overdose_death_and_acs_data_prep_for_modeling

September 23, 2019

1 Notebook Goals:

- Normalize death count data to town population (turn raw counts into deaths per 10k residents values)
- Pull out some ACS demographics data - correlation with death data?
- EDA on ACS demographics data, some feature engineering on poverty, population, and other demographics data

2 Output:

- /data/tidy_data/death_count_norm_to_pop_and_acs_town_demographics_merge.csv

[1]:

```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
sns.set_style('darkgrid')
sns.set(font_scale=1.5)
```

[2]:

```
death_data = pd.read_csv("../../data/tidy_data/
 ↪ma_town_opioid_overdose_death_by_place_of_death_2012_to_2018_merge.csv")
town_block_match = pd.read_csv("../../data/tidy_data/census_block_town_match.
 ↪csv")
acs_17 = pd.read_csv("../../data/raw_data/R12288202_SL150.csv")
```

[3]:

```
death_data.head()
```

[3]:

```
  city_death  2012  2013  2014  2015  2016  2017  2018
0   abington     1     2     0     6     1     3     5
1      acton     2     0     1     2     3     0     1
2   acushnet     2     0     0     4     2     4     0
3      adams     1     1     2     3     1     0     4
4     agawam     1     3     1     2     0     4     8
```

[4]:

```
display(town_block_match.head())
# remove extra column
town_block_match.drop('Unnamed: 0', axis=1, inplace=True)
```

```
   Unnamed: 0       TOWN  POP2010    SHAPE_Area       GEOID10    SHAPE_AREA  \
0           0  wellesley    27982  2.726958e+07  2.502140e+11  6.424854e+05
1           0  wellesley    27982  2.726958e+07  2.502140e+11  1.167837e+06
2           0  wellesley    27982  2.726958e+07  2.502140e+11  1.182595e+06
3           0  wellesley    27982  2.726958e+07  2.502140e+11  1.079832e+06
4           0  wellesley    27982  2.726958e+07  2.502140e+11  5.306549e+05

   POP100_RE
0      935.0
1      989.0
2      968.0
3     1145.0
4      664.0
```

[5]:

```
# town mismatch between death count data and the town-census block
print(set(death_data['city_death']) - set(town_block_match['TOWN']))
print(set(town_block_match['TOWN']) - set(death_data['city_death']))
death_data['city_death'] = death_data['city_death'].str.replace('north␣
 ↪attleboro', 'north attleborough')
```

```
{'north attleboro'}
{'north attleborough'}
```

[6]:

```
# grab relevant columns from match file
town_block = town_block_match[['TOWN', 'POP2010', 'SHAPE_Area', 'GEOID10']].
 ↪copy()
```

[7]:

```
print(acs_17.shape)
acs_17.columns
```

```
(4985, 2200)
```

[7]:

```
Index(['Geo_FIPS', 'Geo_GEOID', 'Geo_NAME', 'Geo_QName', 'Geo_STUSAB',
       'Geo_SUMLEV', 'Geo_GEOCOMP', 'Geo_FILEID', 'Geo_LOGRECNO', 'Geo_US',
       ...
       'SE_A10065_001', 'SE_A10065_002', 'SE_A10066_001', 'SE_A10066_002',
       'SE_A10066_003', 'SE_A10066_004', 'SE_A10066_005', 'SE_A10066_006',
       'SE_A10066_007', 'SE_A10066_008'],
      dtype='object', length=2200)
```

[8]:

```
# which columns to match on?
acs_17[['Geo_FIPS', 'Geo_GEOID']].head()
# Geo_FIPS is match for GEOID10 from town - block match df
```

[8]:

```
       Geo_FIPS             Geo_GEOID
0  250010101001  15000US250010101001
1  250010101002  15000US250010101002
```

```
2  250010101003  15000US250010101003
3  250010101004  15000US250010101004
4  250010101005  15000US250010101005
```

[9]:

```
# mismatches between sets?
print(len(set(acs_17['Geo_FIPS']) - set(town_block['GEOID10'])))
print(len(set(town_block['GEOID10']) - set(acs_17['Geo_FIPS'])))
```

```
31
4
```

2.0.1 Potentially interesting columns to pull from ACS:

- A00002_001: Total Population
- A00002_002: Population Density (Per Sq. Mile)
- A12003_001: Civilian Population 16 to 19 Years:
- A12003_002: Not High School Graduate, Not Enrolled (Dropped Out)
- A12003_003: High School Graduate, or Enrolled (In School)
- A12002_001: Population 25 Years and Over:
- A12002_002: Less than High School
- A14006_001: Median Household Income (In 2017 Inflation Adjusted Dollars)
- A14008_001: Average Household Income
- NA- all missing - A14028_001: Gini Index
- NA - all missing - A17004_001: Total Employed Civilian Population 16 Years and Over
- NA - all missing - A17004_002: Employed Civilian Population 16 Years and Over: Agriculture, Forestry, Fishing and Hunting, and Mining
- NA - all missing - A17004_003: Employed Civilian Population 16 Years and Over: Construction
- A01001_011: 65 to 74 Years
- A01001_012: 75 to 84 Years
- A01001_013: 85 Years and Over
- NA- all missing - A13003A_001: Population Under 18 Years of Age for Whom Poverty Status Is Determined:
  - NA- all missing - A13003A_002: Living in Poverty
  - NA- all missing - A13003A_003: At or Above Poverty Level
- NA- all missing -A13003B_001: Population Age 18 to 64 for Whom Poverty Status Is Determined:
  - NA- all missing - A13003B_002: Living in Poverty
  - NA- all missing - A13003B_003: At or Above Poverty Level
- NA- all missing -A13003C_001: Population Age 65 and Over for Whom Poverty Status Is Determined:
  - NA- all missing -A13003C_002: Living in Poverty
  - NA- all missing -A13003C_003: At or Above Poverty Level
- B13004_001: Population for Whom Poverty Status Is Determined:

  - B13004_002: Population for Whom Poverty Status Is Determined: Under 1.00 (Doing Poorly)
  - B13004_003: Population for Whom Poverty Status Is Determined: 1.00 to 1.99 (Struggling)
  - B13004_004: Population for Whom Poverty Status Is Determined: Under 2.00 (Poor or Struggling)
  - B13004_005: Population for Whom Poverty Status Is Determined: 2.00 and Over (Doing Ok)

- A13004_001: Population for Whom Poverty Status Is Determined:
  - A13004_002: Population for Whom Poverty Status Is Determined: Under .50
  - NA- all missing - A13004_003: Population for Whom Poverty Status Is Determined: .50 to .74
  - NA- all missing - A13004_004: Population for Whom Poverty Status Is Determined: .75 to .99
  - A13004_005: Population for Whom Poverty Status Is Determined: 1.00 to 1.49
  - A13004_006: Population for Whom Poverty Status Is Determined: 1.50 to 1.99
  - A13004_007: Population for Whom Poverty Status Is Determined: 2.00 and Over

[10]:

```
acs_17_sub = acs_17[['Geo_FIPS', 'SE_A00002_001', 'SE_A00002_002',
     'SE_A12003_001', 'SE_A12003_002',
    'SE_A12002_001', 'SE_A12002_002', 'SE_A14006_001',
     'SE_A14008_001',
    # age 65+ cols:
     'SE_A01001_011', 'SE_A01001_012', 'SE_A01001_012',
    # poverty summarized:
    'SE_B13004_001', 'SE_B13004_002', 'SE_B13004_003', 'SE_B13004_004',␣
 ↪'SE_B13004_005'
    # poverty raw?:
    #'SE_A13004_001', 'SE_A13004_002', 'SE_A13004_003', 'SE_A13004_004',␣
 ↪'SE_A13004_005', 'SE_A13004_006', 'SE_A13004_007'
]].copy()
```

[11]:

```
acs_17_sub.head()
```

[11]:

```
       Geo_FIPS  SE_A00002_001  SE_A00002_002  SE_A12003_001  SE_A12003_002  \
0  250010101001            998       116.1545              8              0
1  250010101002            314       613.6218              0              0
2  250010101003            750      3997.7830             12              0
3  250010101004            500      2019.0900              2              0
4  250010101005            390      2952.7180              0              0

   SE_A12002_001  SE_A12002_002  SE_A14006_001  SE_A14008_001  SE_A01001_011  \
0            894             46        52340.0   75538.664323            172
1            292              8        37841.0   65213.419913            107
2            638             28        58098.0   84414.854111            133
3            437             23        30396.0   46373.442623             46
4            377             28        47895.0   66060.344828             62
```

```
   SE_A01001_012  SE_A01001_012  SE_B13004_001  SE_B13004_002  SE_B13004_003  \
0             51             51            998            122            271
1             43             43            314             55             36
2             82             82            741             59             81
3             78             78            500             46            206
4             15             15            390             32             59

   SE_B13004_004  SE_B13004_005
0            393            605
1             91            223
2            140            601
3            252            248
4             91            299
```

[12]:

```
# readable names:
acs_17_sub.columns = [
    'GEOID10', 'tot_pop_17', 'pop_density',
    'civ_pop_16_19', 'civ_pop_16_19_drop',
    'pop_over_25', 'pop_over_25_less_school',
    'med_house_inc', 'mean_house_inc',
    'age_65_to_74', 'age_75_to_84', 'age_85_over',
    'pop_det_poverty', 'pop_doing_poorly', 'pop_struggling',␣
 ↪'pop_poor_or_strug', 'pop_doing_ok'
]
```

[13]:

```
acs_17_sub.head()
```

[13]:

```
        GEOID10  tot_pop_17  pop_density  civ_pop_16_19  civ_pop_16_19_drop  \
0  250010101001         998     116.1545              8                   0
1  250010101002         314     613.6218              0                   0
2  250010101003         750    3997.7830             12                   0
3  250010101004         500    2019.0900              2                   0
4  250010101005         390    2952.7180              0                   0

   pop_over_25  pop_over_25_less_school  med_house_inc  mean_house_inc  \
0          894                       46        52340.0    75538.664323
1          292                        8        37841.0    65213.419913
2          638                       28        58098.0    84414.854111
3          437                       23        30396.0    46373.442623
4          377                       28        47895.0    66060.344828

   age_65_to_74  age_75_to_84  age_85_over  pop_det_poverty  pop_doing_poorly  \
0           172            51           51              998               122
1           107            43           43              314                55
2           133            82           82              741                59
3            46            78           78              500                46
4            62            15           15              390                32
```

```
   pop_struggling  pop_poor_or_strug  pop_doing_ok
0             271                393           605
1              36                 91           223
2              81                140           601
3             206                252           248
4              59                 91           299
```

[14]:
```
acs_17_sub['mean_med_inc_desp'] = acs_17_sub['mean_house_inc'] -␣
 ↪acs_17_sub['med_house_inc']
acs_17_sub.head()
```

[14]:
```
        GEOID10  tot_pop_17  pop_density  civ_pop_16_19  civ_pop_16_19_drop  \
0  250010101001         998     116.1545              8                   0
1  250010101002         314     613.6218              0                   0
2  250010101003         750    3997.7830             12                   0
3  250010101004         500    2019.0900              2                   0
4  250010101005         390    2952.7180              0                   0

   pop_over_25  pop_over_25_less_school  med_house_inc  mean_house_inc  \
0          894                       46        52340.0    75538.664323
1          292                        8        37841.0    65213.419913
2          638                       28        58098.0    84414.854111
3          437                       23        30396.0    46373.442623
4          377                       28        47895.0    66060.344828

   age_65_to_74  age_75_to_84  age_85_over  pop_det_poverty  pop_doing_poorly  \
0           172            51           51              998               122
1           107            43           43              314                55
2           133            82           82              741                59
3            46            78           78              500                46
4            62            15           15              390                32

   pop_struggling  pop_poor_or_strug  pop_doing_ok  mean_med_inc_desp
0             271                393           605       23198.664323
1              36                 91           223       27372.419913
2              81                140           601       26316.854111
3             206                252           248       15977.442623
4              59                 91           299       18165.344828
```

[15]:
```
# calculate num and prop of residents
acs_17_sub['over_65_count'] = acs_17_sub['age_65_to_74'] +␣
 ↪acs_17_sub['age_75_to_84'] + acs_17_sub['age_85_over']
acs_17_sub.drop(['age_65_to_74', 'age_75_to_84', 'age_85_over'], axis = 1,␣
 ↪inplace=True)
acs_17_sub.head()
```

[15]:
```
        GEOID10  tot_pop_17  pop_density  civ_pop_16_19  civ_pop_16_19_drop  \
0  250010101001         998     116.1545              8                   0
```

```
1  250010101002          314     613.6218               0                    0
2  250010101003          750    3997.7830              12                    0
3  250010101004          500    2019.0900               2                    0
4  250010101005          390    2952.7180               0                    0

   pop_over_25  pop_over_25_less_school  med_house_inc  mean_house_inc  \
0          894                       46        52340.0    75538.664323
1          292                        8        37841.0    65213.419913
2          638                       28        58098.0    84414.854111
3          437                       23        30396.0    46373.442623
4          377                       28        47895.0    66060.344828

   pop_det_poverty  pop_doing_poorly  pop_struggling  pop_poor_or_strug  \
0              998               122             271                393
1              314                55              36                 91
2              741                59              81                140
3              500                46             206                252
4              390                32              59                 91

   pop_doing_ok  mean_med_inc_desp  over_65_count
0           605       23198.664323            274
1           223       27372.419913            193
2           601       26316.854111            297
3           248       15977.442623            202
4           299       18165.344828             92
```

[16]:
```
acs_17_sub.describe()
```

[16]:
```
            GEOID10   tot_pop_17    pop_density  civ_pop_16_19  \
count  4.985000e+03  4985.000000    4978.000000    4985.000000
mean   2.501713e+11  1361.949649    8442.368002      76.123170
std    7.723758e+07   670.479216   12666.048861     137.109958
min    2.500101e+11     0.000000       0.000000       0.000000
25%    2.500927e+11   880.000000    1082.917000      23.000000
50%    2.501735e+11  1220.000000    3632.338000      51.000000
75%    2.502354e+11  1696.000000   10744.957500      91.000000
max    2.502776e+11  6760.000000  183026.000000    3499.000000

       civ_pop_16_19_drop  pop_over_25  pop_over_25_less_school  \
count         4985.000000  4985.000000              4985.000000
mean             2.065998   944.139619                91.891675
std              7.653031   455.980232               101.193132
min              0.000000     0.000000                 0.000000
25%              0.000000   619.000000                23.000000
50%              0.000000   851.000000                58.000000
75%              0.000000  1184.000000               128.000000
max            110.000000  3897.000000               783.000000
```

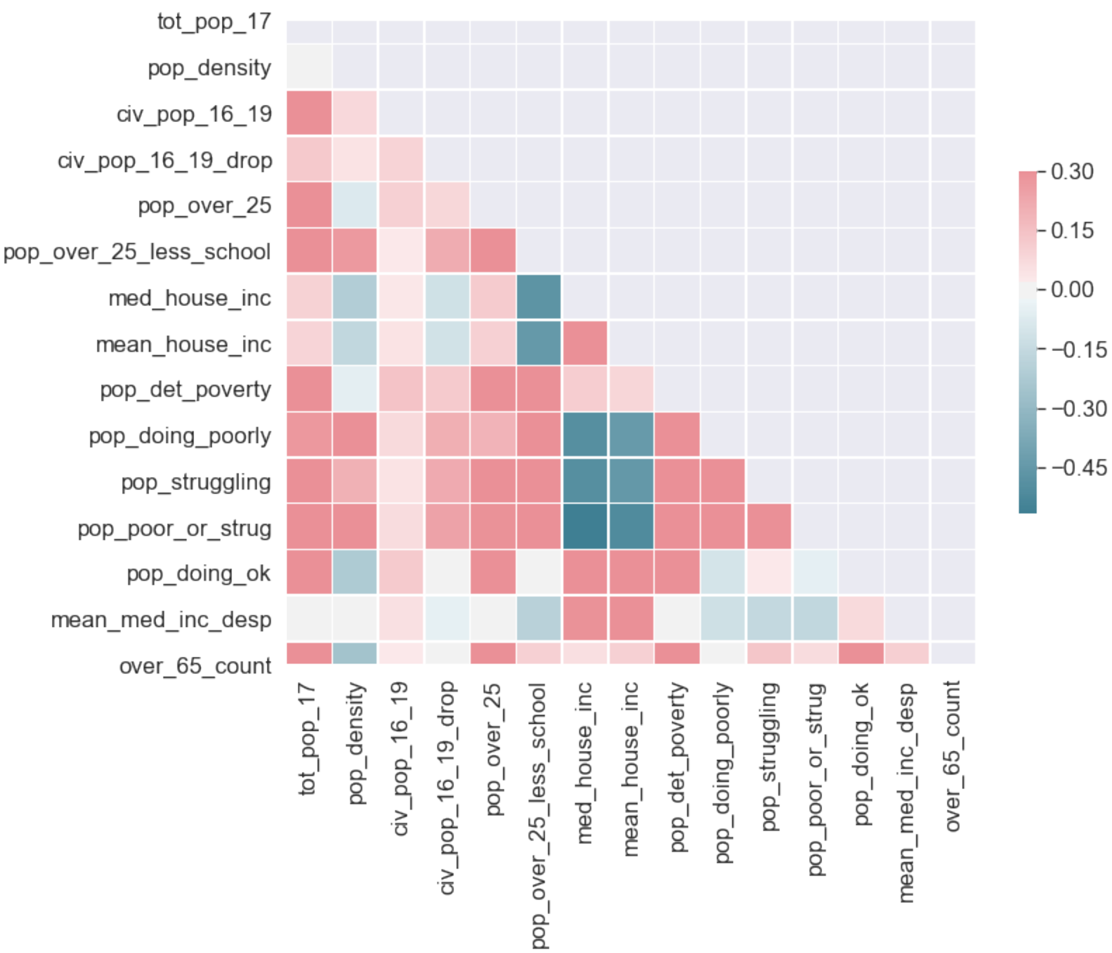
```
       med_house_inc  mean_house_inc  pop_det_poverty  pop_doing_poorly  \
count    4754.000000     4945.000000      4985.000000       4985.000000
mean    82522.340766   101843.077887      1314.412638        145.947041
std     40805.023166    52403.666245       642.014615        175.211379
min      2499.000000    14219.285714         0.000000          0.000000
25%     53333.000000    66678.928571       855.000000         34.000000
50%     77321.000000    92363.461538      1184.000000         85.000000
75%    104048.250000   123559.710145      1650.000000        191.000000
max    250001.000000   526877.386935      4882.000000       2259.000000

       pop_struggling  pop_poor_or_strug  pop_doing_ok  mean_med_inc_desp  \
count     4985.000000        4985.000000   4985.000000        4754.000000
mean       165.163290         311.110331   1003.302307       20133.424207
std        157.779113         289.346330    588.097455       23260.818374
min          0.000000           0.000000      0.000000      -28320.588235
25%         53.000000         109.000000    601.000000        7708.925394
50%        121.000000         225.000000    877.000000       14932.428493
75%        227.000000         423.000000   1285.000000       25253.478921
max       1392.000000        3260.000000   4279.000000      276876.386935

       over_65_count
count    4985.000000
mean      240.608626
std       171.729713
min         0.000000
25%       121.000000
50%       206.000000
75%       319.000000
max      2178.000000
```

[17]:

```
acs_sub_corr = acs_17_sub.drop('GEOID10', axis=1).corr()
# Generate a mask for the upper triangle
mask = np.zeros_like(acs_sub_corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(11, 9))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(acs_sub_corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
```

[17]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1df79f3f4a8>
```



[18]:
```
acs_17_sub.columns
```

[18]:
```
Index(['GEOID10', 'tot_pop_17', 'pop_density', 'civ_pop_16_19',
       'civ_pop_16_19_drop', 'pop_over_25', 'pop_over_25_less_school',
       'med_house_inc', 'mean_house_inc', 'pop_det_poverty',
       'pop_doing_poorly', 'pop_struggling', 'pop_poor_or_strug',
       'pop_doing_ok', 'mean_med_inc_desp', 'over_65_count'],
      dtype='object')
```

[19]:
```
acs_17_sub.head()
```

[19]:
```
        GEOID10  tot_pop_17  pop_density  civ_pop_16_19  civ_pop_16_19_drop  \
0  250010101001         998     116.1545              8                   0
1  250010101002         314     613.6218              0                   0
2  250010101003         750    3997.7830             12                   0
3  250010101004         500    2019.0900              2                   0
4  250010101005         390    2952.7180              0                   0

   pop_over_25  pop_over_25_less_school  med_house_inc  mean_house_inc  \
0          894                       46        52340.0    75538.664323
```

```
1          292                        8        37841.0    65213.419913
2          638                       28        58098.0    84414.854111
3          437                       23        30396.0    46373.442623
4          377                       28        47895.0    66060.344828

   pop_det_poverty  pop_doing_poorly  pop_struggling  pop_poor_or_strug  \
0              998               122             271                393
1              314                55              36                 91
2              741                59              81                140
3              500                46             206                252
4              390                32              59                 91

   pop_doing_ok  mean_med_inc_desp  over_65_count
0           605       23198.664323            274
1           223       27372.419913            193
2           601       26316.854111            297
3           248       15977.442623            202
4           299       18165.344828             92
```

[20]:

```
print(acs_17_sub.columns)
print(town_block.columns)
```

```
Index(['GEOID10', 'tot_pop_17', 'pop_density', 'civ_pop_16_19',
       'civ_pop_16_19_drop', 'pop_over_25', 'pop_over_25_less_school',
       'med_house_inc', 'mean_house_inc', 'pop_det_poverty',
       'pop_doing_poorly', 'pop_struggling', 'pop_poor_or_strug',
       'pop_doing_ok', 'mean_med_inc_desp', 'over_65_count'],
      dtype='object')
Index(['TOWN', 'POP2010', 'SHAPE_Area', 'GEOID10'], dtype='object')
```

[21]:

```
town_block.columns = ['city_death', 'tot_pop_10', 'shape_area', 'GEOID10']
town_block.head()
```

[21]:

```
  city_death  tot_pop_10    shape_area       GEOID10
0  wellesley       27982  2.726958e+07  2.502140e+11
1  wellesley       27982  2.726958e+07  2.502140e+11
2  wellesley       27982  2.726958e+07  2.502140e+11
3  wellesley       27982  2.726958e+07  2.502140e+11
4  wellesley       27982  2.726958e+07  2.502140e+11
```

[22]:

```
town_acs_merge = town_block.merge(acs_17_sub, on='GEOID10', how='inner')
```

[23]:

```
town_acs_merge.columns
```

[23]:

```
Index(['city_death', 'tot_pop_10', 'shape_area', 'GEOID10', 'tot_pop_17',
       'pop_density', 'civ_pop_16_19', 'civ_pop_16_19_drop', 'pop_over_25',
       'pop_over_25_less_school', 'med_house_inc', 'mean_house_inc',
       'pop_det_poverty', 'pop_doing_poorly', 'pop_struggling',
       'pop_poor_or_strug', 'pop_doing_ok', 'mean_med_inc_desp',
       'over_65_count'],
      dtype='object')
```

[24]:
```
town_acs_merge.head()
```

[24]:
```
  city_death  tot_pop_10    shape_area       GEOID10  tot_pop_17  pop_density  \
0  wellesley       27982  2.726958e+07  2.502140e+11        1101     4438.051
1  wellesley       27982  2.726958e+07  2.502140e+11         924     2064.697
2  wellesley       27982  2.726958e+07  2.502140e+11         881     1947.536
3  wellesley       27982  2.726958e+07  2.502140e+11        1177     2961.899
4  wellesley       27982  2.726958e+07  2.502140e+11         767     3843.039

   civ_pop_16_19  civ_pop_16_19_drop  pop_over_25  pop_over_25_less_school  \
0             96                   0          636                        0
1            108                   0          634                        0
2              9                   0          552                       11
3             38                   0          685                       30
4             10                   0          590                       22

   med_house_inc  mean_house_inc  pop_det_poverty  pop_doing_poorly  \
0       183879.0   214803.395062             1101                 0
1       250001.0   505804.304636              924                 0
2       181786.0   244652.447552              875                12
3       129071.0   240321.641791             1177               144
4        86827.0   145115.151515              767                64

   pop_struggling  pop_poor_or_strug  pop_doing_ok  mean_med_inc_desp  \
0               0                  0          1101       30924.395062
1               0                  0           924      255803.304636
2               9                 21           854       62866.447552
3             100                244           933      111250.641791
4              95                159           608       58288.151515

   over_65_count
0            137
1            197
2            231
3            105
4            275
```

[25]:
```
sum_stat_cols = [
    'city_death', 'tot_pop_17', 'over_65_count',
    'civ_pop_16_19', 'civ_pop_16_19_drop',
    'pop_over_25', 'pop_over_25_less_school',
    'pop_det_poverty', 'pop_doing_poorly', 'pop_struggling',␣
 ↪'pop_poor_or_strug', 'pop_doing_ok'
]
town_17_pop = town_acs_merge.groupby('city_death').sum().
 ↪reset_index()[sum_stat_cols]
```

```
town_17_pop.head()
```

[25]:

```
  city_death  tot_pop_17  over_65_count  civ_pop_16_19  civ_pop_16_19_drop  \
0   abington       16275           2469            753                  26
1      acton       23455           4001           1476                  18
2   acushnet       10443           2431            564                  62
3      adams        8211           1764            333                  23
4     agawam       27769           6195           1177                   0

   pop_over_25  pop_over_25_less_school  pop_det_poverty  pop_doing_poorly  \
0        11377                      615            16194               579
1        16161                      397            23307               893
2         7635                     1397            10336               422
3         6095                      723             8209               910
4        20674                     1602            26925              2553

   pop_struggling  pop_poor_or_strug  pop_doing_ok
0            1626               2205         13989
1             973               1866         21441
2            1844               2266          8070
3            1187               2097          6112
4            3841               6394         20531
```

[26]:

```
# get mean of other stats:
mean_stat_cols = ['city_death', 'tot_pop_10', 'shape_area', 'pop_density',␣
 ↪'med_house_inc', 'mean_house_inc', 'mean_med_inc_desp']
town_stats = town_acs_merge.groupby('city_death').mean().
 ↪reset_index()[mean_stat_cols]
town_stats.head()
```

[26]:

```
  city_death  tot_pop_10    shape_area  pop_density  med_house_inc  \
0   abington     15985.0  2.639085e+07  1932.969130   87156.000000
1      acton     21924.0  5.256453e+07  1257.583593  139890.466667
2   acushnet     10303.0  4.889337e+07  1152.357871   69624.714286
3      adams      8485.0  5.946649e+07  1982.318840   48445.400000
4     agawam     28438.0  6.302191e+07  1897.273569   65490.125000

   mean_house_inc  mean_med_inc_desp
0    98809.035505       11653.035505
1   156680.203867       16789.737200
2    80333.175842       10708.461556
3    60968.594660       12523.194660
4    79464.234446       13974.109446
```

[27]:

```
town_merge = town_17_pop.merge(town_stats, on='city_death', how='inner')
print(town_merge.shape)
town_merge.head()
```

```
(347, 18)
```

[27]:

```
  city_death  tot_pop_17  over_65_count  civ_pop_16_19  civ_pop_16_19_drop  \
0   abington       16275           2469            753                  26
1      acton       23455           4001           1476                  18
2   acushnet       10443           2431            564                  62
3      adams        8211           1764            333                  23
4     agawam       27769           6195           1177                   0

   pop_over_25  pop_over_25_less_school  pop_det_poverty  pop_doing_poorly  \
0        11377                      615            16194               579
1        16161                      397            23307               893
2         7635                     1397            10336               422
3         6095                      723             8209               910
4        20674                     1602            26925              2553

   pop_struggling  pop_poor_or_strug  pop_doing_ok  tot_pop_10    shape_area  \
0            1626               2205         13989     15985.0  2.639085e+07
1             973               1866         21441     21924.0  5.256453e+07
2            1844               2266          8070     10303.0  4.889337e+07
3            1187               2097          6112      8485.0  5.946649e+07
4            3841               6394         20531     28438.0  6.302191e+07

   pop_density  med_house_inc  mean_house_inc  mean_med_inc_desp
0  1932.969130   87156.000000    98809.035505       11653.035505
1  1257.583593  139890.466667   156680.203867       16789.737200
2  1152.357871   69624.714286    80333.175842       10708.461556
3  1982.318840   48445.400000    60968.594660       12523.194660
4  1897.273569   65490.125000    79464.234446       13974.109446
```

[28]:

```
town_merge['drop_out'] = (town_merge['civ_pop_16_19_drop'] * 100) /␣
 ↪town_merge['civ_pop_16_19']
town_merge['less_than_hs_ed'] = (town_merge['pop_over_25_less_school'] * 100) /␣
 ↪town_merge['pop_over_25']
town_merge.drop(['pop_over_25', 'pop_over_25_less_school',␣
 ↪'civ_pop_16_19_drop', 'civ_pop_16_19'], axis = 1, inplace=True)
town_merge.head()
```

[28]:

```
  city_death  tot_pop_17  over_65_count  pop_det_poverty  pop_doing_poorly  \
0   abington       16275           2469            16194               579
1      acton       23455           4001            23307               893
2   acushnet       10443           2431            10336               422
3      adams        8211           1764             8209               910
4     agawam       27769           6195            26925              2553

   pop_struggling  pop_poor_or_strug  pop_doing_ok  tot_pop_10    shape_area  \
0            1626               2205         13989     15985.0  2.639085e+07
1             973               1866         21441     21924.0  5.256453e+07
2            1844               2266          8070     10303.0  4.889337e+07
3            1187               2097          6112      8485.0  5.946649e+07
```

```
4          3841             6394         20531      28438.0  6.302191e+07

   pop_density  med_house_inc  mean_house_inc  mean_med_inc_desp   drop_out  \
0  1932.969130   87156.000000    98809.035505       11653.035505   3.452855
1  1257.583593  139890.466667   156680.203867       16789.737200   1.219512
2  1152.357871   69624.714286    80333.175842       10708.461556  10.992908
3  1982.318840   48445.400000    60968.594660       12523.194660   6.906907
4  1897.273569   65490.125000    79464.234446       13974.109446   0.000000

   less_than_hs_ed
0         5.405643
1         2.456531
2        18.297315
3        11.862182
4         7.748863
```

[29]:

```
# before calculated dropout by block - had many zeroes - is this alterntive␣
 ↪method more informative?
town_merge[['drop_out', 'less_than_hs_ed']].describe()
```

[29]:

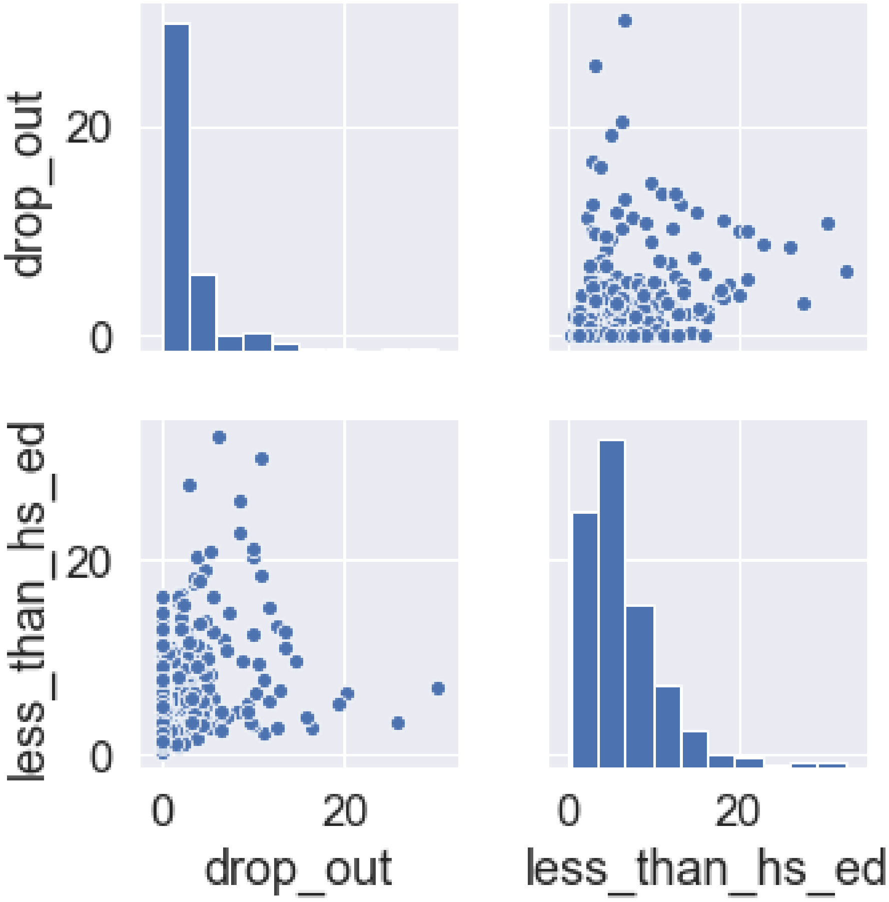
```
         drop_out  less_than_hs_ed
count  346.000000       347.000000
mean     2.355802         6.544580
std      4.012968         4.750990
min      0.000000         0.000000
25%      0.000000         3.235427
50%      0.318954         5.405643
75%      3.184586         8.318470
max     30.000000        32.336132
```

[30]:

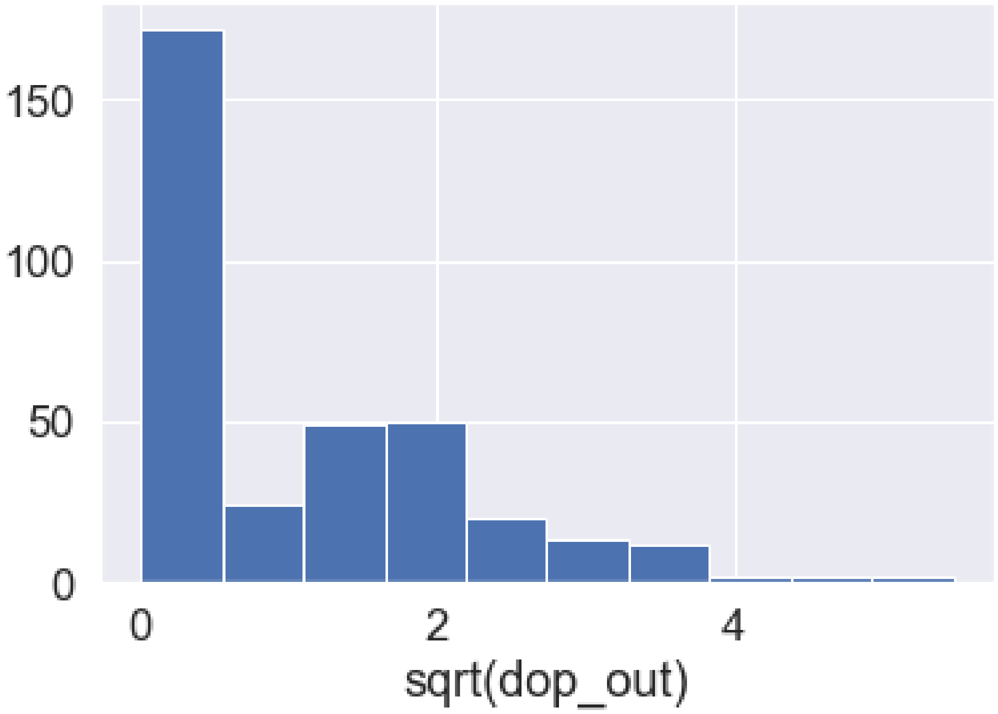
```
sns.pairplot(town_merge[['drop_out', 'less_than_hs_ed']].dropna())
```

[30]:

```
<seaborn.axisgrid.PairGrid at 0x1df7a572320>
```



[31]:
```
np.sqrt(town_merge['drop_out']).hist(bins=10)
plt.xlabel('sqrt(dop_out)')
plt.show()
```



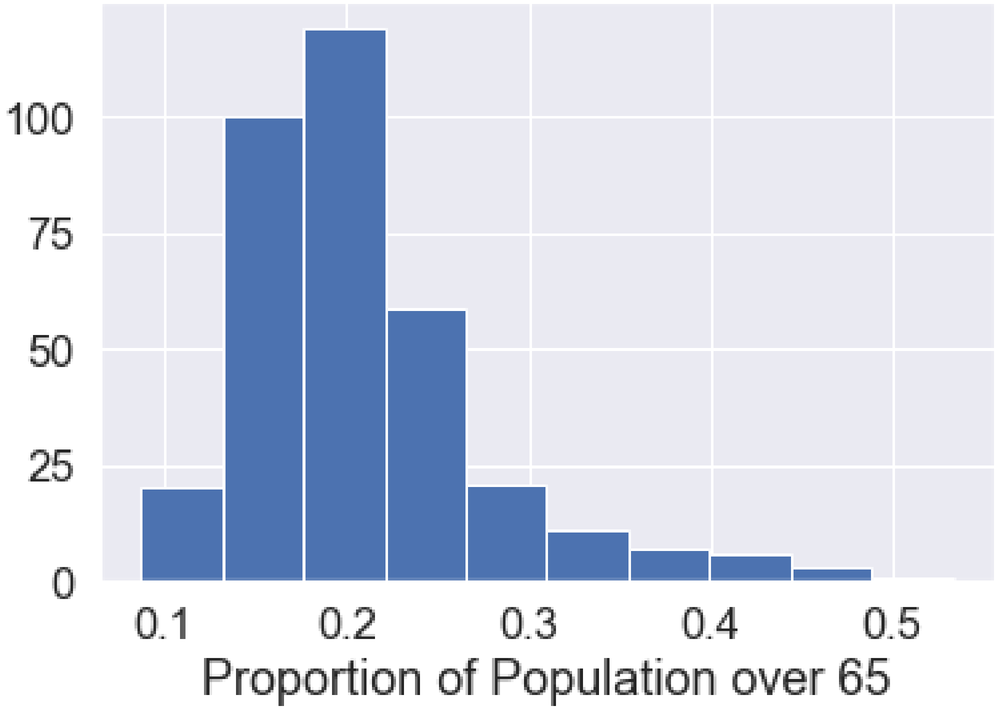
[32]:
```
town_merge.head()
```

[32]:
```
   city_death  tot_pop_17  over_65_count  pop_det_poverty  pop_doing_poorly  \
0    abington       16275           2469            16194               579
1       acton       23455           4001            23307               893
2    acushnet       10443           2431            10336               422
3       adams        8211           1764             8209               910
4      agawam       27769           6195            26925              2553

   pop_struggling  pop_poor_or_strug  pop_doing_ok  tot_pop_10    shape_area  \
0            1626               2205         13989     15985.0  2.639085e+07
1             973               1866         21441     21924.0  5.256453e+07
2            1844               2266          8070     10303.0  4.889337e+07
3            1187               2097          6112      8485.0  5.946649e+07
4            3841               6394         20531     28438.0  6.302191e+07

   pop_density  med_house_inc  mean_house_inc  mean_med_inc_desp   drop_out  \
0  1932.969130   87156.000000    98809.035505       11653.035505   3.452855
1  1257.583593  139890.466667   156680.203867       16789.737200   1.219512
2  1152.357871   69624.714286    80333.175842       10708.461556  10.992908
3  1982.318840   48445.400000    60968.594660       12523.194660   6.906907
4  1897.273569   65490.125000    79464.234446       13974.109446   0.000000

   less_than_hs_ed
```

```
0         5.405643
1         2.456531
2        18.297315
3        11.862182
4         7.748863
```

[34]:

```
town_merge['over_65_prop'] = town_merge['over_65_count'] /␣
 ↪town_merge['tot_pop_17']
town_merge['over_65_prop'].hist()
plt.xlabel('Proportion of Population over 65')
plt.show()
```

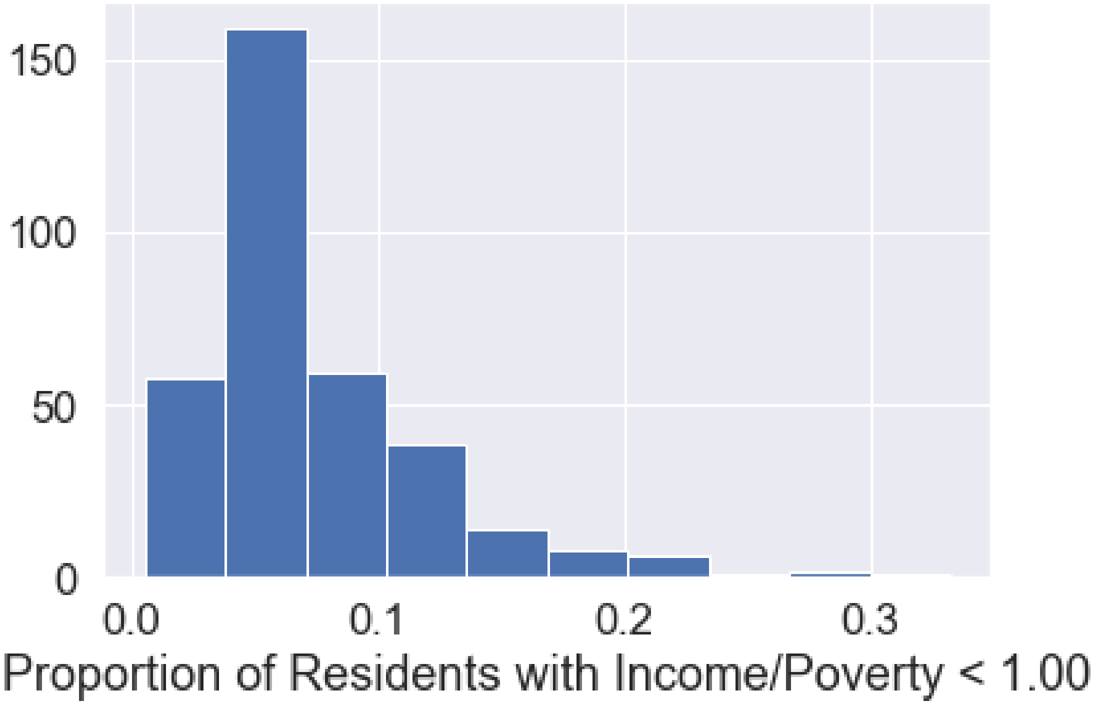


```
B13004_001:     Population for Whom Poverty Status Is Determined:
B13004_002:     Population for Whom Poverty Status Is Determined: Under 1.00 (Doing Poorly)
B13004_003:     Population for Whom Poverty Status Is Determined: 1.00 to 1.99 (Struggling)
B13004_004:     Population for Whom Poverty Status Is Determined: Under 2.00 (Poor or Struggl
B13004_005:     Population for Whom Poverty Status Is Determined: 2.00 and Over (Doing Ok)
```

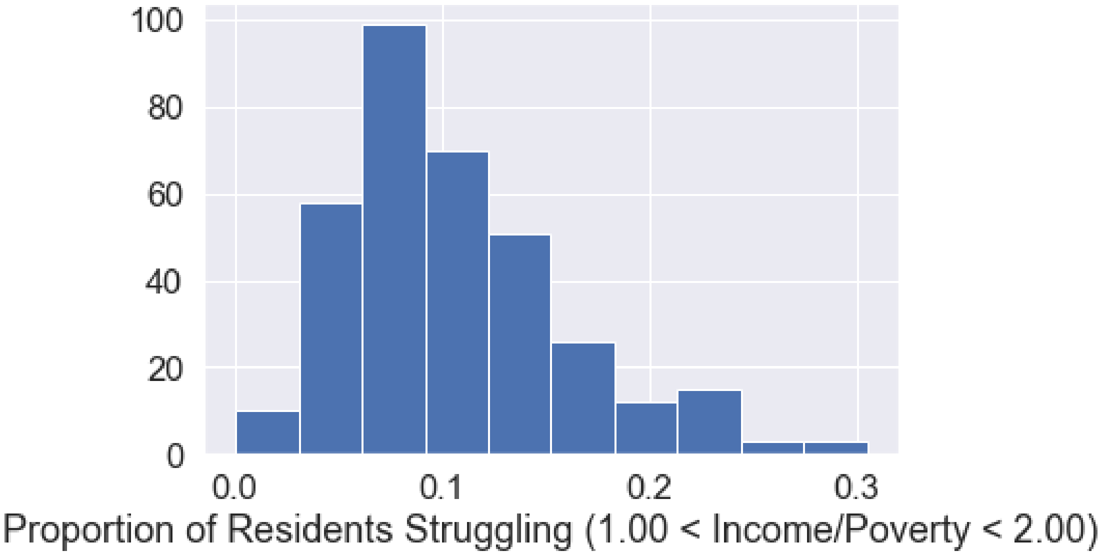
[43]:

```
# poverty calc
town_merge.head()
town_merge['at_or_below_pov_prop'] = town_merge['pop_doing_poorly'] /␣
 ↪town_merge['pop_det_poverty']
town_merge['at_or_below_pov_prop'].hist(bins=10)
```

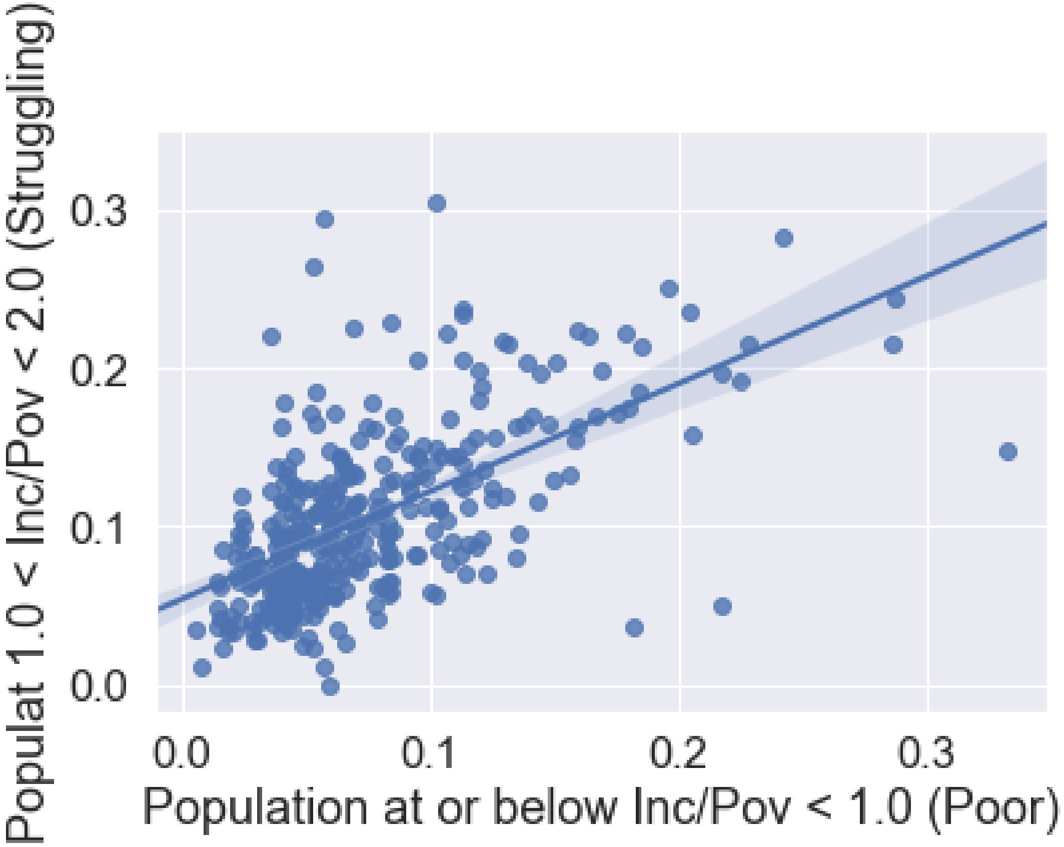
```
plt.xlabel('Proportion of Residents with Income/Poverty < 1.00')
plt.show()
```



[47]:
```
town_merge['pop_struggling_prop'] = town_merge['pop_struggling'] /␣
 ↪town_merge['pop_det_poverty']
town_merge['pop_struggling_prop'].hist(bins=10)
plt.xlabel('Proportion of Residents Struggling (1.00 < Income/Poverty < 2.00)')
plt.show()
```



[50]:
```
sns.regplot(x='at_or_below_pov_prop', y='pop_struggling_prop', data=town_merge)
plt.xlabel('Population at or below Inc/Pov < 1.0 (Poor)')
plt.ylabel('Populat 1.0 < Inc/Pov < 2.0 (Struggling)')
plt.show()
```



[52]:
```
town_merge.drop(['pop_det_poverty', 'pop_doing_poorly', 'pop_struggling',␣
 ↪'pop_poor_or_strug', 'pop_doing_ok'], axis=1, inplace=True)
town_merge.head()
```

[52]:
```
  city_death  tot_pop_17  over_65_count  tot_pop_10    shape_area  \
0   abington       16275           2469     15985.0  2.639085e+07
1      acton       23455           4001     21924.0  5.256453e+07
2   acushnet       10443           2431     10303.0  4.889337e+07
3      adams        8211           1764      8485.0  5.946649e+07
4     agawam       27769           6195     28438.0  6.302191e+07

   pop_density  med_house_inc  mean_house_inc  mean_med_inc_desp   drop_out  \
0  1932.969130   87156.000000    98809.035505       11653.035505   3.452855
1  1257.583593  139890.466667   156680.203867       16789.737200   1.219512
2  1152.357871   69624.714286    80333.175842       10708.461556  10.992908
3  1982.318840   48445.400000    60968.594660       12523.194660   6.906907
4  1897.273569   65490.125000    79464.234446       13974.109446   0.000000

   less_than_hs_ed  over_65_prop  at_or_below_pov_prop  pop_struggling_prop
0         5.405643      0.151705              0.035754             0.100408
1         2.456531      0.170582              0.038315             0.041747
2        18.297315      0.232788              0.040828             0.178406
3        11.862182      0.214834              0.110854             0.144597
4         7.748863      0.223090              0.094819             0.142656
```

[54]:
```
town_merge.describe()
```

[54]:
```
          tot_pop_17  over_65_count     tot_pop_10    shape_area  \
count     347.000000     347.000000     347.000000  3.470000e+02
mean    19490.746398    3434.824207   18858.389049  5.969708e+07
std     41540.511381    5642.967441   39009.479522  3.390152e+07
min        34.000000      15.000000      75.000000  3.249309e+06
25%      4196.000000     781.000000    4008.000000  3.731440e+07
50%     10560.000000    1977.000000   10300.000000  5.455734e+07
75%     22704.000000    4385.000000   21691.500000  7.446341e+07
max    668541.000000   85040.000000  617594.000000  2.661817e+08

        pop_density  med_house_inc  mean_house_inc  mean_med_inc_desp  \
count    347.000000     346.000000      347.000000         346.000000
mean    2292.685930   88305.727278   109444.035932       21079.291563
std     4049.633320   29088.836206    39888.981321       15309.458177
min        2.578370   38909.750000    50750.537570        2129.112803
25%      285.202885   68215.428571    82839.316239       12204.613762
50%      933.183133   83124.625000   100209.367399       16659.458813
75%     2452.889962  102446.289216   126078.167762       24196.761231
max    30236.970333  203026.750000   316351.858774      113325.108774
```

```
         drop_out  less_than_hs_ed  over_65_prop  at_or_below_pov_prop  \
count  346.000000       347.000000    347.000000            347.000000
mean     2.355802         6.544580      0.207933              0.073728
std      4.012968         4.750990      0.068754              0.047828
min      0.000000         0.000000      0.086886              0.005354
25%      0.000000         3.235427      0.166202              0.042404
50%      0.318954         5.405643      0.193279              0.059730
75%      3.184586         8.318470      0.230995              0.092880
max     30.000000        32.336132      0.532847              0.332260

       pop_struggling_prop
count           347.000000
mean              0.104279
std               0.054009
min               0.000000
25%               0.064869
50%               0.092496
75%               0.132362
max               0.304869
```

[53]:
```python
# combine town info + opioid overdose death count data
full_merge = town_merge.merge(death_data, on='city_death', how='inner')
print(full_merge.shape)
full_merge.head()
```

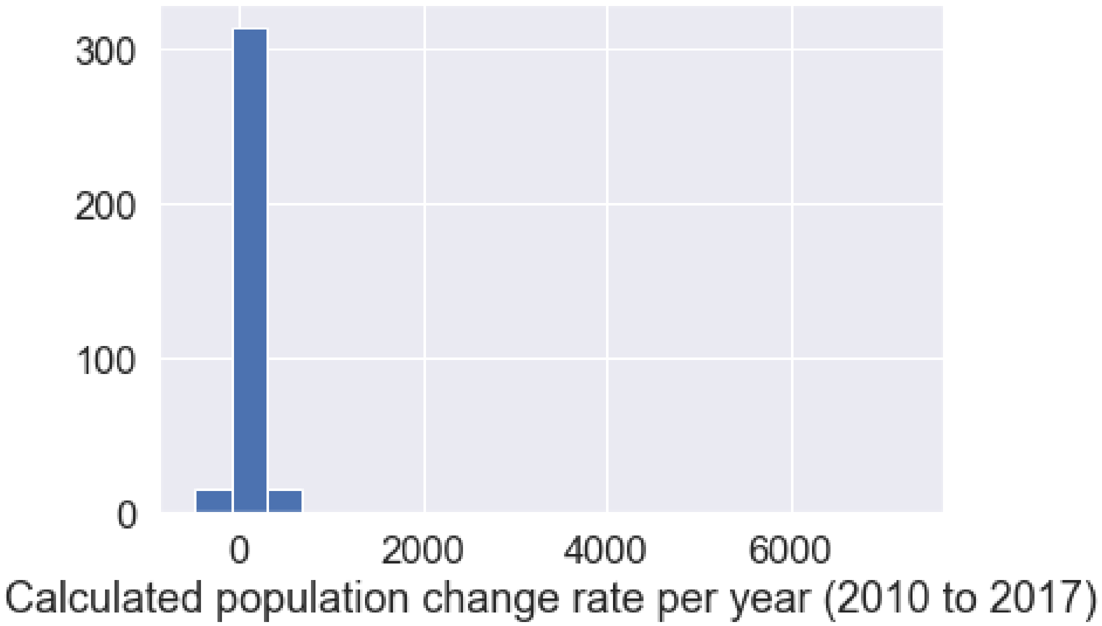
```
(347, 21)
```

[53]:
```
  city_death  tot_pop_17  over_65_count  tot_pop_10    shape_area  \
0   abington       16275           2469     15985.0  2.639085e+07
1      acton       23455           4001     21924.0  5.256453e+07
2   acushnet       10443           2431     10303.0  4.889337e+07
3      adams        8211           1764      8485.0  5.946649e+07
4     agawam       27769           6195     28438.0  6.302191e+07

   pop_density  med_house_inc  mean_house_inc  mean_med_inc_desp   drop_out  \
0  1932.969130   87156.000000    98809.035505       11653.035505   3.452855
1  1257.583593  139890.466667   156680.203867       16789.737200   1.219512
2  1152.357871   69624.714286    80333.175842       10708.461556  10.992908
3  1982.318840   48445.400000    60968.594660       12523.194660   6.906907
4  1897.273569   65490.125000    79464.234446       13974.109446   0.000000

   ...  over_65_prop  at_or_below_pov_prop  pop_struggling_prop  2012  2013  \
0  ...      0.151705              0.035754             0.100408     1     2
1  ...      0.170582              0.038315             0.041747     2     0
2  ...      0.232788              0.040828             0.178406     2     0
3  ...      0.214834              0.110854             0.144597     1     1
4  ...      0.223090              0.094819             0.142656     1     3
```

```
   2014  2015  2016  2017  2018
0     0     6     1     3     5
1     1     2     3     0     1
2     0     4     2     4     0
3     2     3     1     0     4
4     1     2     0     4     8

[5 rows x 21 columns]
```

[123]:

```
full_merge['pop_change_rate'] = (full_merge['tot_pop_17'] -␣
 ↪full_merge['tot_pop_10']) / (2017 - 2010)
full_merge['pop_change_rate'].hist(bins=20)
plt.xlabel('Calculated population change rate per year (2010 to 2017)')
plt.show()
```



[124]:

```
full_merge[full_merge['pop_change_rate'] > 1000]
```

[124]:

```
   city_death  tot_pop_17  over_65_count  tot_pop_10    shape_area  \
35     boston      668541          85040    617594.0  1.295200e+08

     pop_density  med_house_inc  mean_house_inc  mean_med_inc_desp  drop_out  \
35  27786.891612   71196.049505    92167.940523       22125.401865  2.033172

    ...      tot_pop_18  death_rate_12  death_rate_13  death_rate_14  \
35  ...  675819.142857       0.980779       1.266756       2.582315

    death_rate_15  death_rate_16  death_rate_17  death_rate_18  town_status  \
35       3.455738       3.916748       4.173267        3.62523        grown

    urb_v_rur
35      urban

[1 rows x 37 columns]
```

[ ]:

```
full_merge['tot_pop_16'] = full_merge['tot_pop_17'] -␣
 ↪full_merge['pop_change_rate']
full_merge['tot_pop_15'] = full_merge['tot_pop_17'] -␣
 ↪full_merge['pop_change_rate'] * 2
full_merge['tot_pop_14'] = full_merge['tot_pop_17'] -␣
 ↪full_merge['pop_change_rate'] * 3
full_merge['tot_pop_13'] = full_merge['tot_pop_17'] -␣
 ↪full_merge['pop_change_rate'] * 4
full_merge['tot_pop_12'] = full_merge['tot_pop_17'] -␣
 ↪full_merge['pop_change_rate'] * 5
full_merge['tot_pop_18'] = full_merge['tot_pop_17'] +␣
 ↪full_merge['pop_change_rate']
full_merge.head()
```

[57]:

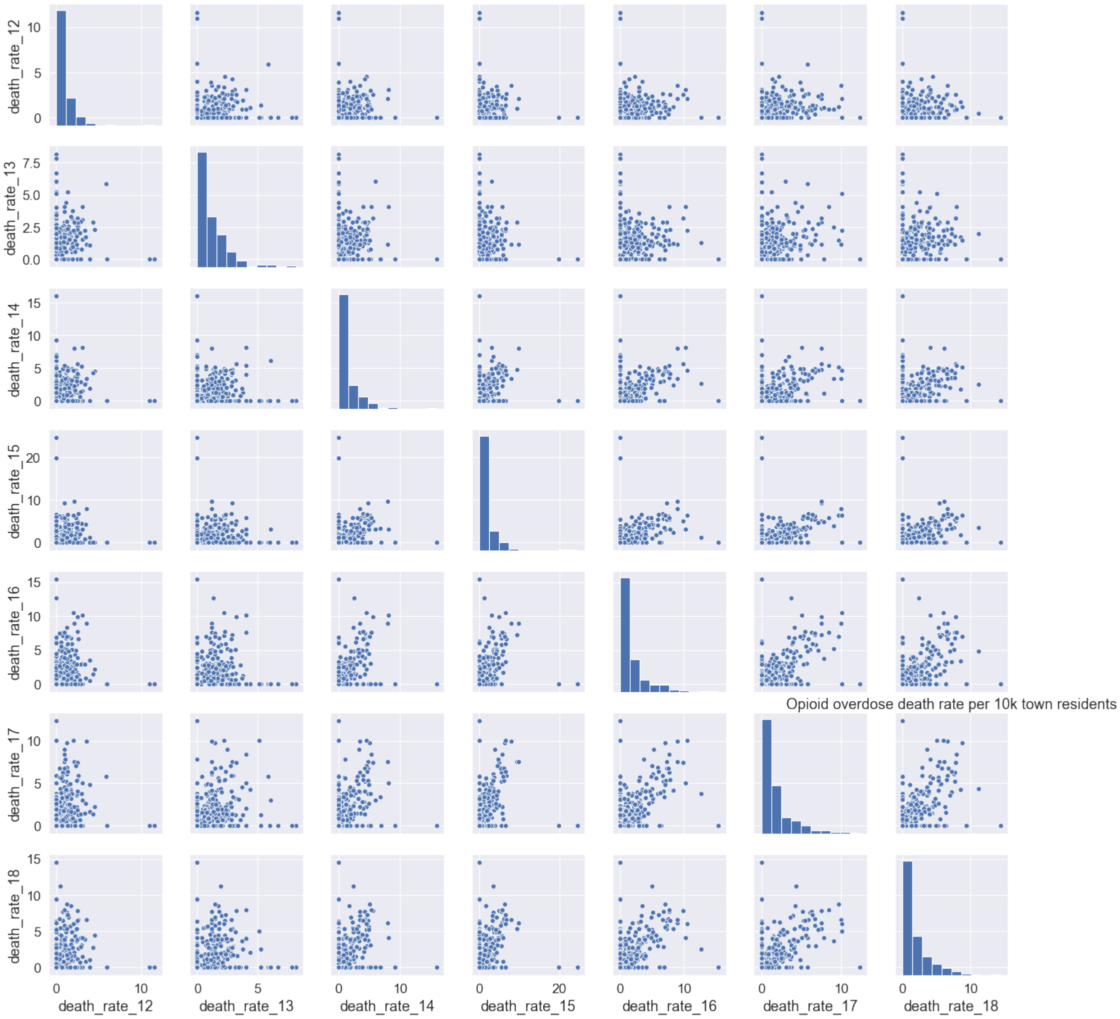
```
# calculate opioid overdose death rate per 10k residents (so that numbers␣
 ↪aren't just small decimals)
full_merge['death_rate_12'] = (full_merge['2012'] / full_merge['tot_pop_12']) *␣
 ↪10000
full_merge['death_rate_13'] = (full_merge['2013'] / full_merge['tot_pop_13']) *␣
 ↪10000
full_merge['death_rate_14'] = (full_merge['2014'] / full_merge['tot_pop_14']) *␣
 ↪10000
full_merge['death_rate_15'] = (full_merge['2015'] / full_merge['tot_pop_15']) *␣
 ↪10000
full_merge['death_rate_16'] = (full_merge['2016'] / full_merge['tot_pop_16']) *␣
 ↪10000
full_merge['death_rate_17'] = (full_merge['2017'] / full_merge['tot_pop_17']) *␣
 ↪10000
full_merge['death_rate_18'] = (full_merge['2018'] / full_merge['tot_pop_18']) *␣
 ↪10000
full_merge.head()
```

[57]:

```
  city_death  tot_pop_17  over_65_count  tot_pop_10    shape_area  \
0   abington       16275           2469     15985.0  2.639085e+07
1      acton       23455           4001     21924.0  5.256453e+07
2   acushnet       10443           2431     10303.0  4.889337e+07
3      adams        8211           1764      8485.0  5.946649e+07
4     agawam       27769           6195     28438.0  6.302191e+07

   pop_density  med_house_inc  mean_house_inc  mean_med_inc_desp   drop_out  \
0  1932.969130   87156.000000   98809.035505       11653.035505   3.452855
1  1257.583593  139890.466667  156680.203867       16789.737200   1.219512
2  1152.357871   69624.714286   80333.175842       10708.461556  10.992908
3  1982.318840   48445.400000   60968.594660       12523.194660   6.906907
4  1897.273569   65490.125000   79464.234446       13974.109446   0.000000

   ...    tot_pop_13    tot_pop_12    tot_pop_18  death_rate_12  \
0  ...  16109.285714  16067.857143  16316.428571       0.622361
1  ...  22580.142857  22361.428571  23673.714286       0.894397
2  ...  10363.000000  10343.000000  10463.000000       1.933675
3  ...   8367.571429   8406.714286   8171.857143       1.189525
4  ...  28151.285714  28246.857143  27673.428571       0.354022

   death_rate_13  death_rate_14  death_rate_15  death_rate_16  death_rate_17  \
0       1.241520       0.000000       3.705501       0.616007       1.843318
1       0.000000       0.438618       0.868901       1.291084       0.000000
2       0.000000       0.000000       3.845045       1.918833       3.830317
3       1.195090       2.401413       3.619130       1.212100       0.000000
4       1.065671       0.356434       0.715304       0.000000       1.440455

   death_rate_18
0       3.064396
1       0.422409
2       0.000000
3       4.894848
4       2.890860

[5 rows x 35 columns]
```

[67]:

```
sns.pairplot(full_merge.iloc[:, 28:35])
plt.title('Opioid overdose death rate per 10k town residents')
plt.show()
```



```
[70]: full_merge['town_status'] = ['grown' if x > 0 else 'shrunk' for x in␣
        ↪full_merge['pop_change_rate']]
      full_merge['town_status'].value_counts()
```

```
[70]: grown     274
      shrunk     73
      Name: town_status, dtype: int64
```

```
[92]: full_merge['urb_v_rur'] = ['urban' if x >= 50000 else 'rural' for x in␣
        ↪full_merge['tot_pop_17']]
      full_merge['urb_v_rur'].value_counts()
```

```
[92]: rural    322
      urban     25
      Name: urb_v_rur, dtype: int64
```

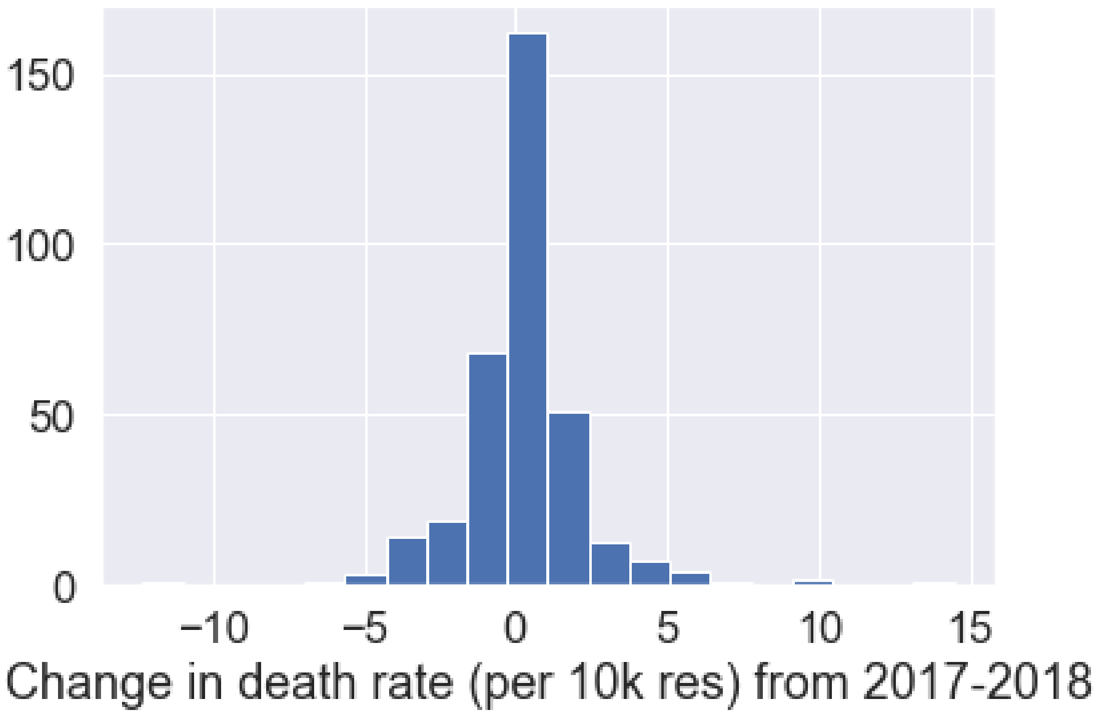
```
[93]: full_merge.columns
```

```
[93]: Index(['city_death', 'tot_pop_17', 'over_65_count', 'tot_pop_10', 'shape_area',
              'pop_density', 'med_house_inc', 'mean_house_inc', 'mean_med_inc_desp',
              'drop_out', 'less_than_hs_ed', 'over_65_prop', 'at_or_below_pov_prop',
              'pop_struggling_prop', '2012', '2013', '2014', '2015', '2016', '2017',
              '2018', 'pop_change_rate', 'tot_pop_16', 'tot_pop_15', 'tot_pop_14',
              'tot_pop_13', 'tot_pop_12', 'tot_pop_18', 'death_rate_12',
              'death_rate_13', 'death_rate_14', 'death_rate_15', 'death_rate_16',
              'death_rate_17', 'death_rate_18', 'town_status', 'urb_v_rur'],
             dtype='object')
```

```
[113]: full_merge_17 = full_merge.iloc[:, np.r_[0:2, 5:14, 21, 33:37]].copy()
       full_merge_17.head()
```

```
[113]:   city_death  tot_pop_17  pop_density  med_house_inc  mean_house_inc  \
       0  abington       16275  1932.969130   87156.000000    98809.035505
       1     acton       23455  1257.583593  139890.466667   156680.203867
       2  acushnet       10443  1152.357871   69624.714286    80333.175842
       3     adams        8211  1982.318840   48445.400000    60968.594660
       4    agawam       27769  1897.273569   65490.125000    79464.234446

          mean_med_inc_desp   drop_out  less_than_hs_ed  over_65_prop  \
       0       11653.035505   3.452855         5.405643      0.151705
       1       16789.737200   1.219512         2.456531      0.170582
       2       10708.461556  10.992908        18.297315      0.232788
       3       12523.194660   6.906907        11.862182      0.214834
       4       13974.109446   0.000000         7.748863      0.223090

          at_or_below_pov_prop  pop_struggling_prop  pop_change_rate  death_rate_17  \
       0              0.035754             0.100408        41.428571       1.843318
       1              0.038315             0.041747       218.714286       0.000000
       2              0.040828             0.178406        20.000000       3.830317
       3              0.110854             0.144597       -39.142857       0.000000
       4              0.094819             0.142656       -95.571429       1.440455

          death_rate_18 town_status urb_v_rur
       0       3.064396       grown     rural
       1       0.422409       grown     rural
       2       0.000000       grown     rural
       3       4.894848      shrunk     rural
       4       2.890860      shrunk     rural
```

```
[114]: full_merge_17['rate_chng_17_to_18'] = full_merge_17['death_rate_18'] -␣
        ↪full_merge_17['death_rate_17']
       full_merge_17['rate_chng_17_to_18'].hist(bins=20)
       plt.xlabel('Change in death rate (per 10k res) from 2017-2018')
       plt.show()
```



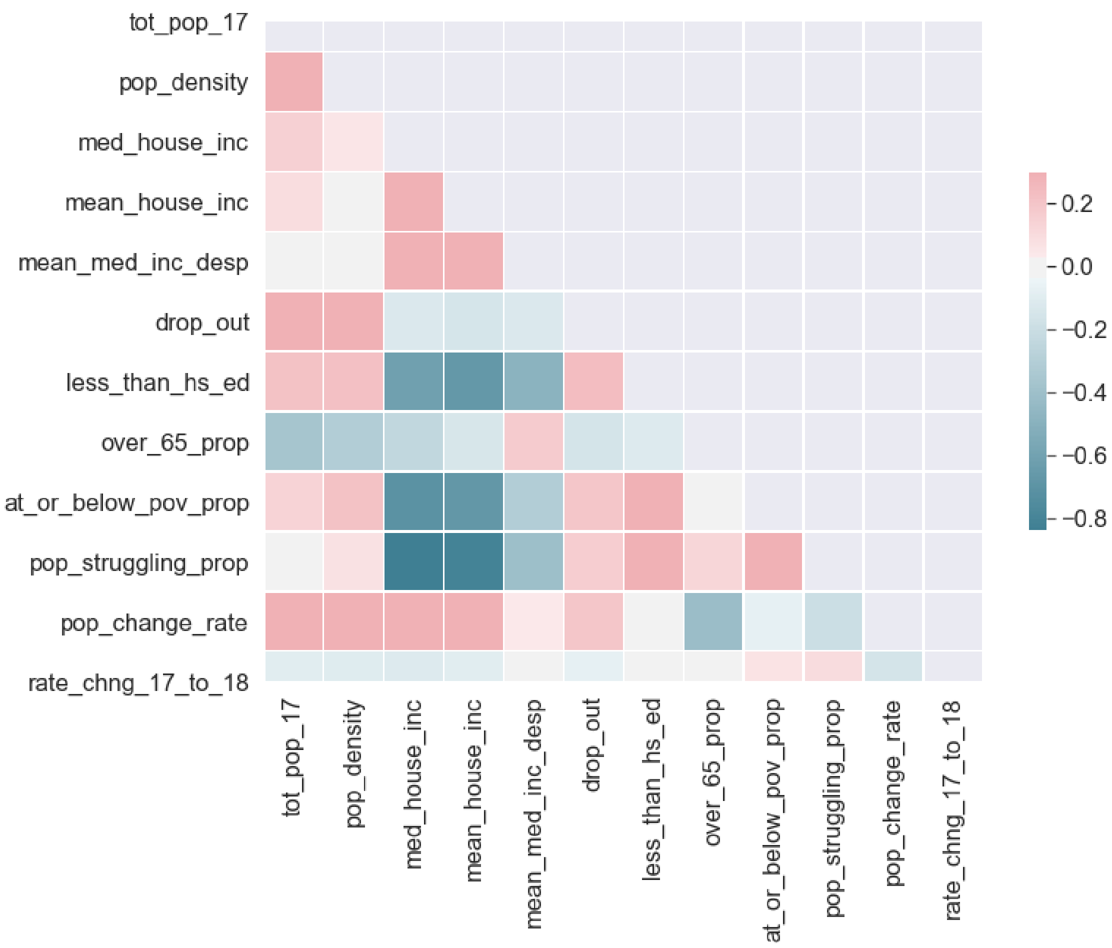
[115]:
```
full_merge_17.describe()
```

[115]:
```
          tot_pop_17   pop_density   med_house_inc   mean_house_inc  \
count     347.000000    347.000000      346.000000       347.000000
mean    19490.746398   2292.685930    88305.727278    109444.035932
std     41540.511381   4049.633320    29088.836206     39888.981321
min        34.000000      2.578370    38909.750000     50750.537570
25%      4196.000000    285.202885    68215.428571     82839.316239
50%     10560.000000    933.183133    83124.625000    100209.367399
75%     22704.000000   2452.889962   102446.289216    126078.167762
max    668541.000000  30236.970333   203026.750000    316351.858774

       mean_med_inc_desp    drop_out  less_than_hs_ed  over_65_prop  \
count         346.000000  346.000000       347.000000    347.000000
mean        21079.291563    2.355802         6.544580      0.207933
std         15309.458177    4.012968         4.750990      0.068754
min          2129.112803    0.000000         0.000000      0.086886
25%         12204.613762    0.000000         3.235427      0.166202
50%         16659.458813    0.318954         5.405643      0.193279
75%         24196.761231    3.184586         8.318470      0.230995
max        113325.108774   30.000000        32.336132      0.532847

       at_or_below_pov_prop  pop_struggling_prop  pop_change_rate  \
count            347.000000           347.000000       347.000000
```

```
mean               0.073728             0.104279        90.336764
std                0.047828             0.054009       408.250591
min                0.005354             0.000000      -472.714286
25%                0.042404             0.064869         4.428571
50%                0.059730             0.092496        37.571429
75%                0.092880             0.132362       109.214286
max                0.332260             0.304869      7278.142857

       death_rate_17  death_rate_18  rate_chng_17_to_18
count     347.000000     347.000000          347.000000
mean        1.627136       1.766947            0.139812
std         2.148897       2.270682            2.109397
min         0.000000       0.000000          -12.330456
25%         0.000000       0.000000           -0.618454
50%         0.964227       1.073858            0.000000
75%         2.248725       2.531146            0.848789
max        12.330456      14.453851           14.453851
```

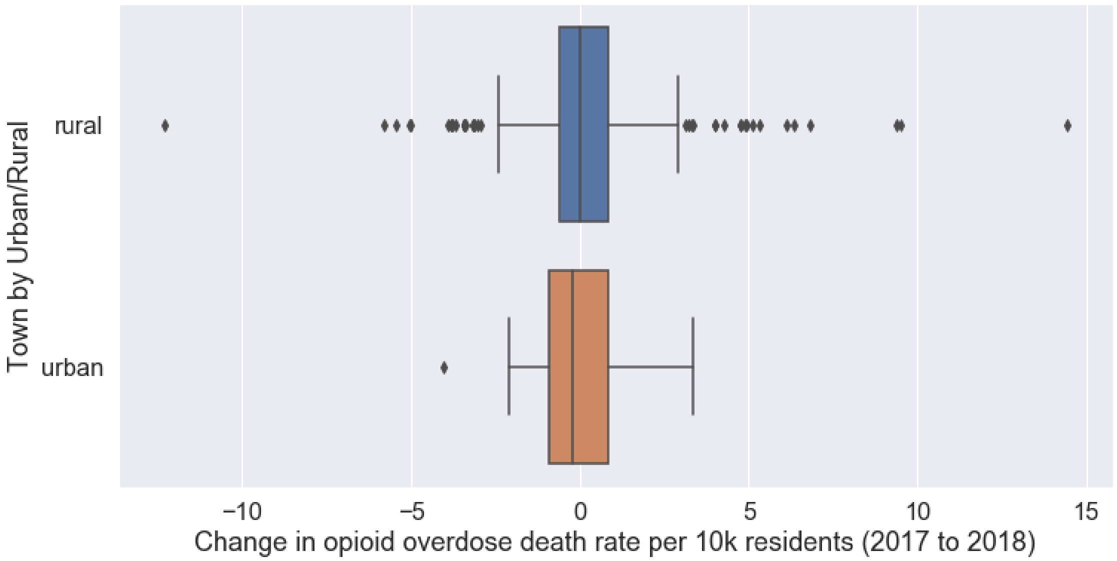
[116]:

```
full_merge_17_corr = full_merge_17.drop(['city_death', 'death_rate_17',␣
 ↪'death_rate_18'], axis=1).dropna().corr(method='spearman')
mask = np.zeros_like(full_merge_17_corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True
f, ax = plt.subplots(figsize=(11, 9))
cmap = sns.diverging_palette(220, 10, as_cmap=True)
sns.heatmap(full_merge_17_corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
plt.show()
```



[117]:

```
plt.figure(figsize=(12, 6))
sns.boxplot(y='urb_v_rur', x='rate_chng_17_to_18', orient='h',␣
 ↪data=full_merge_17)
plt.ylabel('Town by Urban/Rural')
plt.xlabel('Change in opioid overdose death rate per 10k residents (2017 to␣
 ↪2018)')
plt.show()
```

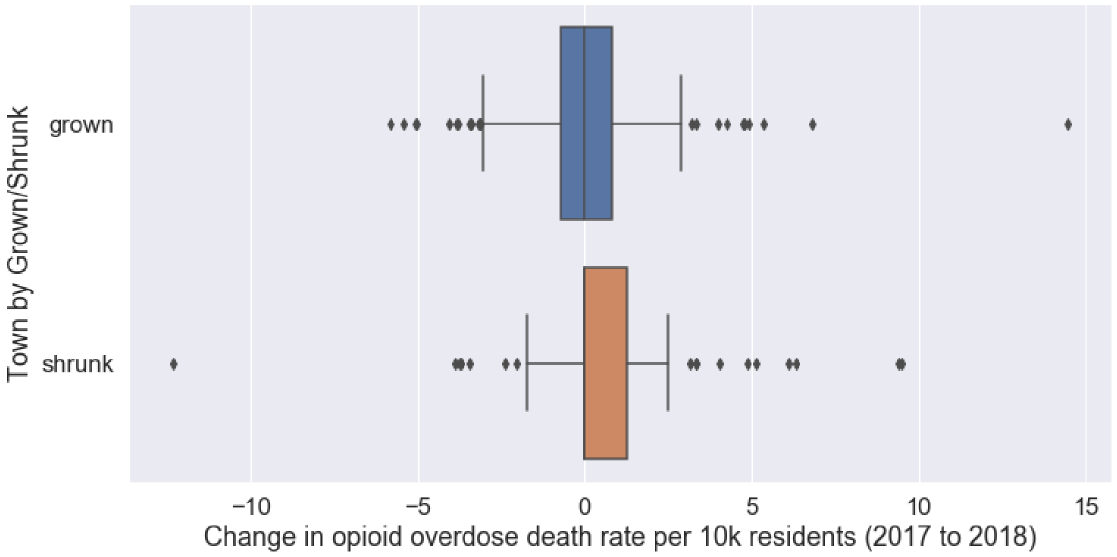


[118]:
```
# mean rate of change:
print(full_merge_17['rate_chng_17_to_18'].mean())
# sem of the change in rate:
print(full_merge_17[['rate_chng_17_to_18']].sem(axis=0))
full_merge_17[['urb_v_rur', 'rate_chng_17_to_18']].groupby('urb_v_rur').mean()
```

```
0.1398118818327503
rate_chng_17_to_18    0.113238
dtype: float64
```

[118]:
```
           rate_chng_17_to_18
urb_v_rur
rural                0.161618
urban               -0.141045
```

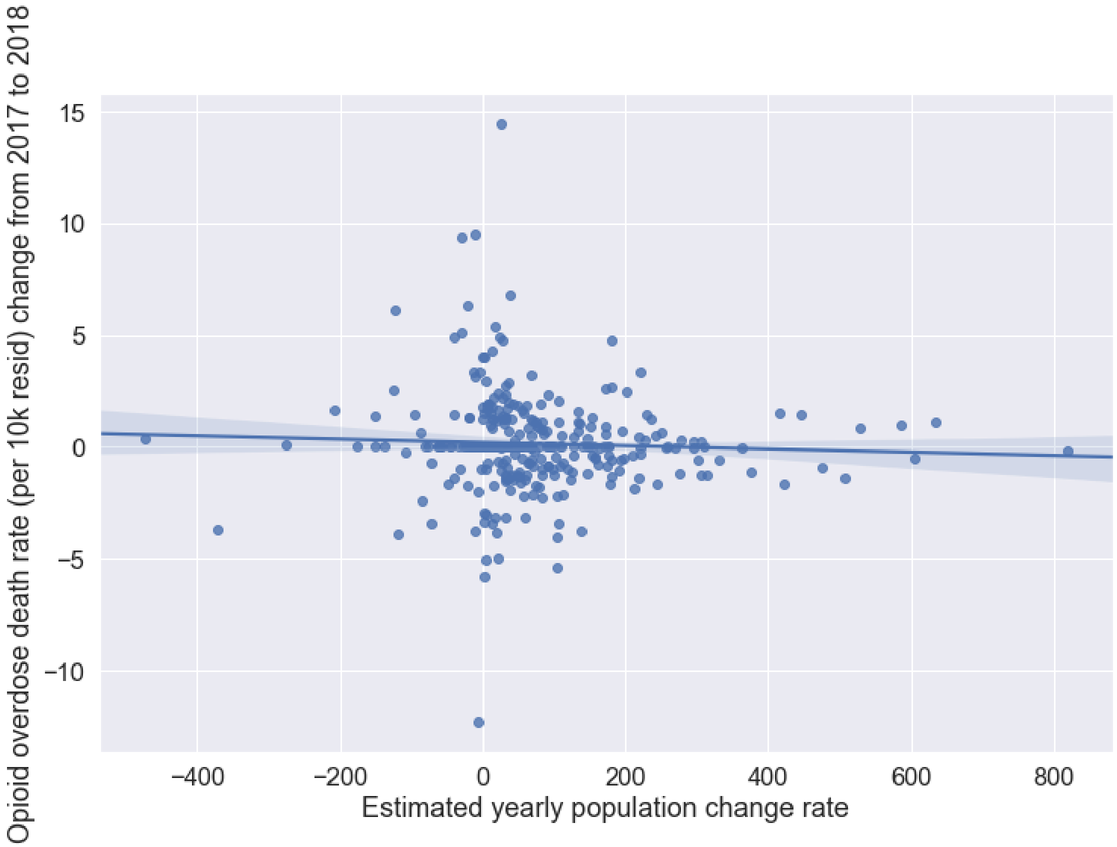
[119]:
```
plt.figure(figsize=(12, 6))
sns.boxplot(y='town_status', x='rate_chng_17_to_18', orient='h',␣
 ↪data=full_merge_17)
plt.ylabel('Town by Grown/Shrunk')
plt.xlabel('Change in opioid overdose death rate per 10k residents (2017 to␣
 ↪2018)')
plt.show()
```



[120]:
```
full_merge_17[['town_status', 'rate_chng_17_to_18']].groupby('town_status').
 ↪mean()
```

[120]:
```
             rate_chng_17_to_18
town_status
grown                  0.063617
shrunk                 0.425805
```

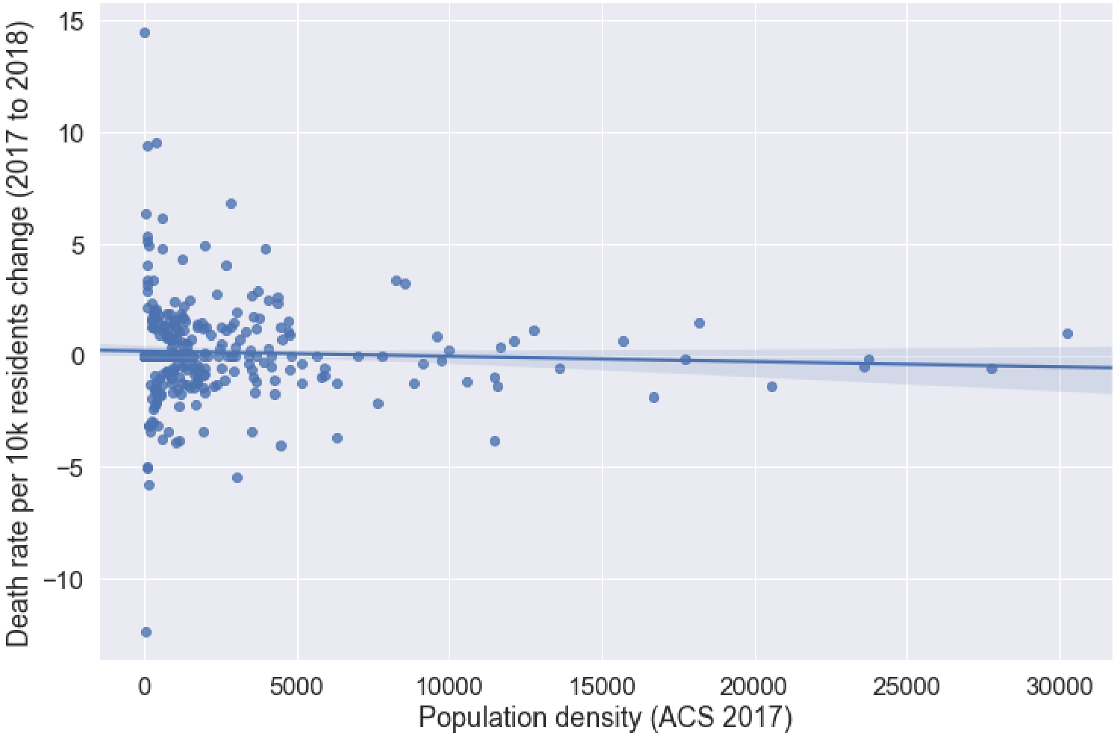
[126]:
```
plt.figure(figsize=(12, 8))
sns.regplot(x='pop_change_rate', y='rate_chng_17_to_18',␣
 ↪data=full_merge_17[full_merge_17['pop_change_rate'] < 1000])
plt.xlabel('Estimated yearly population change rate')
plt.ylabel('Opioid overdose death rate (per 10k resid) change from 2017 to␣
 ↪2018')
plt.show()
```



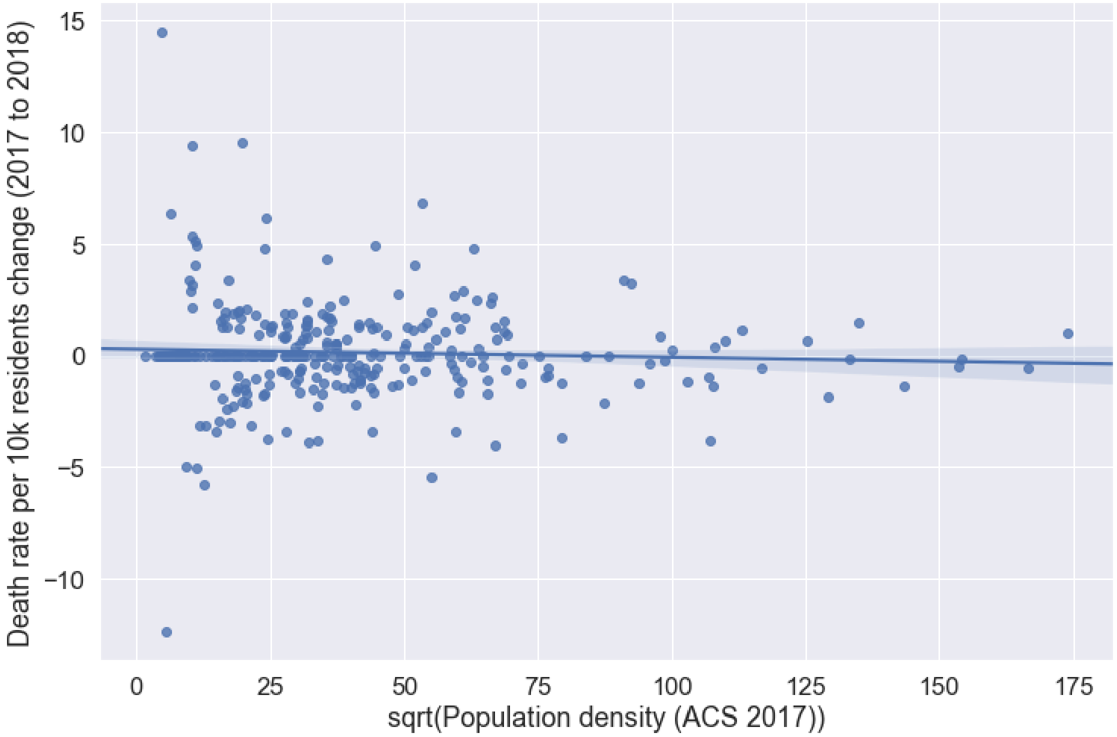
Think the estimated population change will probably not be useful, also most likely these two variables are confounded because population estimates for each year were calculated using the population change rate.

[127]:

```
plt.figure(figsize=(12, 8))
sns.regplot(x='pop_density', y='rate_chng_17_to_18', data=full_merge_17)
plt.xlabel('Population density (ACS 2017)')
plt.ylabel('Death rate per 10k residents change (2017 to 2018)')
plt.show()
```



[128]:
```
full_merge_17['pop_den_sqrt'] = np.sqrt(full_merge_17['pop_density'])
plt.figure(figsize=(12, 8))
sns.regplot(x='pop_den_sqrt', y='rate_chng_17_to_18', data=full_merge_17)
plt.xlabel('sqrt(Population density (ACS 2017))')
plt.ylabel('Death rate per 10k residents change (2017 to 2018)')
plt.show()
```



[130]:
```
full_merge.head()
```

[130]:
```
   city_death  tot_pop_17  over_65_count  tot_pop_10    shape_area  \
0   abington       16275           2469     15985.0  2.639085e+07
1      acton       23455           4001     21924.0  5.256453e+07
2   acushnet       10443           2431     10303.0  4.889337e+07
3      adams        8211           1764      8485.0  5.946649e+07
4     agawam       27769           6195     28438.0  6.302191e+07

   pop_density  med_house_inc  mean_house_inc  mean_med_inc_desp   drop_out  \
0  1932.969130   87156.000000    98809.035505       11653.035505   3.452855
1  1257.583593  139890.466667   156680.203867       16789.737200   1.219512
2  1152.357871   69624.714286    80333.175842       10708.461556  10.992908
3  1982.318840   48445.400000    60968.594660       12523.194660   6.906907
4  1897.273569   65490.125000    79464.234446       13974.109446   0.000000

   ...     tot_pop_18  death_rate_12  death_rate_13  death_rate_14  \
0  ...  16316.428571       0.622361       1.241520       0.000000
1  ...  23673.714286       0.894397       0.000000       0.438618
2  ...  10463.000000       1.933675       0.000000       0.000000
3  ...   8171.857143       1.189525       1.195090       2.401413
4  ...  27673.428571       0.354022       1.065671       0.356434

   death_rate_15  death_rate_16  death_rate_17  death_rate_18  town_status  \
0       3.705501       0.616007       1.843318       3.064396       grown
1       0.868901       1.291084       0.000000       0.422409       grown
2       3.845045       1.918833       3.830317       0.000000       grown
3       3.619130       1.212100       0.000000       4.894848      shrunk
4       0.715304       0.000000       1.440455       2.890860      shrunk

   urb_v_rur
0      rural
1      rural
2      rural
3      rural
4      rural

[5 rows x 37 columns]
```

[131]:

```
full_merge.columns
```

[131]:

```
Index(['city_death', 'tot_pop_17', 'over_65_count', 'tot_pop_10', 'shape_area',
       'pop_density', 'med_house_inc', 'mean_house_inc', 'mean_med_inc_desp',
       'drop_out', 'less_than_hs_ed', 'over_65_prop', 'at_or_below_pov_prop',
       'pop_struggling_prop', '2012', '2013', '2014', '2015', '2016', '2017',
       '2018', 'pop_change_rate', 'tot_pop_16', 'tot_pop_15', 'tot_pop_14',
       'tot_pop_13', 'tot_pop_12', 'tot_pop_18', 'death_rate_12',
       'death_rate_13', 'death_rate_14', 'death_rate_15', 'death_rate_16',
       'death_rate_17', 'death_rate_18', 'town_status', 'urb_v_rur'],
      dtype='object')
```

[146]:

```
full_merge_cols = list(full_merge.columns)
full_merge_select = full_merge_cols[:3] + full_merge_cols[11:12] +␣
 ↪full_merge_cols[6:11] + full_merge_cols[12:14] + full_merge_cols[35:] +␣
 ↪full_merge_cols[28:35]
print(full_merge_select)
full_merge_for_csv = full_merge[full_merge_select].copy()
full_merge_for_csv.head()
```

```
['city_death', 'tot_pop_17', 'over_65_count', 'over_65_prop', 'med_house_inc',
'mean_house_inc', 'mean_med_inc_desp', 'drop_out', 'less_than_hs_ed',
'at_or_below_pov_prop', 'pop_struggling_prop', 'town_status', 'urb_v_rur',
'death_rate_12', 'death_rate_13', 'death_rate_14', 'death_rate_15',
'death_rate_16', 'death_rate_17', 'death_rate_18']
```

[146]:

```
  city_death  tot_pop_17  over_65_count  over_65_prop  med_house_inc  \
0   abington       16275           2469      0.151705   87156.000000
1      acton       23455           4001      0.170582  139890.466667
2   acushnet       10443           2431      0.232788   69624.714286
3      adams        8211           1764      0.214834   48445.400000
4     agawam       27769           6195      0.223090   65490.125000

   mean_house_inc  mean_med_inc_desp   drop_out  less_than_hs_ed  \
0    98809.035505       11653.035505   3.452855         5.405643
1   156680.203867       16789.737200   1.219512         2.456531
2    80333.175842       10708.461556  10.992908        18.297315
3    60968.594660       12523.194660   6.906907        11.862182
4    79464.234446       13974.109446   0.000000         7.748863

   at_or_below_pov_prop  pop_struggling_prop town_status urb_v_rur  \
0              0.035754             0.100408       grown     rural
1              0.038315             0.041747       grown     rural
2              0.040828             0.178406       grown     rural
3              0.110854             0.144597      shrunk     rural
4              0.094819             0.142656      shrunk     rural

   death_rate_12  death_rate_13  death_rate_14  death_rate_15  death_rate_16  \
0       0.622361       1.241520       0.000000       3.705501       0.616007
1       0.894397       0.000000       0.438618       0.868901       1.291084
2       1.933675       0.000000       0.000000       3.845045       1.918833
3       1.189525       1.195090       2.401413       3.619130       1.212100
4       0.354022       1.065671       0.356434       0.715304       0.000000

   death_rate_17  death_rate_18
0       1.843318       3.064396
1       0.000000       0.422409
2       3.830317       0.000000
3       0.000000       4.894848
4       1.440455       2.890860
```

[148]:

```
#full_merge_for_csv.to_csv("../../data/tidy_data/
 ↪death_count_norm_to_pop_and_acs_town_demographics_merge.csv", index=False)
```