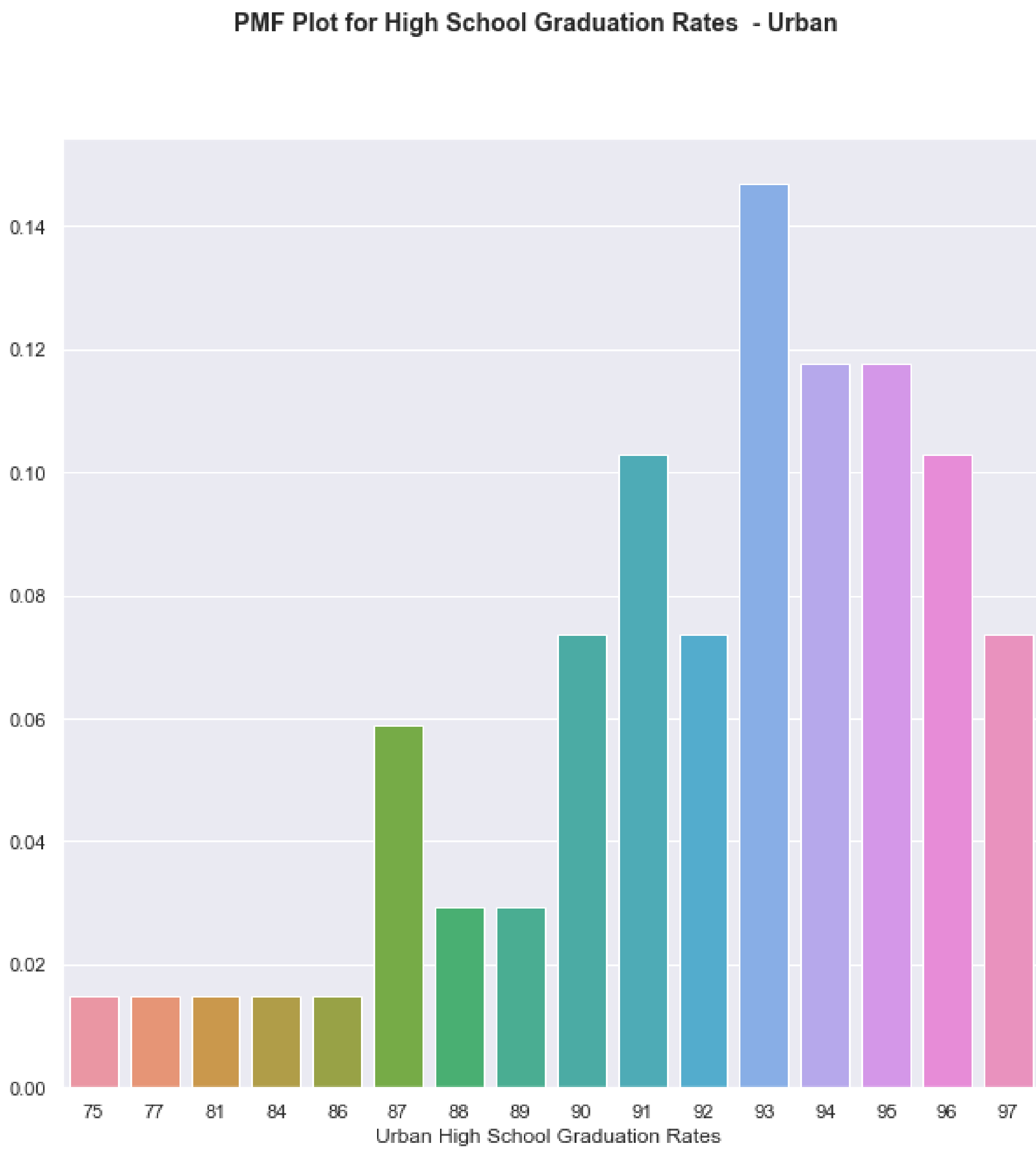

High School Graduation Rates for Rural vs Urban
Frequency
0
10
20
30
40
50
60
70
80
70
80
90
100
Households - Rural
Frequency
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
75
80
85
90
95
Households - Urban



[19]:
```
# =========================================================================
# Using pg. 29 of your text as an example, compare two scenarios in your data␣
↪using a
# PMF. Reminder, this isn't comparing two variables against each other
#  - it is the same variable, but a different scenario. Almost like a filter.
#  The example in the book is first babies compared to all other babies, it
#  is still the same variable, but breaking the data out based on criteria
#  we are exploring (Chapter 3).
# =========================================================================
```

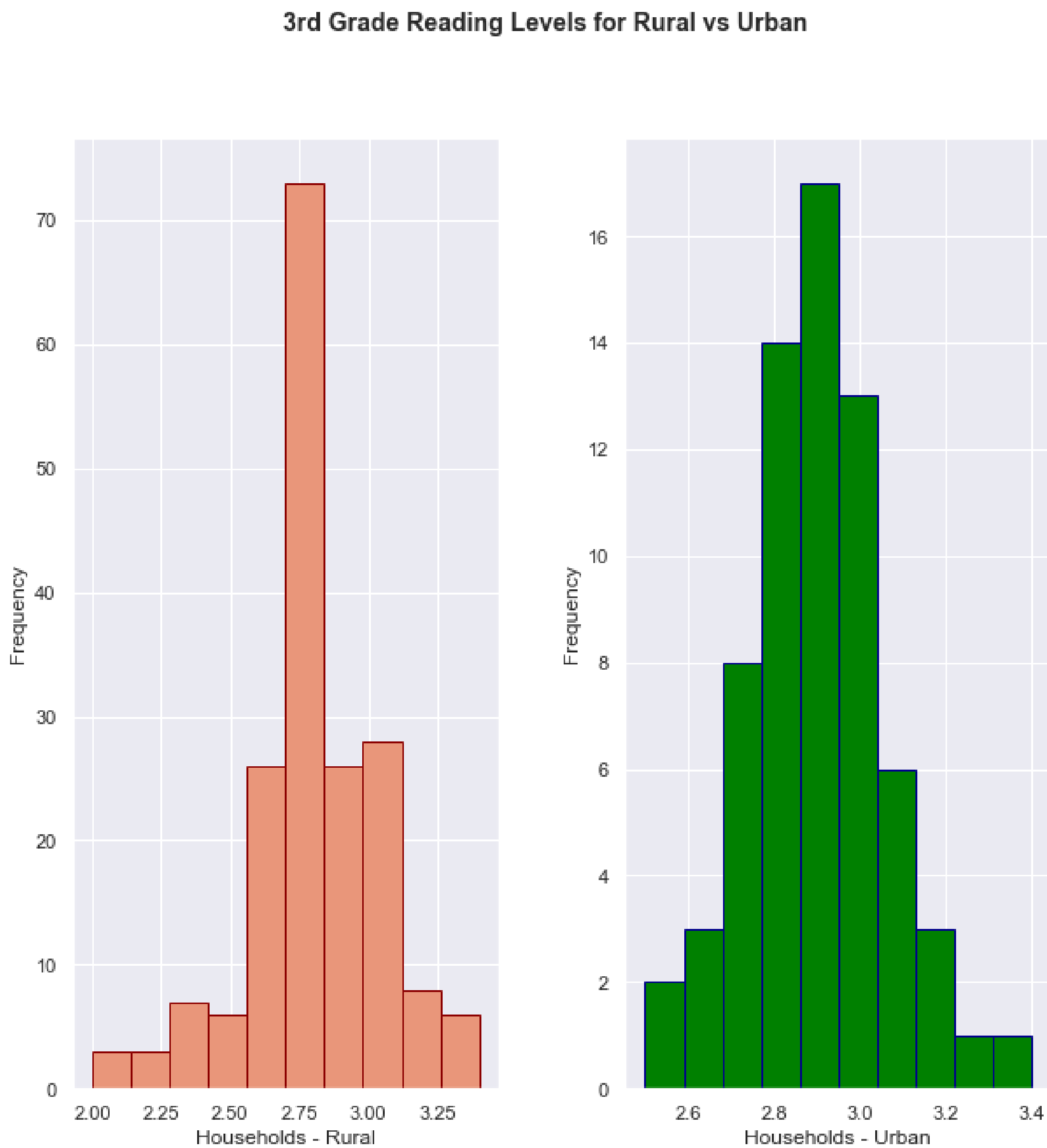
[20]:
```
subtitle = 'PMF Plot for High School Graduation Rates - Rural'
data = grad
xlab = 'Rural High School Graduation Rates '
Pmf_plot(subtitle, data, xlab)
subtitle = 'PMF Plot for High School Graduation Rates  - Urban'
data = grad1
xlab = 'Urban High School Graduation Rates '
Pmf_plot(subtitle, data, xlab)
```

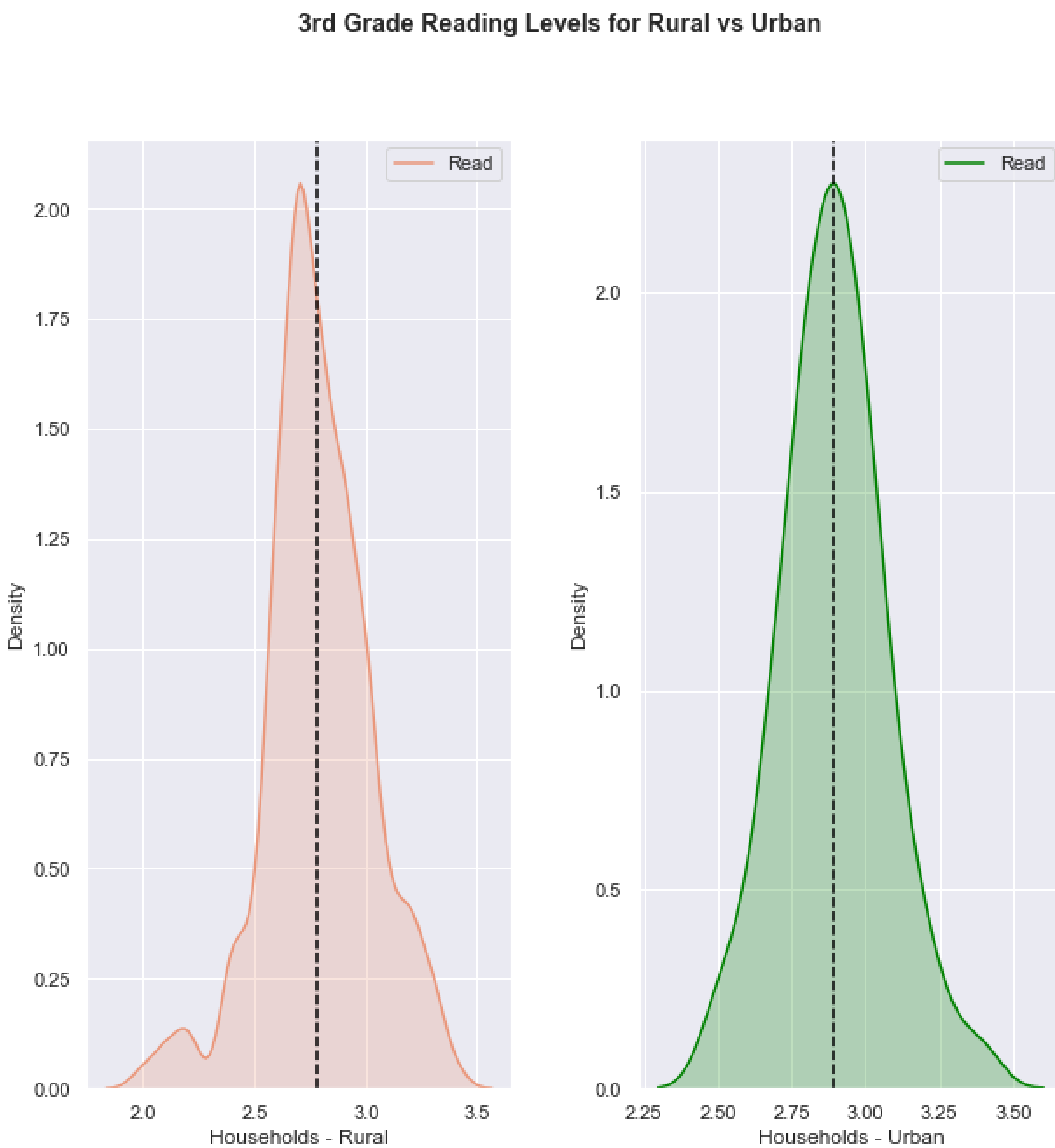




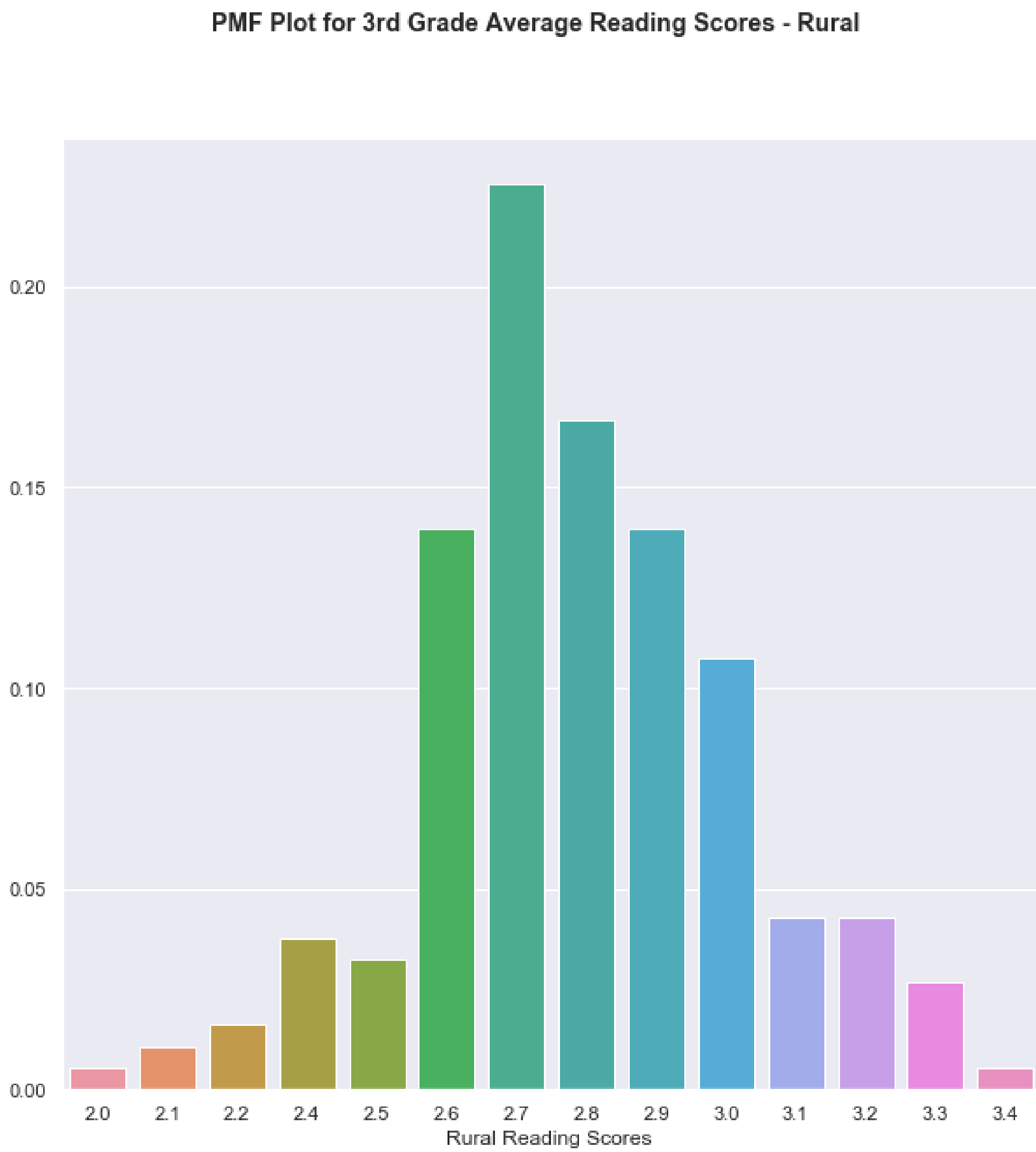
[21]:
```
# ============================================================================
# # Histograms and PDFs 3rd grade Reading levels
# ============================================================================
subtitle = "3rd Grade Reading Levels for Rural vs Urban"
xlab1 = "Households - Rural"
xlab2 = "Households - Urban"
mean1 = rr_mean
mean2 = ur_mean
ser1 = read
ser2 = read1
```

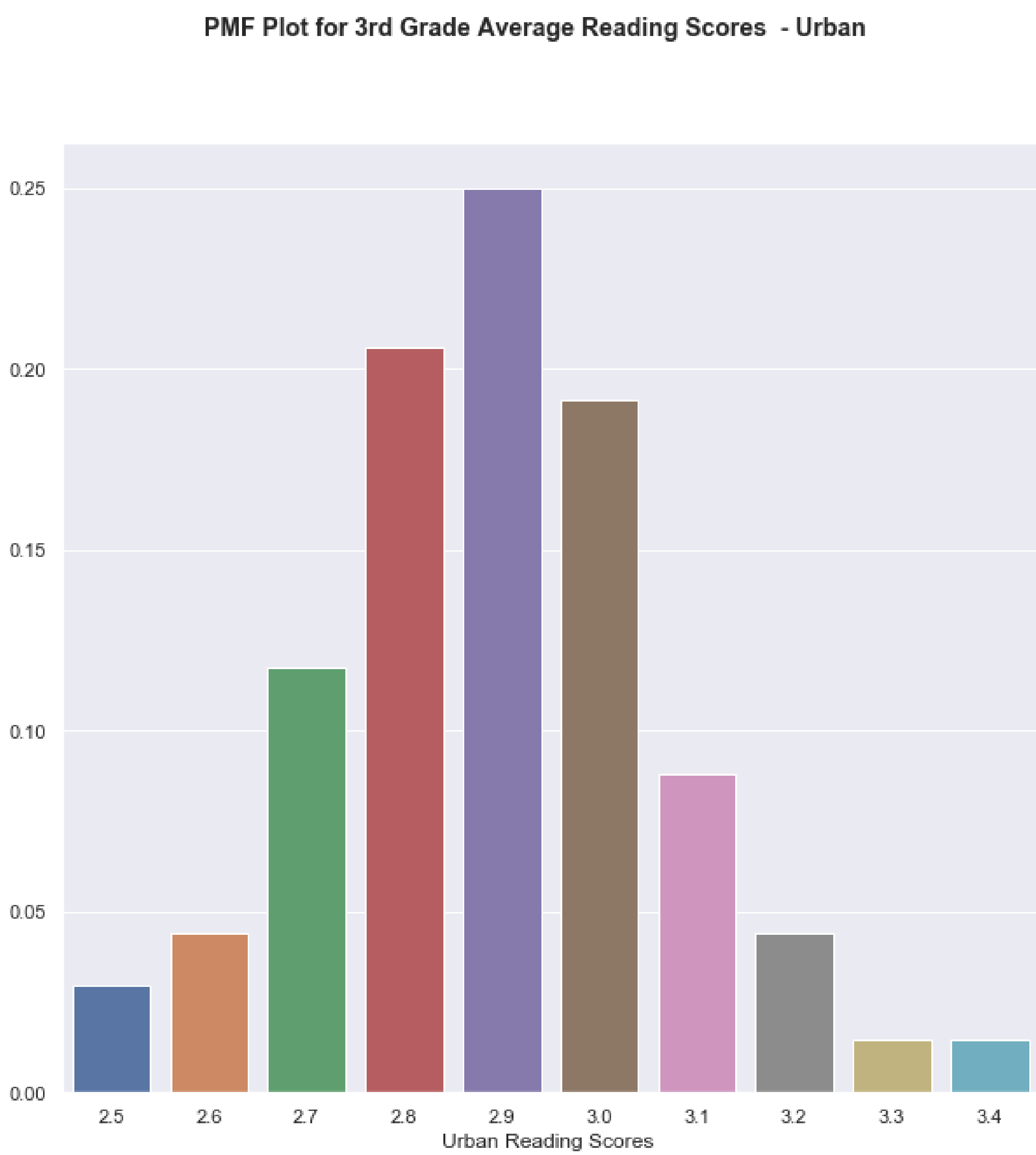
```
Hist_Plot(subtitle, xlab1, xlab2, ser1, ser2)


# KDE/PDF
Sns_Kde(subtitle,xlab1, xlab2, ser1, mean1, ser2, mean2)
```





[22]:
```
subtitle = 'PMF Plot for 3rd Grade Average Reading Scores - Rural'
data = read
xlab = 'Rural Reading Scores '
Pmf_plot(subtitle, data, xlab)
subtitle = 'PMF Plot for 3rd Grade Average Reading Scores  - Urban'
data = read1
xlab = 'Urban Reading Scores '
Pmf_plot(subtitle, data, xlab)
```

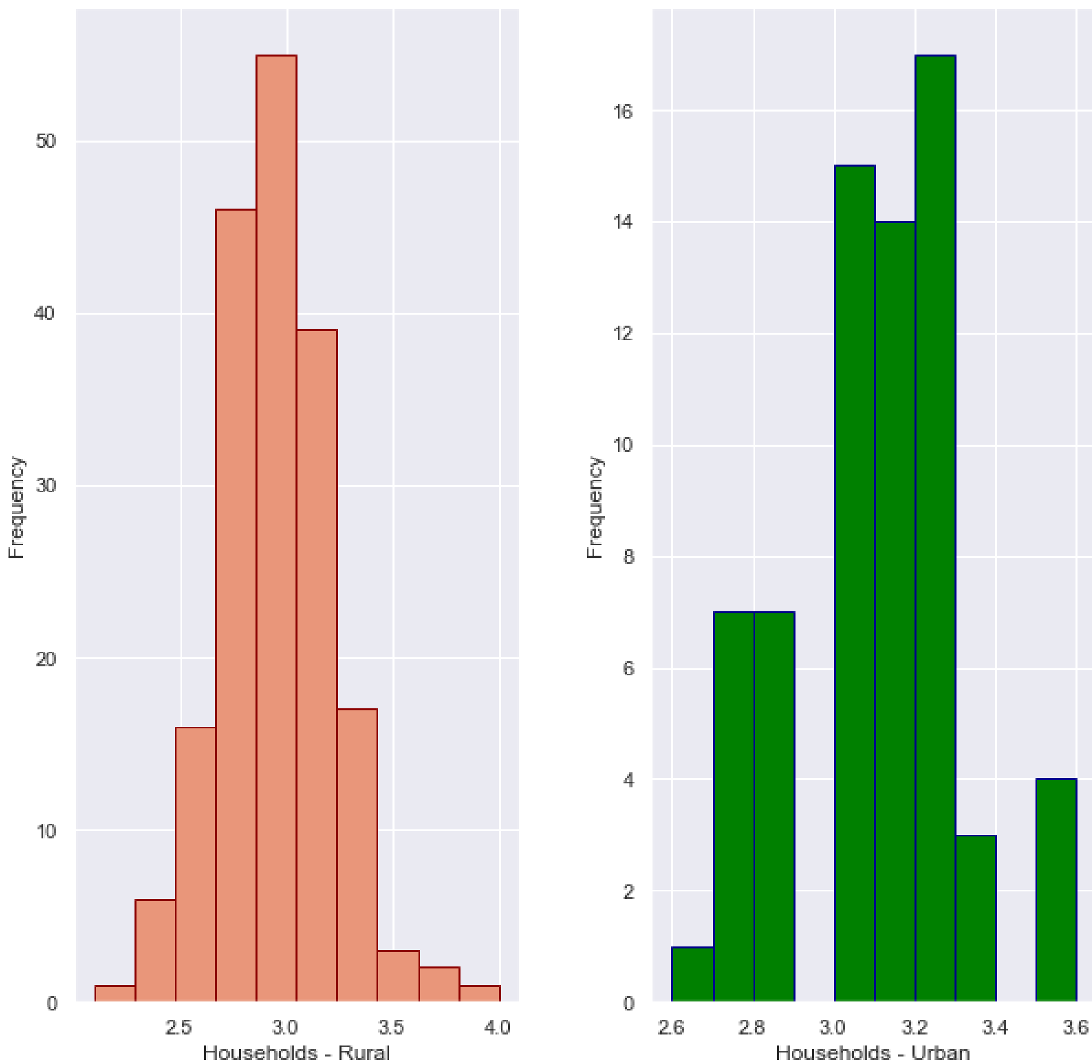

PMF Plot for 3rd Grade Average Reading Scores - Rural
0.20
0.15
0.10
0.05
0.00
2.0
2.1
2.2
2.4
2.5
2.6
2.7
2.8
2.9
3.0
3.1
3.2
3.3
3.4
Rural Reading Scores



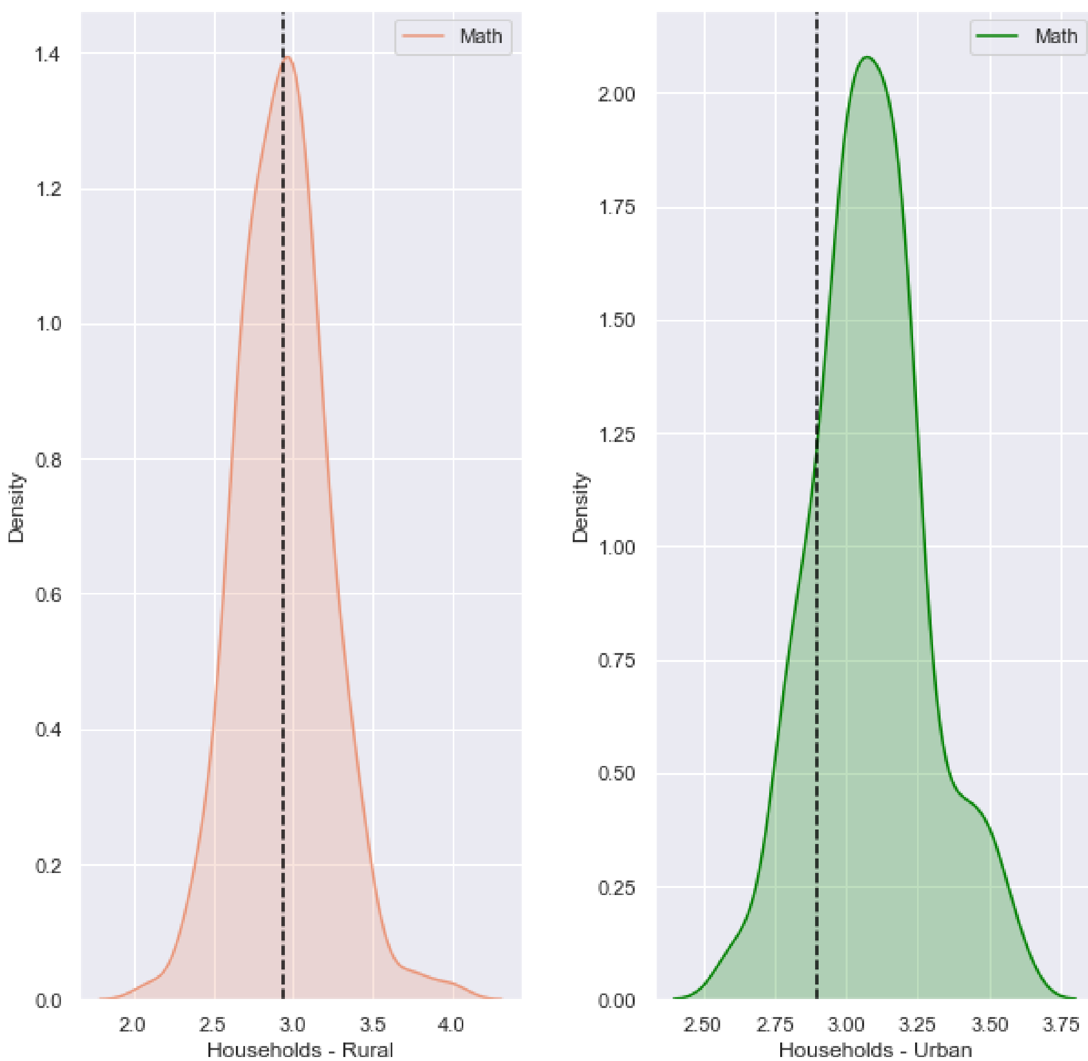
[23]:
```
# ============================================================================
# # Histograms  and PDFs 3rd grade Math levels
# ============================================================================
subtitle = "3rd Grade Math Levels for Rural vs Urban"
xlab1 = "Households - Rural"
xlab2 = "Households - Urban"
mean1 = rm_mean
mean2 = ur_mean
ser1 = maths
ser2 = maths1
```

```
Hist_Plot(subtitle, xlab1, xlab2, ser1, ser2)

# KDE/PDFs
Sns_Kde(subtitle,xlab1, xlab2, ser1, mean1, ser2, mean2)
```

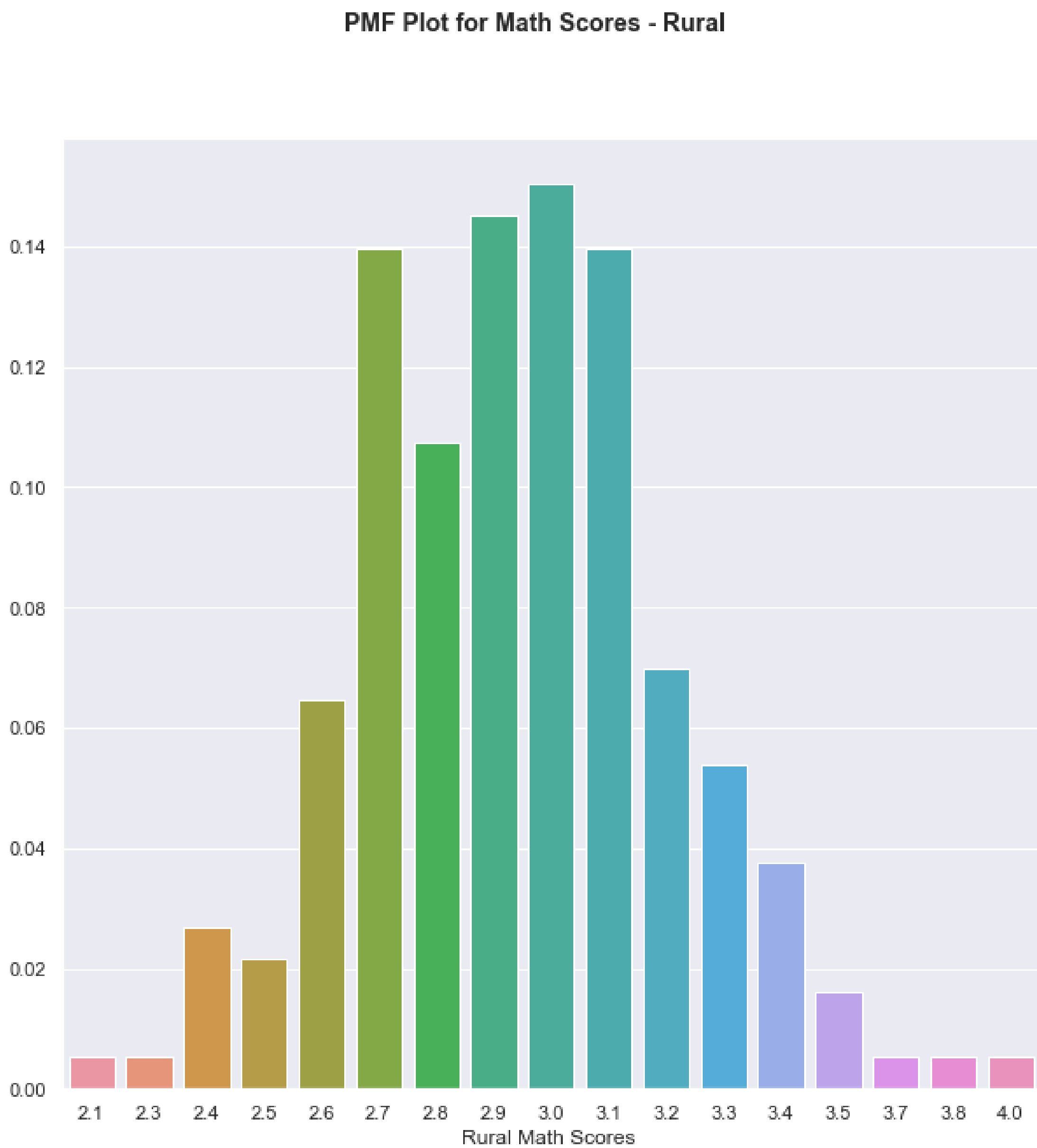
3rd Grade Math Levels for Rural vs Urban

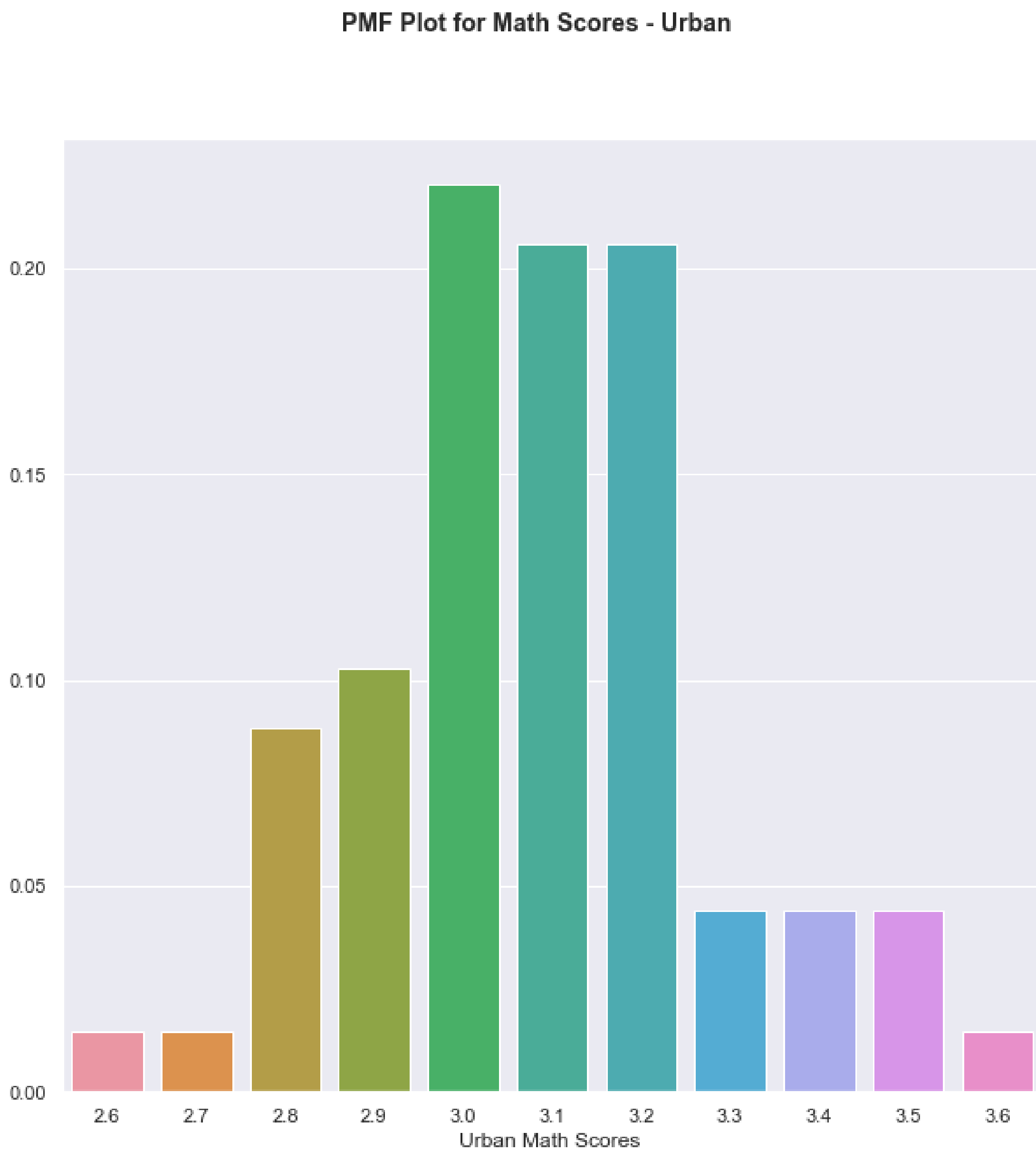


3rd Grade Math Levels for Rural vs Urban



[24]:
```
subtitle = 'PMF Plot for Math Scores - Rural'
data = maths
xlab = 'Rural Math Scores '
Pmf_plot(subtitle, data, xlab)
subtitle = 'PMF Plot for Math Scores - Urban'
data = maths1
xlab = 'Urban Math Scores '
Pmf_plot(subtitle, data, xlab)
```


PMF Plot for Math Scores - Rural
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
2.1
2.3
2.4
2.5
2.6
2.7
2.8
2.9
3.0
3.1
3.2
3.3
3.4
3.5
3.7
3.8
4.0
Rural Math Scores



[25]:
```
# ===============================================================================
# Conduct Correlation Tests - Chapter 9
# ===============================================================================
# what if any is the correlation between 3rd grade levels and high school
# graduation
# need to normalize the data
# normalize the data  sklearn

scaler = MinMaxScaler()
rural_school = rural[['Read', 'Math', 'Grad_Rate']].copy()
```

```python
urban_school = urban[['Read', 'Math', 'Grad_Rate']].copy()

rural_school[['Read', 'Math', 'Grad_Rate']] = scaler.
 ↪fit_transform(rural_school[['Read',\
     'Math', 'Grad_Rate']])

urban_school[['Read', 'Math', 'Grad_Rate']] = scaler.
 ↪fit_transform(urban_school[['Read',\
     'Math', 'Grad_Rate']])

#Pearson
corr_rural1 = rural_school.corr(method="pearson")
print("Pearson correlation coefficient Rural :")
print(corr_rural1,"\n")

corr_urban1 = urban_school.corr(method="pearson")
print("Pearson correlation coefficient Urban:")
print(corr_urban1, "\n")

#Spearman
corr_rural2 = rural_school.corr(method="spearman")
print("Spearman correlation coefficient Rural :")
print(corr_rural2, "\n")

corr_urban2 = urban_school.corr(method="spearman")
print("Spearman correlation coefficient Urban :")
print(corr_urban2, "\n")

#Kendall's Tau
corr_rural3 = rural_school.corr(method="kendall")
print("Kendall Tau correlation coefficient Rural :")
print(corr_rural3, "\n")

corr_urban3 = urban_school.corr(method="kendall")
print("Kendall Tau correlation coefficient Urban:")
print(corr_urban3, "\n")
```

```
Pearson correlation coefficient Rural :
               Read      Math  Grad_Rate
Read       1.000000  0.739300   0.192063
Math       0.739300  1.000000   0.144729
Grad_Rate  0.192063  0.144729   1.000000

Pearson correlation coefficient Urban:
               Read      Math  Grad_Rate
Read       1.000000  0.875327   0.424968
Math       0.875327  1.000000   0.377365
```

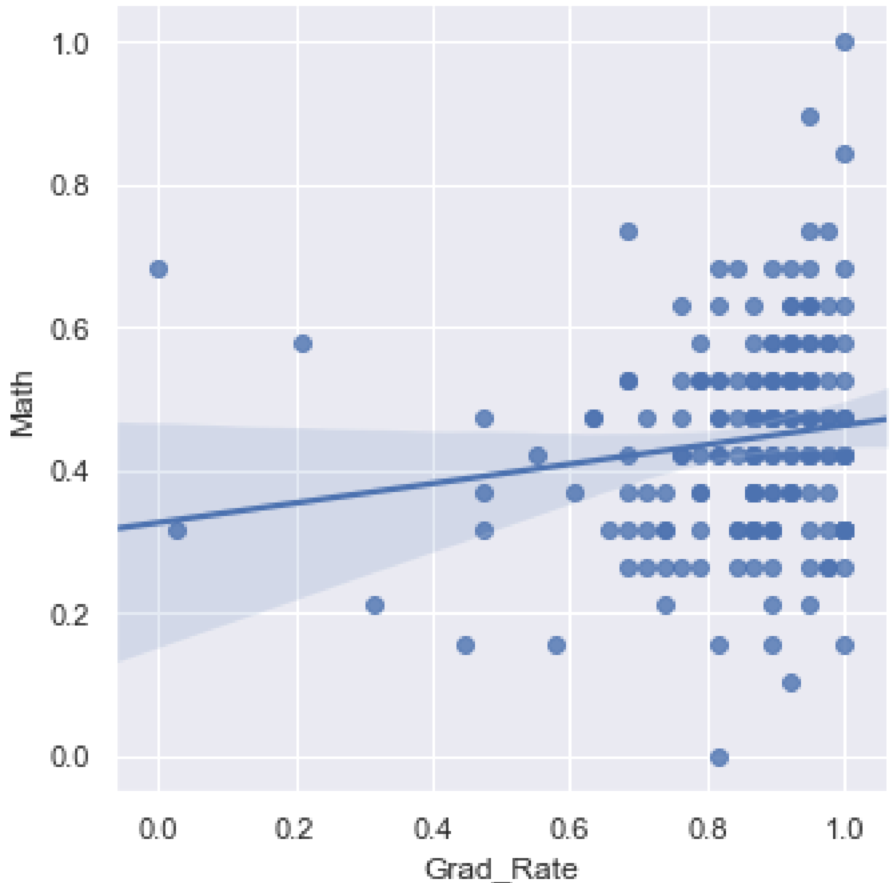
```
Grad_Rate  0.424968  0.377365   1.000000

Spearman correlation coefficient Rural :
               Read      Math  Grad_Rate
Read       1.000000  0.725848   0.278714
Math       0.725848  1.000000   0.173201
Grad_Rate  0.278714  0.173201   1.000000

Spearman correlation coefficient Urban :
               Read      Math  Grad_Rate
Read       1.000000  0.838901   0.438993
Math       0.838901  1.000000   0.317306
Grad_Rate  0.438993  0.317306   1.000000

Kendall Tau correlation coefficient Rural :
               Read      Math  Grad_Rate
Read       1.000000  0.602315   0.211071
Math       0.602315  1.000000   0.134194
Grad_Rate  0.211071  0.134194   1.000000

Kendall Tau correlation coefficient Urban:
               Read      Math  Grad_Rate
Read       1.000000  0.745942   0.330658
Math       0.745942  1.000000   0.246029
Grad_Rate  0.330658  0.246029   1.000000


/Users/corosco/anaconda3/lib/python3.7/site-
packages/sklearn/preprocessing/data.py:334: DataConversionWarning: Data with
input dtype int64, float64 were all converted to float64 by MinMaxScaler.
  return self.partial_fit(X, y)
/Users/corosco/anaconda3/lib/python3.7/site-
packages/sklearn/preprocessing/data.py:334: DataConversionWarning: Data with
input dtype int64, float64 were all converted to float64 by MinMaxScaler.
  return self.partial_fit(X, y)
```

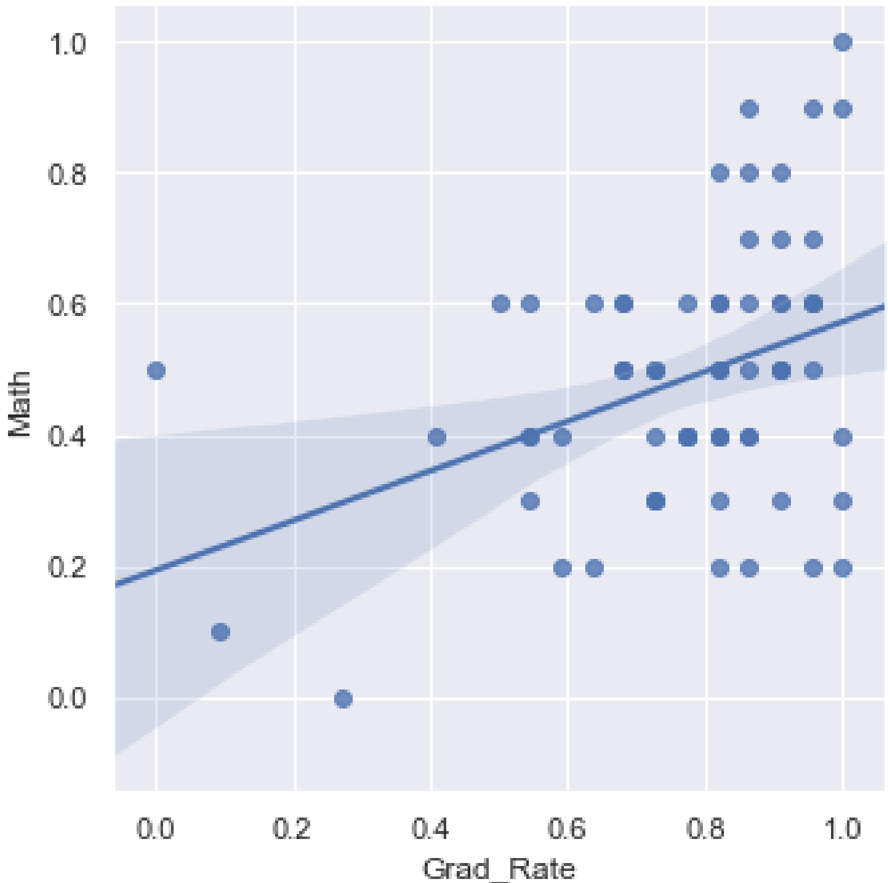
[26]:

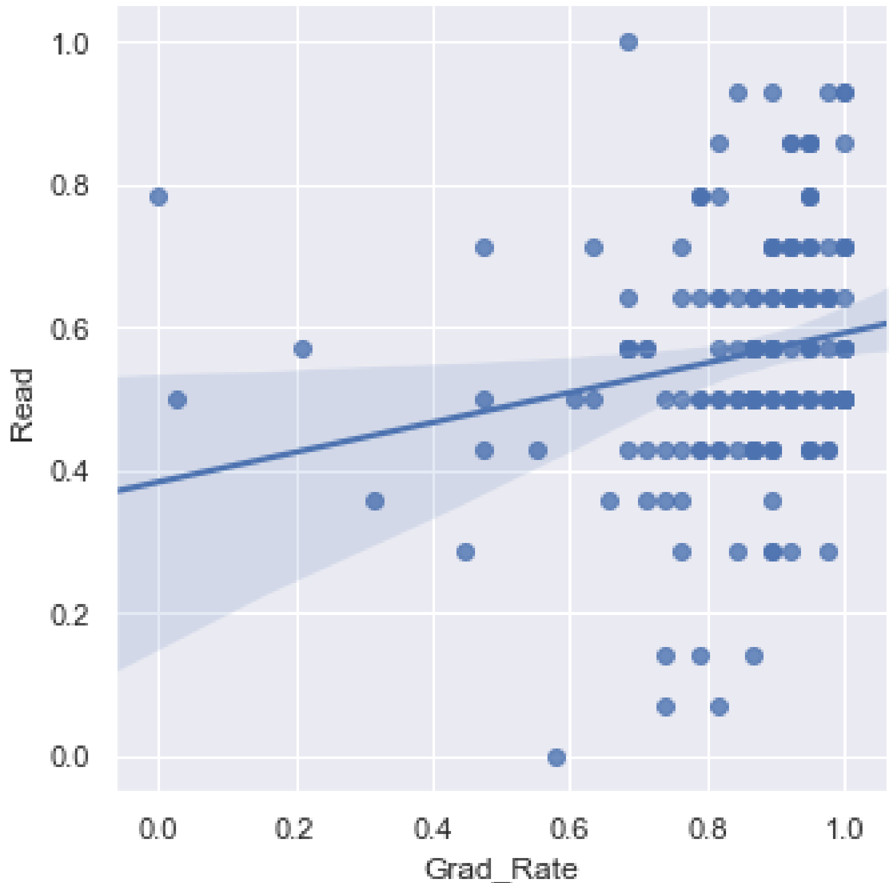
```
# Linear Relationship
subtitle = 'Graduation Rates and Reading Scores - Rural'
x_val = "Grad_Rate"
y_val = 'Math'
data = rural_school
sns.lmplot(x_val, y_val, data)

# Linear Relationship
subtitle = 'Graduation Rates and Reading Scores - Urban'
x_val = "Grad_Rate"
y_val = 'Math'
data = urban_school
```

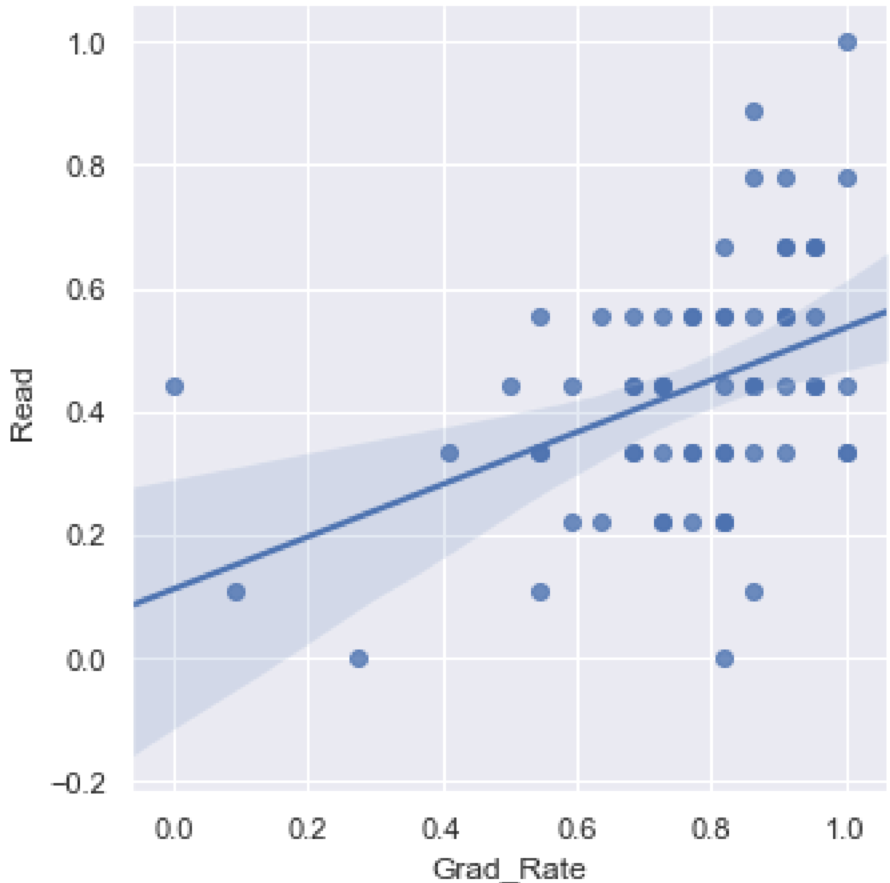
```
sns.lmplot(x_val, y_val, data)

# Linear Relationship
subtitle = 'Graduation Rates and Reading Scores - Rural'
x_val = "Grad_Rate"
y_val = 'Read'
data = rural_school
sns.lmplot(x_val, y_val, data)

# Linear Relationship
subtitle = 'Graduation Rates and Reading Scores - Urban'
x_val = "Grad_Rate"
y_val = 'Read'
data = urban_school
sns.lmplot(x_val, y_val, data)

# Math and Reading
subtitle = 'Math and Reading Scores - Rural'
x_val = "Math"
y_val = 'Read'
data = rural_school
sns.lmplot(x_val, y_val, data)

# Math and Reading
subtitle = 'Math and Reading Scores - Urban'
x_val = "Math"
y_val = 'Read'
data = urban_school
sns.lmplot(x_val, y_val, data)
```

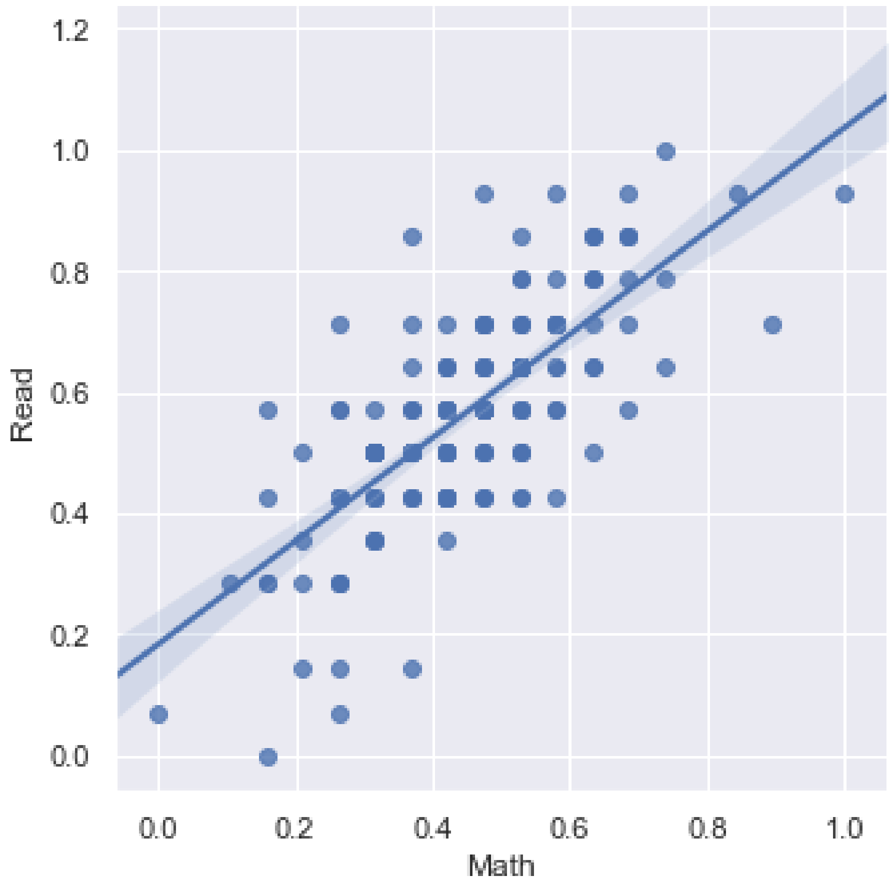
```
[26]: <seaborn.axisgrid.FacetGrid at 0x123cde5c0>
```


1.0
0.8
0.6
0.4
0.2
0.0
Math
0.0
0.2
0.4
0.6
0.8
1.0
Grad_Rate

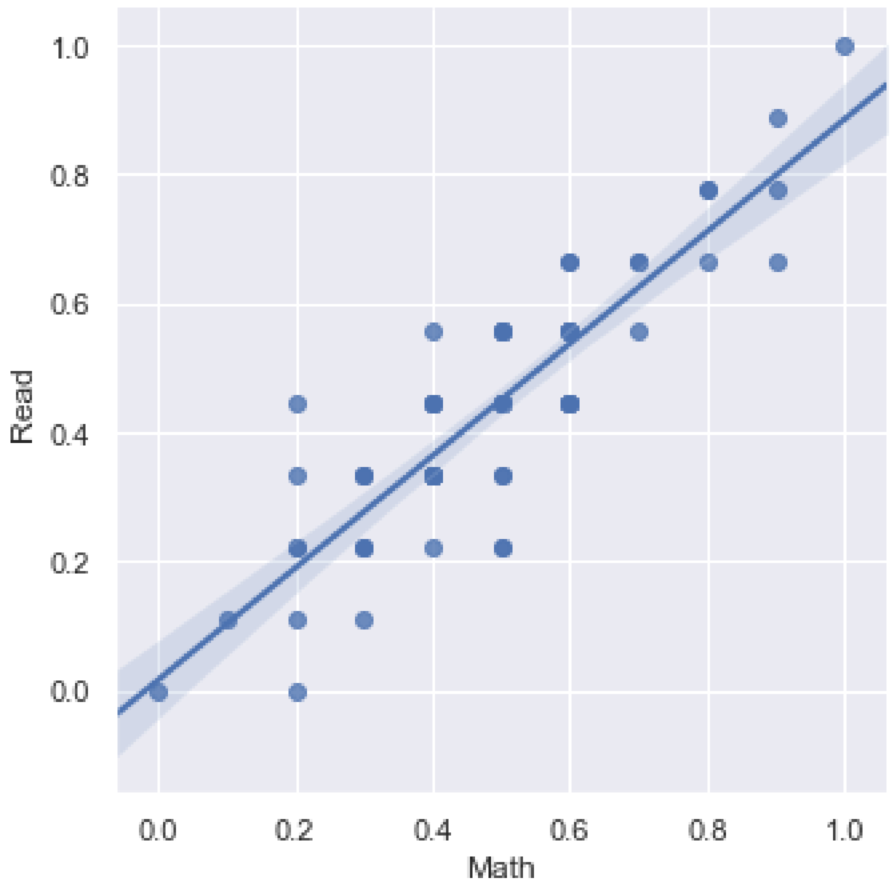

1.0
0.8
0.6
0.4
0.2
0.0
Math
0.0
0.2
0.4
0.6
0.8
1.0
Grad_Rate


1.0
0.8
0.6
0.4
0.2
0.0
Read
0.0
0.2
0.4
0.6
0.8
1.0
Grad_Rate


1.0
0.8
0.6
0.4
0.2
0.0
−0.2
Read
0.0
0.2
0.4
0.6
0.8
1.0
Grad_Rate



1.2
1.0
0.8
0.6
0.4
0.2
0.0
Read
0.0
0.2
0.4
0.6
0.8
1.0
Math



[27]:
```
#Include a histogram of each of the 5 variables - in your summary and analysis,␣
 ↪identify
#any outliers and explain the reasoning for them being outliers and how you␣
 ↪believe they
#should be handled (Chapter 2).
```

0.5 Is there a correlation between life expectancy and poor health,

0.6 lack of sleep, no insurance, housing costs, access to food, and

0.7 availability of doctors?

0.8 Is there a correlation between poor health and availability of doctors,

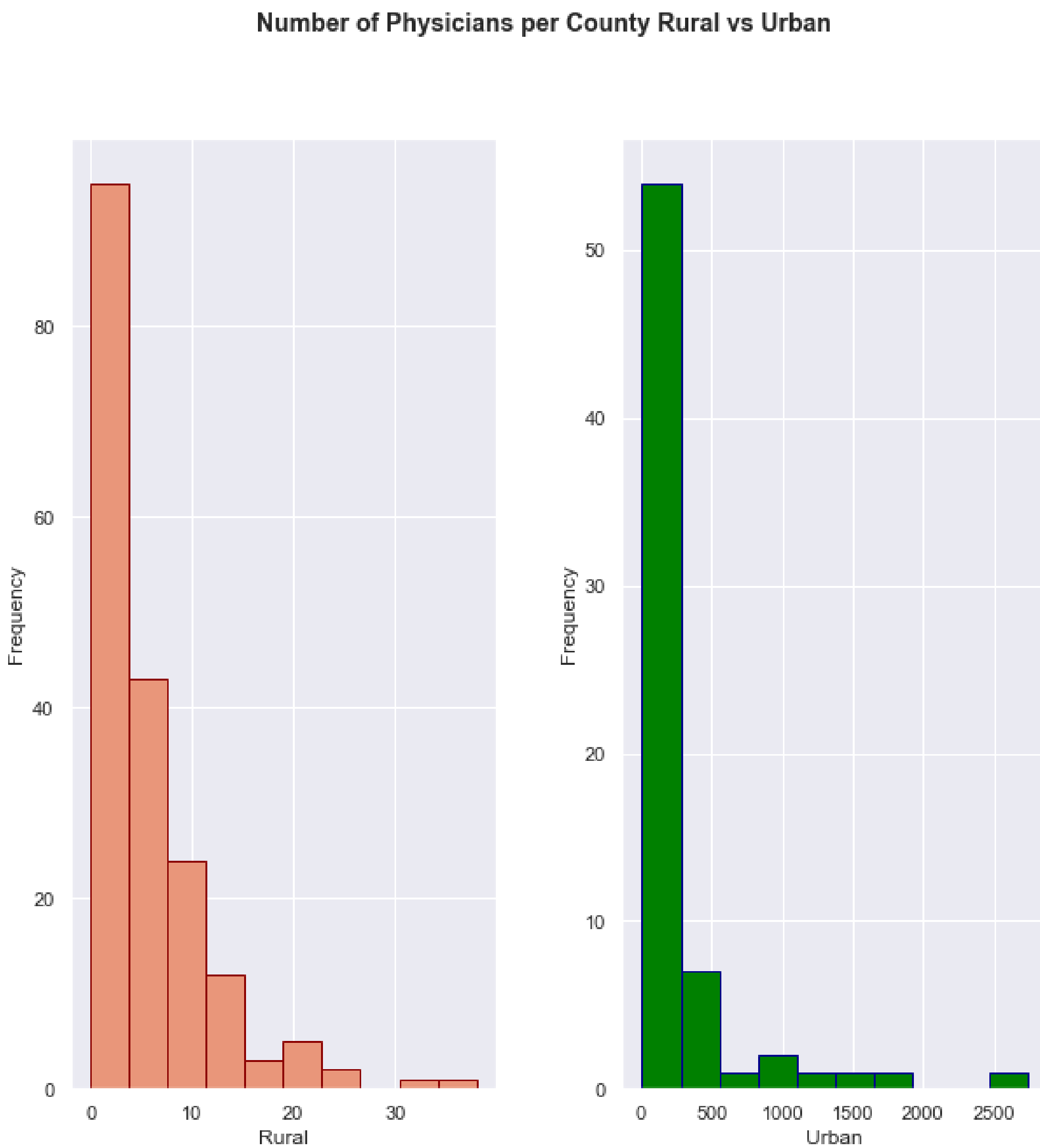
0.9 lack of sleep, no insurance, housing costs, and access to food?

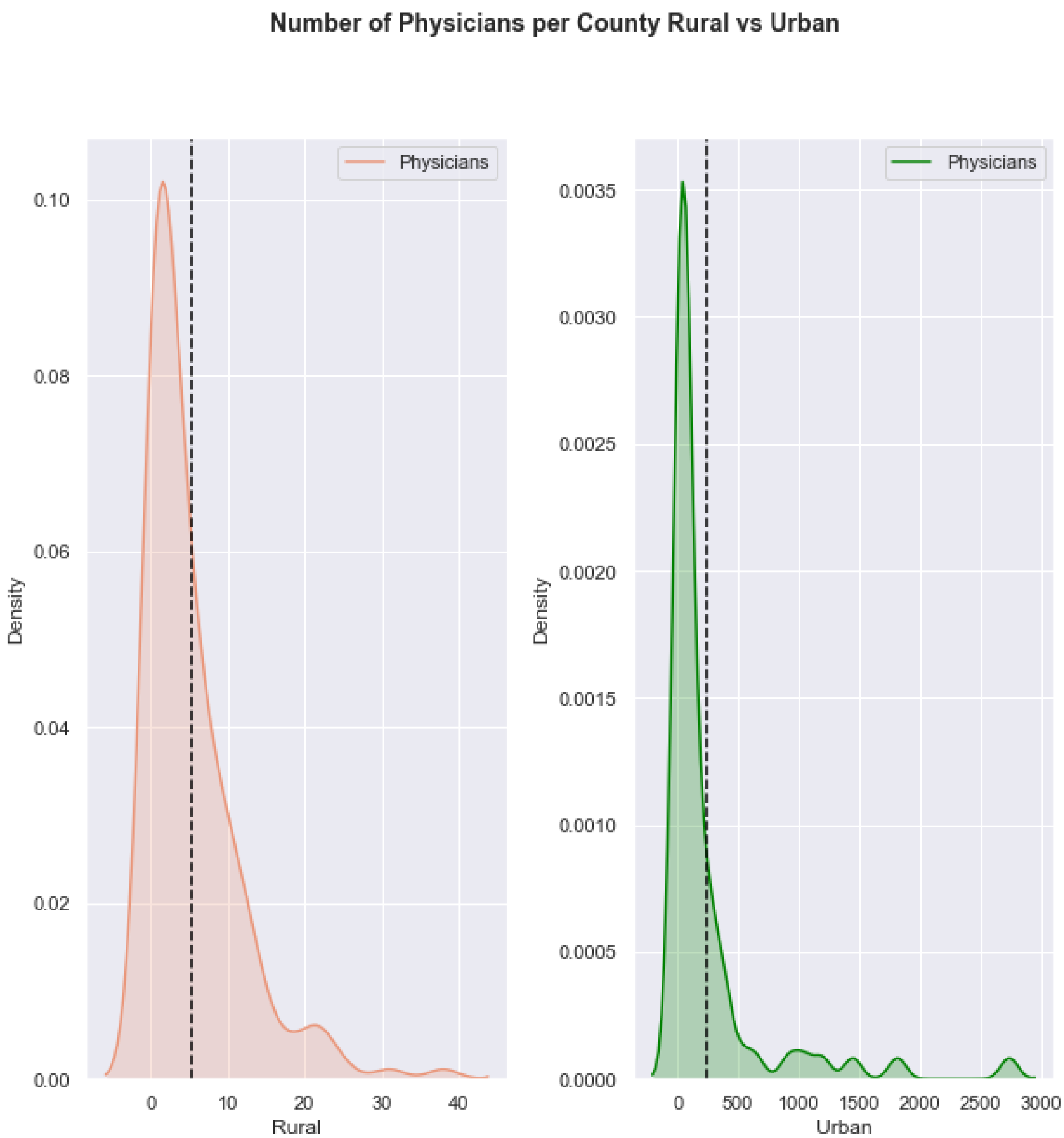
[28]:
```
# ==========================================================================
# 3. Is there a correlation between life expectancy and poor health,
#  lack of sleep, no insurance, housing costs, access to food, and
#  availability of doctors?
```

```
#
# 4. Is there a correlation between poor health and availability of doctors,
#  lack of sleep,  no insurance, housing costs, and access to food?
# ==============================================================================
```

0.9.1 Histograms and PDFs

[29]:
```
# Histogram and PDFs Physicians rural vs urban
# ==============================================================================
# plot side by side for comparison
subtitle = "Number of Physicians per County Rural vs Urban"
xlab1 = "Rural"
xlab2 = "Urban"
ser1 = rural['Physicians']

ser2 = urban.Physicians
mean1 = rural.Physicians.mean()
mean2 = urban.Physicians.mean()
Hist_Plot(subtitle, xlab1, xlab2, ser1, ser2)

# KDE/PDFs
Sns_Kde(subtitle,xlab1, xlab2, ser1, mean1, ser2, mean2)
```


Number of Physicians per County Rural vs Urban
Frequency
Rural
Frequency
Urban
0
20
40
60
80
0
10
20
30
0
10
20
30
40
50
0
500
1000
1500
2000
2500

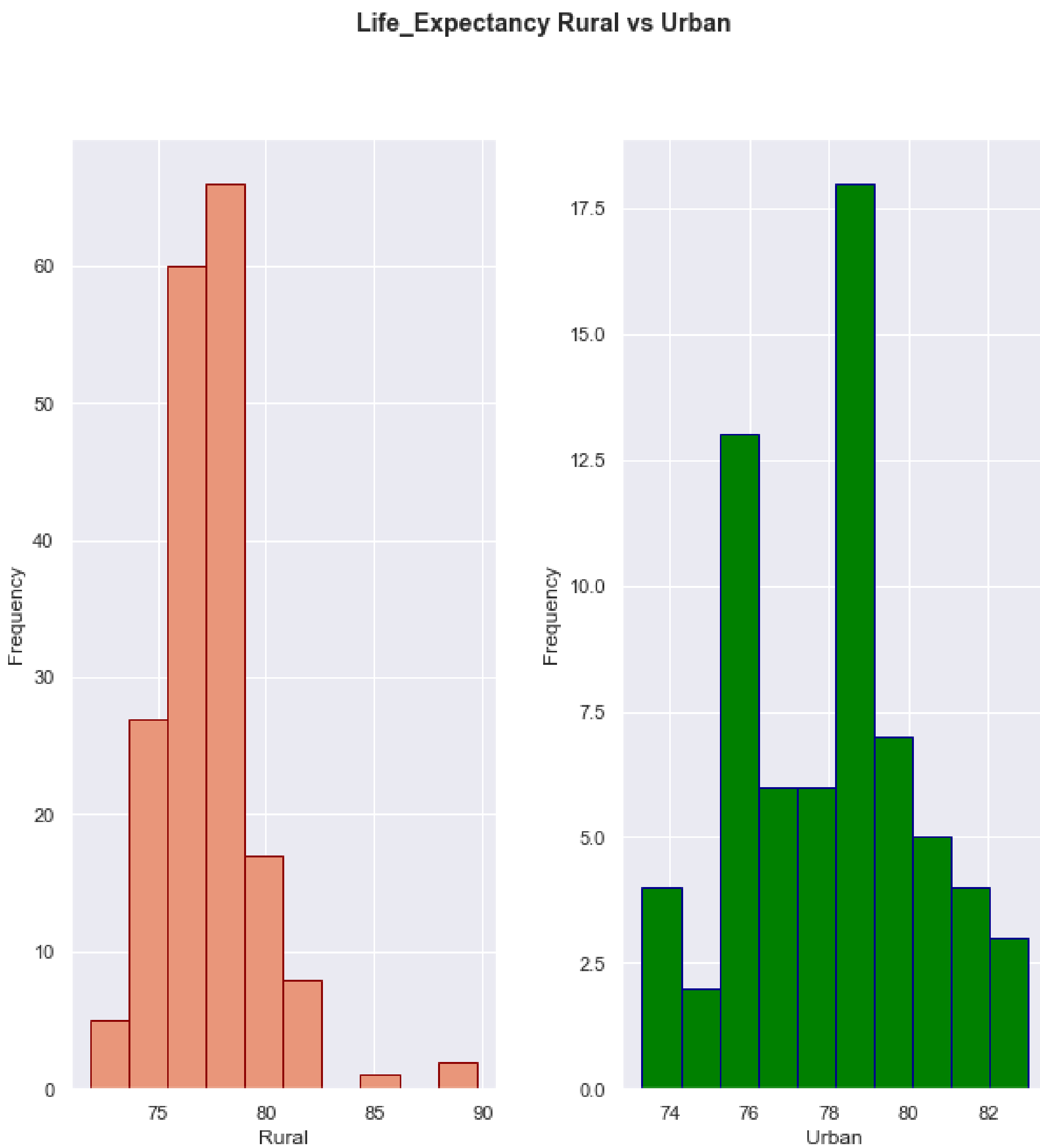


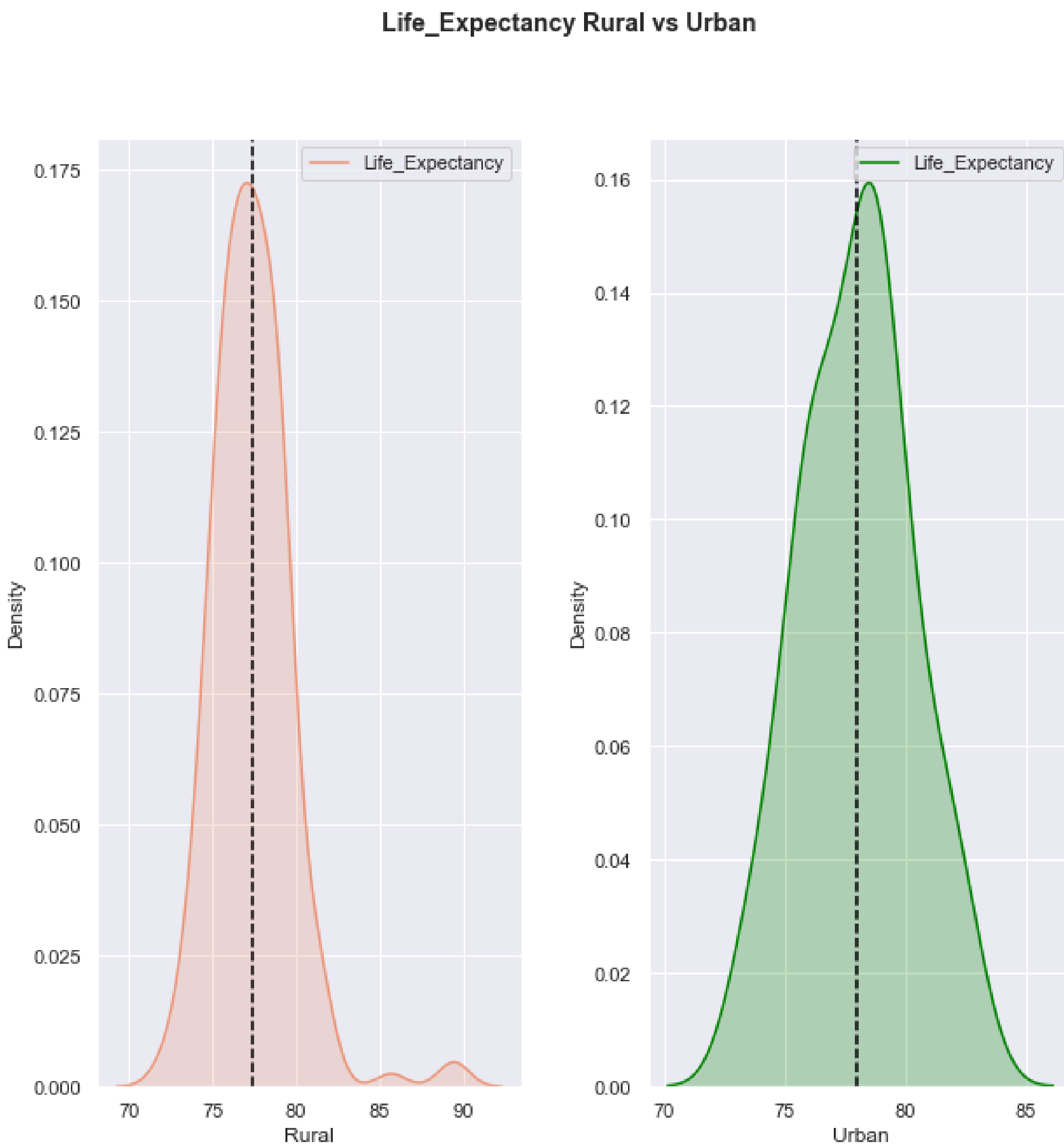
[30]:
```
# Cohen's d while I have the mean
mean1 = rural.Physicians.var()
mean2 = urban.Physicians.var()
ser1 = rural.Physicians
ser2 = urban.Physicians
title = 'Cohens d for Physicians Rural vs Urban'
Compute_Cohend(mean1, mean2,ser1,ser2, var1, title)
```

```
Cohens d for Physicians Rural vs Urban = -375877.59850149235
```

[30]: -375877.59850149235

[31]:
```
# Histogram and PDFs Life_Expectancy rural vs urban
# ==============================================================================
# plot side by side for comparison
subtitle = "Life_Expectancy Rural vs Urban"
ser1 = rural['Life_Expectancy']

ser2 = urban.Life_Expectancy
mean1 = rural.Life_Expectancy.mean()
mean2 = urban.Life_Expectancy.mean()
Hist_Plot(subtitle, xlab1, xlab2, ser1, ser2)

# KDE/PDFs
Sns_Kde(subtitle,xlab1, xlab2, ser1, mean1, ser2, mean2)
```


Life_Expectancy Rural vs Urban
Frequency
0
10
20
30
40
50
60
75
80
85
90
Rural
Frequency
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
74
76
78
80
82
Urban

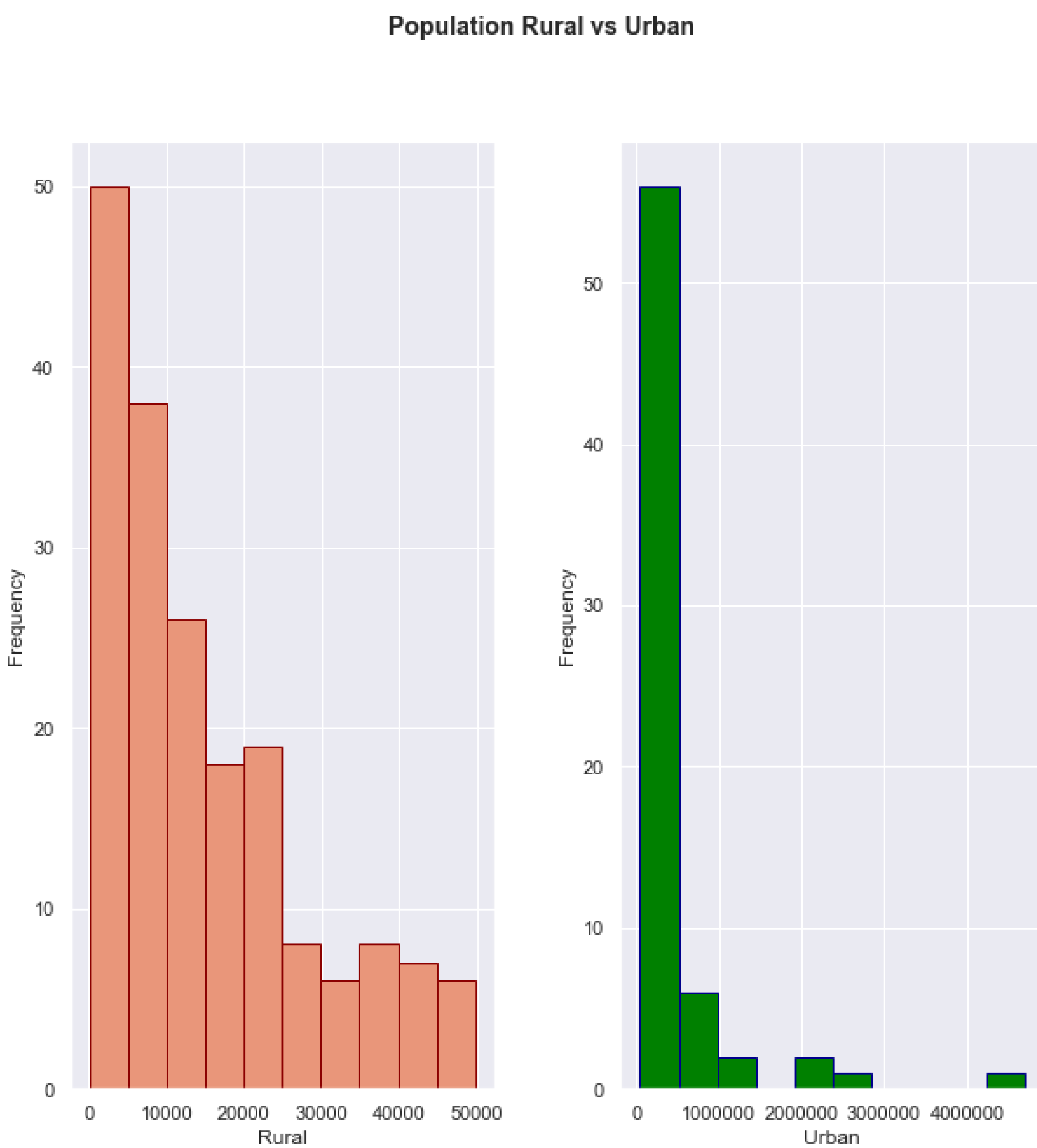


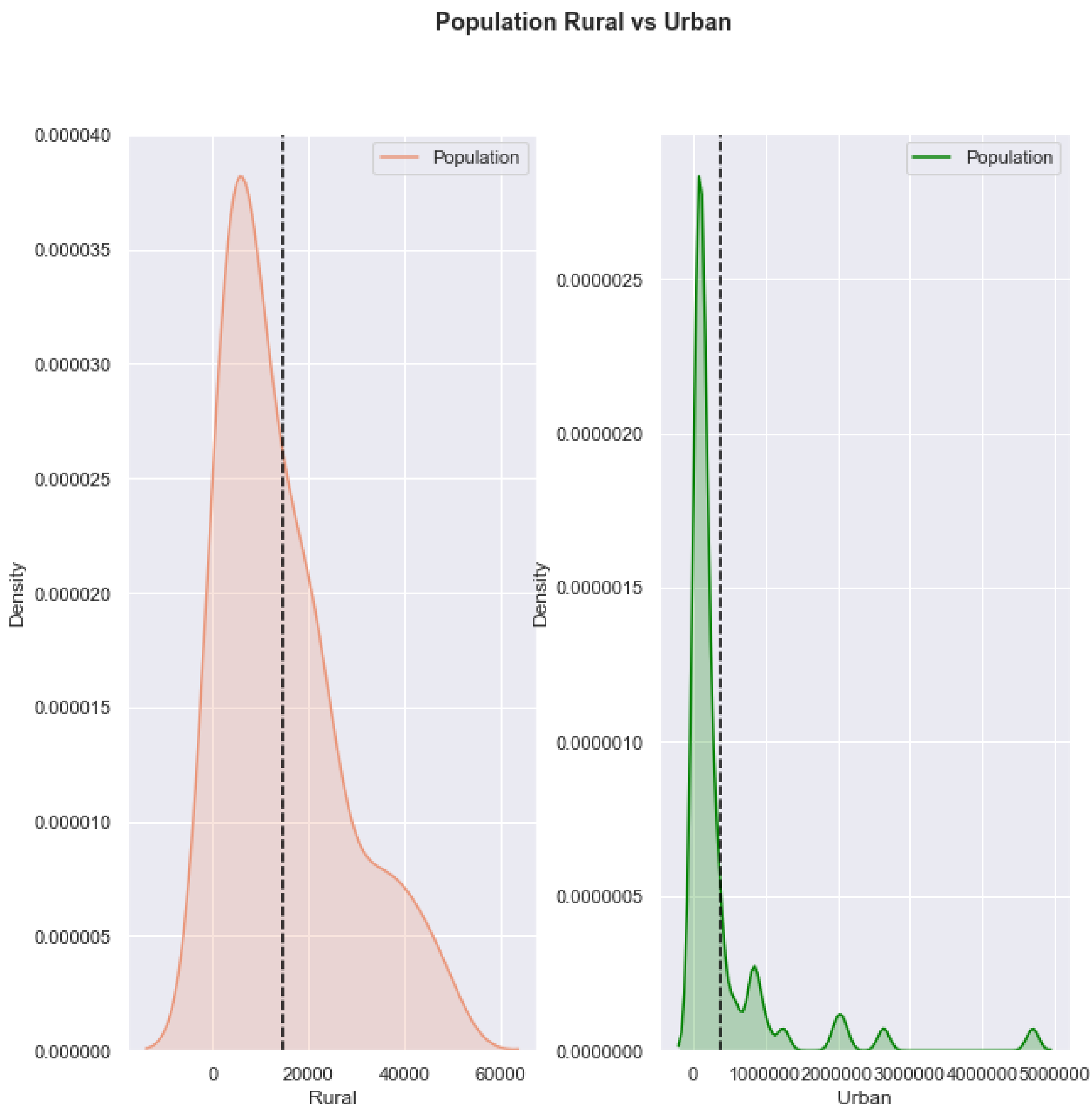
[32]:
```
# Cohen's d while I have the mean
rural.Life_Expectancy.var()
title = 'Cohens d for Life Expectancy Rural vs Urban'
Compute_Cohend(mean1, mean2,ser1,ser2, var1, title)
```

```
Cohens d for Life Expectancy Rural vs Urban = -1.099904255686382
```

[32]:
```
-1.099904255686382
```

[33]:
```python
# Histogram and PDFs  rural vs urban
# ============================================================================
# plot side by side for comparison
subtitle = "Population Rural vs Urban"
ser1 = rural['Population']

ser2 = urban.Population
mean1 = rural.Population.mean()
mean2 = urban.Population.mean()
Hist_Plot(subtitle, xlab1, xlab2, ser1, ser2)

# KDE/PDFs
Sns_Kde(subtitle,xlab1, xlab2, ser1, mean1, ser2, mean2)
```





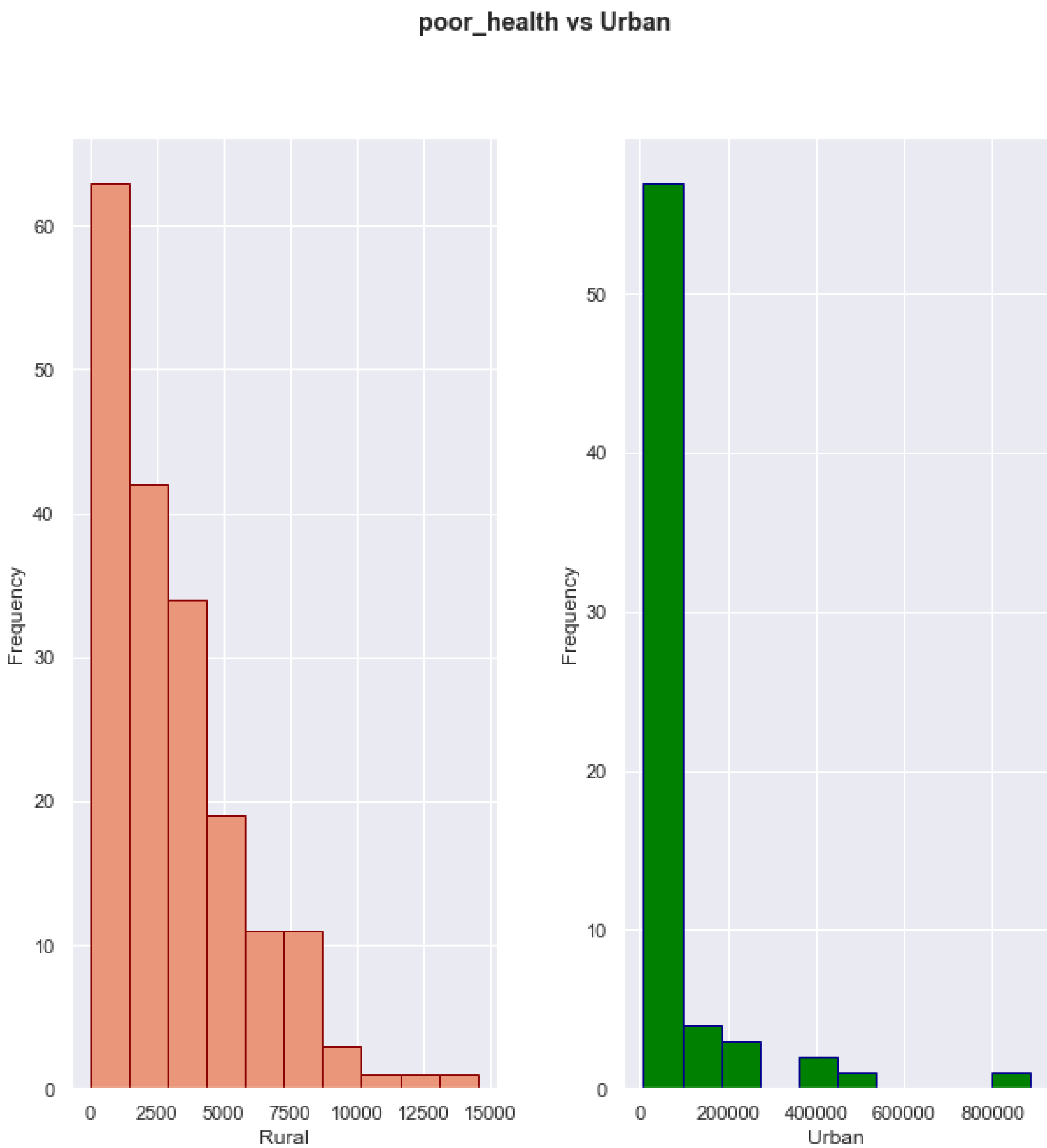
[34]:
```
# Cohen's d while I have the mean
rural.Population.var()
title = 'Cohens d for Population Rural vs Urban'
Compute_Cohend(mean1, mean2,ser1,ser2, var1, title)
```

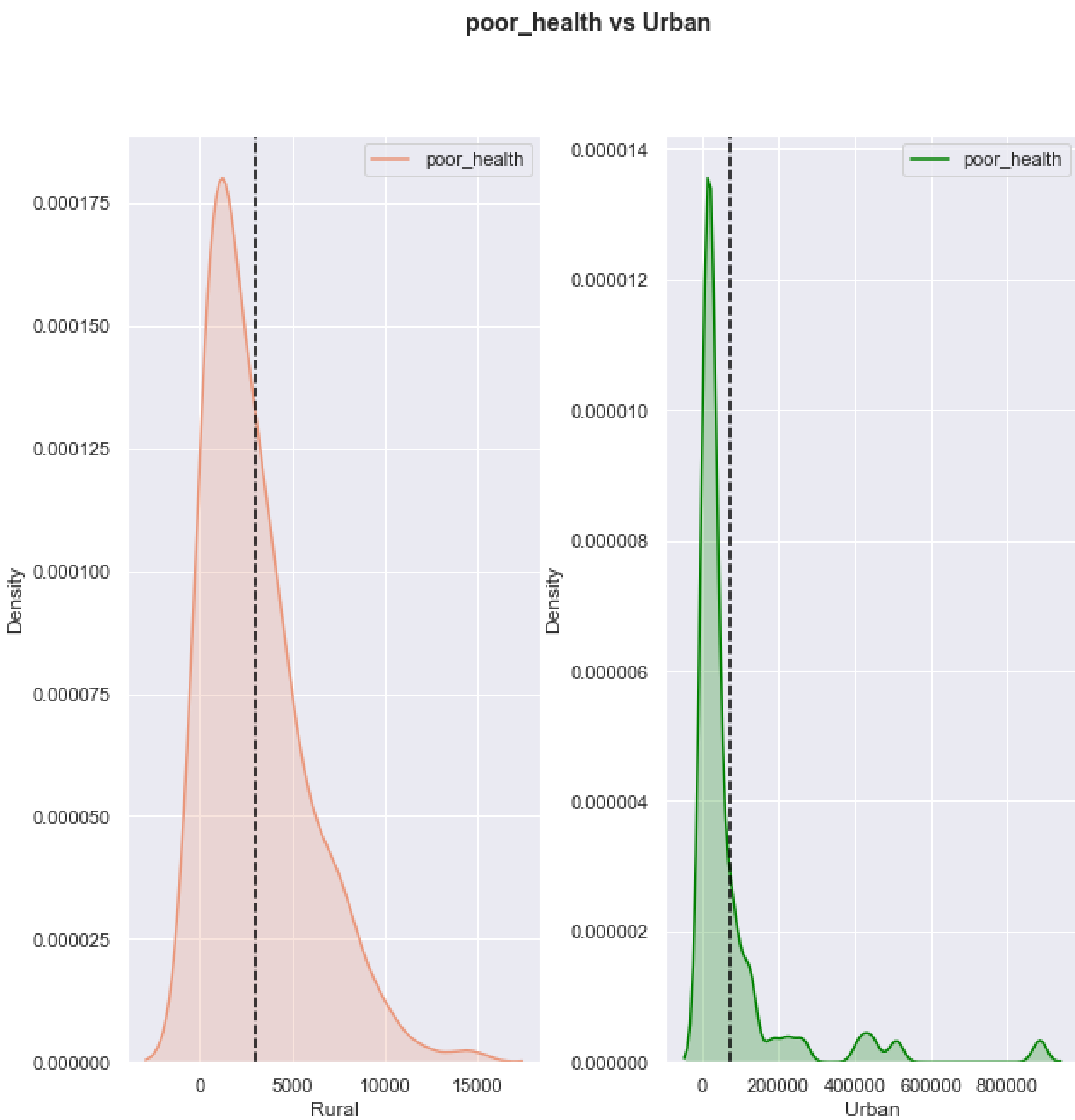
```
Cohens d for Population Rural vs Urban = -643614.5781972056
```

[34]:
```
-643614.5781972056
```

[35]:

```
# Histogram and PDFs  rural vs urban
# ============================================================================
# plot side by side for comparison
subtitle = "poor_health vs Urban"
ser1 = rural['poor_health']

ser2 = urban.poor_health
mean1 = rural.poor_health.mean()
mean2 = urban.poor_health.mean()
Hist_Plot(subtitle, xlab1, xlab2, ser1, ser2)

# KDE/PDFs
Sns_Kde(subtitle,xlab1, xlab2, ser1, mean1, ser2, mean2)
```



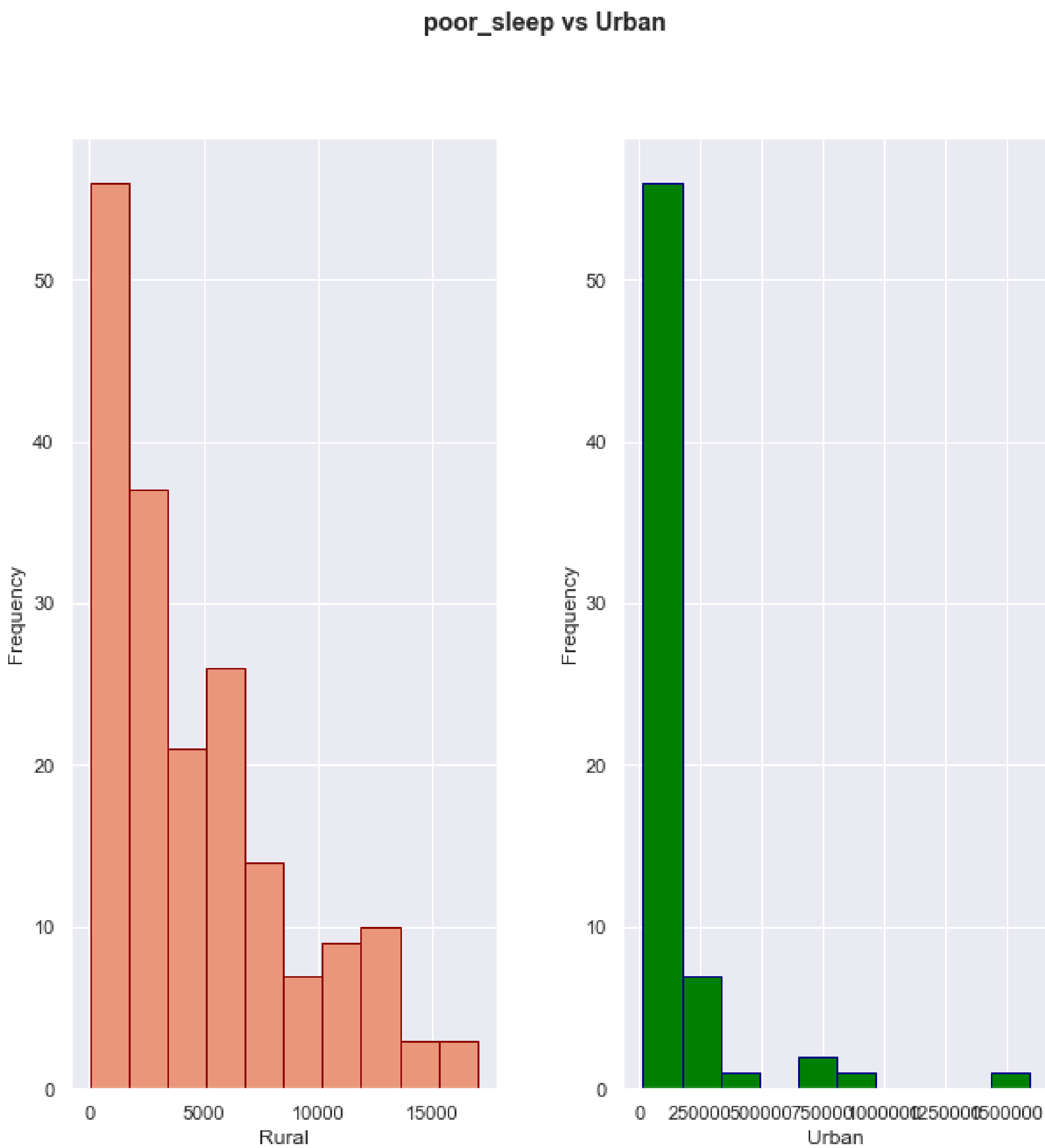


[36]:
```
# Cohen's d while I have the mean
var1 = rural.poor_health.var()
title = 'Cohens d for Poor Health vs Urban'
Compute_Cohend(mean1, mean2,ser1,ser2, var1, title)
```

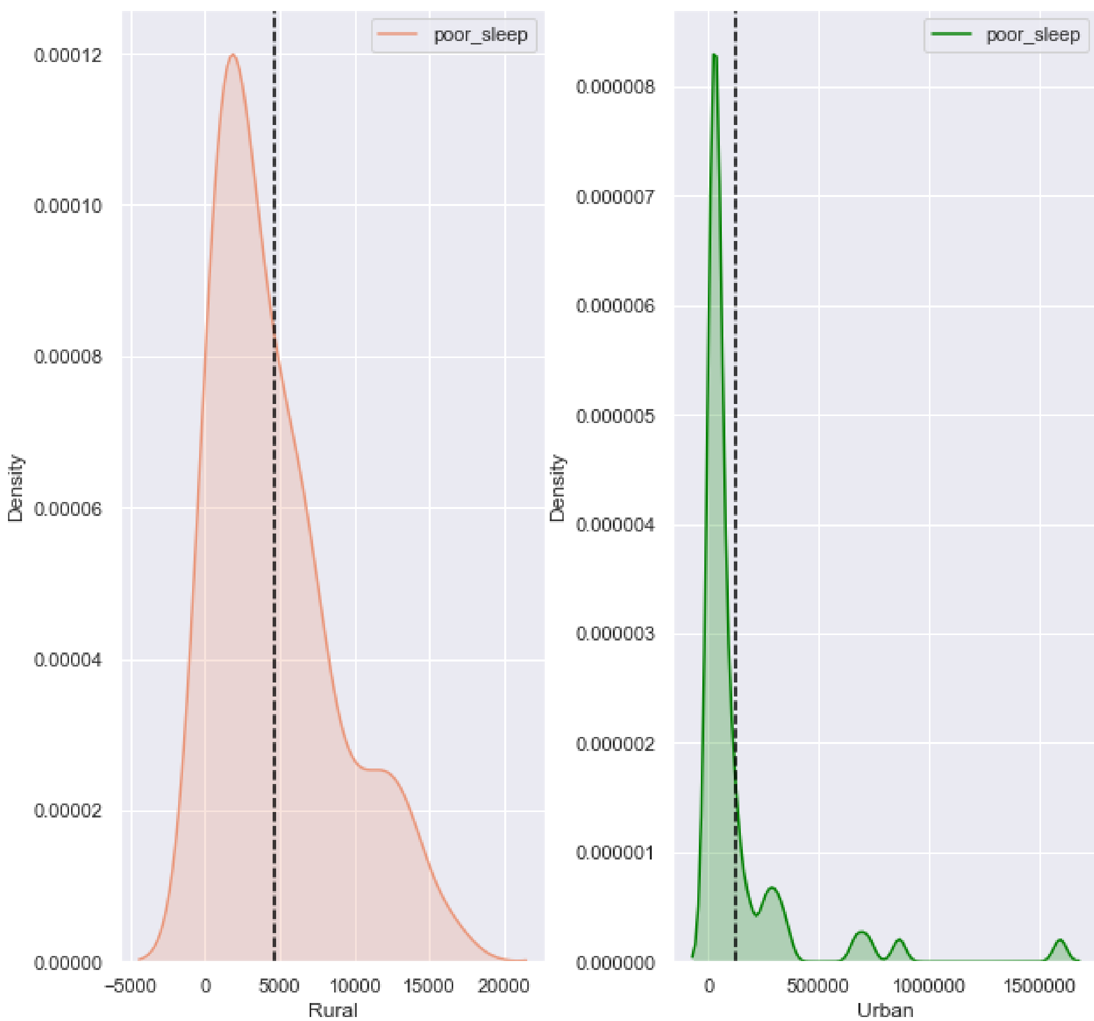
```
Cohens d for Poor Health vs Urban = -31.33146101365113
```

[36]: -31.33146101365113

```
[37]: # Histogram and PDFs  rural vs urban
# ============================================================================
# plot side by side for comparison
subtitle = "poor_sleep vs Urban"
ser1 = rural['poor_sleep']

ser2 = urban.poor_sleep
mean1 = rural.poor_sleep.mean()
mean2 = urban.poor_sleep.mean()
Hist_Plot(subtitle, xlab1, xlab2, ser1, ser2)

# KDE/PDFs
Sns_Kde(subtitle,xlab1, xlab2, ser1, mean1, ser2, mean2)
```



poor_sleep vs Urban

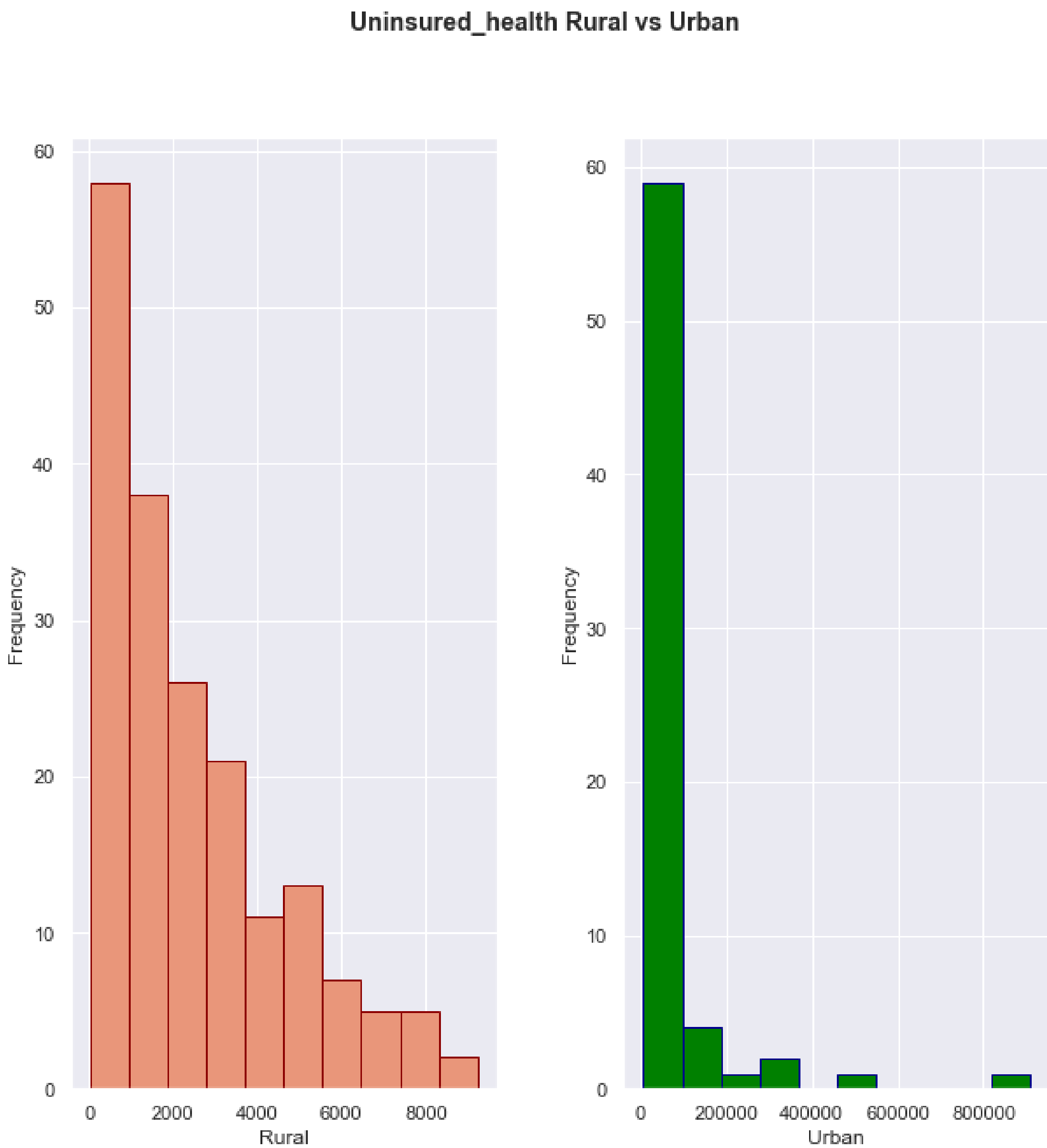


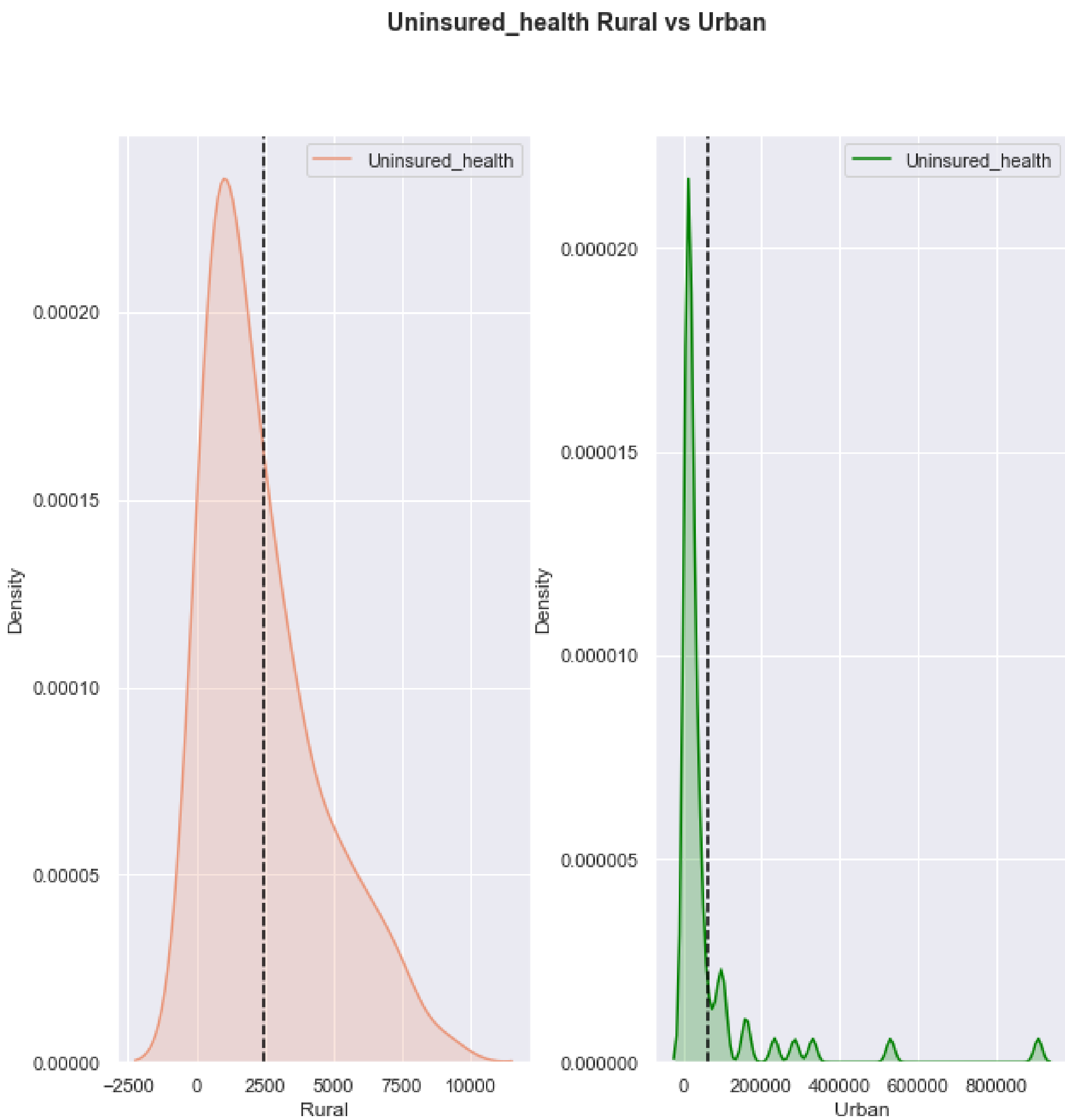
[38]:
```
# Cohen's d while I have the mean
var1 = rural.poor_sleep.var()
title = 'Cohens d for Poor Sleep  Rural vs Urban'
Compute_Cohend(mean1, mean2,ser1,ser2, var1, title)
```

```
Cohens d for Poor Sleep  Rural vs Urban = -35.08603547270512
```

[38]:
```
-35.08603547270512
```

[39]:
```
# Histogram and PDFs  rural vs urban
# ==============================================================================
# plot side by side for comparison
subtitle = "Uninsured_health Rural vs Urban"
ser1 = rural['Uninsured_health']

ser2 = urban.Uninsured_health
mean1 = rural.Uninsured_health.mean()
mean2 = urban.Uninsured_health.mean()
Hist_Plot(subtitle, xlab1, xlab2, ser1, ser2)

# KDE/PDFs
Sns_Kde(subtitle,xlab1, xlab2, ser1, mean1, ser2, mean2)
```





[40]:
```
# Cohen's d while I have the mean
var1 = rural.Uninsured_health.var()
title = 'Cohens d for Uninsured  Rural vs Urban'
Compute_Cohend(mean1, mean2,ser1,ser2, var1, title)
```

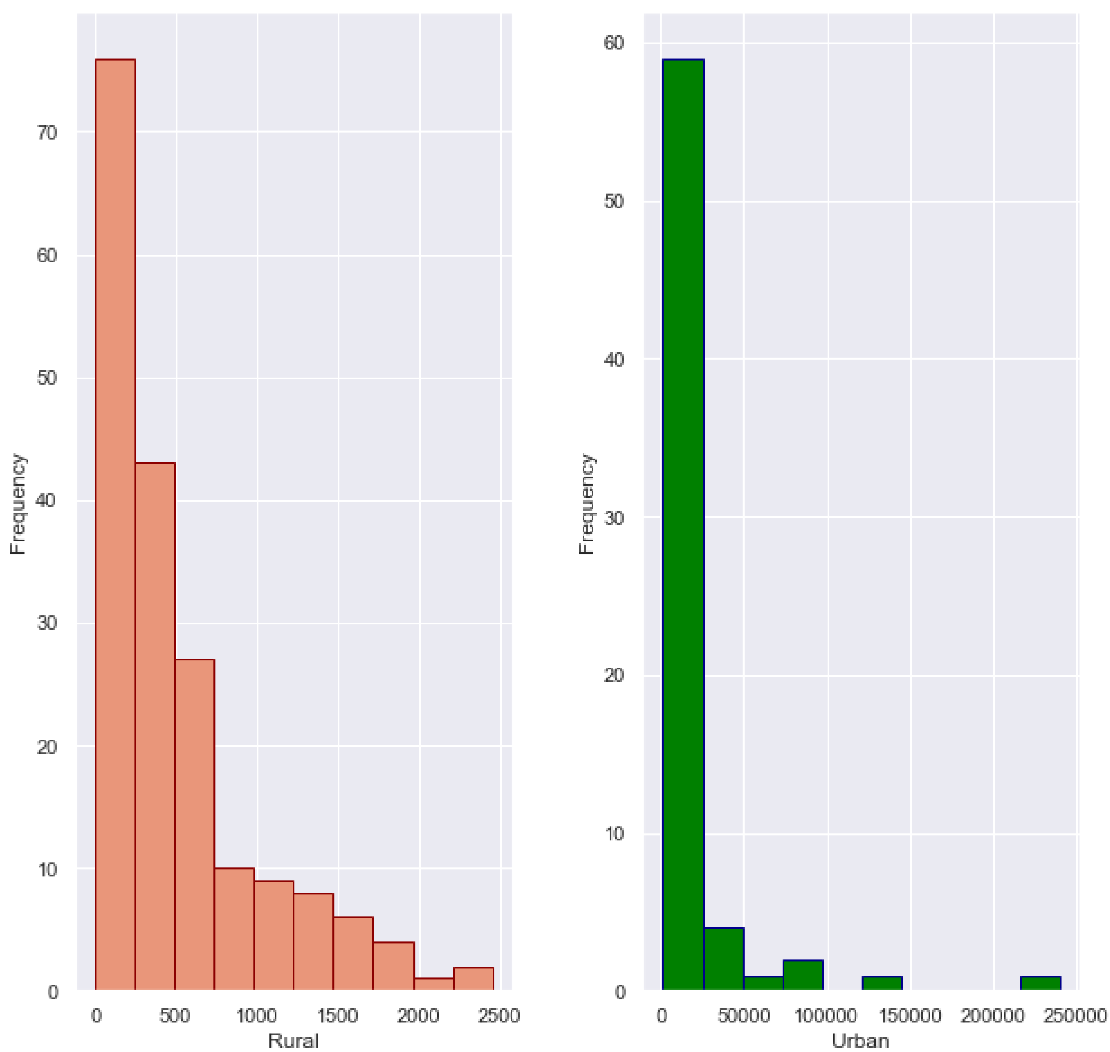
```
Cohens d for Uninsured  Rural vs Urban = -33.68266402418818
```

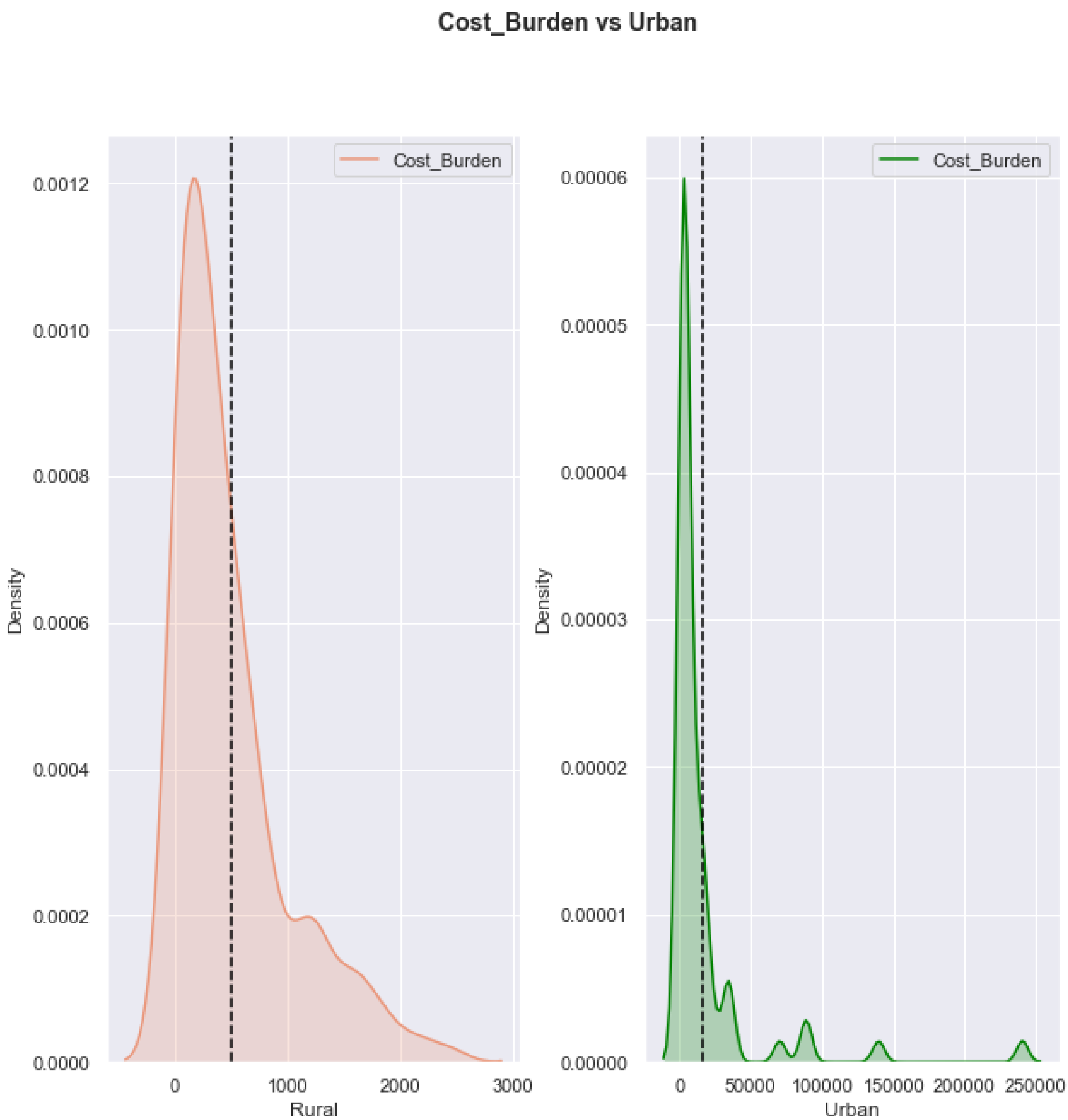
[40]:
```
-33.68266402418818
```

[41]:

```
# Histogram and PDFs  rural vs urban
# ===========================================================================
# plot side by side for comparison
subtitle = "Cost_Burden vs Urban"
ser1 = rural.Cost_Burden

ser2 = urban.Cost_Burden
mean1 = rural.Cost_Burden.mean()
mean2 = urban.Cost_Burden.mean()
Hist_Plot(subtitle, xlab1, xlab2, ser1, ser2)

# KDE/PDFs
Sns_Kde(subtitle,xlab1, xlab2, ser1, mean1, ser2, mean2)
```

Cost_Burden vs Urban





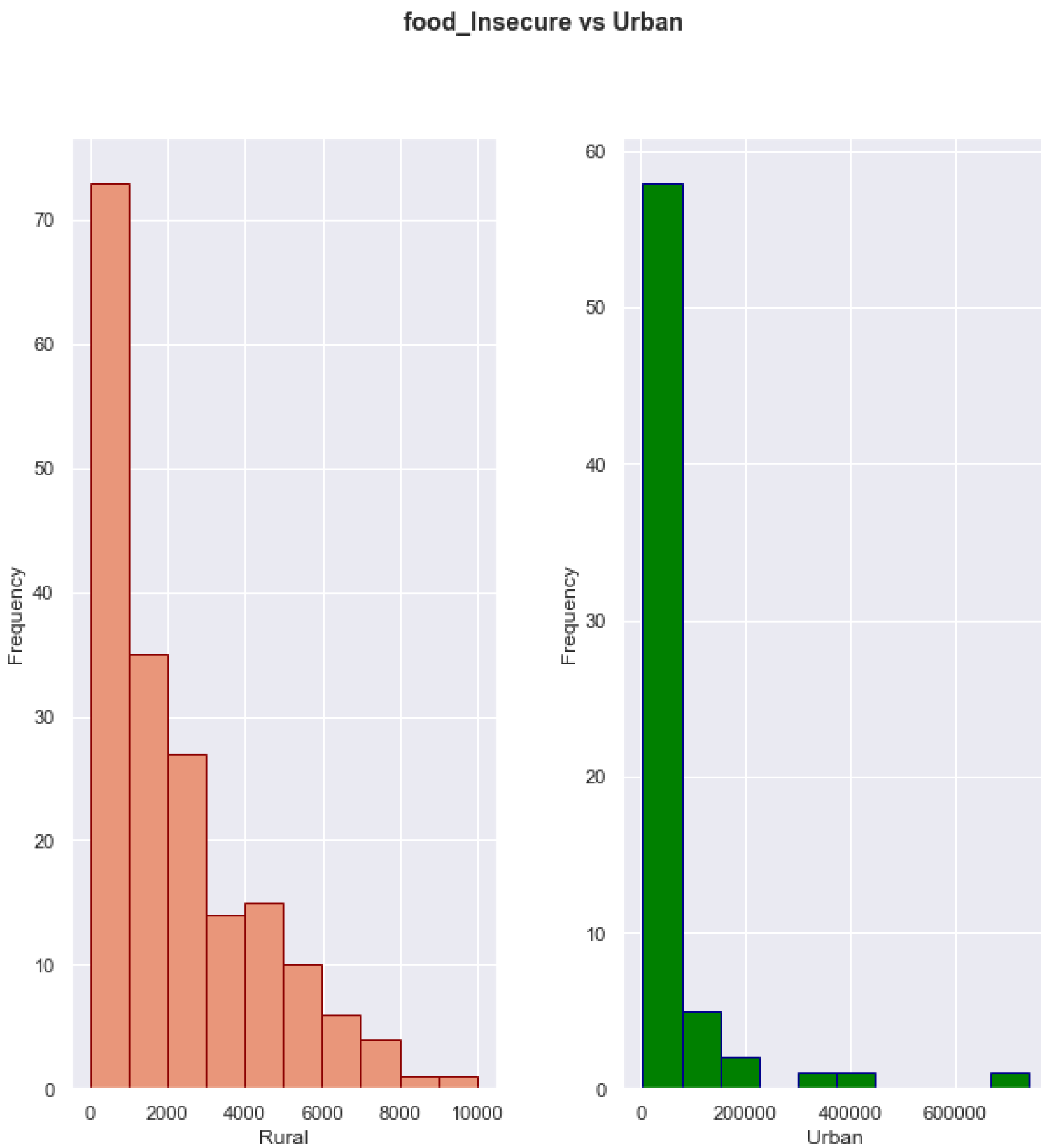
[42]:
```
# Cohen's d while I have the mean
var1 = rural.Cost_Burden.var()
title = 'Cohens d for Uninsured  Rural vs Urban'
Compute_Cohend(mean1, mean2,ser1,ser2, var1, title)
```

```
Cohens d for Uninsured  Rural vs Urban = -37.88726489156317
```

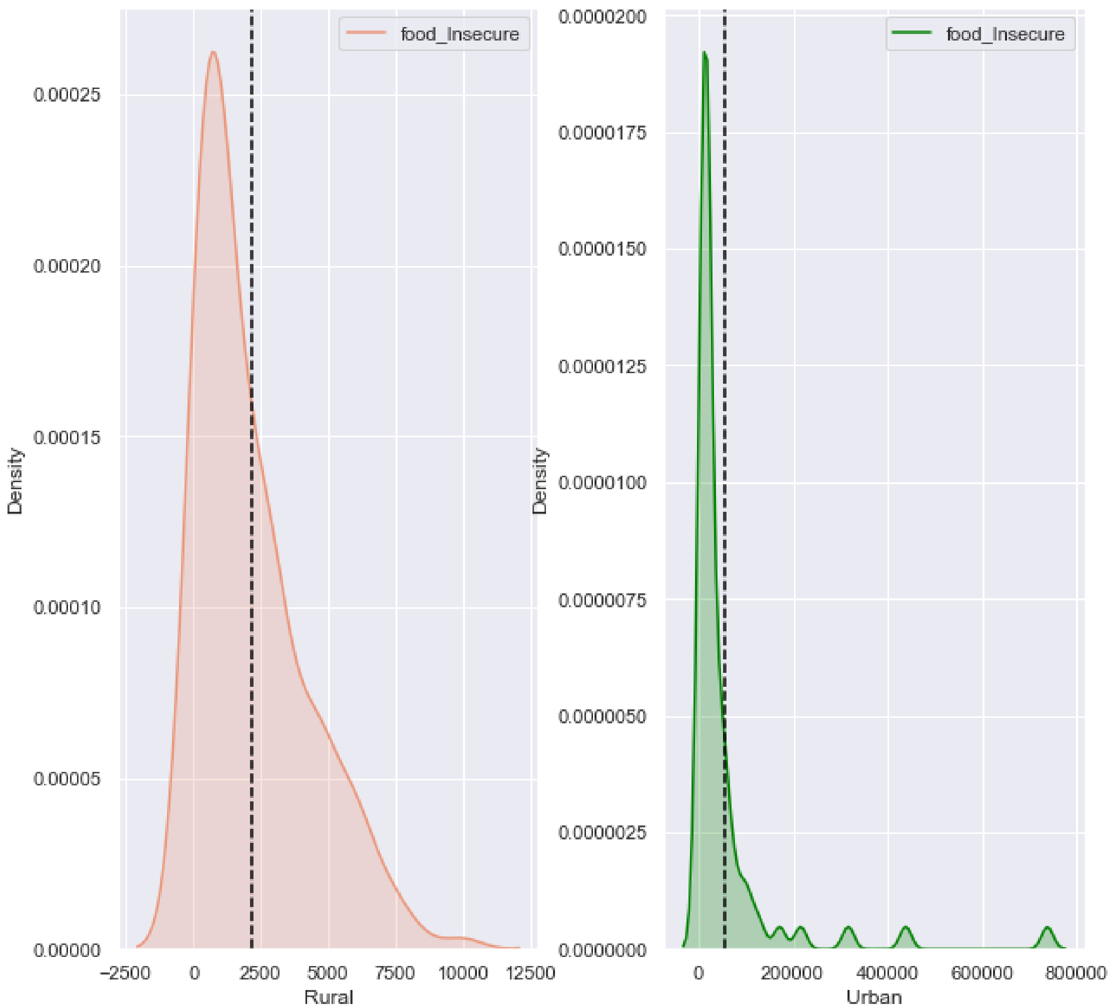
[42]: -37.88726489156317

[43]:

```
# Histogram and PDFs  rural vs urban
# ============================================================================
# plot side by side for comparison
subtitle = "food_Insecure vs Urban"
ser1 = rural.food_Insecure

ser2 = urban.food_Insecure
mean1 = rural.food_Insecure.mean()
mean2 = urban.food_Insecure.mean()
Hist_Plot(subtitle, xlab1, xlab2, ser1, ser2)

# KDE/PDFs
Sns_Kde(subtitle,xlab1, xlab2, ser1, mean1, ser2, mean2)
```



food_Insecure vs Urban



[44]:
```
# Cohen's d while I have the mean
var1 = rural.food_Insecure.var()
title = 'Cohens d for Uninsured  Rural vs Urban'
Compute_Cohend(mean1, mean2,ser1,ser2, var1, title)
```

```
Cohens d for Uninsured  Rural vs Urban = -30.063165548759553
```

[44]:
```
-30.063165548759553
```

0.9.2 Correlations

[45]:
```
# ============================================================================
# Run correlation for bad health habits rural vs urban.  Hypothesis Do
#   rural residents have worse health outcomes due to poor health, lack
#   of availability of doctors, access to food due to housing costs
#   which may have an impact on poor sleep and health?
#
# ============================================================================

# normalize the data with sklearn
scaler = MinMaxScaler()
rural_df = rural[['Population', 'poor_health', 'poor_sleep',␣
 ↪'Uninsured_health',\
       'Life_Expectancy', 'Physicians', 'food_Insecure','Cost_Burden']].copy()


rural_df[['Population','poor_health','poor_sleep','Uninsured_health',\
       'Life_Expectancy','Physicians','food_Insecure','Cost_Burden']]\
        = scaler.fit_transform(rural_df[['Population', 'poor_health', \
        'poor_sleep', 'Uninsured_health', 'Life_Expectancy', 'Physicians',\
       'food_Insecure', 'Cost_Burden']])


urban_df = urban[['Population', 'poor_health', 'poor_sleep',␣
 ↪'Uninsured_health',\
       'Life_Expectancy', 'Physicians', 'food_Insecure', 'Cost_Burden']].copy()


urban_df[['Population','poor_health','poor_sleep','Uninsured_health',\
       'Life_Expectancy','Physicians','food_Insecure','Cost_Burden']]\
        = scaler.fit_transform(urban_df[['Population', 'poor_health', \
        'poor_sleep', 'Uninsured_health', 'Life_Expectancy', 'Physicians',\
       'food_Insecure', 'Cost_Burden']])


#Pearson Correlation
corr_rural1 = rural_df.corr(method="pearson")

corr_urban1 = urban_df.corr(method="pearson")

print("Pearson correlation coefficient Rural : \n")
print(corr_rural1,"\n")
print("Pearson correlation coefficient Urban : \n")
print(corr_urban1,"\n")
```

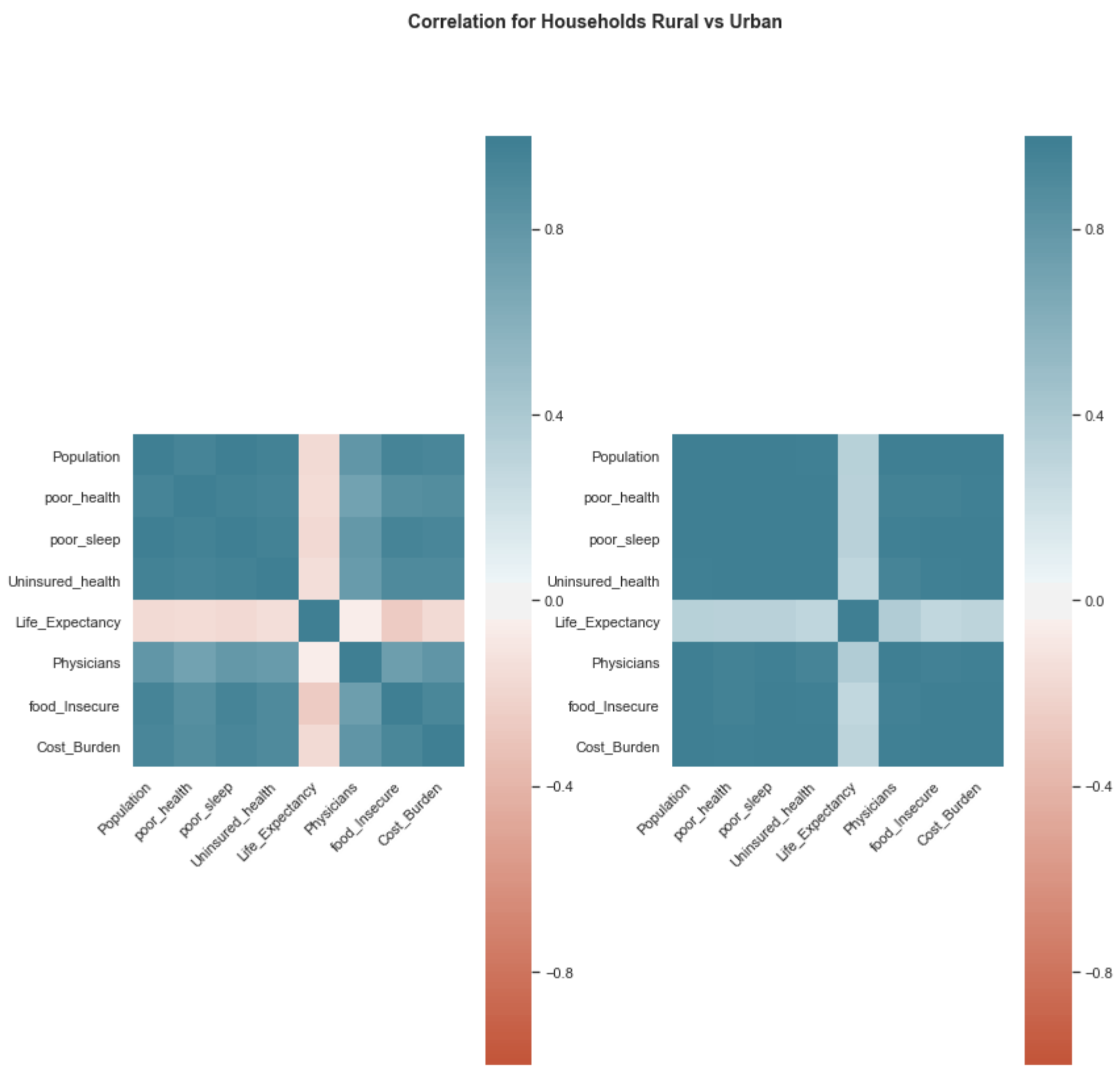
```
Pearson correlation coefficient Rural :
```

```
                  Population  poor_health  poor_sleep  Uninsured_health  \
Population          1.000000     0.949782    0.997272          0.968661
poor_health         0.949782     1.000000    0.961490          0.949579
poor_sleep          0.997272     0.961490    1.000000          0.968746
Uninsured_health    0.968661     0.949579    0.968746          1.000000
Life_Expectancy    -0.169082    -0.157482   -0.179557         -0.147392
Physicians          0.802969     0.716882    0.785917          0.765350
food_Insecure       0.949488     0.866604    0.948382          0.901662
Cost_Burden         0.941897     0.886859    0.938154          0.904360

                  Life_Expectancy  Physicians  food_Insecure  Cost_Burden
Population              -0.169082    0.802969       0.949488     0.941897
poor_health             -0.157482    0.716882       0.866604     0.886859
poor_sleep              -0.179557    0.785917       0.948382     0.938154
Uninsured_health        -0.147392    0.765350       0.901662     0.904360
Life_Expectancy          1.000000   -0.047904      -0.253418    -0.171704
Physicians              -0.047904    1.000000       0.738383     0.807168
food_Insecure           -0.253418    0.738383       1.000000     0.927326
Cost_Burden             -0.171704    0.807168       0.927326     1.000000

Pearson correlation coefficient Urban :

                  Population  poor_health  poor_sleep  Uninsured_health  \
Population          1.000000     0.986811    0.999027          0.983531
poor_health         0.986811     1.000000    0.989802          0.985677
poor_sleep          0.999027     0.989802    1.000000          0.985493
Uninsured_health    0.983531     0.985677    0.985493          1.000000
Life_Expectancy     0.343420     0.330408    0.330367          0.293629
Physicians          0.985984     0.961588    0.980984          0.950631
food_Insecure       0.989885     0.968455    0.989285          0.984261
Cost_Burden         0.992718     0.978460    0.991086          0.986810

                  Life_Expectancy  Physicians  food_Insecure  Cost_Burden
Population               0.343420    0.985984       0.989885     0.992718
poor_health              0.330408    0.961588       0.968455     0.978460
poor_sleep               0.330367    0.980984       0.989285     0.991086
Uninsured_health         0.293629    0.950631       0.984261     0.986810
Life_Expectancy          1.000000    0.368765       0.283458     0.299450
Physicians               0.368765    1.000000       0.971714     0.978157
food_Insecure            0.283458    0.971714       1.000000     0.993071
Cost_Burden              0.299450    0.978157       0.993071     1.000000

/Users/corosco/anaconda3/lib/python3.7/site-
packages/sklearn/preprocessing/data.py:334: DataConversionWarning: Data with
input dtype int64, float64 were all converted to float64 by MinMaxScaler.
  return self.partial_fit(X, y)
/Users/corosco/anaconda3/lib/python3.7/site-
```

```
packages/sklearn/preprocessing/data.py:334: DataConversionWarning: Data with
input dtype int64, float64 were all converted to float64 by MinMaxScaler.
  return self.partial_fit(X, y)
```

[46]:

```
# ============================================================================
# Display correlation
# ============================================================================
subtitle = "Correlation for Households Rural vs Urban"
xlab1 = "Rural"
xlab2 = "Urban"
data1 = corr_rural1
data2 = corr_urban1
Heatmap_Plot(subtitle, xlab1, xlab2, data1, data2)
```



```
[47]: # ==========================================================================
# Include the other descriptive characteristics about the variables: Mean,
#  Mode, Spread, and Tails (Chapter 2)
# ==========================================================================
# ==========================================================================
# # Display descriptive statistics
# ==========================================================================
rural_cp = rural[['Population', 'poor_health', 'poor_sleep',␣
 ↪'Uninsured_health',\
       'Life_Expectancy', 'Physicians', 'food_Insecure','Cost_Burden']].copy()

urban_cp = urban[['Population', 'poor_health', 'poor_sleep',␣
 ↪'Uninsured_health',\
       'Life_Expectancy', 'Physicians', 'food_Insecure','Cost_Burden']].copy()


# before scaling
print('RURAL \n')
print(rural_cp.describe(), '\n')
print('URBAN \n')
print(urban_cp.describe(), '\n')
```

```
RURAL

         Population   poor_health    poor_sleep  Uninsured_health  \
count    186.000000    186.000000    186.000000        186.000000
mean   14770.026882   3064.365591   4692.655914       2444.564516
std    12605.944718   2673.077929   4040.692191       2083.528517
min      152.000000     23.000000     50.000000         27.000000
25%     4470.000000    857.250000   1418.500000        812.750000
50%    10989.000000   2335.500000   3414.500000       1827.500000
75%    21421.000000   4372.750000   6814.750000       3549.000000
max    49728.000000  14489.000000  16987.000000       9222.000000

       Life_Expectancy  Physicians  food_Insecure  Cost_Burden
count       186.000000  186.000000     186.000000   186.000000
mean         77.393548    5.317204    2178.870968   496.537634
std           2.376930    6.139057    2018.025879   505.374179
min          71.900000    0.000000      10.000000     0.000000
25%          75.800000    1.000000     572.500000   120.000000
50%          77.300000    3.000000    1490.000000   336.000000
75%          78.975000    8.000000    3105.000000   656.750000
```

```
max          89.700000   38.000000    9970.000000  2451.000000

URBAN

          Population    poor_health    poor_sleep  Uninsured_health  \
count   6.800000e+01      68.000000  6.800000e+01         68.000000
mean    3.816856e+05   74733.455882  1.260119e+05      62499.058824
std     7.236031e+05  141018.568160  2.434585e+05     135041.924584
min     5.003100e+04    8414.000000  1.508600e+04       6687.000000
25%     6.795200e+04   14305.500000  2.276400e+04      11253.500000
50%     1.330275e+05   23471.000000  4.166000e+04      18019.500000
75%     3.150315e+05   68266.000000  1.077918e+05      41986.500000
max     4.698619e+06  885812.000000  1.593969e+06     908742.000000

       Life_Expectancy   Physicians  food_Insecure    Cost_Burden
count        68.000000    68.000000      68.000000      68.000000
mean         78.020588   239.191176   54094.852941   16881.529412
std           2.294286   462.947283  110360.809809   36246.466308
min          73.300000     6.000000    4210.000000    1182.000000
25%          76.200000    23.750000   10707.500000    2361.000000
50%          78.300000    74.000000   17410.000000    4829.500000
75%          79.425000   232.500000   47455.000000   14472.000000
max          83.000000  2742.000000  739120.000000  240521.000000
```

[48]:

```
# after scaling
print('RURAL \n')
print(rural_df.describe(), '\n')
print('URBAN \n')
print(urban_df.describe(), '\n')
```

```
RURAL

       Population  poor_health  poor_sleep  Uninsured_health  Life_Expectancy  \
count  186.000000   186.000000  186.000000        186.000000       186.000000
mean     0.294861     0.210242    0.274113          0.262922         0.308626
std      0.254275     0.184783    0.238572          0.226594         0.133535
min      0.000000     0.000000    0.000000          0.000000         0.000000
25%      0.087099     0.057670    0.080799          0.085454         0.219101
50%      0.218594     0.159858    0.198648          0.195813         0.303371
75%      0.429018     0.300688    0.399407          0.383034         0.397472
max      1.000000     1.000000    1.000000          1.000000         1.000000

       Physicians  food_Insecure  Cost_Burden
count  186.000000     186.000000   186.000000
mean     0.139926       0.217758     0.202586
std      0.161554       0.202613     0.206191
min      0.000000       0.000000     0.000000
```

```
25%      0.026316      0.056476     0.048960
50%      0.078947      0.148594     0.137087
75%      0.210526      0.310743     0.267952
max      1.000000      1.000000     1.000000

URBAN

       Population  poor_health  poor_sleep  Uninsured_health  Life_Expectancy  \
count   68.000000    68.000000   68.000000         68.000000        68.000000
mean     0.071345     0.075587    0.070256          0.061872         0.486659
std      0.155661     0.160724    0.154197          0.149705         0.236524
min      0.000000     0.000000    0.000000          0.000000         0.000000
25%      0.003855     0.006715    0.004863          0.005062         0.298969
50%      0.017854     0.017161    0.016831          0.012563         0.515464
75%      0.057007     0.068215    0.058716          0.039132         0.631443
max      1.000000     1.000000    1.000000          1.000000         1.000000

       Physicians  food_Insecure  Cost_Burden
count   68.000000      68.000000    68.000000
mean     0.085231       0.067879     0.065595
std      0.169206       0.150169     0.151444
min      0.000000       0.000000     0.000000
25%      0.006488       0.008841     0.004926
50%      0.024854       0.017961     0.015240
75%      0.082785       0.058844     0.055528
max      1.000000       1.000000     1.000000
```

[49]:

```
for x in rural_df:
    print(f'Mode for {x} = {rural_cp[x].mode()} \n')
```

```
Mode for Population = 0        152
1        277
2        442
3        648
4        726
5        749
6        823
7        903
8       1200
9       1234
10      1311
11      1362
12      1388
13      1389
14      1515
15      1516
16      1522
```

```
17       1892
18       1928
19       2131
20       2139
21       2204
22       2249
23       2252
24       2836
25       2895
26       2962
27       3028
28       3079
29       3253
        …
156     28360
157     28719
158     28875
159     29989
160     30119
161     31129
162     32587
163     33033
164     33830
165     35108
166     35286
167     35872
168     36354
169     36459
170     36552
171     36810
172     37924
173     40574
174     40822
175     41260
176     41619
177     42446
178     42454
179     43247
180     45129
181     45641
182     47542
183     49208
184     49565
185     49728
Length: 186, dtype: int64

Mode for poor_health = 0         23
1          48
```

2	82
3	118
4	122
5	134
6	136
7	193
8	206
9	218
10	232
11	236
12	243
13	256
14	279
15	280
16	293
17	304
18	348
19	392
20	414
21	468
22	486
23	530
24	537
25	553
26	572
27	586
28	600
29	614
	…
156	5618
157	5677
158	5845
159	6091
160	6332
161	6372
162	6560
163	6605
164	6669
165	6825
166	7006
167	7191
168	7207
169	7256
170	7265
171	7530
172	7593
173	7773
174	7862

```
175     8064
176     8103
177     8582
178     8691
179     8695
180     9580
181     9726
182     9972
183    10456
184    11985
185    14489
Length: 186, dtype: int64

Mode for poor_sleep = 0         50
1          83
2         145
3         185
4         206
5         226
6         257
7         263
8         356
9         365
10        412
11        427
12        428
13        437
14        438
15        443
16        462
17        543
18        568
19        616
20        666
21        676
22        707
23        732
24        878
25        950
26        951
27        957
28        970
29        977
       …
156     9041
157     9102
158     9160
159     9355
```

```
160     9747
161    10314
162    10697
163    10756
164    10898
165    11119
166    11123
167    11172
168    11496
169    11762
170    12105
171    12330
172    12594
173    12803
174    13014
175    13035
176    13220
177    13328
178    13467
179    13576
180    13619
181    14246
182    14571
183    15987
184    16130
185    16987
Length: 186, dtype: int64

Mode for Uninsured_health = 0     767
1    1896
2    3023
dtype: int64

Mode for Life_Expectancy = 0    79.0
dtype: float64

Mode for Physicians = 0    1
dtype: int64

Mode for food_Insecure = 0     320
1     910
2    1130
dtype: int64

Mode for Cost_Burden = 0    120
dtype: int64
```

[50]:
```
for x in rural_df:
    print(f'Mode for {x} = {urban_cp[x].mode()} \n')
```

```
Mode for Population = 0       50031
1       50224
2       50310
3       50921
4       52405
5       52592
6       53126
7       54450
8       56019
9       57207
10      58057
11      58485
12      60537
13      64525
14      65711
15      66726
16      66893
17      68305
18      72480
19      74808
20      82299
21      83572
22      86323
23      86976
24      87092
25      92035
26      94324
27      96493
28     100657
29     118189
        …
38     148373
39     162124
40     163694
41     171361
42     172578
43     179436
44     222631
45     226758
46     230221
47     254607
48     255001
49     275910
50     307412
```

```
51     337890
52     355642
53     362265
54     370200
55     423908
56     566719
57     590925
58     787858
59     840758
60     859064
61     865939
62    1005146
63    1248743
64    1986049
65    2084931
66    2637772
67    4698619
Length: 68, dtype: int64

Mode for poor_health = 0       8414
1        8712
2        9253
3        9300
4        9585
5        9991
6       10335
7       11250
8       11290
9       11310
10      11453
11      11585
12      11913
13      12292
14      13583
15      13785
16      14142
17      14360
18      14900
19      15368
20      15380
21      17568
22      17694
23      17798
24      17823
25      18203
26      19091
27      20089
28      20212
```

```
29      20567
        …
38      28581
39      28787
40      28948
41      29108
42      30214
43      33891
44      40119
45      40756
46      42572
47      51644
48      53336
49      63214
50      68029
51      68977
52      72158
53      84503
54      85533
55      88737
56      95886
57     121121
58     123953
59     125970
60     132923
61     185748
62     225358
63     264110
64     415851
65     446703
66     509327
67     885812
Length: 68, dtype: int64

Mode for poor_sleep = 0       15086
1        15135
2        15302
3        16181
4        16246
5        16618
6        17000
7        17291
8        17911
9        18041
10       18346
11       19510
12       20464
13       20981
```

```
14       21030
15       21403
16       22542
17       22838
18       24462
19       24752
20       26805
21       27961
22       28220
23       28577
24       29626
25       30307
26       30384
27       30538
28       33839
29       39214
        …
38       49183
39       50714
40       51023
41       51336
42       54293
43       60314
44       66437
45       76393
46       76815
47       81512
48       89747
49       98229
50      105184
51      115615
52      117231
53      118163
54      129043
55      146194
56      180301
57      188136
58      251871
59      255958
60      288446
61      306354
62      324257
63      357721
64      672071
65      723866
66      865481
67     1593969
Length: 68, dtype: int64
```

```
Mode for Uninsured_health = 0       6687
1        6717
2        6890
3        7161
4        7653
5        7924
6        8075
7        8086
8        8108
9        8418
10       8753
11       8985
12       9311
13       9427
14       9875
15      10748
16      10811
17      11401
18      11728
19      11910
20      12598
21      13186
22      13501
23      14200
24      14374
25      14751
26      14914
27      15267
28      15499
29      16015
        …
38      21633
39      23333
40      25349
41      27461
42      29225
43      29371
44      30839
45      32046
46      36912
47      37306
48      40118
49      41152
50      41367
51      43845
52      44276
53      54780
```

```
54     57906
55     69387
56     85425
57     92077
58     96650
59    104621
60    104680
61    158704
62    163112
63    233591
64    285140
65    331573
66    530742
67    908742
Length: 68, dtype: int64

Mode for Life_Expectancy = 0    78.4
dtype: float64

Mode for Physicians = 0    20
dtype: int64

Mode for food_Insecure = 0    15950
dtype: int64

Mode for Cost_Burden = 0       1182
1       1340
2       1348
3       1486
4       1638
5       1676
6       1808
7       1861
8       1867
9       1881
10      1902
11      1915
12      2070
13      2153
14      2197
15      2249
16      2331
17      2371
18      2485
19      2507
20      2794
21      3115
22      3378
```

```
23      3576
24      3577
25      3695
26      4050
27      4096
28      4119
29      4299
       …
38      5483
39      5498
40      5760
41      6036
42      6515
43      6806
44      9782
45     10936
46     11094
47     11150
48     12132
49     13384
50     14406
51     14670
52     17388
53     17445
54     17459
55     17587
56     18634
57     20379
58     25022
59     32496
60     34287
61     35537
62     35969
63     70498
64     88496
65     89430
66    139743
67    240521
Length: 68, dtype: int64
```

[51]:
```
urban_df
```

[51]:
```
     Population  poor_health  poor_sleep  Uninsured_health  Life_Expectancy  \
1      0.001727     0.003464    0.003406          0.000525         0.010309
3      0.007973     0.011157    0.009640          0.009769         0.288660
7      0.000060     0.003988    0.000970          0.001371         0.515464
```

11	0.007948	0.010577	0.008545	0.009512	0.443299
14	0.065743	0.072651	0.072176	0.037061	0.525773
15	0.416474	0.499533	0.416107	0.308687	0.577320
19	0.009528	0.010724	0.011877	0.005790	0.237113
20	0.068874	0.067945	0.063671	0.041670	0.597938
21	0.038017	0.036861	0.038829	0.028112	0.824742
31	0.080428	0.141907	0.083038	0.108568	0.783505
37	0.000551	0.003232	0.001872	0.002290	0.247423
43	0.205463	0.133983	0.195816	0.108633	0.958763
46	0.021155	0.016095	0.018916	0.010926	0.680412
50	0.005330	0.006122	0.005938	0.001919	0.432990
57	0.556672	0.570907	0.538605	0.580957	0.577320
61	0.174038	0.131684	0.149970	0.099731	0.876289
68	0.024113	0.029037	0.022761	0.025147	0.206186
70	0.027837	0.022985	0.028646	0.023030	0.515464
71	0.170100	0.247258	0.184477	0.173410	0.742268
79	0.158721	0.128456	0.152558	0.094662	1.000000
84	0.061924	0.069026	0.064694	0.041193	0.453608
91	0.018061	0.016158	0.017106	0.015675	0.298969
92	0.015849	0.018029	0.016556	0.016569	0.247423
94	0.024451	0.023586	0.022565	0.013589	0.659794
100	0.001544	0.000000	0.001397	0.000000	0.247423
101	1.000000	1.000000	1.000000	1.000000	0.649485
102	0.003591	0.004420	0.004722	0.003038	0.309278
105	0.037130	0.036135	0.032524	0.026774	0.731959
107	0.006941	0.007392	0.007422	0.007205	0.144330
108	0.175517	0.291425	0.173135	0.251541	0.907216
..	…	…	…	…	…
155	0.044008	0.049271	0.042072	0.033944	0.494845
162	0.001819	0.013851	0.002802	0.007554	0.536082
163	0.000191	0.002189	0.000031	0.000033	0.608247
165	0.026362	0.023220	0.024832	0.024985	0.567010
170	0.116357	0.091547	0.109603	0.087287	0.659794
174	0.003373	0.006777	0.003734	0.005588	0.422680
178	0.067167	0.086721	0.065285	0.056780	0.525773
181	0.007215	0.006528	0.008154	0.004572	0.072165
184	0.019004	0.012169	0.016053	0.011725	0.525773
187	0.000000	0.001797	0.000694	0.001539	0.000000
188	0.014976	0.023403	0.016037	0.018453	0.103093
191	0.018552	0.013306	0.017913	0.009120	0.587629
199	0.010891	0.005891	0.009689	0.005226	0.783505
201	0.000951	0.003614	0.000735	0.001551	0.360825
205	0.003627	0.007939	0.004001	0.004502	0.298969
212	0.038762	0.038931	0.039097	0.033507	0.515464
214	0.003118	0.019008	0.004910	0.010341	0.597938
220	0.437746	0.464370	0.448912	0.360162	0.597938
221	0.018846	0.019813	0.017776	0.013474	0.257732

226	0.014662	0.016292	0.015282	0.011589	0.463918
227	0.257866	0.202114	0.217011	0.168523	0.876289
234	0.001288	0.000956	0.001212	0.002909	0.319588
235	0.009036	0.013447	0.009209	0.008329	0.525773
236	0.004829	0.007926	0.006122	0.002548	0.525773
237	0.000666	0.003278	0.002065	0.003534	0.628866
240	0.048591	0.099695	0.052659	0.069508	0.721649
243	0.017647	0.024846	0.021596	0.012309	0.226804
246	0.111149	0.087895	0.104640	0.053315	0.896907
247	0.000042	0.000340	0.000137	0.000225	0.639175
249	0.003931	0.003301	0.003765	0.006553	0.298969

	Physicians	food_Insecure	Cost_Burden
1	0.005117	0.008586	0.001270
3	0.016813	0.016818	0.010007
7	0.000731	0.000000	0.000000
11	0.006213	0.007933	0.004968
14	0.101608	0.079942	0.055252
15	0.527778	0.288484	0.364813
19	0.020833	0.021731	0.011983
20	0.083333	0.060416	0.040754
21	0.067251	0.053585	0.068543
31	0.073465	0.059273	0.068008
37	0.005482	0.006667	0.002616
43	0.333333	0.171286	0.145346
46	0.033626	0.015036	0.015309
50	0.004020	0.013172	0.004458
57	0.662281	0.591392	0.578932
61	0.191520	0.146481	0.130835
68	0.031798	0.015117	0.016629
70	0.023392	0.024642	0.017970
71	0.145833	0.102938	0.143541
79	0.235380	0.128710	0.099608
84	0.087354	0.066756	0.056355
91	0.020468	0.023363	0.016796
92	0.036915	0.028180	0.020281
94	0.018275	0.017853	0.014281
100	0.001827	0.007538	0.003063
101	1.000000	1.000000	1.000000
102	0.004751	0.012246	0.005444
105	0.031798	0.029296	0.041414
107	0.006944	0.013594	0.008076
108	0.139254	0.124124	0.138318
..	…	…	…
155	0.066155	0.055449	0.050982
162	0.003289	0.002082	0.003710
163	0.002924	0.000313	0.000694

```
165     0.019371        0.016614     0.018033
170     0.127193        0.094569     0.080208
174     0.014620        0.013498     0.010003
178     0.107091        0.050959     0.067950
181     0.004386        0.015975     0.006735
184     0.019371        0.018165     0.013383
187     0.008406        0.006355     0.002921
188     0.030702        0.021581     0.022282
191     0.027047        0.018070     0.013023
199     0.025585        0.008926     0.009175
201     0.001827        0.007361     0.002064
205     0.004386        0.005538     0.004801
212     0.082602        0.049380     0.035932
214     0.002558        0.005416     0.001905
220     0.434942        0.425590     0.368716
221     0.033260        0.025105     0.019128
226     0.026316        0.015049     0.015171
227     0.379020        0.227960     0.289614
234     0.001462        0.006096     0.002862
235     0.024123        0.010355     0.010500
236     0.005117        0.015975     0.012175
237     0.000000        0.006205     0.003008
240     0.030336        0.028629     0.045751
243     0.032529        0.027486     0.023498
246     0.135234        0.081017     0.067711
247     0.006579        0.000435     0.000660
249     0.007675        0.006722     0.004241

[68 rows x 8 columns]
```

[52]:
```
rural_df
```

[52]:
```
      Population  poor_health  poor_sleep  Uninsured_health  Life_Expectancy  \
2       0.362595     0.247200    0.336837          0.376183         0.314607
4       0.476844     0.336375    0.422625          0.440566         0.337079
5       0.174157     0.082746    0.147370          0.142904         0.387640
6       0.035098     0.014448    0.029108          0.024687         0.308989
8       0.601844     0.353242    0.530850          0.528004         0.393258
9       0.138676     0.129545    0.135443          0.173573         0.325843
10      0.457318     0.265588    0.400189          0.325829         0.432584
12      0.069187     0.040854    0.060459          0.052529         0.101124
13      0.654248     0.535739    0.653776          0.427297         0.258427
16      0.232976     0.130375    0.196906          0.203263         0.387640
17      0.010005     0.004079    0.007971          0.006199         0.398876
18      0.373951     0.225702    0.321367          0.330179         0.247191
22      0.183859     0.136458    0.160949          0.153127         0.505618
23      0.027513     0.018664    0.024325          0.035998         0.398876
```

24	0.140431	0.186368	0.146602	0.102664	0.292135
25	0.761901	0.482718	0.752967	0.594236	0.213483
26	0.367859	0.222453	0.327508	0.305275	0.269663
27	0.955906	0.541891	0.838165	0.819902	0.410112
28	0.869271	0.687751	0.857354	0.819250	0.308989
29	0.431842	0.310659	0.412293	0.370092	0.365169
30	0.279208	0.160653	0.237882	0.221642	0.247191
32	0.259823	0.184156	0.249159	0.237847	0.202247
33	0.118061	0.052744	0.099250	0.088091	0.348315
34	0.604466	0.367897	0.572534	0.403371	0.230337
35	0.151545	0.126434	0.145480	0.203263	0.443820
36	0.853276	0.500622	0.798607	0.649918	0.337079
38	0.144001	0.099751	0.136506	0.098097	0.230337
39	0.207843	0.116826	0.185688	0.162153	0.342697
40	0.054139	0.056270	0.053551	0.069386	0.213483
41	0.064910	0.041477	0.054732	0.049701	0.269663
..	…	…	…	…	…
210	0.509642	0.384764	0.515085	0.557151	0.179775
211	0.059041	0.037951	0.053138	0.080479	0.460674
213	0.178796	0.109775	0.162189	0.150952	0.303371
215	0.187208	0.128785	0.175120	0.192061	0.235955
216	0.023378	0.017766	0.022259	0.023056	0.398876
217	0.024407	0.014724	0.021373	0.021968	0.398876
218	0.072737	0.047422	0.064415	0.070038	0.533708
219	0.147450	0.127748	0.139104	0.132028	0.219101
222	0.013535	0.012650	0.012222	0.014682	0.398876
223	0.244776	0.203926	0.233867	0.255900	0.202247
224	0.027493	0.016107	0.022849	0.030016	0.398876
225	0.663244	0.518941	0.640491	0.757042	0.320225
228	0.294255	0.204065	0.270060	0.235454	0.044944
229	0.434565	0.254251	0.384661	0.273953	0.213483
230	0.829192	0.459422	0.765425	0.661120	0.174157
231	0.070982	0.053436	0.066127	0.073844	0.348315
232	0.538446	0.500000	0.511189	0.536378	0.398876
233	0.989511	1.000000	0.940958	1.000000	0.404494
238	0.233339	0.168257	0.214678	0.222295	0.162921
239	0.705099	0.438891	0.628624	0.552909	0.466292
241	0.836433	0.660653	0.792171	0.810223	0.280899
242	0.101642	0.066639	0.090630	0.113214	0.146067
244	0.255527	0.184571	0.234398	0.241218	0.230337
245	0.430914	0.555855	0.448899	0.363567	0.325843
248	0.152655	0.125190	0.142469	0.150843	0.151685
250	0.907233	0.496613	0.777588	0.688961	0.286517
251	0.170223	0.131273	0.156698	0.195541	0.353933
252	0.360921	0.224043	0.308791	0.353888	0.140449
253	0.283161	0.347712	0.287359	0.388146	0.359551
254	0.238644	0.337965	0.244081	0.199891	0.219101

	Physicians	food_Insecure	Cost_Burden
2	0.236842	0.147590	0.138311
4	0.236842	0.410643	0.482252
5	0.131579	0.122490	0.098327
6	0.000000	0.024096	0.026520
8	0.157895	0.430723	0.403509
9	0.078947	0.079317	0.045288
10	0.157895	0.309237	0.251326
12	0.131579	0.058233	0.028968
13	0.184211	0.454819	0.517340
16	0.131579	0.144578	0.174215
17	0.000000	0.007028	0.000816
18	0.263158	0.279116	0.263566
22	0.157895	0.112450	0.168095
23	0.000000	0.020080	0.010608
24	0.026316	0.106426	0.139535
25	0.500000	0.599398	0.508772
26	0.184211	0.284137	0.218278
27	0.578947	0.611446	0.641779
28	0.315789	0.508032	0.686659
29	0.289474	0.272088	0.255406
30	0.026316	0.223896	0.220726
32	0.289474	0.231928	0.267646
33	0.026316	0.076305	0.032640
34	0.210526	0.635542	0.420645
35	0.026316	0.074297	0.068951
36	0.105263	0.596386	0.630763
38	0.263158	0.127510	0.095471
39	0.105263	0.166667	0.129743
40	0.026316	0.037149	0.018768
41	0.026316	0.050201	0.046920
..	…	…	…
210	0.131579	0.529116	0.354549
211	0.000000	0.031124	0.025296
213	0.157895	0.147590	0.134231
215	0.078947	0.155622	0.115055
216	0.000000	0.012048	0.005304
217	0.026316	0.015060	0.008568
218	0.078947	0.030120	0.025296
219	0.026316	0.113454	0.096695
222	0.000000	0.008032	0.011832
223	0.105263	0.145582	0.157895
224	0.026316	0.025100	0.019176
225	0.473684	0.500000	0.383517
228	0.052632	0.280120	0.213790
229	0.131579	0.415663	0.268054

```
230    0.315789      0.728916    0.542636
231    0.052632      0.042169    0.031824
232    0.315789      0.242972    0.303550
233    0.368421      0.458835    0.643003
238    0.078947      0.115462    0.132191
239    0.552632      0.586345    0.597715
241    0.421053      0.626506    0.719298
242    0.052632      0.090361    0.096695
244    0.157895      0.213855    0.170951
245    0.210526      0.307229    0.234190
248    0.052632      0.081325    0.082823
250    0.552632      0.723896    0.858833
251    0.078947      0.060241    0.048960
252    0.315789      0.282129    0.251326
253    0.026316      0.161647    0.187271
254    0.052632      0.172691    0.133415

[186 rows x 8 columns]
```

0.9.3 Hypothesis Test

[66]:
```
# ============================================================================
# Chapter 9 Test on Hypothesis.
# Normality Test
# ============================================================================
# # Shapiro-Wilk Test
# # Sample has a Gaussian Distribution
# ============================================================================
# create same sample size

s_rural = rural_df.sample(n=60, random_state=1)
s_rural.reset_index(drop=True, inplace=True)

s_urban = urban_df.sample(n=60, random_state=1)
s_urban.reset_index(drop=True, inplace=True)


stat, p = shapiro(rural_df)
print(f"Shapiro-Wilk Test - Rural \n")
print(f'stat= {stat} p = {p} \n')
if p > 0.05:
    print('Probably Gaussian \n')
else:
    print('Probably not Gaussian \n')

print(f"Shapiro-Wilk Test - Urban \n")
stat, p = shapiro(urban_df)
```

```
print(f'stat= {stat} p = {p} \n')

if p > 0.05:
    print('Probably Gaussian \n')
else:
        print('Probably not Gaussian \n')

# ============================================================================
# #-D'Agostinos K^2 test
# # p > 0.05
# ============================================================================
stat, p = normaltest(rural_df)

print(f"D'Agostinos K^2 test - Rural \n")
print(f'stat= {stat}\n')
print(f'p = {p} \n')

stat, p = normaltest(urban_df)

print(f"D'Agostinos K^2 test - Urban \n")
print(f'stat= {stat}\n')
print(f'p = {p} \n')

# ============================================================================
# Check the means of the samples
# HO = mean = mean indpendent and identical distribution
# show the how significant the difference is between the means.  Meaning
# could the differences have happened by chance. Larger the t-score the more
# difference between the groups.
# https://towardsdatascience.com/
 ↪inferential-statistics-series-t-test-using-numpy-2718f8f9bf2f
# A t-score of 3 means the groups are 3x as different from each other
# small t = more similar the groups are.
# low p = data did not occur by chance baseline = .05%
# ============================================================================
t, p = ttest_ind(rural_df, urban_df)
print( "Student's t-test Rural and Urban \n")

print(f't= {t}\n')
print(f'p = {p} \n')

# ============================================================================
# # Calculate CI for difference of the means
# ============================================================================
ci = sms.CompareMeans(sms.DescrStatsW(rural_df), sms.DescrStatsW(urban_df))
print('Difference between the means CI')
print(ci.tconfint_diff(usevar='unequal'),'\n')
```

```python
# ============================================================================
# Paired Student's t-test
# ============================================================================

t, p = ttest_rel(s_rural, s_urban)
print( "Paired Student's t-test Rural and Urban \n")
print(f't= {t}\n')
print(f'p = {p} \n')
```

```
Shapiro-Wilk Test - Rural

stat= 0.8858976364135742 p = 9.19647064970336e-32

Probably not Gaussian

Shapiro-Wilk Test - Urban

stat= 0.6095304489135742 p = 3.1120191727302785e-33

Probably not Gaussian

D'Agostinos K^2 test - Rural

stat= [25.79760919 44.65363099 26.77023061 29.80436106 77.21659653 96.44366863
 35.93508877 56.87876197]

p = [2.50103829e-06 2.01181125e-10 1.53786525e-06 3.37337971e-07
 1.70855557e-17 1.14162494e-21 1.57323870e-08 4.45588290e-13]

D'Agostinos K^2 test - Urban

stat= [89.55656942 84.98611489 91.2761902  99.01825946  0.70700863 77.26905094
 98.02255886 96.24116205]

p = [3.57304133e-20 3.51155627e-19 1.51226233e-20 3.15107074e-22
 7.02222963e-01 1.66432746e-17 5.18408116e-22 1.26327295e-21]

Student's t-test Rural and Urban

t= [ 6.79323141  5.31725255  6.55877629  6.79038486 -7.51255979  2.35885894
  5.56395097  5.00468522]

p = [7.85440886e-11 2.32278625e-07 3.05527250e-10 7.98651687e-11
 1.00808010e-12 1.90950891e-02 6.72848316e-08 1.05122247e-06]

Difference between the means CI
```

```
(array([ 0.17118857,  0.08771362,  0.15333928,  0.15249002, -0.23831231,
        0.00776219,  0.10346571,  0.09001562]), array([ 0.27584289,  0.18159802,
0.25437533,  0.24960902, -0.11775222,
        0.10162928,  0.19629283,  0.18396512]))

Paired Student's t-test Rural and Urban

t= [ 6.79875785  5.51777929  6.56017156  6.5975982  -7.00952344  2.69525087
  5.53527142  5.12666291]

p = [5.92225149e-09 8.03380888e-07 1.49548235e-08 1.29351795e-08
 2.60678077e-09 9.14884204e-03 7.52365180e-07 3.42963082e-06]
```

[ ]:
```
t, p = ttest_rel(s_rural, s_urban)
```

[67]:
```
# ============================================================================
# Conduct linear regression analysis
# Using life expectancy as the reponse how do
# poor health, lack of sleep, no insuranceand availability of Physicians
# affect LE. Use poor_health as the response variable, how do the
# factors affect poor_health.
# ============================================================================
# ============================================================================
# For this project, conduct a regression analysis on either one dependent and
# one explanatory variable, or multiple explanatory variables (Chapter 10 & 11)
# ============================================================================
# ============================================================================
# Create two scatter plots comparing two variables and provide your analysis
#  on correlation and causation. Remember, covariance, Pearson's correlation,
#  and Non- Linear Relationships should also be considered during your analysis
#  (Chapter 7).
# ============================================================================
# ============================================================================
#  How do the factors affect life expectancy
# ============================================================================
```

[55]:
```
# Rename variables
life = s_rural.Life_Expectancy
health = s_rural.poor_health
sleep = s_rural.poor_sleep
uninsured = s_rural.Uninsured_health
docs = s_rural.Physicians
food = s_rural.food_Insecure
burden = s_rural.Cost_Burden

life1 = s_urban.Life_Expectancy
```

```python
health1 = s_urban.poor_health
sleep1 = s_urban.poor_sleep
uninsured1 = s_urban.Uninsured_health
docs1 = s_urban.Physicians
food1 = s_urban.food_Insecure
burden1 = s_urban.Cost_Burden

# Fit the models
# Rural
mod1 = smf.ols('life ~ health + sleep + uninsured + docs\
                + food + burden',
                data=s_rural).fit()
print('                     RURAL', '\n')
print(mod1.summary(),'\n')

# Urban
mod2 = smf.ols('life1 ~ health1 + sleep1 + uninsured1 + docs1\
                 + food1 + burden1',
                 data=s_urban).fit()
print('-                    URBAN', '\n')
print(mod2.summary(), '\n')
```

```
                     RURAL

                            OLS Regression Results
==============================================================================
Dep. Variable:                   life   R-squared:                       0.212
Model:                            OLS   Adj. R-squared:                  0.123
Method:                 Least Squares   F-statistic:                     2.376
Date:                Fri, 29 May 2020   Prob (F-statistic):             0.0417
Time:                        08:32:57   Log-Likelihood:                 49.587
No. Observations:                  60   AIC:                            -85.17
Df Residuals:                      53   BIC:                            -70.51
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.2873      0.024     12.035      0.000       0.239       0.335
health        -0.0988      0.396     -0.249      0.804      -0.894       0.696
sleep          0.0571      0.487      0.117      0.907      -0.920       1.034
uninsured      0.1549      0.314      0.494      0.623      -0.474       0.784
docs           0.3275      0.200      1.634      0.108      -0.074       0.729
food          -0.4867      0.362     -1.344      0.185      -1.213       0.240
burden         0.0758      0.341      0.223      0.825      -0.608       0.759
==============================================================================
Omnibus:                        2.409   Durbin-Watson:                   2.265
```

```
Prob(Omnibus):                  0.300   Jarque-Bera (JB):               1.619
Skew:                           0.220   Prob(JB):                       0.445
Kurtosis:                       3.674   Cond. No.                        54.7
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.

-                     URBAN

                            OLS Regression Results
==============================================================================
Dep. Variable:                  life1   R-squared:                       0.492
Model:                            OLS   Adj. R-squared:                  0.434
Method:                 Least Squares   F-statistic:                     8.541
Date:                Fri, 29 May 2020   Prob (F-statistic):           1.67e-06
Time:                        08:32:57   Log-Likelihood:                 24.084
No. Observations:                  60   AIC:                            -34.17
Df Residuals:                      53   BIC:                            -19.51
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.4333      0.029     14.940      0.000       0.375       0.491
health1        0.0309      1.951      0.016      0.987      -3.883       3.944
sleep1         4.2851      2.546      1.683      0.098      -0.822       9.393
uninsured1     0.4955      1.930      0.257      0.798      -3.375       4.366
docs1          3.2563      0.914      3.562      0.001       1.422       5.090
food1         -8.2411      2.112     -3.902      0.000     -12.477      -4.005
burden1        0.4006      1.819      0.220      0.827      -3.249       4.050
==============================================================================
Omnibus:                        0.808   Durbin-Watson:                   2.328
Prob(Omnibus):                  0.668   Jarque-Bera (JB):                0.555
Skew:                          -0.236   Prob(JB):                        0.758
Kurtosis:                       2.998   Cond. No.                         161.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

[56]:
```
# ==============================================================================
# How do the factors affect health
# ==============================================================================
```

```python
# Rural
mod2 = smf.ols('health ~ life + sleep + uninsured + docs\
                + food + burden', data=s_rural).fit()
print('                        RURAL', '\n')
print(mod2.summary(), '\n')

# Urban
mod2 = smf.ols('health1 ~ life1 + sleep1 + uninsured1 + docs1\
                + food1 + burden1', data=s_urban).fit()
print('                         URBAN', '\n')
print(mod2.summary(), '\n')
```

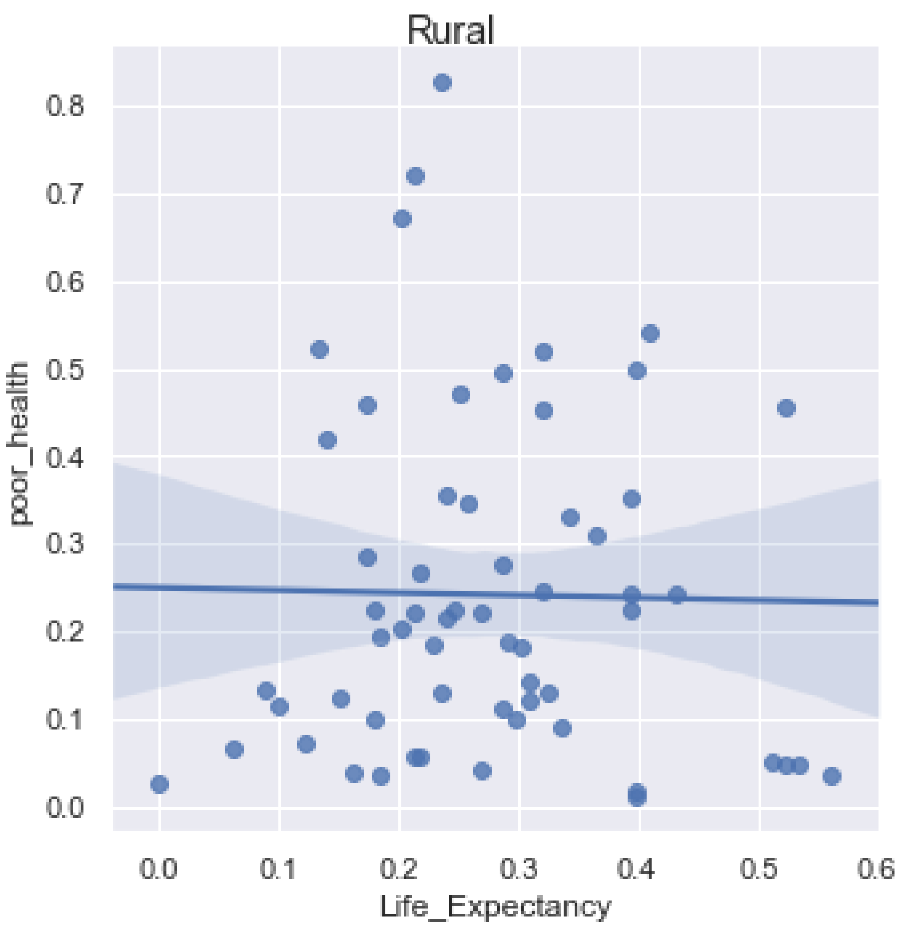
```
                        RURAL

                            OLS Regression Results
==============================================================================
Dep. Variable:                 health   R-squared:                       0.962
Model:                            OLS   Adj. R-squared:                  0.958
Method:                 Least Squares   F-statistic:                     226.4
Date:                Fri, 29 May 2020   Prob (F-statistic):           6.13e-36
Time:                        08:32:57   Log-Likelihood:                 113.20
No. Observations:                  60   AIC:                            -212.4
Df Residuals:                      53   BIC:                            -197.7
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.0134      0.016      0.843      0.403      -0.018       0.045
life          -0.0119      0.048     -0.249      0.804      -0.107       0.084
sleep          0.7822      0.130      6.010      0.000       0.521       1.043
uninsured      0.3364      0.099      3.412      0.001       0.139       0.534
docs          -0.2776      0.060     -4.621      0.000      -0.398      -0.157
food          -0.5702      0.101     -5.662      0.000      -0.772      -0.368
burden         0.2940      0.111      2.648      0.011       0.071       0.517
==============================================================================
Omnibus:                        7.787   Durbin-Watson:                   2.153
Prob(Omnibus):                  0.020   Jarque-Bera (JB):                8.483
Skew:                           0.546   Prob(JB):                       0.0144
Kurtosis:                       4.483   Cond. No.                         41.8
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.

                         URBAN
```

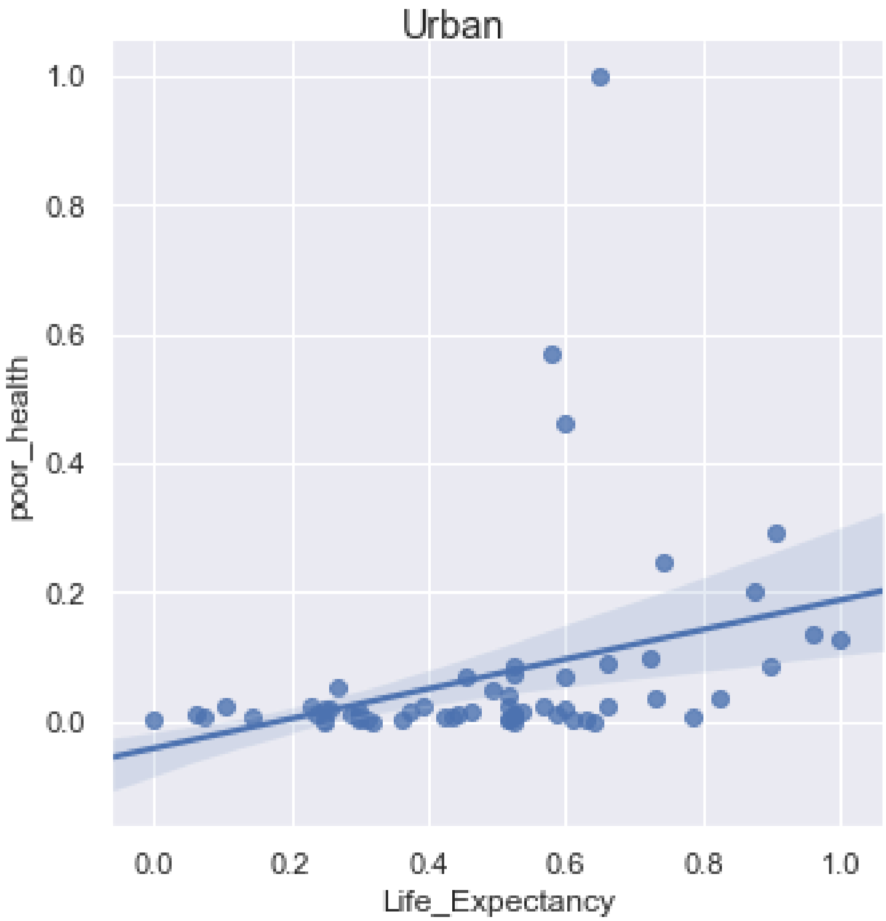
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                health1   R-squared:                       0.995
Model:                            OLS   Adj. R-squared:                  0.994
Method:                 Least Squares   F-statistic:                     1720.
Date:                Fri, 29 May 2020   Prob (F-statistic):           7.26e-59
Time:                        08:32:57   Log-Likelihood:                 183.30
No. Observations:                  60   AIC:                            -352.6
Df Residuals:                      53   BIC:                            -337.9
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.0067      0.005      1.473      0.147      -0.002       0.016
life1          0.0002      0.010      0.016      0.987      -0.019       0.020
sleep1         0.9546      0.129      7.396      0.000       0.696       1.214
uninsured1     0.7020      0.096      7.328      0.000       0.510       0.894
docs1         -0.0116      0.072     -0.162      0.872      -0.155       0.132
food1         -0.5735      0.149     -3.845      0.000      -0.873      -0.274
burden1       -0.0463      0.128     -0.362      0.719      -0.303       0.210
==============================================================================
Omnibus:                       12.072   Durbin-Watson:                   1.818
Prob(Omnibus):                  0.002   Jarque-Bera (JB):               23.230
Skew:                           0.543   Prob(JB):                     9.03e-06
Kurtosis:                       5.848   Cond. No.                         140.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

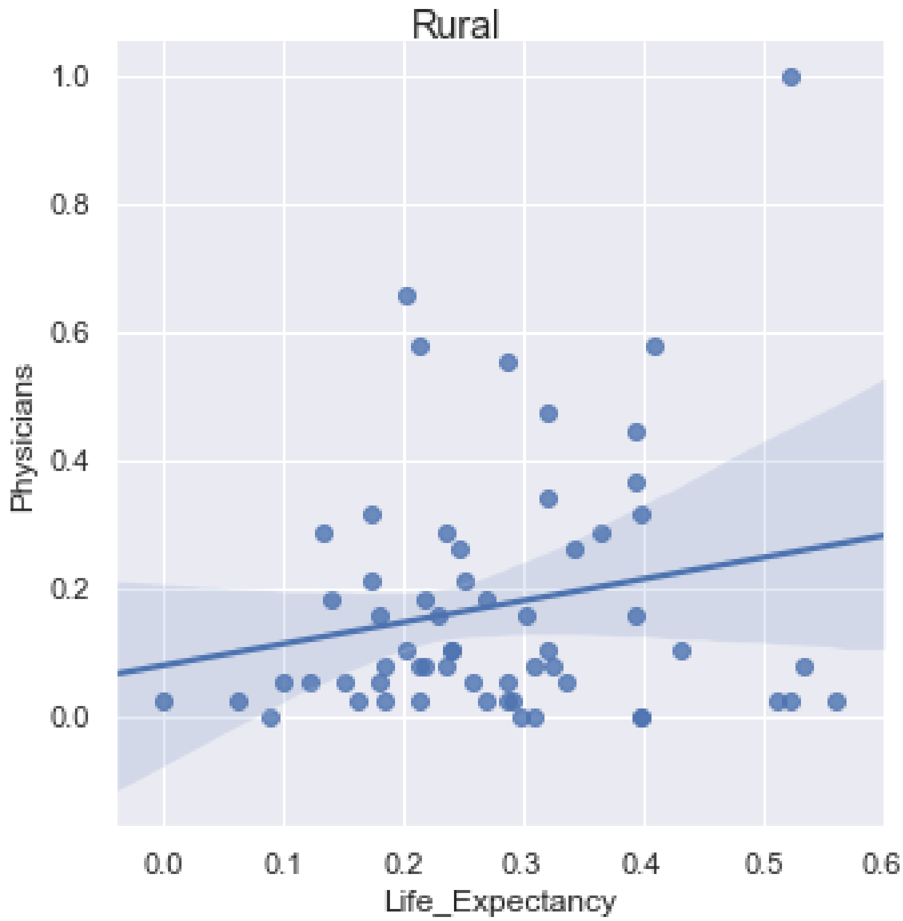
0.9.4 Linear Relationships

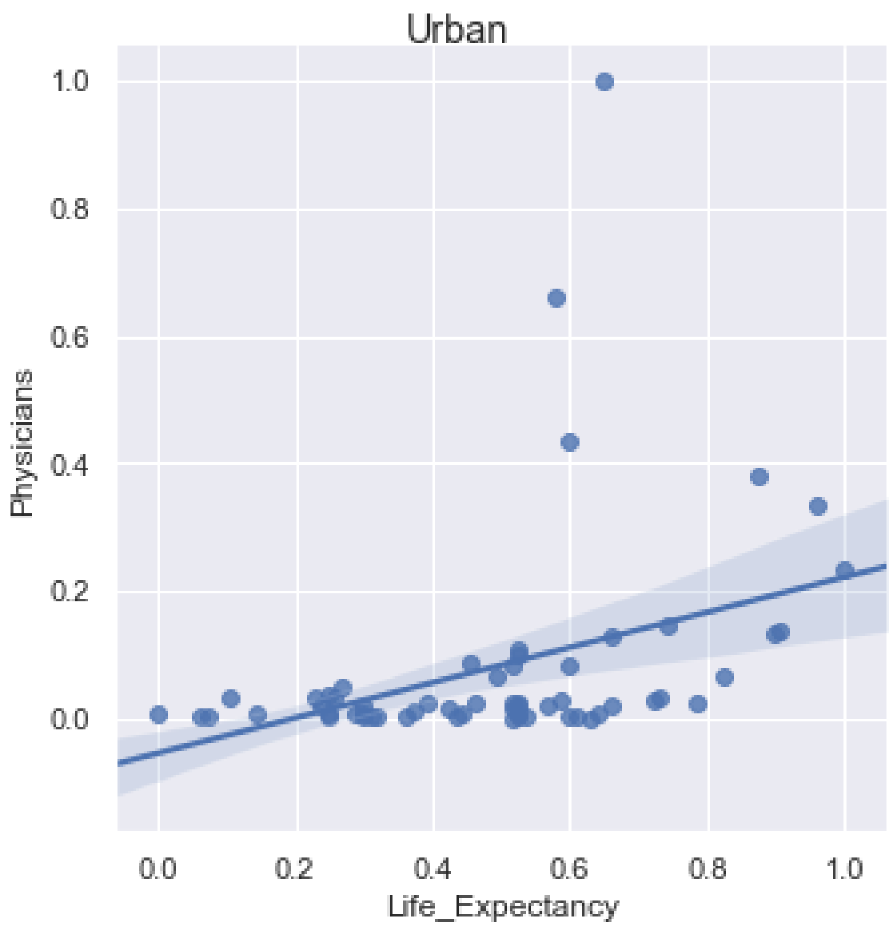
[57]:
```
# Linear Relationship
subtitle = 'Rural'
x_val = "Life_Expectancy"
y_val = 'poor_health'
data = s_rural
fig = sns.lmplot(x_val, y_val, data).fig.suptitle(subtitle)

subtitle = 'Urban'
x_val = "Life_Expectancy"
y_val = 'poor_health'
data = s_urban
```

```
fig = sns.lmplot(x_val, y_val, data).fig.suptitle(subtitle)

subtitle = 'Rural'
x_val = "Life_Expectancy"
y_val = 'Physicians'
data = s_rural
fig = sns.lmplot(x_val, y_val, data).fig.suptitle(subtitle)

subtitle = 'Urban'
x_val = "Life_Expectancy"
y_val = 'Physicians'
data = s_urban
fig = sns.lmplot(x_val, y_val, data).fig.suptitle(subtitle)
```

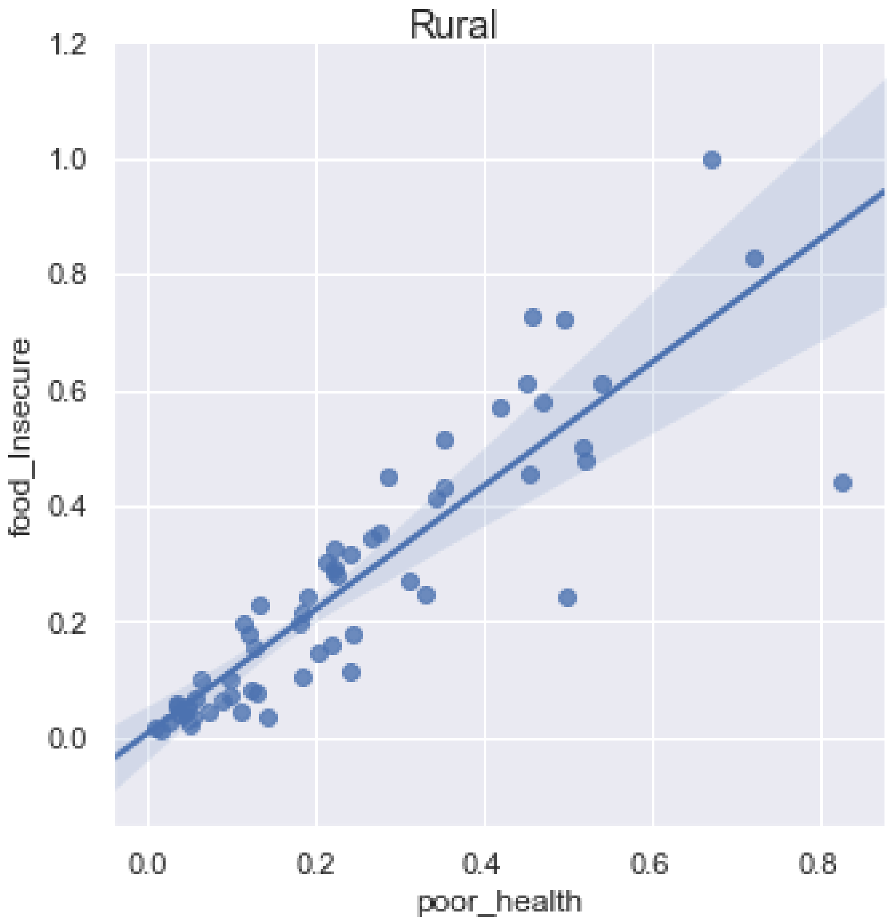



Urban
1.0
0.8
0.6
0.4
0.2
0.0
poor_health
0.0
0.2
0.4
0.6
0.8
1.0
Life_Expectancy

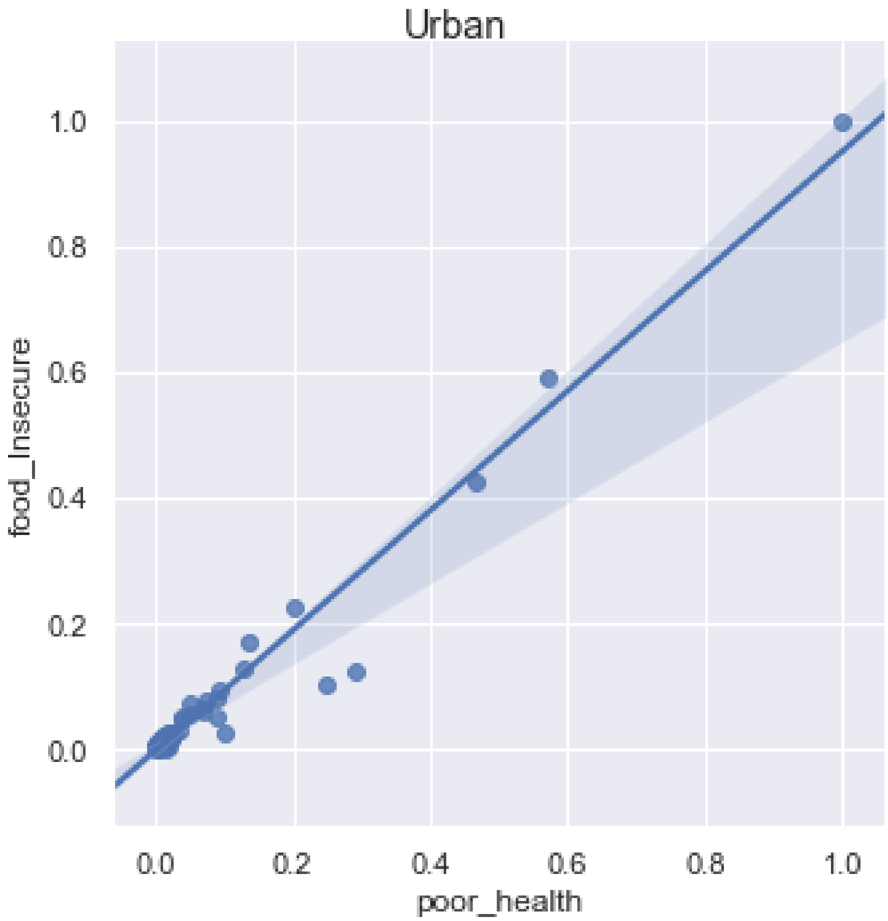

Rural
1.0
0.8
0.6
0.4
0.2
0.0
Physicians
0.0
0.1
0.2
0.3
0.4
0.5
0.6
Life_Expectancy



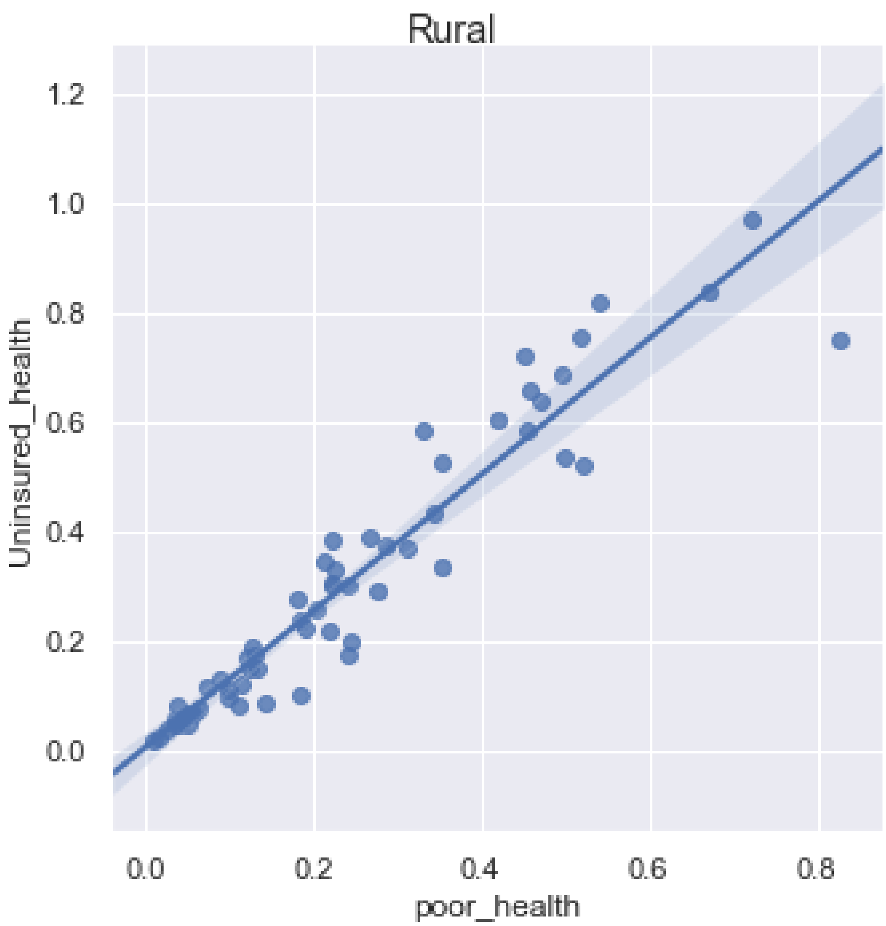
[58]:
```
# Linear Relationship
subtitle = 'Rural'
x_val = 'poor_health'
y_val = 'food_Insecure'
data = s_rural
fig = sns.lmplot(x_val, y_val, data).fig.suptitle(subtitle)

subtitle = 'Urban'
x_val = 'poor_health'
y_val = 'food_Insecure'
data = s_rural
data = s_urban
fig = sns.lmplot(x_val, y_val, data).fig.suptitle(subtitle)
```

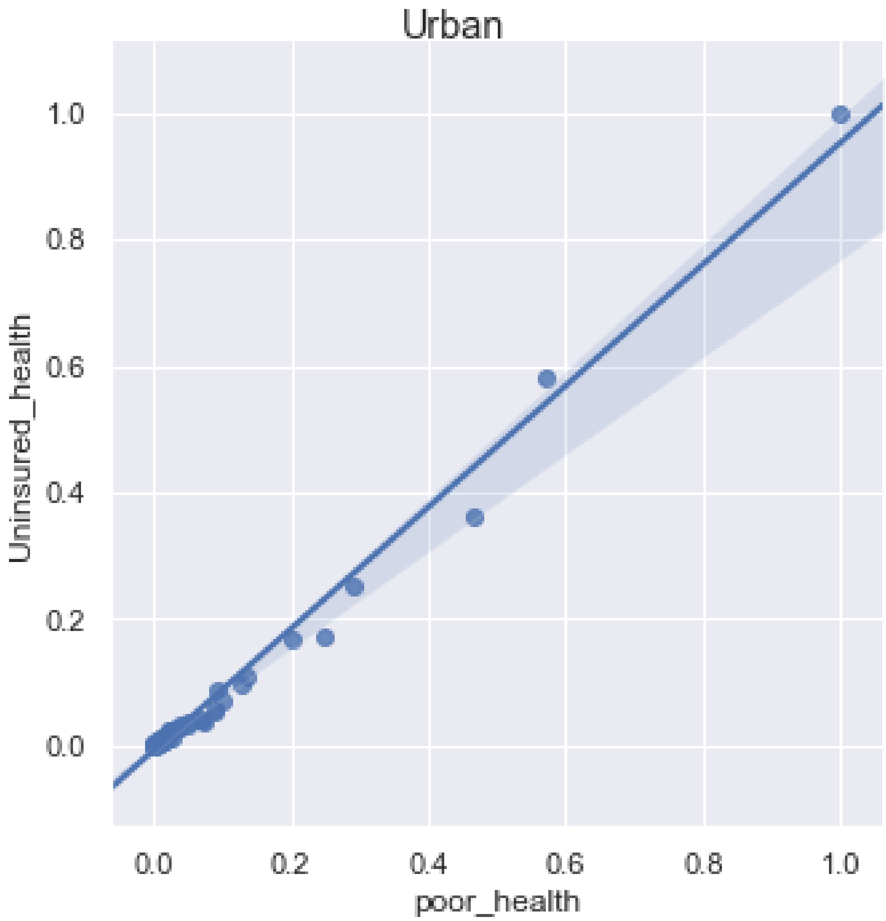


Rural
1.2
1.0
0.8
0.6
0.4
0.2
0.0
food_Insecure
0.0
0.2
0.4
0.6
0.8
poor_health

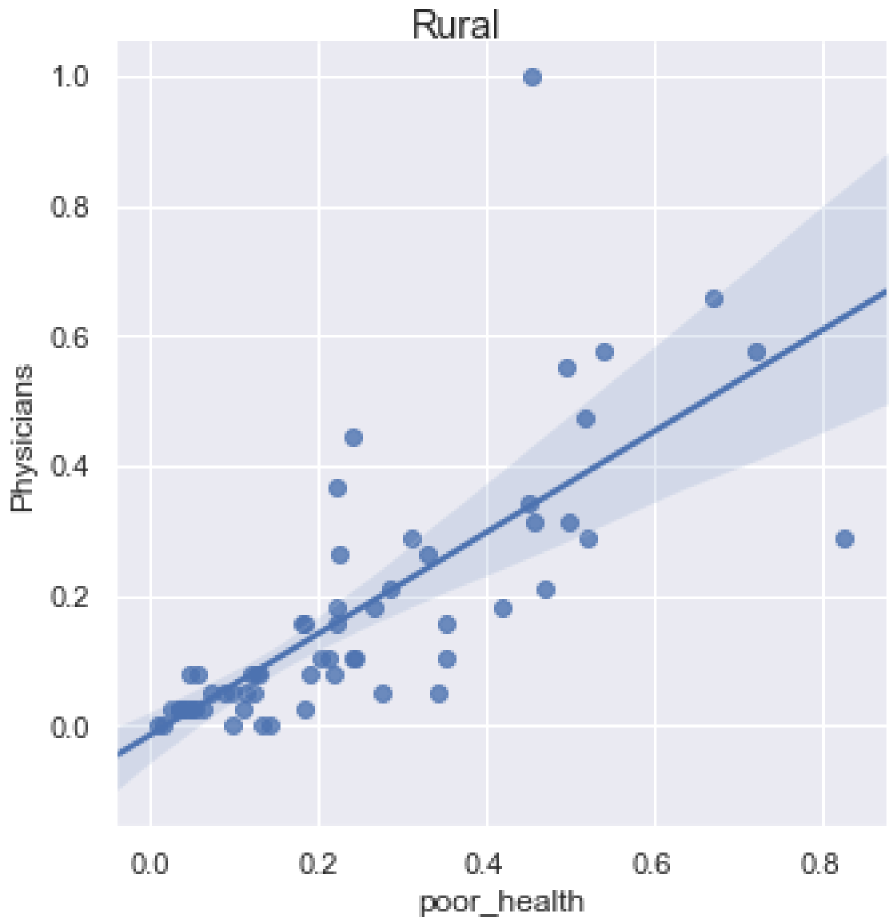


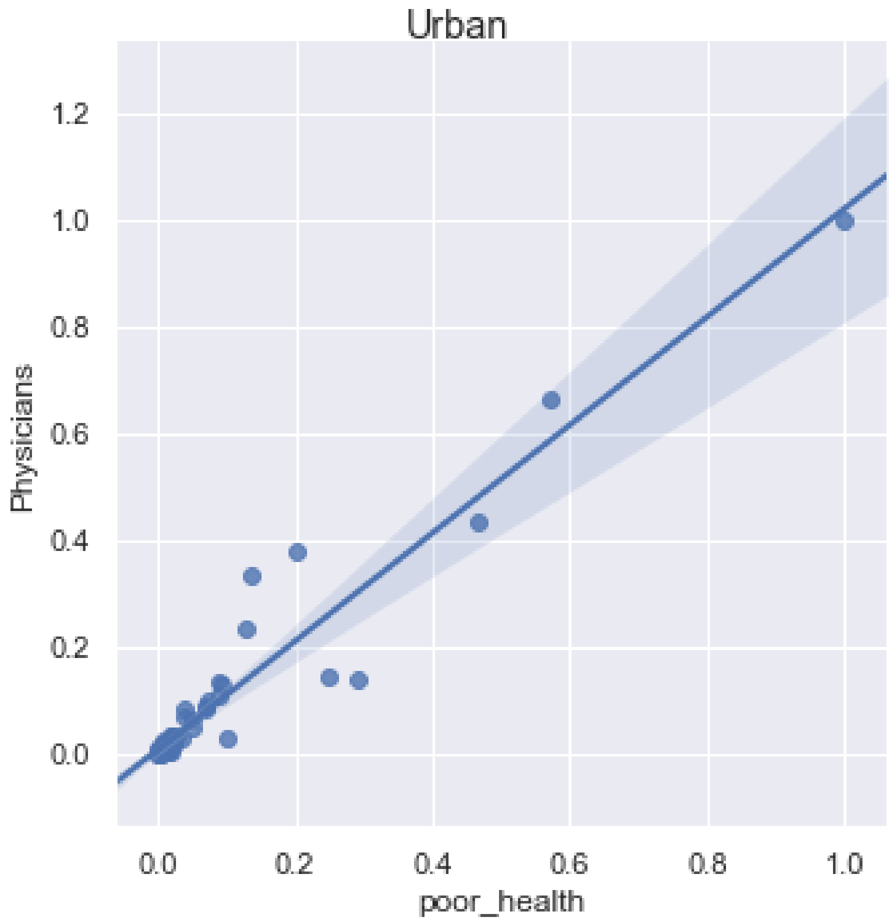
[59]:
```
# Linear Relationship
subtitle = 'Rural'
x_val = 'poor_health'
y_val = 'Uninsured_health'
data = s_rural
fig = sns.lmplot(x_val, y_val, data).fig.suptitle(subtitle)

subtitle = 'Urban'
x_val = 'poor_health'
y_val = 'Uninsured_health'
data = s_rural
data = s_urban
fig = sns.lmplot(x_val, y_val, data).fig.suptitle(subtitle)
```


Rural
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Uninsured_health
0.0
0.2
0.4
0.6
0.8
poor_health

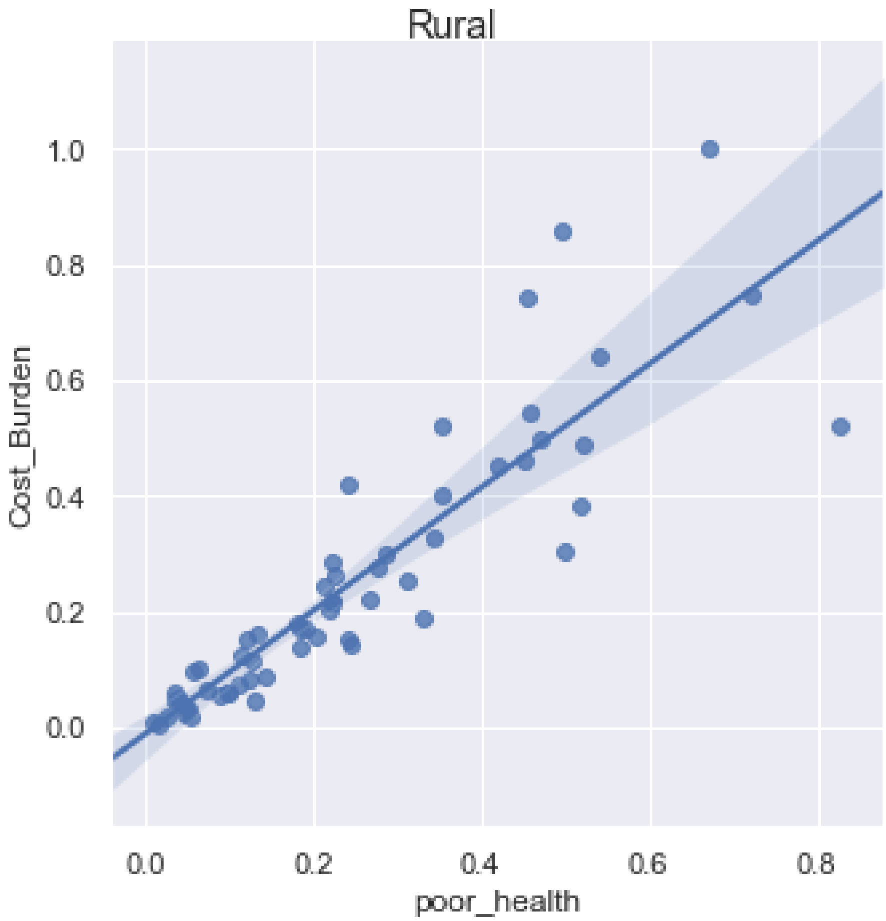


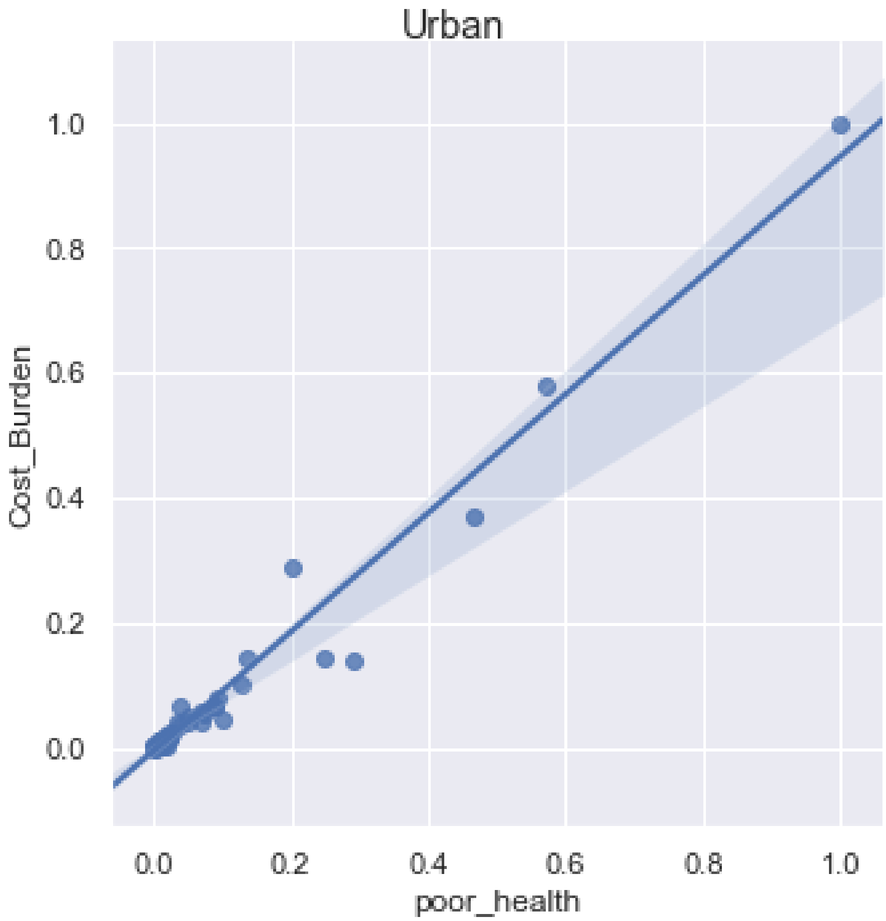
[60]:
```
# Linear Relationship
subtitle = 'Rural'
x_val = 'poor_health'
y_val = 'Physicians'
data = s_rural
fig = sns.lmplot(x_val, y_val, data).fig.suptitle(subtitle)

subtitle = 'Urban'
x_val = 'poor_health'
y_val = 'Physicians'
data = s_urban

fig = sns.lmplot(x_val, y_val, data).fig.suptitle(subtitle)
```


Rural
1.0
0.8
0.6
0.4
0.2
0.0
Physicians
0.0
0.2
0.4
0.6
0.8
poor_health

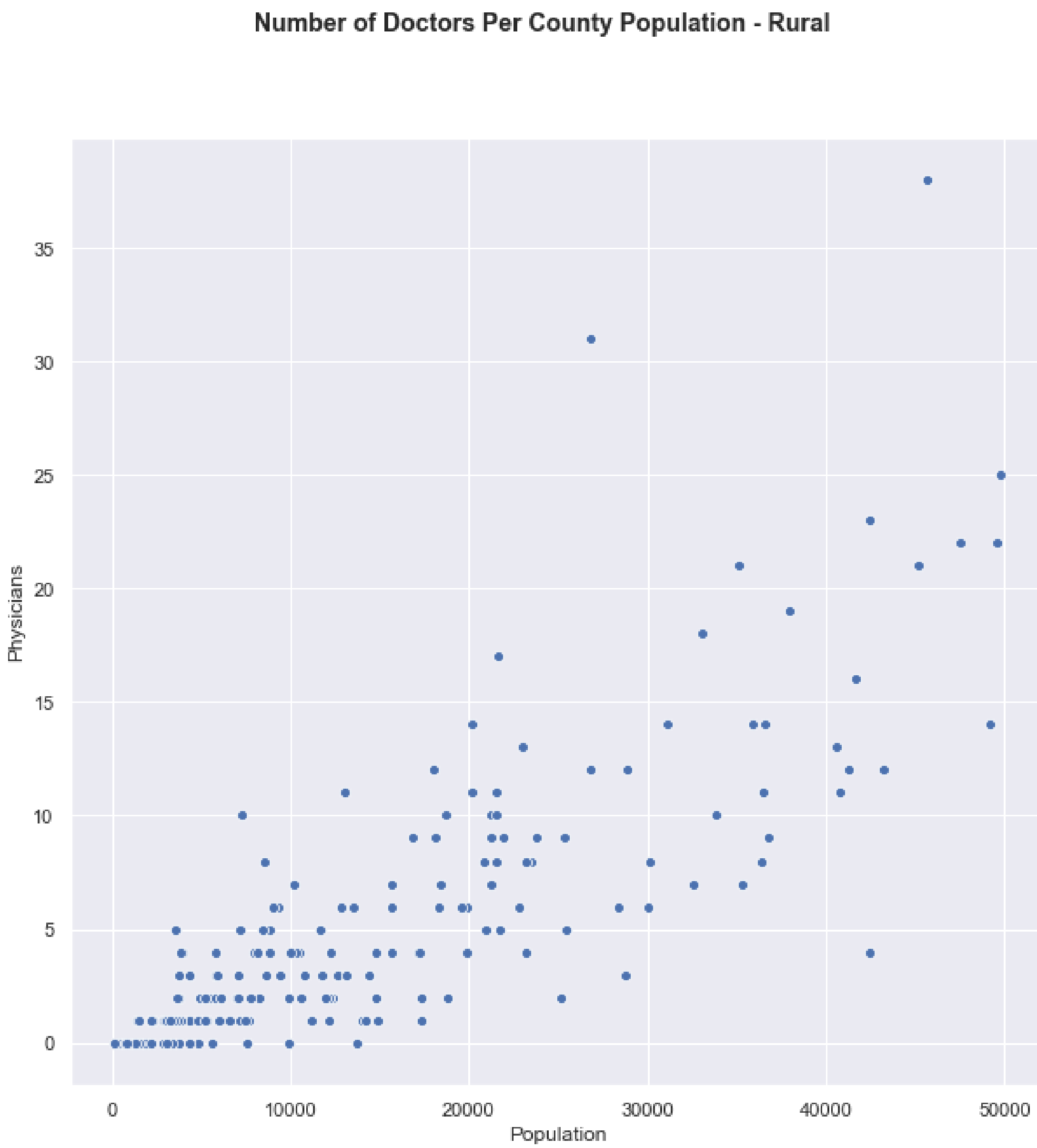


[61]:
```
# Linear Relationship
subtitle = 'Rural'
x_val = 'poor_health'
y_val = 'Cost_Burden'
data = s_rural
fig = sns.lmplot(x_val, y_val, data).fig.suptitle(subtitle)

subtitle = 'Urban'
x_val = 'poor_health'
y_val = 'Cost_Burden'
data = s_urban

fig = sns.lmplot(x_val, y_val, data).fig.suptitle(subtitle)
```


Rural
1.0
0.8
0.6
0.4
0.2
0.0
Cost_Burden
0.0
0.2
0.4
0.6
0.8
poor_health

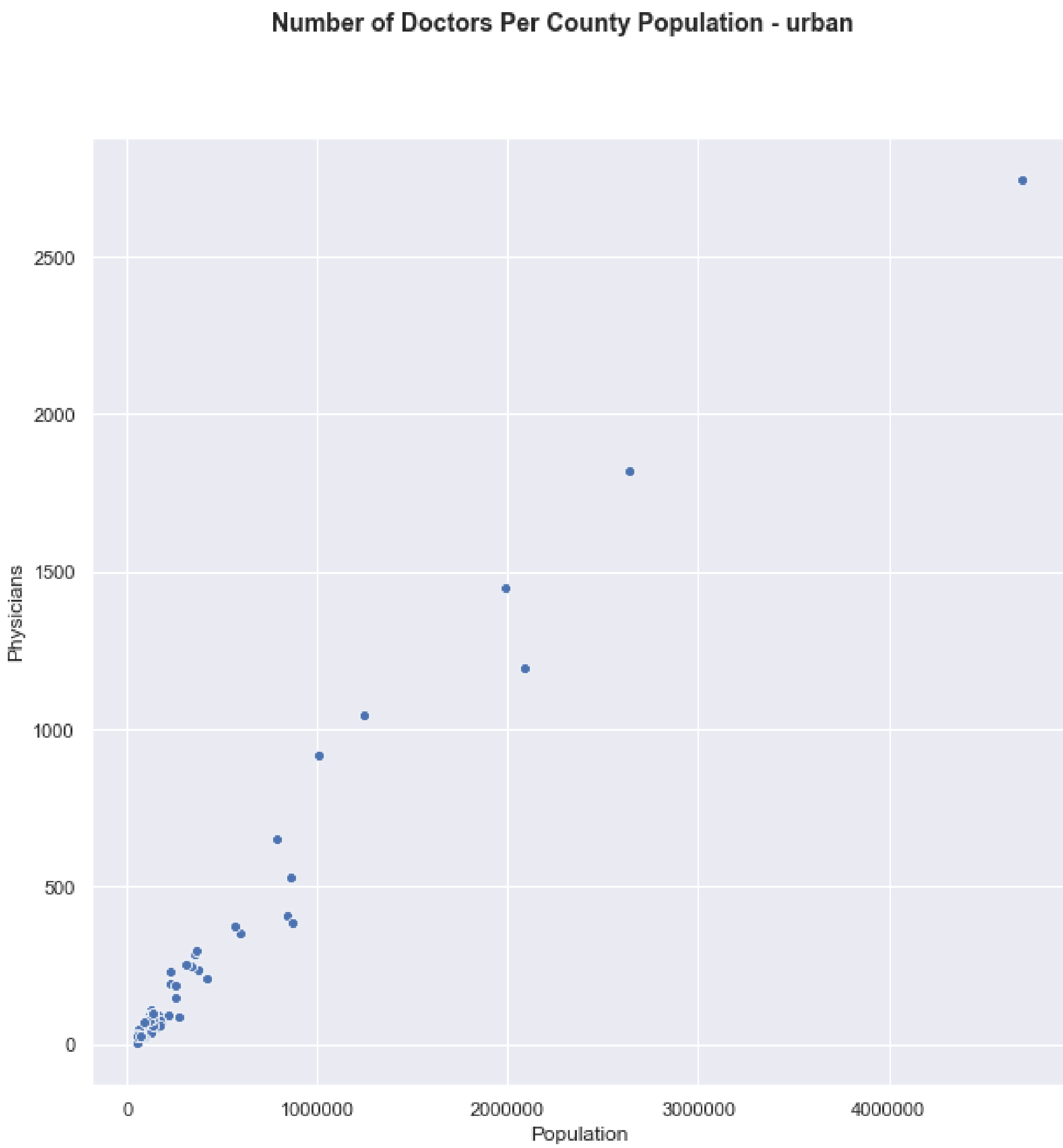



```
[62]: subtitle = 'Number of Doctors Per County Population - Rural'
      x_val = 'Population'
      y_val = 'Physicians'
      xlab = 'Population per County'
      ylab = '# of Physicians'
      data = rural
      sns_Scatter(subtitle, xlab, ylab, x_val, y_val, data)
```



[ ]:

```
[63]: subtitle = 'Number of Doctors Per County Population - urban'
x_val = 'Population'
y_val = 'Physicians'
xlab = 'Population per County'
ylab = '# of Physicians'
data = urban
sns_Scatter(subtitle, xlab, ylab, x_val, y_val, data)
```


Number of Doctors Per County Population - urban
Physicians
2500
2000
1500
1000
500
0
0
1000000
2000000
3000000
4000000
Population

[ ]: