FinalProject_group169

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1 COGS 108 - Final Project

1.1 Names & PID

- Christopher Guan (A13513127)
- Diana Issatayeva (A15541440)
- Angela Liu (A14400029)
- Ana Palma (A13737577)
- Melody Xue (A12782726)

2 Introduction & Background

2.0.1 Overview

We wanted to better understand the factors that correlate to obesity. There have been various studies done in the past showing a high correlation between income and obesity. So instead of solely focusing on income, we wanted to focus on factors that do not have obvious correlation to obesity level such as education level, recreation/gym facility density, and access to stores.

2.0.2 Research Question

How do factors such as access to grocery stores, recreation/fitness facility density, and education levels correlate with obesity levels in the United States?

2.0.3 Background and Prior Work

We are interested in analyzing the prevalence of obesity in the United States and how it is influenced by environmental and educational factors. A sedentary lifestyle has become the norm for most working Americans. Much of their time is spent sitting either at work or at home. Due to demanding work schedules, people lack the time and energy to pursue active lifestyles. The modern work life has also contributed to poor eating habits characterized by high calorie foods and large portion sizes. People in general do not have time to prepare healthy, home cooked meals every day. The convenience of fast food has made it a popular alternative. Lack of physical activity and poor diet choices have largely influenced obesity in the United States.

"Inequality in the Built Environment Underlies Key Health Disparities" describes a study conducted at the University of Minnesota that aimed to assess the geographic and social distributions of physical activity facilities and their relationship to obesity. It was revealed that groups with lower socio-economic status were less likely to have facilities around their neighborhoods, which in turn was associated with decreased physical activity and increased overweight.

In "Neighborhood Impact on Healthy Food Availability and Pricing in Food Stores," the author examines the impact of price and availability of healthy food in food stores and its correlation to obesity, cardiovascular diseases and cancer. The study indicated that a key factor in obesity prevention is the accessibility to grocery stores with healthy food options; however, large chain supermarkets stray away from opening in lower income neighborhoods.

Although, education allows for more food opportunities, Micheal Gard and Jan Wright's study described in "Managing Uncertainty: Obesity Discourses and Physical Education in a Risk Society" argues how how obesity could be a product of expert knowledge taught in physical education classes; this may construct anxiety surrounding body images, and in turn be detrimental to students. We want to examine the consequences and possible correlations between education and obesity.

Despite fitness facility density being correlated to socio-economic status, we will not analyze income as a determining factor for obesity. We aim to find the correlation between factors that directly influence obesity, such as access to grocery stores and gym facilities. It is likely that easier access to these things will enable people to choose healthier lifestyles, thereby preventing obesity. There is insufficient evidence that obesity is directly caused by socio-economic status, but with sufficient data analysis, it is possible to show correlation with the other factors previously mentioned.

Various studies have also shown that obesity is correlated with education. Individuals with lower income or education levels are more likely to suffer from obesity due to their lack of awareness on harmful eating habits and their inability to afford healthier food options.

References (include links): - 1) Inequality in the Built Environment Underlies Key Health Disparities in Physical Activity and Obesity [https://pediatrics.aappublications.org/content/117/2/417] - 2) Managing Uncertainty: Obesity Discourses and Physical Education in a Risk Society [https://link.springer.com/article/10.1023/A:1012238617836] - 3) Neighborhood Impact on Healthy Food Availability and Pricing in Food Stores [https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3071013/]

2.0.4 Hypothesis

We hypothesize that higher education would negatively correlate with obesity the most. Higher education leads to higher paying jobs and thus more opportunities and economic freedom to buy healthier food option. Because eating healthy is often more expensive in the United States, people with lower incomes or less education are more likely to lean towards cheaper fast food options.

3 Dataset(s)

We will analyze two sources of data from the United States Department of Agriculture Economic Research Service:

1)

- Dataset Name: Food Environment Atlas
- Link: https://www.ers.usda.gov/data-products/food-environment-atlas/data-access-and-documentation-downloads.aspx

- Number of observations: ~3000

2)

- Dataset Name: Education
- Link: https://www.ers.usda.gov/data-products/county-level-data-sets/
- Number of observations: ~3000

Each of these datasets has roughly 3000 observations as they are organized by all of the different counties in the United States. Coming from a federal government department, it is a trustworthy dataset that will provide us granular and enough data to be able to draw conclusions on our question.

The Food Environment Atlas provides us with 278 variables regarding poverty rate, percentage of races, and food assistance programs that we can use to analyze and help us answer our question. Although we might use more factors available to us in this dataset as we continue to work on the project, we wanted to focus on a smaller number to begin with. In particular, these variables aim to give us a better idea of what kind of resources are available to each county. The variables we will be using include PCT_OBSESE_ADULTS13 (adult obesity rate 2013), GROC14 (grocery stores 2014), GROCPTH14 (grocery stores per one thousand population 2014), REFFAC14 (recreation facilities 2014), and RECFACPTH14 (recreation facilities per one thousand population 2014).

The Education dataset has 31 variables, corresponding to various years that data was collected and 4 different levels of education: less than high school diploma, high school diploma, some college, and Bachelor's degree or higher. These 4 levels are described with percentage of adults and population count who have achieved the different levels of education. Because we also wanted to consider factors that are not directly related to food and health, analyzing a population's education level would produce new insights into if it is a factor in or has a correlation to obesity.

We will be merging the two datasets together by finding the corresponding county codes in each of the datasets.

4 Setup

In [1]:
```
# Import libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import patsy
import statsmodels.api as sm

# Libraries needed for maps
import plotly.graph_objs as go
from plotly.offline import download_plotlyjs, init_notebook_mode, plot, iplot
import plotly.figure_factory as ff

init_notebook_mode(connected=True)

# Configure libraries
```

```
# The seaborn library makes plots look nicer
sns.set()
sns.set_context('talk')

# Don't display too many rows/cols of DataFrames
pd.options.display.max_rows = 7
pd.options.display.max_columns = 8

# Round decimals when displaying DataFrames
pd.set_option('precision', 2)
```

5 Data Cleaning

We dropped unneccessary columns in education and food environment datasets. Next, we removed the null values and merged the datasets by matching the FPID (standard county code).

5.0.1 Education Dataset Cleaning

```
In [2]: xls_Education = pd.ExcelFile("Education.xls")
        df_ed = xls_Education.parse('Education')
        display(df_ed)
```

```
      FIPS Code State           Area name  2003 Rural-urban Continuum Code  \
0             0    US       United States                              NaN
1          1000    AL             Alabama                              NaN
2          1001    AL      Autauga County                              2.0
...         ...   ...                 ...                              ...
3280      72149    PR  Villalba Municipio                              2.0
3281      72151    PR  Yabucoa Municipio                               1.0
3282      72153    PR     Yauco Municipio                              3.0

      ...  Percent of adults with less than a high school diploma, 2013-17  \
0     ...                                               12.7
1     ...                                               14.7
2     ...                                               12.3
...   ...                                                ...
3280  ...                                               27.3
3281  ...                                               32.0
3282  ...                                               28.4

      Percent of adults with a high school diploma only, 2013-17  \
0                                                  27.3
1                                                  30.9
2                                                  33.6
...                                                 ...
3280                                               33.6
3281                                               24.9
3282                                               31.3
```

```
      Percent of adults completing some college or associate's degree, 2013-17  \
0                                                  29.1
1                                                  29.9
2                                                  29.1
...                                                 ...
3280                                               19.4
3281                                               26.0
3282                                               17.8

      Percent of adults with a bachelor's degree or higher, 2013-17
0                                                  30.9
1                                                  24.5
2                                                  25.0
...                                                 ...
3280                                               19.7
3281                                               17.2
3282                                               22.5

[3283 rows x 47 columns]
```

```
In [3]: # Drop columns from previous years and keep most recent (2013-2017)
        list(df_ed)

        df_ed=df_ed.drop(['2003 Urban Influence Code','2013 Rural-urban Continuum Code','2003 I
         'High school diploma only, 1970',
         'Some college (1-3 years), 1970',
         'Four years of college or higher, 1970',
         'Percent of adults with less than a high school diploma, 1970',
         'Percent of adults with a high school diploma only, 1970',
         'Percent of adults completing some college (1-3 years), 1970',
         'Percent of adults completing four years of college or higher, 1970',
         'Less than a high school diploma, 1980',
         'High school diploma only, 1980',
         'Some college (1-3 years), 1980',
         'Four years of college or higher, 1980',
         'Percent of adults with less than a high school diploma, 1980',
         'Percent of adults with a high school diploma only, 1980',
         'Percent of adults completing some college (1-3 years), 1980',
         'Percent of adults completing four years of college or higher, 1980',
         'Less than a high school diploma, 1990',
         'High school diploma only, 1990',
         "Some college or associate's degree, 1990",
         "Bachelor's degree or higher, 1990",
         'Percent of adults with less than a high school diploma, 1990',
         'Percent of adults with a high school diploma only, 1990',
         "Percent of adults completing some college or associate's degree, 1990",
```

```
 "Percent of adults with a bachelor's degree or higher, 1990",
 'Less than a high school diploma, 2000',
 'High school diploma only, 2000',
 "Some college or associate's degree, 2000",
 "Bachelor's degree or higher, 2000",
 'Percent of adults with less than a high school diploma, 2000',
 'Percent of adults with a high school diploma only, 2000',
 "Percent of adults completing some college or associate's degree, 2000",
 "Percent of adults with a bachelor's degree or higher, 2000",],axis=1)

# Display the new dataframe and the column names
display(df_ed)
list(df_ed)
```

```
      FIPS Code State           Area name  \
0             0    US       United States
1          1000    AL             Alabama
2          1001    AL      Autauga County
...         ...   ...                 ...
3280      72149    PR  Villalba Municipio
3281      72151    PR   Yabucoa Municipio
3282      72153    PR     Yauco Municipio

      Less than a high school diploma, 2013-17  ...  \
0                                     2.74e+07  ...
1                                     4.81e+05  ...
2                                     4.52e+03  ...
...                                        ...  ...
3280                                  4.23e+03  ...
3281                                  7.72e+03  ...
3282                                  7.51e+03  ...

      Percent of adults with less than a high school diploma, 2013-17  \
0                                                  12.7
1                                                  14.7
2                                                  12.3
...                                                 ...
3280                                               27.3
3281                                               32.0
3282                                               28.4

      Percent of adults with a high school diploma only, 2013-17  \
0                                                  27.3
1                                                  30.9
2                                                  33.6
...                                                 ...
3280                                               33.6
3281                                               24.9
```

```
3282                                                    31.3

      Percent of adults completing some college or associate's degree, 2013-17  \
0                                                       29.1
1                                                       29.9
2                                                       29.1
...                                                      ...
3280                                                    19.4
3281                                                    26.0
3282                                                    17.8

      Percent of adults with a bachelor's degree or higher, 2013-17
0                                                       30.9
1                                                       24.5
2                                                       25.0
...                                                      ...
3280                                                    19.7
3281                                                    17.2
3282                                                    22.5

[3283 rows x 11 columns]
```

```
Out[3]: ['FIPS Code',
         'State',
         'Area name',
         'Less than a high school diploma, 2013-17',
         'High school diploma only, 2013-17',
         "Some college or associate's degree, 2013-17",
         "Bachelor's degree or higher, 2013-17",
         'Percent of adults with less than a high school diploma, 2013-17',
         'Percent of adults with a high school diploma only, 2013-17',
         "Percent of adults completing some college or associate's degree, 2013-17",
         "Percent of adults with a bachelor's degree or higher, 2013-17"]
```

```
In [4]: # Rename the FIPS column name to be able to merge later
        df_ed=df_ed.rename(index=str, columns={"FIPS Code": "FIPS", })
```

5.0.2 Food Environmental Atlas Dataset Cleaning

We extract only the data that we want to use in our analysis from the Atlas.

```
In [5]: # Read in the data from Food Evironmental Atlas excel spreadsheet into pandas data fra
        stores_df = pd.read_excel('FoodEnvironmentAtlas.xls', sheet_name='STORES')
        health_df = pd.read_excel('FoodEnvironmentAtlas.xls', sheet_name='HEALTH')
        income_df = pd.read_excel('FoodEnvironmentAtlas.xls', sheet_name='SOCIOECONOMIC')
```

```
In [6]: # Separate the neccessary columns from the table
        stores_var_list = ['GROC14', 'GROCPTH14', 'FIPS']
```

```
stores_df = stores_df[stores_var_list]

health_var_list = ['PCT_OBESE_ADULTS13', 'RECFAC14', 'RECFACPTH14', 'FIPS']
health_df = health_df[health_var_list]

income_var_list = ['MEDHHINC15','FIPS']
income_df = income_df[income_var_list]
```

In [7]:
```
stores_df
```

Out[7]:
```
      GROC14  GROCPTH14   FIPS
0          4       0.07   1001
1         29       0.14   1003
2          5       0.19   1005
...      ...        ...    ...
3140       2       0.10  56041
3141       2       0.24  56043
3142       4       0.56  56045

[3143 rows x 3 columns]
```

In [8]:
```
health_df
```

Out[8]:
```
      PCT_OBESE_ADULTS13  RECFAC14  RECFACPTH14   FIPS
0                   34.1         5         0.09   1001
1                   27.4        25         0.12   1003
2                   44.4         0         0.00   1005
...                  ...       ...          ...    ...
3140                27.9         2         0.10  56041
3141                27.7         1         0.12  56043
3142                29.2         0         0.00  56045

[3143 rows x 4 columns]
```

In [9]:
```
income_df
```

Out[9]:
```
      MEDHHINC15   FIPS
0        56580.0   1001
1        52387.0   1003
2        31433.0   1005
...          ...    ...
3140     62968.0  56041
3141     56088.0  56043
3142     60986.0  56045

[3143 rows x 2 columns]
```

In [10]:
```
# Merging two Atlas dataframes on FIPS column
df_merged = stores_df.merge(health_df, left_on='FIPS', right_on='FIPS')
df_merged = df_merged.merge(income_df, left_on='FIPS', right_on='FIPS')
```

In [11]:
```
# Put FIPS column first
# Get a list of columns
cols = list(df_merged)

# Move the column to head of list using index, pop and insert
cols.insert(0, cols.pop(cols.index('FIPS')))
df_merged = df_merged.loc[:, cols]
df_merged
```

Out[11]:
```
       FIPS  GROC14  GROCPTH14  PCT_OBESE_ADULTS13  RECFAC14  RECFACPTH14  \
0      1001       4       0.07                34.1         5         0.09
1      1003      29       0.14                27.4        25         0.12
2      1005       5       0.19                44.4         0         0.00
...     ...     ...        ...                 ...       ...          ...
3140  56041       2       0.10                27.9         2         0.10
3141  56043       2       0.24                27.7         1         0.12
3142  56045       4       0.56                29.2         0         0.00

      MEDHHINC15
0        56580.0
1        52387.0
2        31433.0
...          ...
3140     62968.0
3141     56088.0
3142     60986.0

[3143 rows x 7 columns]
```

In [12]:
```
# Rename the column names to be more clear
df_merged = df_merged.rename(index=str, columns={"GROC14": "GROC_STORES_COUNT_2014", "
```

In [13]:
```
# rename the median income column
df_merged = df_merged.rename(index=str, columns={'MEDHHINC15': 'Median_household_incor
```

In [14]:
```
# Check for data types from the Atlas dataset
df_merged.dtypes
```

Out[14]:
```
FIPS                                      int64
GROC_STORES_COUNT_2014                    int64
GROC_STORES_PER1000_2014                float64
ADULT_OBESITY_RATE_2013                 float64
RECREATION_FITNESS_FACIL_COUNT_2014       int64
RECREATION_FITNESS_FACIL_PER1000_2014   float64
Median_household_income_2015            float64
dtype: object
```

In [15]:
```
# Check for data types from the Education dataset
df_ed.dtypes
```

```
Out[15]: FIPS                                                                        int64
         State                                                                      object
         Area name                                                                  object
                                                                                     ...
         Percent of adults with a high school diploma only, 2013-17                float64
         Percent of adults completing some college or associate's degree, 2013-17  float64
         Percent of adults with a bachelor's degree or higher, 2013-17             float64
         Length: 11, dtype: object
```

```
In [16]: # Merging the Education and Food Environmental Atlas dataframes together on FIPS colu
         df = df_ed.merge(df_merged, left_on='FIPS', right_on='FIPS')
         display(df)
```

```
       FIPS State         Area name  Less than a high school diploma, 2013-17  \
0      1001    AL    Autauga County                                    4521.0
1      1003    AL    Baldwin County                                   13997.0
2      1005    AL    Barbour County                                    4960.0
...     ...   ...               ...                                       ...
3138  56041    WY      Uinta County                                    1067.0
3139  56043    WY   Washakie County                                     654.0
3140  56045    WY     Weston County                                     410.0

      ...  ADULT_OBESITY_RATE_2013  RECREATION_FITNESS_FACIL_COUNT_2014  \
0     ...                     34.1                                    5
1     ...                     27.4                                   25
2     ...                     44.4                                    0
...   ...                      ...                                  ...
3138  ...                     27.9                                    2
3139  ...                     27.7                                    1
3140  ...                     29.2                                    0

      RECREATION_FITNESS_FACIL_PER1000_2014  Median_household_income_2015
0                                      0.09                       56580.0
1                                      0.12                       52387.0
2                                      0.00                       31433.0
...                                     ...                           ...
3138                                   0.10                       62968.0
3139                                   0.12                       56088.0
3140                                   0.00                       60986.0

[3141 rows x 17 columns]
```

Next, we want to reduce the 4 columns of education data to 2: either having some college or higher OR having high school or less. We want to see how the effects of having a college education and analyze how different education levels can affect obesity rates.

```
In [17]: # Create and add a new column for % adults w/ a high school diploma or less
         df['HIGH_SCHOOL'] =  df[['Percent of adults with less than a high school diploma, 201
```

```
# Create and add a new column for % adults w/ some college or higher
df['COLLEGE'] =  df[['Percent of adults completing some college or associate\'s degre
```

```
In [18]: # Display the columns in the final, merged dataframe
         list(df)
```

```
Out[18]: ['FIPS',
          'State',
          'Area name',
          'Less than a high school diploma, 2013-17',
          'High school diploma only, 2013-17',
          "Some college or associate's degree, 2013-17",
          "Bachelor's degree or higher, 2013-17",
          'Percent of adults with less than a high school diploma, 2013-17',
          'Percent of adults with a high school diploma only, 2013-17',
          "Percent of adults completing some college or associate's degree, 2013-17",
          "Percent of adults with a bachelor's degree or higher, 2013-17",
          'GROC_STORES_COUNT_2014',
          'GROC_STORES_PER1000_2014',
          'ADULT_OBESITY_RATE_2013',
          'RECREATION_FITNESS_FACIL_COUNT_2014',
          'RECREATION_FITNESS_FACIL_PER1000_2014',
          'Median_household_income_2015',
          'HIGH_SCHOOL',
          'COLLEGE']
```

```
In [19]: df
```

```
Out[19]:        FIPS State        Area name  Less than a high school diploma, 2013-17  \
         0      1001    AL   Autauga County                                    4521.0
         1      1003    AL   Baldwin County                                   13997.0
         2      1005    AL   Barbour County                                    4960.0
         ...     ...   ...              ...                                      ...
         3138  56041    WY     Uinta County                                    1067.0
         3139  56043    WY  Washakie County                                     654.0
         3140  56045    WY    Weston County                                     410.0

               ...  RECREATION_FITNESS_FACIL_PER1000_2014  \
         0     ...                                   0.09
         1     ...                                   0.12
         2     ...                                   0.00
         ...   ...                                    ...
         3138  ...                                   0.10
         3139  ...                                   0.12
         3140  ...                                   0.00

               Median_household_income_2015  HIGH_SCHOOL  COLLEGE
         0                          56580.0         45.9     54.1
```

```
1                           52387.0         37.6     62.4
2                           31433.0         62.4     37.5
...                             ...          ...      ...
3138                        62968.0         45.6     54.4
3139                        56088.0         40.5     59.6
3140                        60986.0         42.5     57.5

[3141 rows x 19 columns]
```

6 Data Analysis & Results

Each point on the following scatter plots represents one of the counties in the United States.

6.1 Obesity Rate vs. Recreation/Fitness Facilities Per 1000 People

Here, we plot the obesity rate against how many recreation/fitness facilities a county has per 1000 people to give us an idea about how facility access can affect obesity rates.

```
In [20]: rec_mean = df['RECREATION_FITNESS_FACIL_PER1000_2014'].mean(axis=0)
         rec_median = df['RECREATION_FITNESS_FACIL_PER1000_2014'].median(axis=0)
         rec_min = df['RECREATION_FITNESS_FACIL_PER1000_2014'].min()
         rec_max = df['RECREATION_FITNESS_FACIL_PER1000_2014'].max()

         print("Rec/Fitness Facilities Per 1000 People --- Avg:", rec_mean, "Median:", rec_medi
```

```
Rec/Fitness Facilities Per 1000 People --- Avg: 0.06885208660012736 Median: 0.0610165 Min: 0.0
```

6.1.1 OLS Regression

```
In [21]: outcome, predictors = patsy.dmatrices('ADULT_OBESITY_RATE_2013 ~ RECREATION_FITNESS_F
         mod = sm.OLS(outcome, predictors)
         res = mod.fit()
         print(res.summary())
```

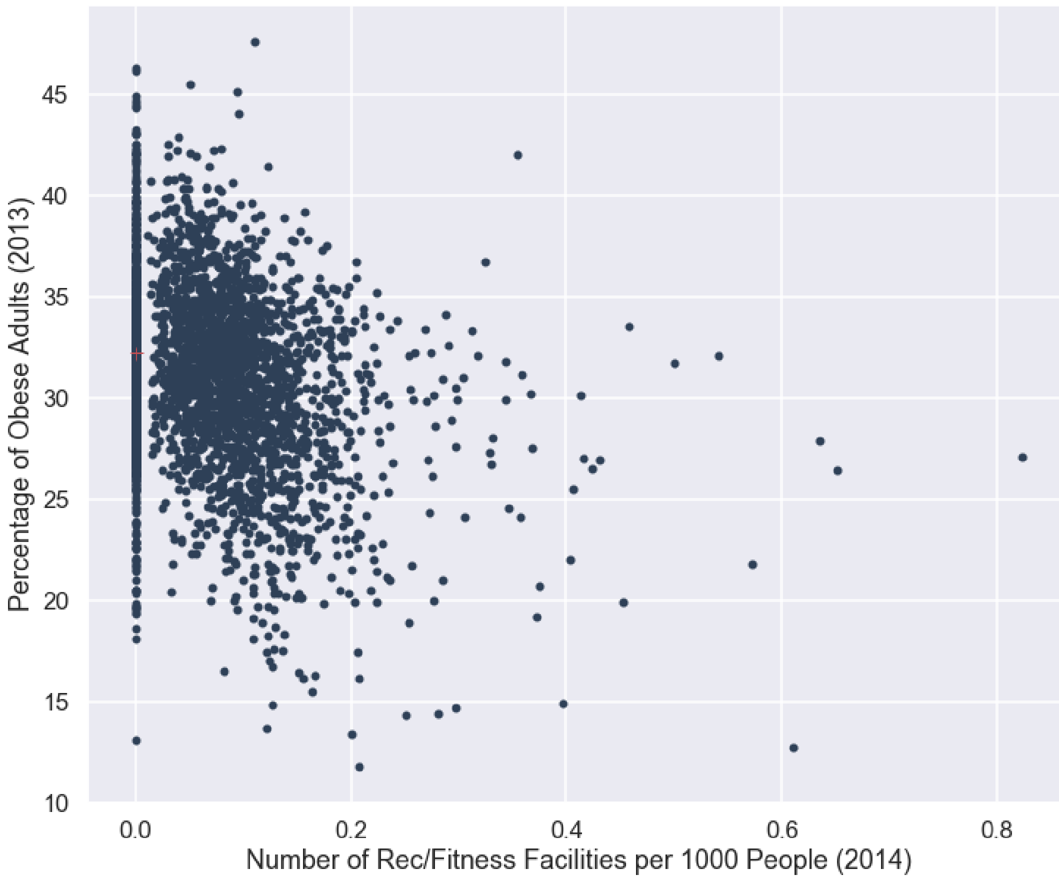
```
                            OLS Regression Results
===============================================================================
Dep. Variable:     ADULT_OBESITY_RATE_2013   R-squared:                  0.075
Model:                                 OLS   Adj. R-squared:             0.074
Method:                      Least Squares   F-statistic:                252.9
Date:                     Sun, 09 Jun 2019   Prob (F-statistic):      8.04e-55
Time:                             22:18:13   Log-Likelihood:          -9069.7
No. Observations:                     3140   AIC:                   1.814e+04
Df Residuals:                         3138   BIC:                   1.816e+04
Df Model:                                1
Covariance Type:                 nonrobust
==================================================================================
                                            coef    std err          t      P>|t|      [0.025
```

```
------------------------------------------------------------------------------------------
Intercept                                 32.1909      0.107    300.044      0.000      31.981
RECREATION_FITNESS_FACIL_PER1000_2014   -17.1050      1.076    -15.902      0.000     -19.214
==============================================================================
Omnibus:                       51.524   Durbin-Watson:                   1.038
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               72.163
Skew:                          -0.195   Prob(JB):                     2.14e-16
Kurtosis:                       3.632   Cond. No.                         13.9
==============================================================================

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

6.1.2 Scatter Plot & Regression Line

In [22]:
```python
df.plot.scatter(x='RECREATION_FITNESS_FACIL_PER1000_2014', y='ADULT_OBESITY_RATE_2013

# Plot model fit line
xs = np.arange(df['RECREATION_FITNESS_FACIL_PER1000_2014'].min(), df['RECREATION_FITNE
ys = 32.1909 - 17.105 * xs
plt.plot(xs, ys, 'r+', linewidth=10, label='Model')

plt.xlabel('Number of Rec/Fitness Facilities per 1000 People (2014)\n')
plt.ylabel('\nPercentage of Obese Adults (2013)')
```

Out[22]:
```
Text(0, 0.5, '\nPercentage of Obese Adults (2013)')
```



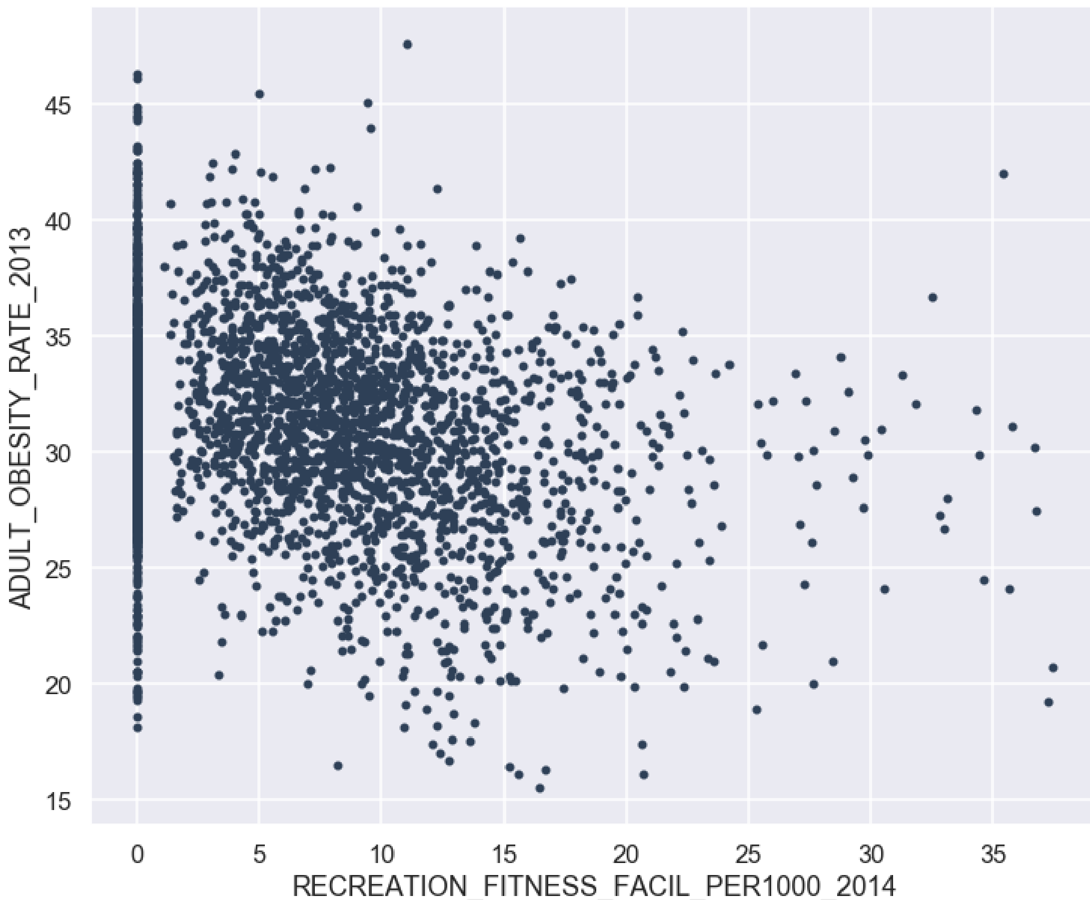
Refining the graph The above plot shows number of recreation facilities against the perecentage of obsese adults. We noticed that the points beyond 0.4 of the x-axis are rather sparse. The points beyond 0.4 number of rec/fitness facilities per 1000 people were removed to refine the graph.

```
In [23]: def standardize_percentage(number):
             return (number * 100);
```

```
In [24]: #threshold at 0.4 since most of the data points fall behind that point
         df2 = df[df['RECREATION_FITNESS_FACIL_PER1000_2014'] <= 0.4]

         #multiply x by 100 to make # of facilities per 100 so both axes are in %
         df2['RECREATION_FITNESS_FACIL_PER1000_2014'] = df2['RECREATION_FITNESS_FACIL_PER1000_

         #remove 0
         df2 = df2.dropna(axis=0, how='any', subset=['RECREATION_FITNESS_FACIL_PER1000_2014',

         #for y > 15 since most data points fall after that point
         df2 = df2[df2['ADULT_OBESITY_RATE_2013'] > 15]
```

```
#doesn't make sense to do log transform since we are working with percentages
#plot data
df2.plot.scatter(x='RECREATION_FITNESS_FACIL_PER1000_2014', y='ADULT_OBESITY_RATE_2013
```

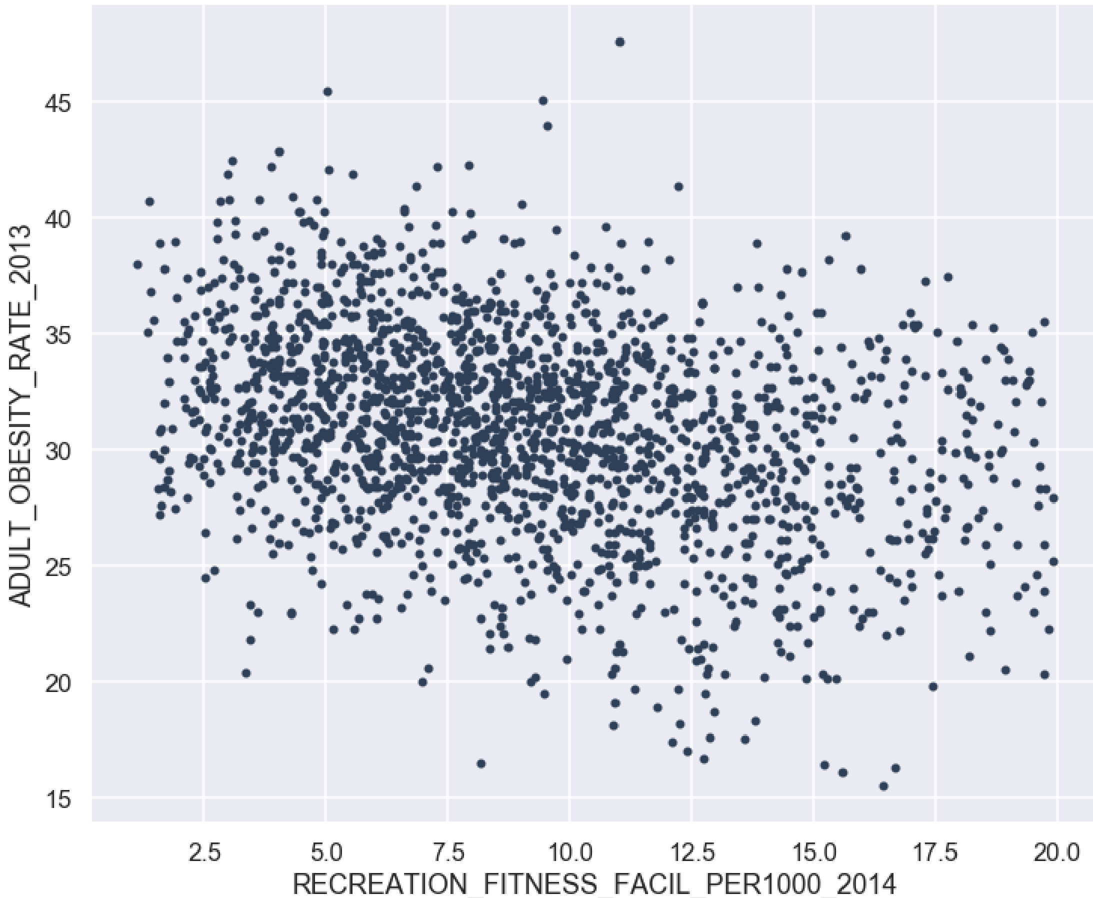
Out[24]: <matplotlib.axes._subplots.AxesSubplot at 0x130541710>



Refining the graph further

```
In [25]: #threshold at 20 since most of the data points fall behind that point
df2 = df2[df2['RECREATION_FITNESS_FACIL_PER1000_2014'] <= 20]
#remove 0
df2 = df2[df2['RECREATION_FITNESS_FACIL_PER1000_2014'] >= 0.1]

df2.plot.scatter(x='RECREATION_FITNESS_FACIL_PER1000_2014', y='ADULT_OBESITY_RATE_2013
```

Out[25]: <matplotlib.axes._subplots.AxesSubplot at 0x1222ccda0>

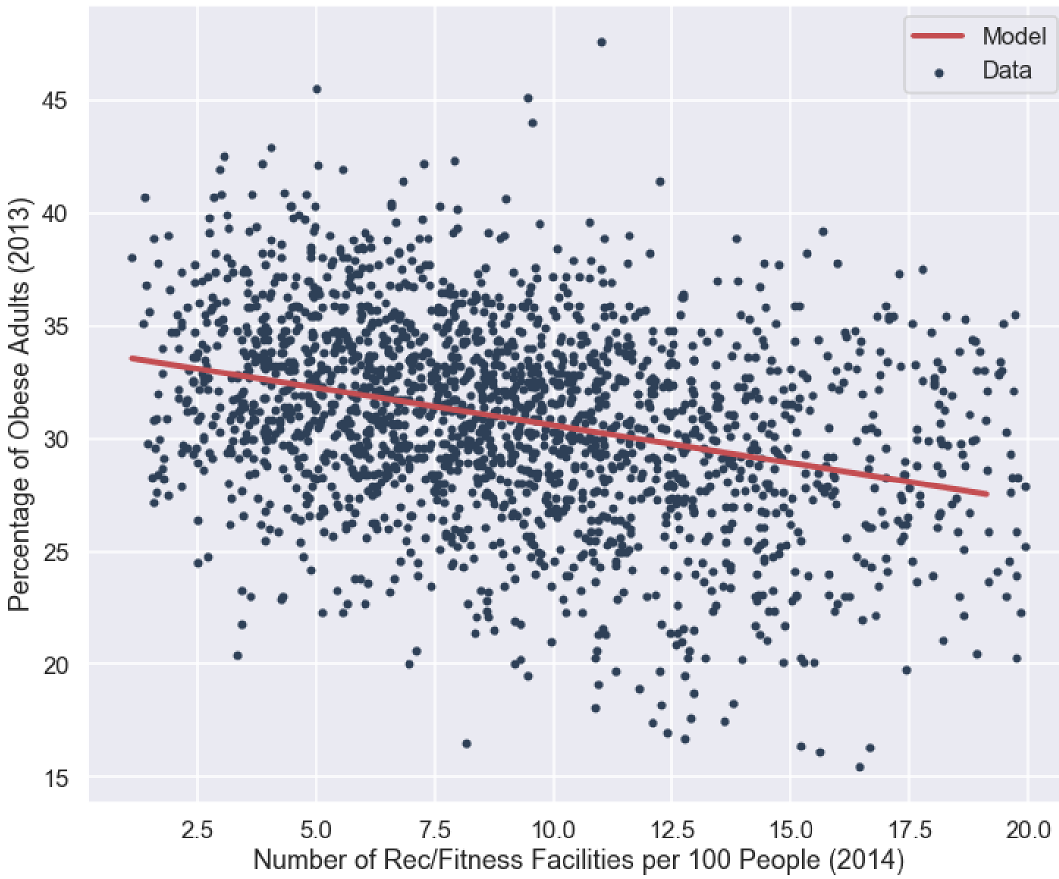



```
In [26]: #OLS regression with cleaned data
         outcome2, predictors2 = patsy.dmatrices('ADULT_OBESITY_RATE_2013 ~ RECREATION_FITNESS_
         mod2 = sm.OLS(outcome2, predictors2)
         res2 = mod2.fit()
         print(res2.summary())
```

```
                            OLS Regression Results
==================================================================================
Dep. Variable:     ADULT_OBESITY_RATE_2013   R-squared:                       0.103
Model:                                 OLS   Adj. R-squared:                  0.103
Method:                      Least Squares   F-statistic:                     230.8
Date:                     Sun, 09 Jun 2019   Prob (F-statistic):           2.01e-49
Time:                             22:18:15   Log-Likelihood:                -5694.1
No. Observations:                     2007   AIC:                         1.139e+04
Df Residuals:                         2005   BIC:                         1.140e+04
Df Model:                                1
Covariance Type:                 nonrobust
===================================================================================================
                                            coef    std err          t      P>|t|      [0.025
```

```
--------------------------------------------------------------------------------------------
Intercept                                    33.9236      0.219    154.635      0.000      33.493
RECREATION_FITNESS_FACIL_PER1000_2014        -0.3338      0.022    -15.192      0.000      -0.377
==============================================================================
Omnibus:                       17.039   Durbin-Watson:                   1.166
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               18.852
Skew:                          -0.173   Prob(JB):                     8.06e-05
Kurtosis:                       3.325   Cond. No.                         23.9
==============================================================================

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

In [27]:
```python
## Plot the model fit line

# Plot the orginal data (as before)
df2.plot.scatter(x='RECREATION_FITNESS_FACIL_PER1000_2014', y='ADULT_OBESITY_RATE_201

# Generate and plot the model fit line
xs2 = np.arange(df2['RECREATION_FITNESS_FACIL_PER1000_2014'].min(), df2['RECREATION_F
ys2 = -0.3338 * xs2 + 33.9236
plt.plot(xs2, ys2, '--k', linewidth=4, label='Model', color='r', linestyle='-')

plt.xlabel('Number of Rec/Fitness Facilities per 100 People (2014)\n')
plt.ylabel('\nPercentage of Obese Adults (2013)')
plt.legend();
```



After we refined the graph, we plotted the regression line. We have used the "Number of Recreation/Fitness Facilities per 100 People' to represent the density of gyms within a population. The P-value for acess to fitness facilities is 0.0, which is enough evidence to refute the null hypothesis with a threshold of 0.05, meaning that there is a significant correlation between obesity levels and access to fitness facilities. The coefficient of -0.3338 ś 0.002 shows a negative correlation between access to gym facilites and obesity levels. Our regression model accounts for 10.3% of the the variance in our data.

6.2 Obesity Rate vs. Grocery Stores Per 1000 People

Here, we plot the obesity rate against how many groceries store a county has per 1000 people to give us an idea about how grocery store access can affect obesity rates.

```
In [28]: groc_mean = df['GROC_STORES_PER1000_2014'].mean(axis=0)
         groc_median = df['GROC_STORES_PER1000_2014'].median(axis=0)
         groc_min = df['GROC_STORES_PER1000_2014'].min()
         groc_max = df['GROC_STORES_PER1000_2014'].max()

         print("Grocery Stores Per 1000 People --- Avg:", groc_mean, "Median:", groc_median, "I
```

```
Grocery Stores Per 1000 People --- Avg: 0.2514458976150908 Median: 0.194454167 Min: 0.0 Max 3.
```

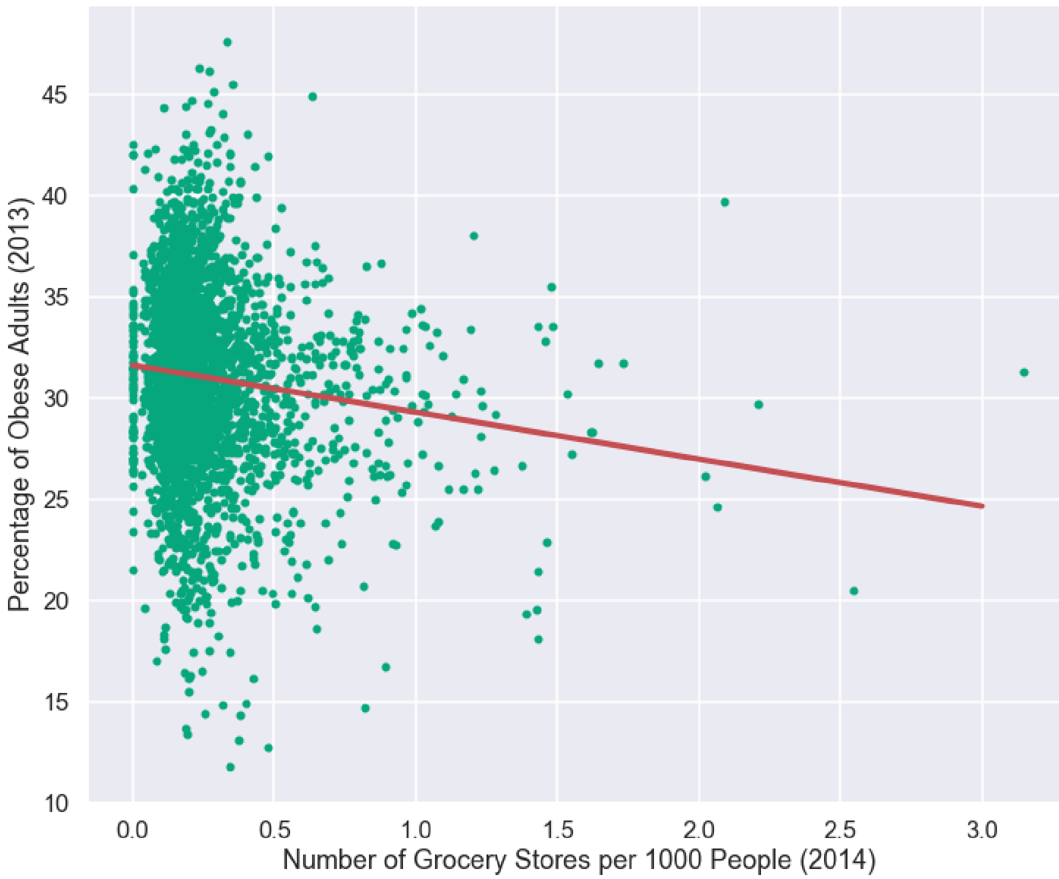
6.2.1 OLS Regression

```
In [29]: outcome, predictors = patsy.dmatrices('ADULT_OBESITY_RATE_2013 ~ GROC_STORES_PER1000_2
         mod = sm.OLS(outcome, predictors)
         res = mod.fit()
         print(res.summary())
```

```
                            OLS Regression Results
===================================================================================
Dep. Variable:     ADULT_OBESITY_RATE_2013   R-squared:                       0.013
Model:                                 OLS   Adj. R-squared:                  0.012
Method:                      Least Squares   F-statistic:                     40.28
Date:                     Sun, 09 Jun 2019   Prob (F-statistic):           2.51e-10
Time:                             22:18:15   Log-Likelihood:                -9171.4
No. Observations:                     3140   AIC:                         1.835e+04
Df Residuals:                         3138   BIC:                         1.836e+04
Df Model:                                1
Covariance Type:                 nonrobust
============================================================================================
                              coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------------------
Intercept                  31.5963      0.122    259.043      0.000      31.357      31.835
GROC_STORES_PER1000_2014   -2.3200      0.366     -6.347      0.000      -3.037      -1.603
==============================================================================
Omnibus:                       91.626   Durbin-Watson:                   1.019
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              145.122
Skew:                          -0.273   Prob(JB):                     3.07e-32
Kurtosis:                       3.901   Cond. No.                         4.86
==============================================================================

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

6.2.2 Scatter Plot & Regression Line

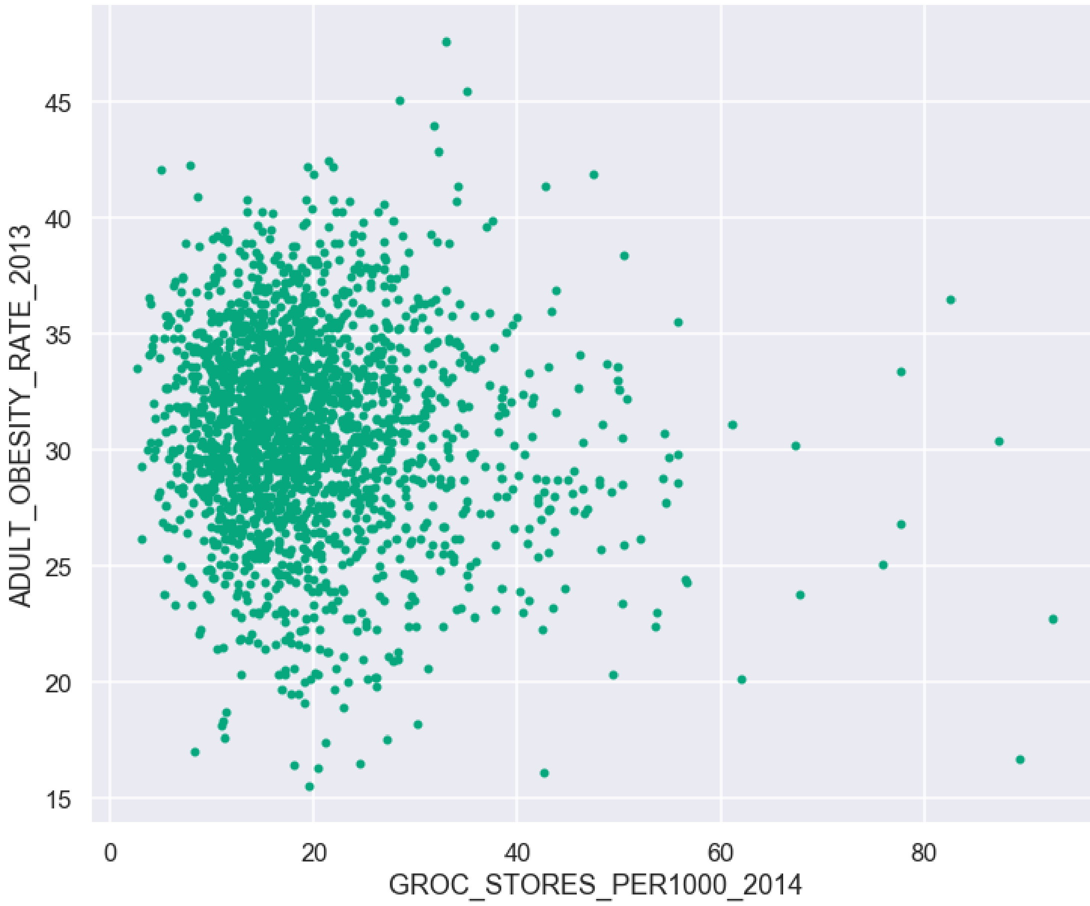
```
In [30]: df.plot.scatter(x='GROC_STORES_PER1000_2014', y='ADULT_OBESITY_RATE_2013', c='#06A77D

         # Plot model fit line
         xs = np.arange(df['GROC_STORES_PER1000_2014'].min(), df['GROC_STORES_PER1000_2014'].ma
         ys =  31.5963 - 2.32 * xs
         plt.plot(xs, ys, 'r', linewidth=4, label='Model')

         plt.xlabel('Number of Grocery Stores per 1000 People (2014)\n')
         plt.ylabel('\nPercentage of Obese Adults (2013)')
         plt.show()
```



6.2.3 Refining the graph

We preformed a similar procedure as the previous graph to remove outliers. We removed data-points beyond the 1.0 threshold on the x-axis.

```
In [31]: #threshold at 1.0 since most of the data points fall behind that point
         df2 = df2[df2['GROC_STORES_PER1000_2014'] <= 1.0]

         #multiply x by 100 to make # of facilities per 100 so both axes are in %
         df2['GROC_STORES_PER1000_2014'] = df2['GROC_STORES_PER1000_2014'].apply(standardize_pe

         #remove 0
         df2 = df2[df2['GROC_STORES_PER1000_2014'] >= 0.01]

         df2.plot.scatter(x='GROC_STORES_PER1000_2014', y='ADULT_OBESITY_RATE_2013', c='#06A77D

Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x12e2e6f60>
```



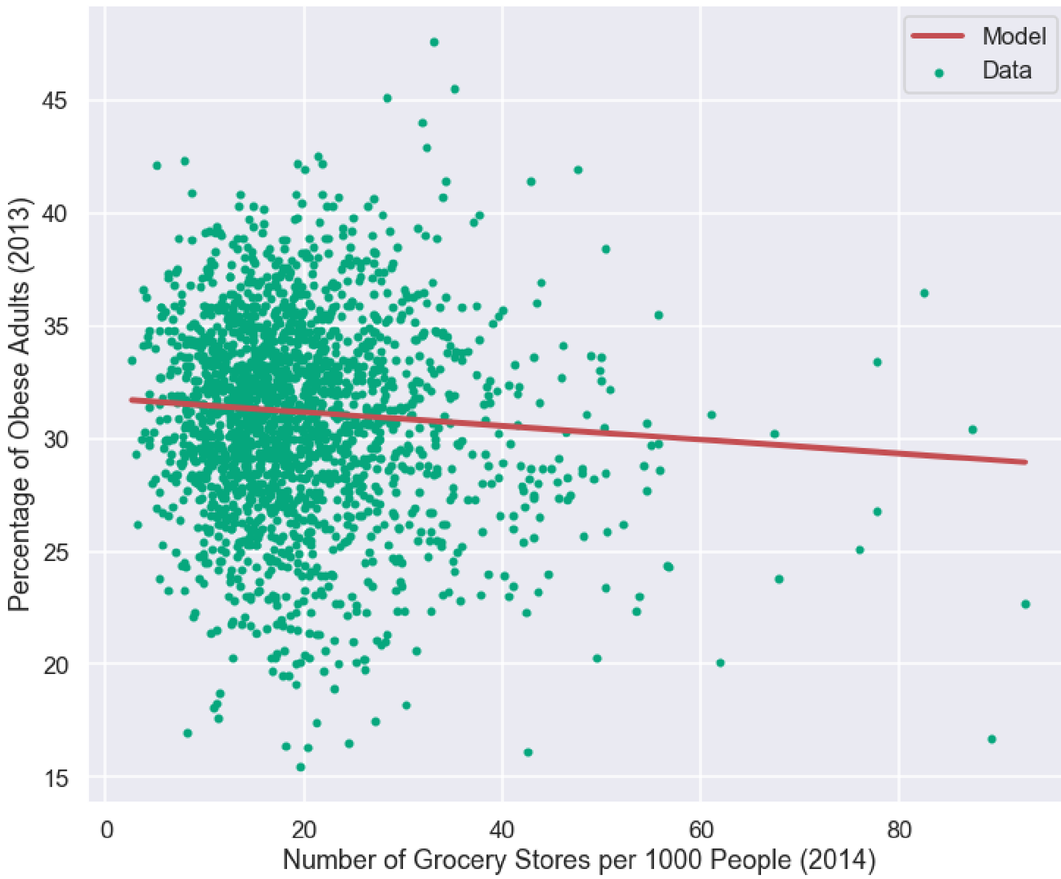
In [32]:
```
outcome2, predictors2 = patsy.dmatrices('ADULT_OBESITY_RATE_2013 ~ GROC_STORES_PER1000
mod2 = sm.OLS(outcome2, predictors2)
res2 = mod2.fit()
print(res2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:     ADULT_OBESITY_RATE_2013   R-squared:                       0.007
Model:                                 OLS   Adj. R-squared:                  0.006
Method:                      Least Squares   F-statistic:                     13.62
Date:                     Sun, 09 Jun 2019   Prob (F-statistic):           0.000229
Time:                             22:18:16   Log-Likelihood:                -5786.5
No. Observations:                     2003   AIC:                         1.158e+04
Df Residuals:                         2001   BIC:                         1.159e+04
Df Model:                                1
Covariance Type:                 nonrobust
===========================================================================================
                              coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------------
```

```
Intercept                    31.6136      0.216    146.561      0.000      31.191      32.037
GROC_STORES_PER1000_2014    -0.0363      0.010     -3.691      0.000      -0.056      -0.017
==============================================================================
Omnibus:                       26.090   Durbin-Watson:                   1.156
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               30.530
Skew:                          -0.212   Prob(JB):                     2.35e-07
Kurtosis:                       3.432   Cond. No.                         48.7
==============================================================================

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

```
In [33]: df2.plot.scatter(x='GROC_STORES_PER1000_2014', y='ADULT_OBESITY_RATE_2013', c='#06A77I

         # Plot model fit line
         xs2 = np.arange(df2['GROC_STORES_PER1000_2014'].min(), df2['GROC_STORES_PER1000_2014']
         ys2 =  31.7806 - 0.0305 * xs2
         plt.plot(xs2, ys2, '--k', linewidth=4, label='Model', color='r', linestyle='-')

         plt.xlabel('Number of Grocery Stores per 1000 People (2014)\n')
         plt.ylabel('\nPercentage of Obese Adults (2013)')
         plt.legend()
```

```
Out[33]: <matplotlib.legend.Legend at 0x12bec6b38>
```



We have used the variable "Number of Grocery Stores per 100 People' to represent the density of grocery stores within a population. The P-value for acess to grocery stores is 0.0, which is enough evidence to refute the null hypothesis with a threshold of 0.05, meaning that there is a significant correlation between obesity levels and access to grocery stores. The coefficient of -0.0363 ś 0.010 shows a negative correlation between access to gym facilites and obesity levels. Our regression model accounts for 0.7% of the the variance in our data.

Using OLS Regression to Analyze Recreations Fitness Facilities and Grocery Stores

```
In [34]: outcome, predictors = patsy.dmatrices('ADULT_OBESITY_RATE_2013 ~ RECREATION_FITNESS_F
         mod = sm.OLS(outcome, predictors)
         res = mod.fit()
         print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:     ADULT_OBESITY_RATE_2013   R-squared:                       0.094
Model:                                 OLS   Adj. R-squared:                  0.094
Method:                      Least Squares   F-statistic:                     163.6
```

```
Date:                    Sun, 09 Jun 2019   Prob (F-statistic):           2.71e-68
Time:                            22:18:17   Log-Likelihood:                -9035.7
No. Observations:                    3140   AIC:                         1.808e+04
Df Residuals:                        3137   BIC:                         1.810e+04
Df Model:                               2
Covariance Type:            nonrobust
==============================================================================================
                                          coef    std err          t      P>|t|      [0.025
----------------------------------------------------------------------------------------------
Intercept                              32.9868      0.143    230.523      0.000      32.706
RECREATION_FITNESS_FACIL_PER1000_2014 -18.0017      1.070    -16.829      0.000     -20.099
GROC_STORES_PER1000_2014               -2.9186      0.352     -8.293      0.000      -3.609
==============================================================================
Omnibus:                       44.520   Durbin-Watson:                   1.059
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               65.804
Skew:                          -0.152   Prob(JB):                     5.14e-15
Kurtosis:                       3.641   Cond. No.                         14.5
==============================================================================

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

A multiple linear regression will give us a better represenation of the relative influence of these two factors on obesity levels. Both fitness facility density and grocery store density show a P-score of 0.0, which is enough to refute the null hypothesis and prove a significant correlation between obesity and these two factors. The coefficient score of fitness facility accessibility is -18.0017 ś 1.070, which means that the correlation between fitness facility density and obesity is negative. Similarly, there is a negative correlation for grocery store accessibility with a coefficient score of -2.9186 ś 0.352. Comparing the two coefficient scores reveals that accessibility to fitness facilites has a much greater influence on obesity levels.

6.3 Obesity Rate vs. Percentage with 'HS Diploma' and 'Less than a HS Diploma'

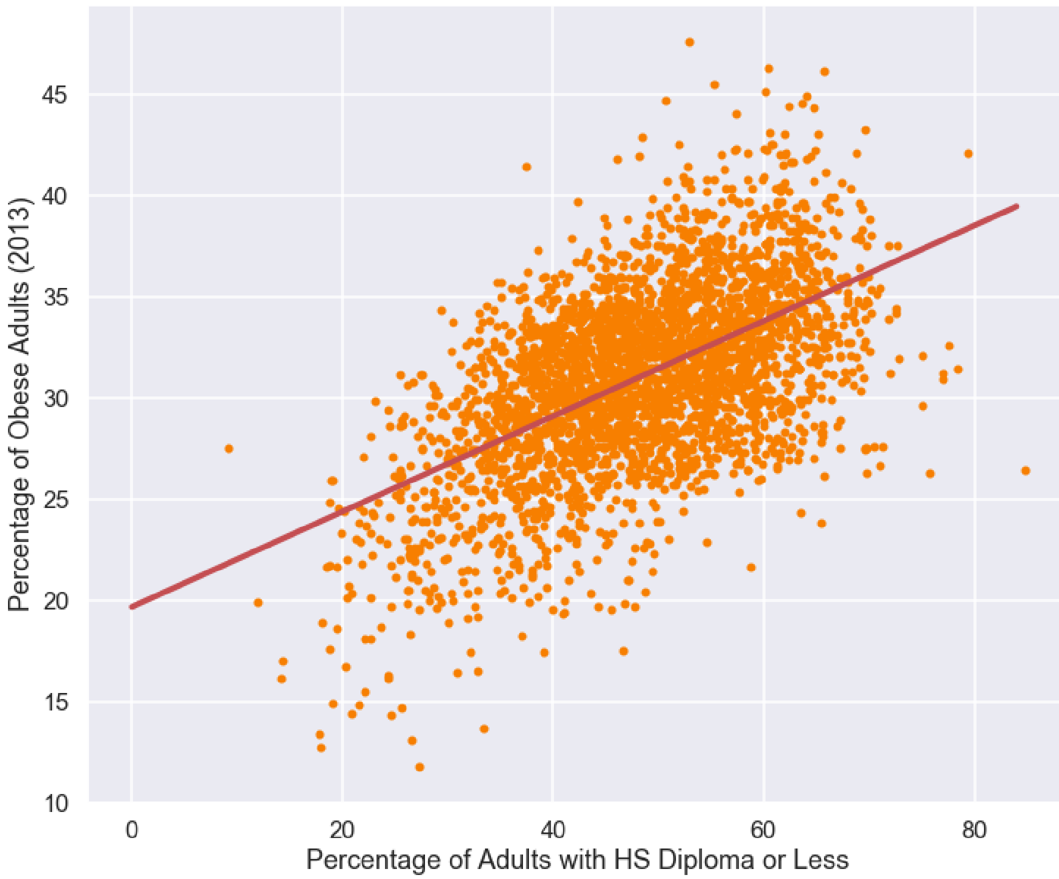
Here, we plot the obesity rate against the percentage of adults in a county that have a high school diploma or less. This is to give us an idea how a population's education level might affect obesity rates.

```
In [35]: # OLS Regression for at least having some college
         outcome, predictors = patsy.dmatrices('ADULT_OBESITY_RATE_2013 ~ HIGH_SCHOOL', df)
         mod = sm.OLS(outcome, predictors)
         res = mod.fit()
         print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:     ADULT_OBESITY_RATE_2013   R-squared:                       0.310
Model:                                 OLS   Adj. R-squared:                  0.310
Method:                      Least Squares   F-statistic:                     1410.
```

```
Date:                    Sun, 09 Jun 2019   Prob (F-statistic):          4.04e-255
Time:                            22:18:17   Log-Likelihood:                -8608.9
No. Observations:                    3140   AIC:                         1.722e+04
Df Residuals:                        3138   BIC:                         1.723e+04
Df Model:                               1
Covariance Type:                nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
Intercept      19.6562      0.310     63.443      0.000      19.049      20.264
HIGH_SCHOOL     0.2355      0.006     37.544      0.000       0.223       0.248
==============================================================================
Omnibus:                       20.700   Durbin-Watson:                   1.145
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               23.803
Skew:                          -0.137   Prob(JB):                     6.78e-06
Kurtosis:                       3.327   Cond. No.                         228.
==============================================================================

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

```
In [36]: df.plot.scatter(x='HIGH_SCHOOL', y='ADULT_OBESITY_RATE_2013', c='#F77F00', figsize=(1

         # Plot model fit line
         xs = np.arange(df['HIGH_SCHOOL'].min(), df['HIGH_SCHOOL'].max())
         ys =  19.6562 + 0.2355 * xs
         plt.plot(xs, ys, 'r', linewidth=4, label='Model')

         plt.xlabel('Percentage of Adults with HS Diploma or Less\n')
         plt.ylabel('\nPercentage of Obese Adults (2013)')
         plt.show()
```



To assess the correlation of education level with obesity, we divided education levels into two distinct categories: (1) Adults with a high school diploma or less and (2) Adults with some college or a Bachelor's degree. From this we obtained the school completion rates of adults by county, allowing us to run a regression analysis and determine the extent to which education and obesity are correlated.

The P-value for Percentage of adults with HS diploma or less is is 0.0, which is enough evidence to refute the null hypothesis with a threshold of 0.05. The coefficient of 0.2355 ś 0.006 shows a positive correlation between the percentage of adults with high school and obesity levels. Our regression model accounts for 31% of the the variance in our data.

Unlike our other graphs, this regression shows a positive correlation because this category includes only adults who completed high school or less. Therefore, it is very likely that adults who do not fit under this category have higher educational attainments. A lower population density for "Percentage of Adults with HS diploma or less" most likely includes adults with higher education, which is why their obesity rates are lower. As we move along the x-axis, we see a higher population density for adults who ONLY completed high school or less, which is why their obesity rates are higher and why we see a positive correlation.

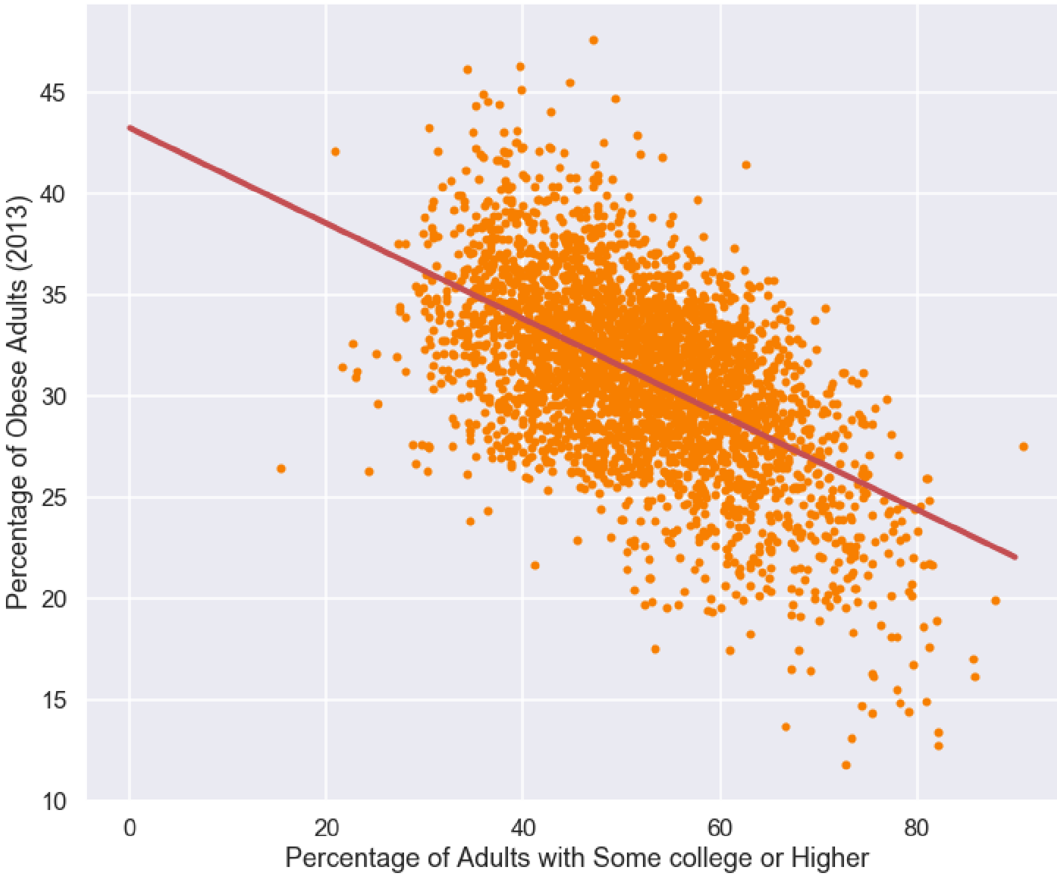
6.4 Obesity Rate vs. Percentage with 'Some College' and 'Bachelor's Degree or Higher'

Here, we plot the obesity rate against the percentage of adults in a county that have some college, an associate's, a bachelor's or higher. This is to give us an idea how a population's education level might affect obesity rates.

In [37]:
```
# OLS Regression for at least having some college
outcome, predictors = patsy.dmatrices('ADULT_OBESITY_RATE_2013 ~ COLLEGE', df)
mod = sm.OLS(outcome, predictors)
res = mod.fit()
print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:     ADULT_OBESITY_RATE_2013   R-squared:                       0.310
Model:                                 OLS   Adj. R-squared:                  0.310
Method:                      Least Squares   F-statistic:                     1409.
Date:                     Sun, 09 Jun 2019   Prob (F-statistic):         4.70e-255
Time:                             22:18:17   Log-Likelihood:                -8609.1
No. Observations:                     3140   AIC:                         1.722e+04
Df Residuals:                         3138   BIC:                         1.723e+04
Df Model:                                1
Covariance Type:                 nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     43.2093      0.332    130.246      0.000      42.559      43.860
COLLEGE       -0.2355      0.006    -37.538      0.000      -0.248      -0.223
==============================================================================
Omnibus:                       20.782   Durbin-Watson:                   1.144
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               23.895
Skew:                          -0.138   Prob(JB):                     6.47e-06
Kurtosis:                       3.327   Cond. No.                         262.
==============================================================================

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

In [38]:
```
df.plot.scatter(x='COLLEGE', y='ADULT_OBESITY_RATE_2013', c='#F77F00', figsize=(12,10)

# Plot model fit line
xs = np.arange(df['COLLEGE'].min(), df['COLLEGE'].max())
ys =  43.2093 - 0.2355 * xs
plt.plot(xs, ys, 'r', linewidth=4, label='Model')

plt.xlabel('Percentage of Adults with Some college or Higher\n')
plt.ylabel('\nPercentage of Obese Adults (2013)')
plt.show()
```



The P-value for Percentage of adults with some college or higher is 0.0, which is enough evidence to refute the null hypothesis with a threshold of 0.05, meaning that there is a significant correlation between obesity levels and education levels. The coefficient of -0.2355 ś 0.006 shows a negative correlation between adults with some college or higher and obesity levels. Our regression model accounts for 31% of the the variance in our data. This is in accordance with our hypothesis that lower education levels are correlated with higher obesity rates.

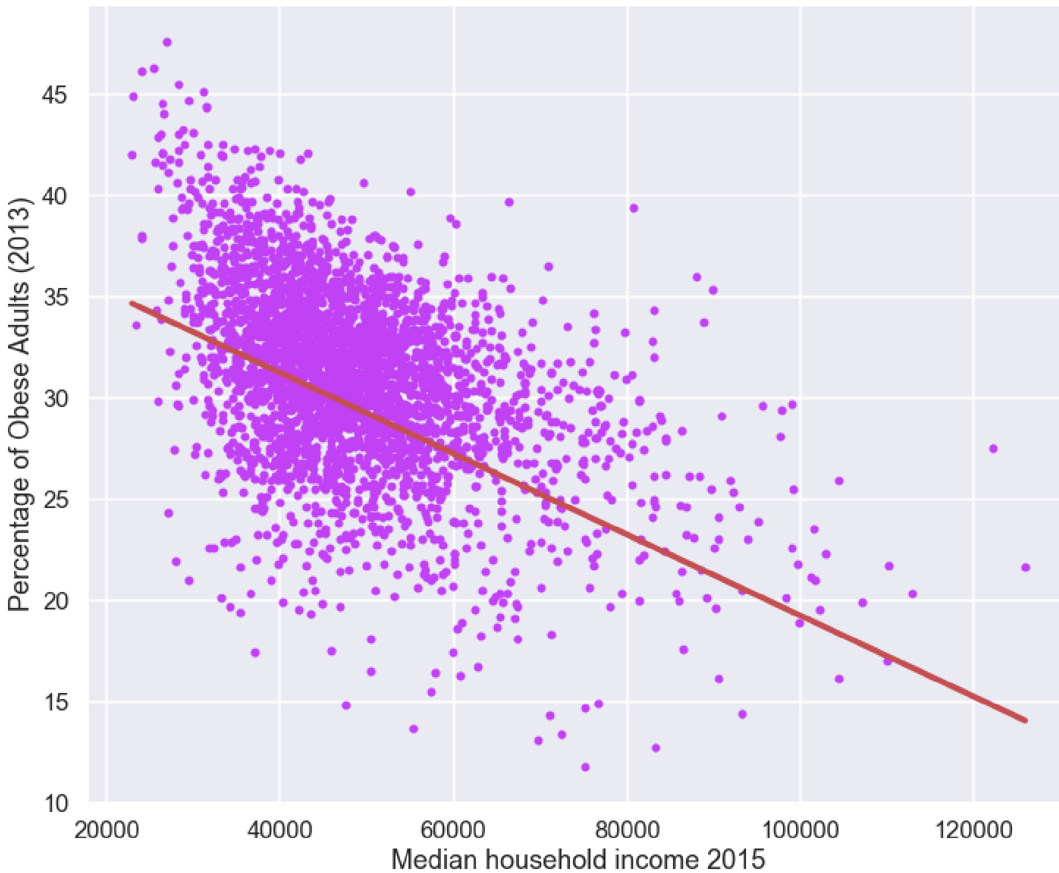
6.5 Obesity Rate vs. Median Household Income 2015

In [39]:
```
# OLS Regression for Median Household Income

outcome, predictors = patsy.dmatrices('ADULT_OBESITY_RATE_2013 ~ Median_household_inco
mod = sm.OLS(outcome, predictors)
res = mod.fit()
print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:     ADULT_OBESITY_RATE_2013   R-squared:                       0.213
```

```
Model:                            OLS   Adj. R-squared:                  0.213
Method:                 Least Squares   F-statistic:                     851.1
Date:                Sun, 09 Jun 2019   Prob (F-statistic):          9.35e-166
Time:                        22:18:18   Log-Likelihood:                -8810.0
No. Observations:                3139   AIC:                         1.762e+04
Df Residuals:                    3137   BIC:                         1.764e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================================
                                 coef    std err          t      P>|t|      [0.025      0.975
----------------------------------------------------------------------------------------------
Intercept                     39.2282      0.290    135.064      0.000      38.659      39.79
Median_household_income_2015  -0.0002   5.79e-06    -29.174      0.000      -0.000      -0.00
==============================================================================
Omnibus:                      116.197   Durbin-Watson:                   1.137
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              146.996
Skew:                          -0.407   Prob(JB):                     1.20e-32
Kurtosis:                       3.680   Cond. No.                     2.04e+05
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.04e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

```
In [40]: df.plot.scatter(x='Median_household_income_2015', y='ADULT_OBESITY_RATE_2013', c='#c1

         # Plot model fit line
         xs = np.arange(df['Median_household_income_2015'].min(), df['Median_household_income_
         ys =  39.2282 -0.0002 * xs
         plt.plot(xs, ys, 'r', linewidth=4, label='Model')

         plt.xlabel('Median household income 2015\n')
         plt.ylabel('\nPercentage of Obese Adults (2013)')
         plt.show()
```



Originally planned to omit income as an independent variable in order to focus on non-traditional factors that affect obesity. However, we found that income was a confounding variable affecting population distribution and location and consequently, access to gyms and grocery stores. We decided to account for this by assessing the impact of income levels on obesity and comparing this to our other variables. Our regression analysis in fact shows a strong correlation between median household income and obesity rates with a P value of 0.0

The P-value for median household income is 0.0, which is enough evidence to refute the null hypothesis with a threshold of 0.05, meaning that there is a significant correlation between obesity and income levels. The coefficient -0.0002 shows a negative correlation between income and obesity levels, indicating that low income populations typically show higher obesity rates. Our regression model accounts for 21.3% of the variance in our data.

6.6 Geospatial Maps

To give us a more visual representation of this data and find potential correlations between areas, below are each of the variables plotted on a map of the USA.