notebook_4_overdose_death_and_acs_by_census_block_merge_and_ed

October 19, 2019

1 Opioid overdose deaths and ACS dataset merge and EDA

1.0.1 Goals:

- Try normalizing death count data to town population (turn raw counts into deaths per 10k residents values) - evaluate if this improves the skew in the overdose death data
- Pull out some ACS demographics data - correlation with death counts/rate?
- EDA on ACS demographics data, some feature engineering on poverty, population, and other demographics data

1.0.2 Output:

Opioid overdose death count (by town for years 2014-2018) merged with ACS demogrpahics data
* data/tidy_data/overdose_death_count_acs_merge.csv
pdf output in case notebook doesn't run: * products/notebook_4_overdose_death_and_acs_by_census_block_

[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_2014_to_2018.csv")
# from notebook 3 (town - census block matching)
town_block_match = pd.read_csv("../../data/tidy_data/census_block_town_match.
 ↪csv")
town_w_2010pop = pd.read_csv("../../data/tidy_data/
 ↪census_block_town_match_2010pop_error.csv")
# 2017 ACS dataset for MA state only, provided by Biobot
acs_17 = pd.read_csv("../../data/raw_data/american_community_survey/
 ↪R12288202_SL150.csv")
```

[3]:
```
death_data.head()
```

[3]:

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

[4]:

```
# town - census block match df:
display(town_block_match.head())
display(town_w_2010pop.head())
```

```
        TOWN       GEOID10
0  wellesley  2.502140e+11
1  wellesley  2.502140e+11
2  wellesley  2.502140e+11
3  wellesley  2.502140e+11
4  wellesley  2.502140e+11
```

```
        TOWN  town_actual_2010_pop  block_est_2010_pop  count_error  \
0  wellesley                 27982             27982.0          0.0
1    needham                 28886             28886.0          0.0
2  petersham                  1234              1234.0          0.0
3    reading                 24747             24747.0          0.0
4     quincy                 92271             89703.0      -2568.0

   percent_error
0       0.000000
1       0.000000
2       0.000000
3       0.000000
4       2.783106
```

[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]:

```
# ACS size:
print(acs_17.shape)
# column name format:
acs_17.columns
```

```
(4985, 2200)
```

[6]:
```
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)
```

[7]:
```
# which columns to match on?
acs_17[['Geo_FIPS', 'Geo_GEOID']].head()
# Geo_FIPS is match for GEOID10 from town - block match df
```

[7]:
```
       Geo_FIPS            Geo_GEOID
0  250010101001  15000US250010101001
1  250010101002  15000US250010101002
2  250010101003  15000US250010101003
3  250010101004  15000US250010101004
4  250010101005  15000US250010101005
```

[8]:
```
# mismatches between sets?
print(len(set(acs_17['Geo_FIPS']) - set(town_block_match['GEOID10'])))
print(len(set(town_block_match['GEOID10']) - set(acs_17['Geo_FIPS'])))
```

```
31
4
```

1.0.3 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

[9]:
```
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()
```

[10]:
```
acs_17_sub.head()
```

[10]:
```
       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
```

[11]:
```python
# 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'
]
```

[12]:
```python
acs_17_sub.head()
```

[12]:
```
        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
```

[13]:
```python
# calculate num and 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()
```

[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

   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	over_65_count
0	605	274
1	223	193
2	601	297
3	248	202
4	299	92

[14]:
```
acs_17_sub.describe()
```

[14]:

	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	

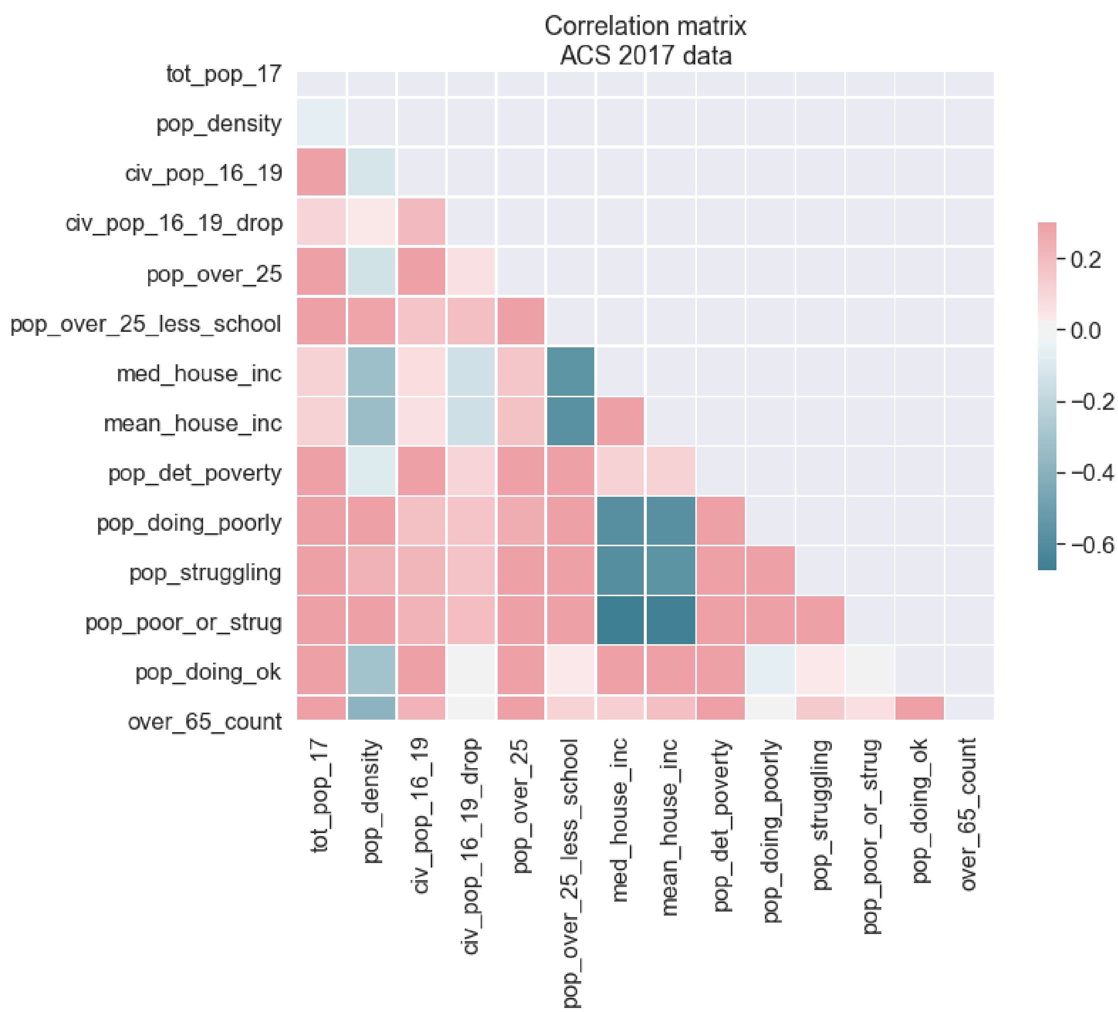
	civ_pop_16_19_drop	pop_over_25	pop_over_25_less_school	\
count	4985.000000	4985.000000	4985.000000	
mean	2.065998	944.139619	91.891675	
std	7.653031	455.980232	101.193132	
min	0.000000	0.000000	0.000000	
25%	0.000000	619.000000	23.000000	
50%	0.000000	851.000000	58.000000	
75%	0.000000	1184.000000	128.000000	
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	over_65_count
count	4985.000000	4985.000000	4985.000000	4985.000000
mean	165.163290	311.110331	1003.302307	240.608626
std	157.779113	289.346330	588.097455	171.729713
min	0.000000	0.000000	0.000000	0.000000
25%	53.000000	109.000000	601.000000	121.000000
50%	121.000000	225.000000	877.000000	206.000000
75%	227.000000	423.000000	1285.000000	319.000000

```
max        1392.000000          3260.000000    4279.000000     2178.000000
```

[15]:
```
# code dapted from https://www.programcreek.com/python/example/96220/seaborn.
↪diverging_palette
acs_sub_corr = acs_17_sub.drop('GEOID10', axis=1).corr(method='spearman')
mask = np.zeros_like(acs_sub_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(acs_sub_corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
ax.set_title('Correlation matrix\nACS 2017 data')
plt.show()
```



Notes: * A lot of features are pretty correlated * poverty counts and mean/med income have strong correlations * Will wait to do any kind of summarizing after the merge with town/census block df

[16]:
```
print(acs_17_sub.columns)
print(town_block_match.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', 'over_65_count'],
      dtype='object')
Index(['TOWN', 'GEOID10'], dtype='object')
```

[17]:
```
town_block = town_block_match.merge(town_w_2010pop, on='TOWN', how='inner')
print(town_block.shape)
print(len(set(town_block['TOWN'])))
print(len(set(town_block['GEOID10'])))
town_block.columns = ['city_death'] + list(town_block.columns)[1:]
# result:
town_block.head()
```

```
(4958, 6)
351
4958
```

[17]:
```
  city_death       GEOID10  town_actual_2010_pop  block_est_2010_pop  \
0  wellesley  2.502140e+11                 27982             27982.0
1  wellesley  2.502140e+11                 27982             27982.0
2  wellesley  2.502140e+11                 27982             27982.0
3  wellesley  2.502140e+11                 27982             27982.0
4  wellesley  2.502140e+11                 27982             27982.0

   count_error  percent_error
0          0.0            0.0
1          0.0            0.0
2          0.0            0.0
3          0.0            0.0
4          0.0            0.0
```

[18]:
```
town_acs_merge = town_block.merge(acs_17_sub, on='GEOID10', how='inner')
print(town_acs_merge.shape)
print(town_acs_merge.columns)
town_acs_merge.head()
```

```
(4954, 20)
Index(['city_death', 'GEOID10', 'town_actual_2010_pop', 'block_est_2010_pop',
       'count_error', 'percent_error', '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', 'over_65_count'],
      dtype='object')
```

[18]:
```
  city_death       GEOID10  town_actual_2010_pop  block_est_2010_pop  \
0  wellesley  2.502140e+11                 27982             27982.0
1  wellesley  2.502140e+11                 27982             27982.0
2  wellesley  2.502140e+11                 27982             27982.0
3  wellesley  2.502140e+11                 27982             27982.0
4  wellesley  2.502140e+11                 27982             27982.0

   count_error  percent_error  tot_pop_17  pop_density  civ_pop_16_19  \
0          0.0            0.0        1101     4438.051             96
1          0.0            0.0         924     2064.697            108
2          0.0            0.0         881     1947.536              9
3          0.0            0.0        1177     2961.899             38
4          0.0            0.0         767     3843.039             10

   civ_pop_16_19_drop  pop_over_25  pop_over_25_less_school  med_house_inc  \
0                   0          636                        0       183879.0
1                   0          634                        0       250001.0
2                   0          552                       11       181786.0
3                   0          685                       30       129071.0
4                   0          590                       22        86827.0

   mean_house_inc  pop_det_poverty  pop_doing_poorly  pop_struggling  \
0   214803.395062             1101                 0               0
1   505804.304636              924                 0               0
2   244652.447552              875                12               9
3   240321.641791             1177               144             100
4   145115.151515              767                64              95

   pop_poor_or_strug  pop_doing_ok  over_65_count
0                  0          1101            137
1                  0           924            197
2                 21           854            231
3                244           933            105
4                159           608            275
```

To summarize, some columns need to be added by town (count columns) and some need to be averaged

First, columns that will be added up by group:

[19]:
```
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()
```

[19]:

```
  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
```

Columns that will be averaged by group: Note: for 2010 actual and estimated error columns, as well as the count and percent error - this will return the values from the original imported df

[20]:

```
mean_stat_cols = ['city_death', 'town_actual_2010_pop', 'block_est_2010_pop',
                  'count_error', 'percent_error', 'pop_density',
                  'med_house_inc', 'mean_house_inc']
town_stats = town_acs_merge.groupby('city_death').mean().
  ↪reset_index()[mean_stat_cols]
town_stats.head()
```

[20]:

```
  city_death  town_actual_2010_pop  block_est_2010_pop  count_error  \
0   abington               15985.0             15985.0          0.0
1      acton               21924.0             21924.0          0.0
2   acushnet               10303.0             10303.0          0.0
3      adams                8485.0              8485.0          0.0
4     agawam               28438.0             27621.0       -817.0

   percent_error  pop_density  med_house_inc  mean_house_inc
0       0.000000  1932.969130   87156.000000    98809.035505
1       0.000000  1257.583593  139890.466667   156680.203867
2       0.000000  1152.357871   69624.714286    80333.175842
3       0.000000  1982.318840   48445.400000    60968.594660
4       2.872917  1897.273569   65490.125000    79464.234446
```

[21]:
```
town_merge = town_17_pop.merge(town_stats, on='city_death', how='inner')
print(town_merge.shape)
town_merge.head()
```

```
(347, 19)
```

[21]:
```
  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  town_actual_2010_pop  \
0            1626               2205         13989               15985.0
1             973               1866         21441               21924.0
2            1844               2266          8070               10303.0
3            1187               2097          6112                8485.0
4            3841               6394         20531               28438.0

   block_est_2010_pop  count_error  percent_error  pop_density  med_house_inc  \
0             15985.0          0.0       0.000000  1932.969130   87156.000000
1             21924.0          0.0       0.000000  1257.583593  139890.466667
2             10303.0          0.0       0.000000  1152.357871   69624.714286
3              8485.0          0.0       0.000000  1982.318840   48445.400000
4             27621.0       -817.0       2.872917  1897.273569   65490.125000

   mean_house_inc
0    98809.035505
1   156680.203867
2    80333.175842
3    60968.594660
4    79464.234446
```

Some summary stats: * drop out rate among 16-19 year olds * estimate of proportion of population that's over 25 with less than a high school education

[22]:
```
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()
```

[22]:

```
  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  town_actual_2010_pop  \
0            1626               2205         13989               15985.0
1             973               1866         21441               21924.0
2            1844               2266          8070               10303.0
3            1187               2097          6112                8485.0
4            3841               6394         20531               28438.0

   block_est_2010_pop  count_error  percent_error  pop_density  med_house_inc  \
0             15985.0          0.0       0.000000  1932.969130   87156.000000
1             21924.0          0.0       0.000000  1257.583593  139890.466667
2             10303.0          0.0       0.000000  1152.357871   69624.714286
3              8485.0          0.0       0.000000  1982.318840   48445.400000
4             27621.0       -817.0       2.872917  1897.273569   65490.125000

   mean_house_inc   drop_out  less_than_hs_ed
0    98809.035505   3.452855         5.405643
1   156680.203867   1.219512         2.456531
2    80333.175842  10.992908        18.297315
3    60968.594660   6.906907        11.862182
4    79464.234446   0.000000         7.748863
```

[23]:

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

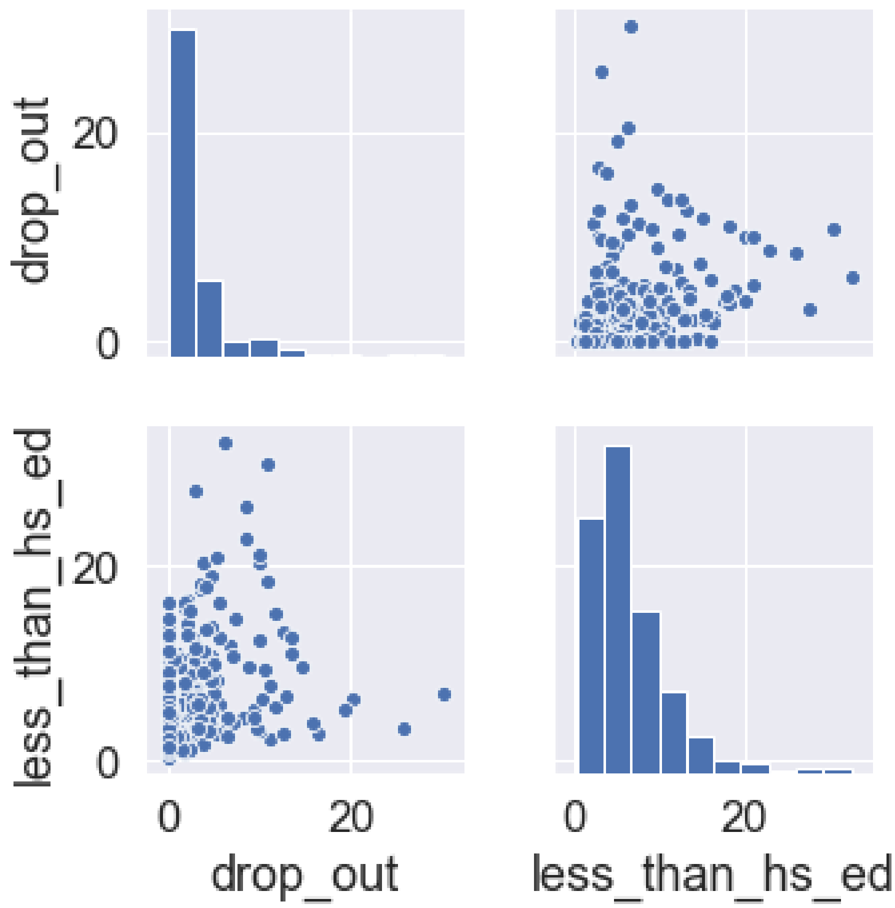
[23]:

```
         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
```

[24]:

```
# what's the distribution of these 2 new variables and what is the relationship␣
↪between them?
sns.pairplot(town_merge[['drop_out', 'less_than_hs_ed']].dropna())
```

```
plt.show()
```



New dropout variable has a lot of zeroes - probably not useful - drop it

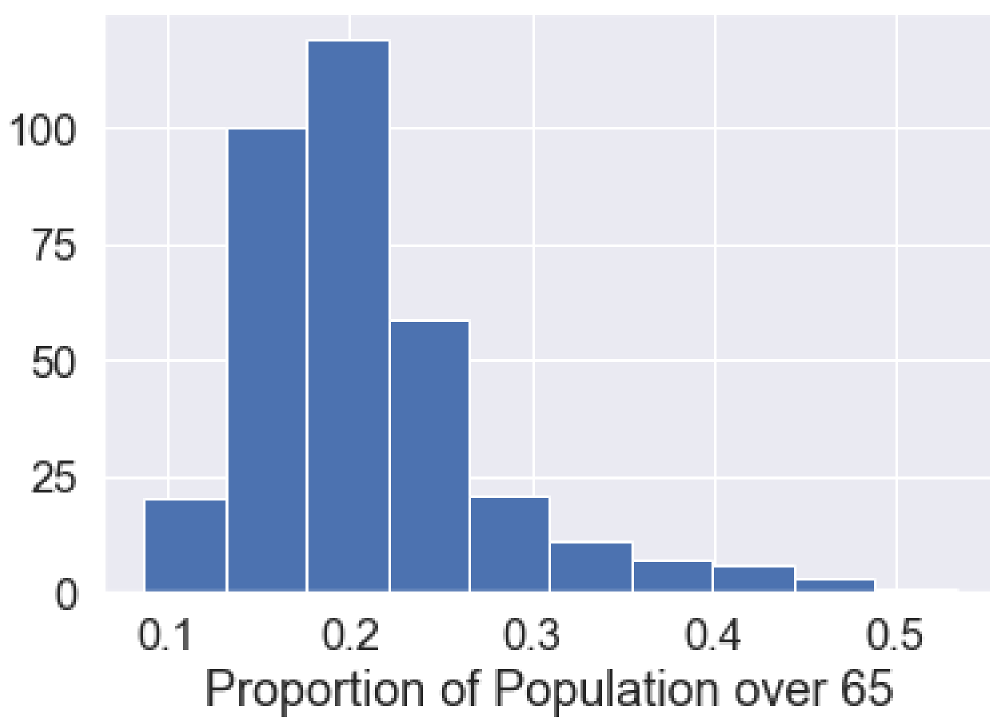
[25]:
```
town_merge.drop('drop_out', axis=1, inplace=True)
town_merge.head()
```

[25]:
```
  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  town_actual_2010_pop  \
0            1626               2205         13989               15985.0
1             973               1866         21441               21924.0
2            1844               2266          8070               10303.0
3            1187               2097          6112                8485.0
4            3841               6394         20531               28438.0
```

```
   block_est_2010_pop  count_error  percent_error  pop_density  med_house_inc  \
0             15985.0          0.0       0.000000  1932.969130   87156.000000
1             21924.0          0.0       0.000000  1257.583593  139890.466667
2             10303.0          0.0       0.000000  1152.357871   69624.714286
3              8485.0          0.0       0.000000  1982.318840   48445.400000
4             27621.0       -817.0       2.872917  1897.273569   65490.125000

   mean_house_inc  less_than_hs_ed
0    98809.035505         5.405643
1   156680.203867         2.456531
2    80333.175842        18.297315
3    60968.594660        11.862182
4    79464.234446         7.748863
```

Maybe the proportion of people over 65 in a town could be useful?

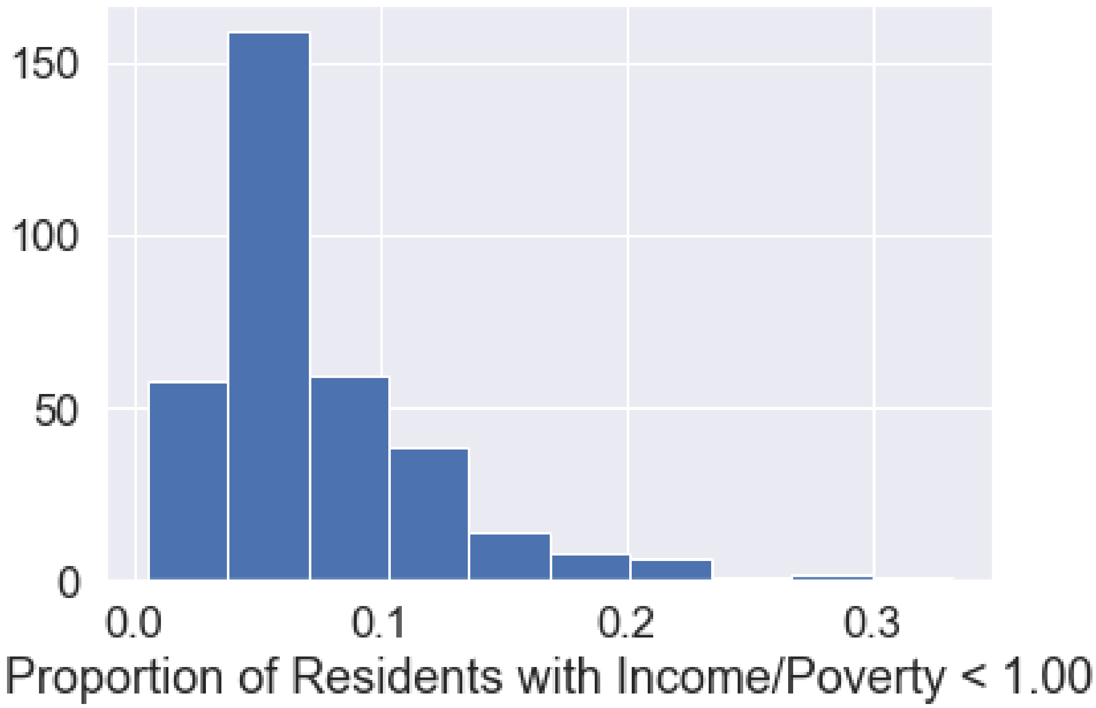
[26]:
```
town_merge['over_65_prop'] = town_merge['over_65_count'] /␣
 ↪town_merge['tot_pop_17']
town_merge['over_65_prop'].hist()
plt.xlabel('Proportion of Population over 65')
plt.show()
```



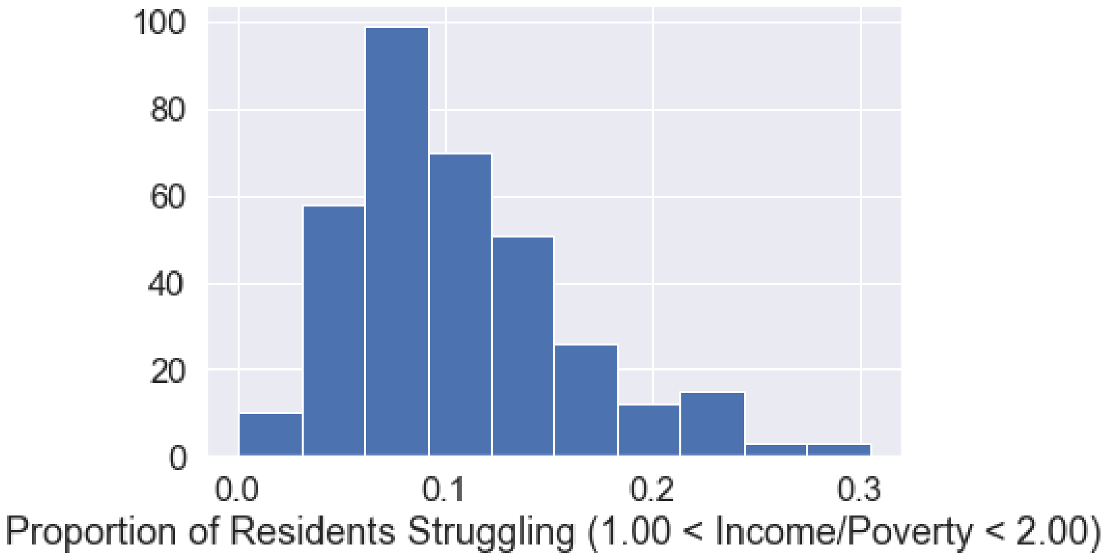
The different columns relating to poverty need to be summarized in some way.

What the different rations of income/poverty mean: * Doing Poorly: Under 1.00 * Struggling: 1.00 to 1.99 * Poor or Struggling: Under 2.00 * Doing OK: 2.00 and Over

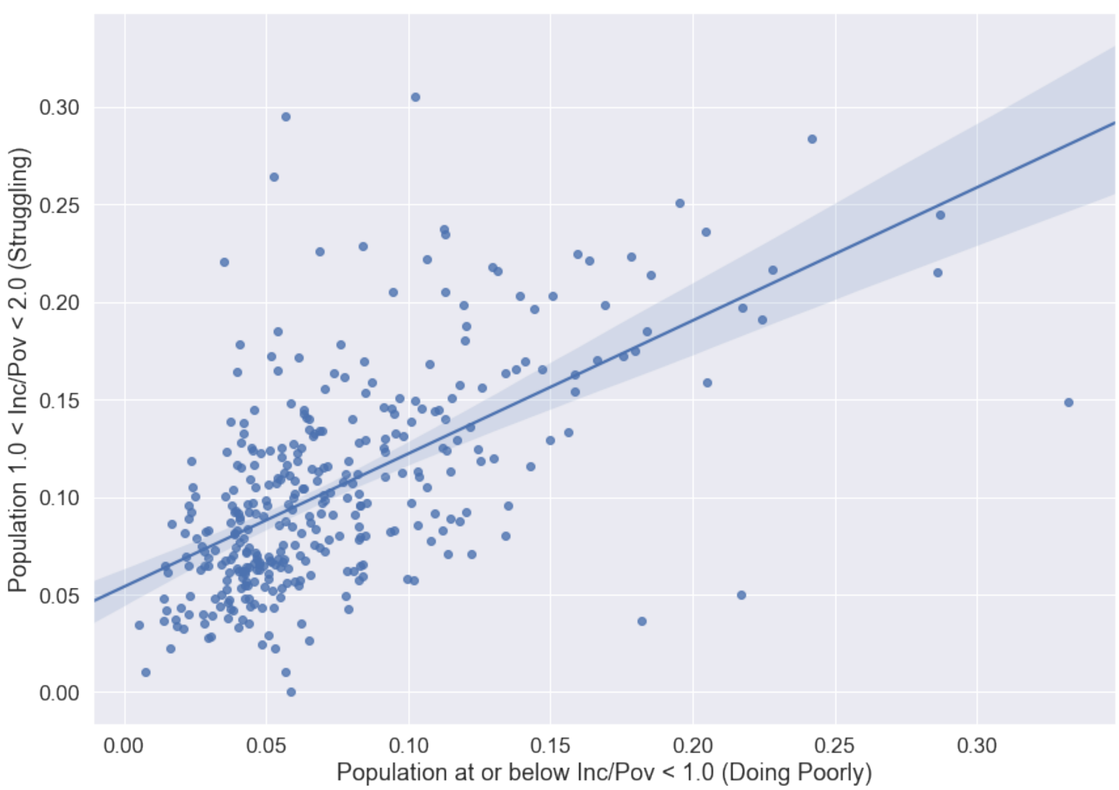
[27]:
```
# poverty calc
town_merge.head()
town_merge['at_or_below_pov_prop'] = town_merge['pop_doing_poorly'] /␣
 ↪town_merge['pop_det_poverty']
town_merge['at_or_below_pov_prop'].hist(bins=10)
plt.xlabel('Proportion of Residents with Income/Poverty < 1.00')
plt.show()
```



[28]:
```
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()
```



[29]:
```python
# what's the relationship between these 2?
plt.figure(figsize=(14,10))
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 (Doing Poorly)')
plt.ylabel('Population 1.0 < Inc/Pov < 2.0 (Struggling)')
plt.show()
```



[30]:
```
# drop count data
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()
```

[30]:
```
  city_death  tot_pop_17  over_65_count  town_actual_2010_pop  \
0   abington       16275           2469               15985.0
1      acton       23455           4001               21924.0
2   acushnet       10443           2431               10303.0
3      adams        8211           1764                8485.0
4     agawam       27769           6195               28438.0

   block_est_2010_pop  count_error  percent_error  pop_density  med_house_inc  \
0             15985.0          0.0       0.000000  1932.969130   87156.000000
1             21924.0          0.0       0.000000  1257.583593  139890.466667
2             10303.0          0.0       0.000000  1152.357871   69624.714286
3              8485.0          0.0       0.000000  1982.318840   48445.400000
4             27621.0       -817.0       2.872917  1897.273569   65490.125000

   mean_house_inc  less_than_hs_ed  over_65_prop  at_or_below_pov_prop  \
0    98809.035505         5.405643      0.151705              0.035754
1   156680.203867         2.456531      0.170582              0.038315
2    80333.175842        18.297315      0.232788              0.040828
3    60968.594660        11.862182      0.214834              0.110854
4    79464.234446         7.748863      0.223090              0.094819

   pop_struggling_prop
0             0.100408
1             0.041747
2             0.178406
3             0.144597
4             0.142656
```

[31]:
```
# distributions of current
town_merge.describe()
```

[31]:
```
          tot_pop_17  over_65_count  town_actual_2010_pop  block_est_2010_pop  \
count     347.000000     347.000000            347.000000          347.000000
mean    19490.746398    3434.824207          18858.389049        18794.827089
std     41540.511381    5642.967441          39009.479522        38920.193487
min        34.000000      15.000000             75.000000           75.000000
25%      4196.000000     781.000000           4008.000000         4008.000000
50%     10560.000000    1977.000000          10300.000000        10209.000000
75%     22704.000000    4385.000000          21691.500000        21691.500000
max    668541.000000   85040.000000         617594.000000       616852.000000

       count_error  percent_error   pop_density  med_house_inc  \
```

```
count    347.000000     347.000000    347.000000     346.000000
mean     -63.561960       5.979779   2292.685930   88305.727278
std      445.473371      44.749992   4049.633320   29088.836206
min    -3861.000000       0.000000      2.578370   38909.750000
25%        0.000000       0.000000    285.202885   68215.428571
50%        0.000000       0.000000    933.183133   83124.625000
75%        0.000000       0.000000   2452.889962  102446.289216
max     1323.000000     733.532934  30236.970333  203026.750000

       mean_house_inc  less_than_hs_ed  over_65_prop  at_or_below_pov_prop  \
count      347.000000       347.000000    347.000000            347.000000
mean    109444.035932         6.544580      0.207933              0.073728
std      39888.981321         4.750990      0.068754              0.047828
min      50750.537570         0.000000      0.086886              0.005354
25%      82839.316239         3.235427      0.166202              0.042404
50%     100209.367399         5.405643      0.193279              0.059730
75%     126078.167762         8.318470      0.230995              0.092880
max     316351.858774        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
```

[32]:

```python
print(set(death_data['city_death']) - set(town_merge['city_death']))
print(set(town_merge['city_death']) - set(death_data['city_death']))
```

```
{'monroe', 'egremont', 'charlemont', 'worthington'}
set()
```

[33]:

```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()
```

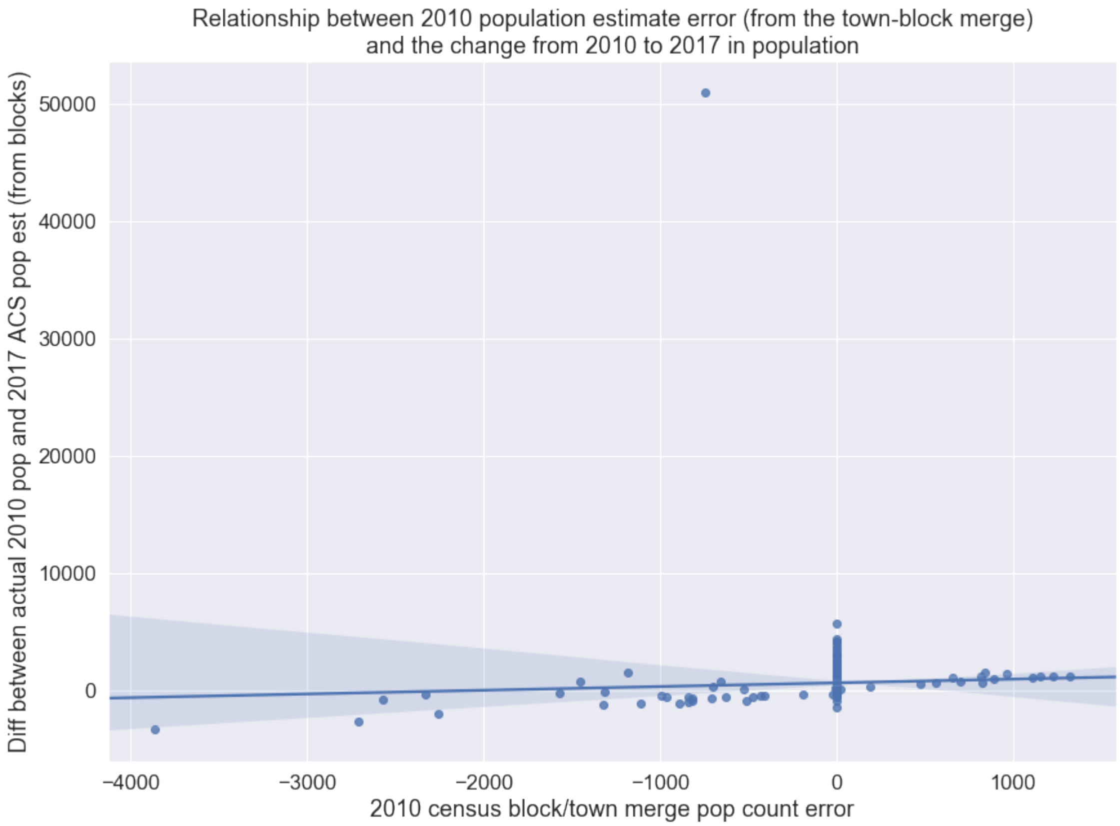
```
(347, 19)
```

[33]:

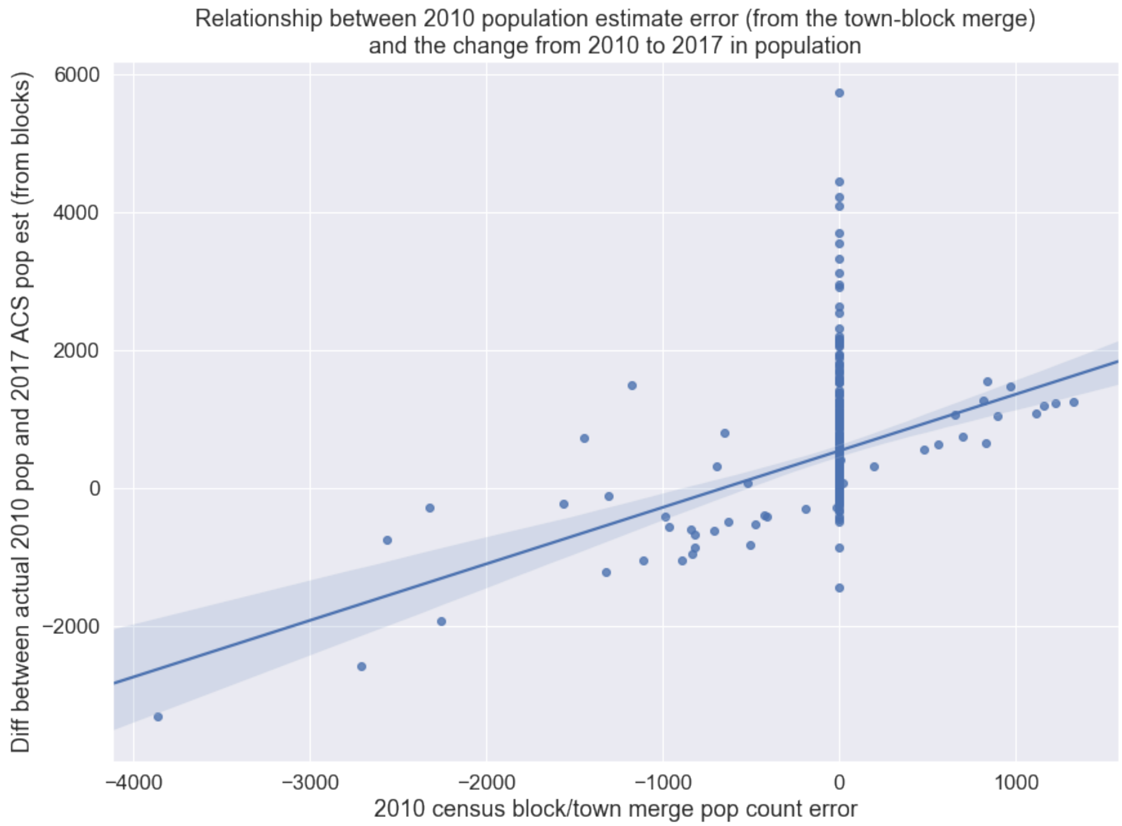
```
  city_death  tot_pop_17  over_65_count  town_actual_2010_pop  \
0   abington       16275           2469               15985.0
1      acton       23455           4001               21924.0
2   acushnet       10443           2431               10303.0
3      adams        8211           1764                8485.0
```

```
4     agawam       27769          6195               28438.0

   block_est_2010_pop  count_error  percent_error  pop_density  med_house_inc  \
0             15985.0          0.0       0.000000  1932.969130   87156.000000
1             21924.0          0.0       0.000000  1257.583593  139890.466667
2             10303.0          0.0       0.000000  1152.357871   69624.714286
3              8485.0          0.0       0.000000  1982.318840   48445.400000
4             27621.0       -817.0       2.872917  1897.273569   65490.125000

   mean_house_inc  less_than_hs_ed  over_65_prop  at_or_below_pov_prop  \
0    98809.035505         5.405643      0.151705              0.035754
1   156680.203867         2.456531      0.170582              0.038315
2    80333.175842        18.297315      0.232788              0.040828
3    60968.594660        11.862182      0.214834              0.110854
4    79464.234446         7.748863      0.223090              0.094819

   pop_struggling_prop  2014  2015  2016  2017  2018
0             0.100408     0     6     1     3     5
1             0.041747     1     2     3     0     1
2             0.178406     0     4     2     4     0
3             0.144597     2     3     1     0     4
4             0.142656     1     2     0     4     8
```

[34]:
```
full_merge['pop_change_10_to_17'] = full_merge['tot_pop_17'] -
 ↪full_merge['town_actual_2010_pop']
plt.figure(figsize=(14,10))
sns.regplot(x='count_error', y='pop_change_10_to_17', data=full_merge)
plt.xlabel('2010 census block/town merge pop count error')
plt.ylabel('Diff between actual 2010 pop and 2017 ACS pop est (from blocks)')
plt.title('Relationship between 2010 population estimate error (from the
 ↪town-block merge)\nand the change from 2010 to 2017 in population')
plt.show()
```

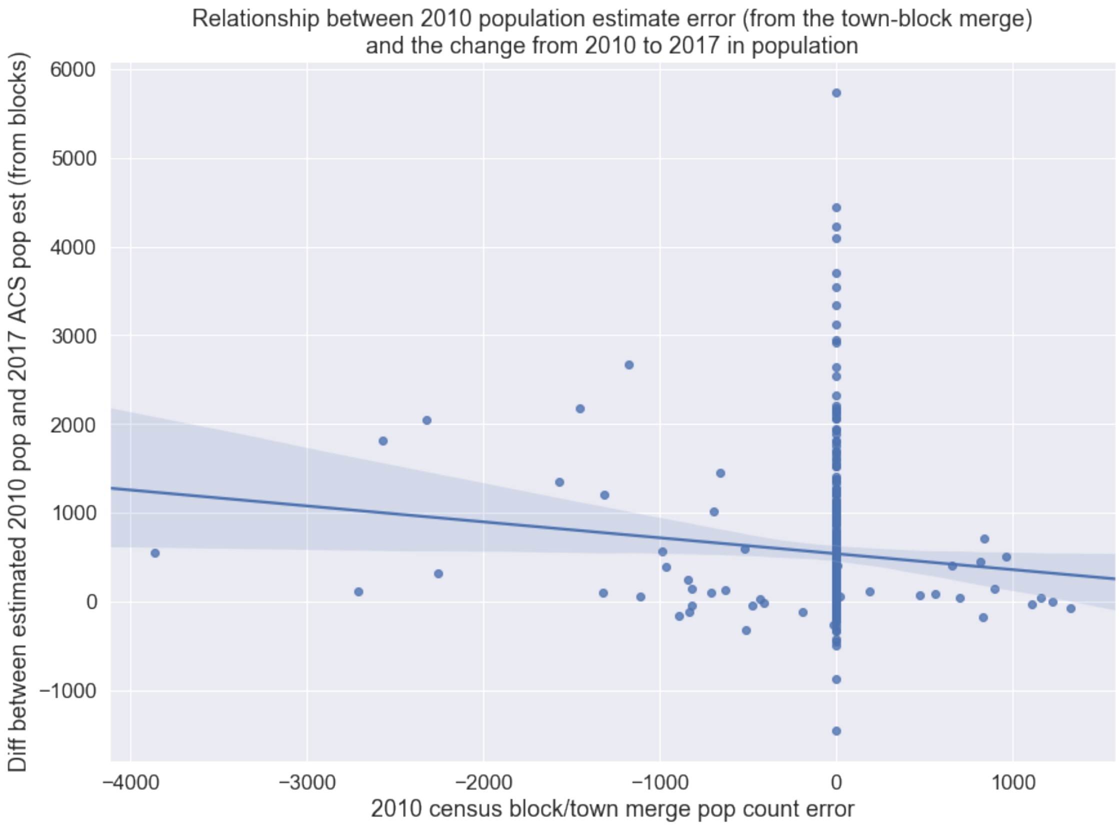


[35]:
```
# take out the one big change point (Boston)
plt.figure(figsize=(14,10))
sns.regplot(x='count_error', y='pop_change_10_to_17',
            data=full_merge[full_merge['pop_change_10_to_17'] < 40000])
plt.xlabel('2010 census block/town merge pop count error')
plt.ylabel('Diff between actual 2010 pop and 2017 ACS pop est (from blocks)')
plt.title('Relationship between 2010 population estimate error (from the␣
↪town-block merge)\nand the change from 2010 to 2017 in population')
plt.show()
```



Notes: * There does seem to be some relationship between the error in the 2010 estimation and the difference between the 2017 population estimate (also derived from census block data) and the 2010 actual count - makes sense * But it's not perfectly 1-to-1 - the difference between (2017 estimate - 2010 actual) and (2010 estimate - 2010 actual) seems to be smaller

[36]:
```
full_merge['pop_change_10_to_17_est'] = full_merge['tot_pop_17'] -␣
 ↪full_merge['block_est_2010_pop']
plt.figure(figsize=(14,10))
sns.regplot(x='count_error', y='pop_change_10_to_17_est',
            data=full_merge[full_merge['pop_change_10_to_17_est'] < 40000])
plt.xlabel('2010 census block/town merge pop count error')
plt.ylabel('Diff between estimated 2010 pop and 2017 ACS pop est (from blocks)')
plt.title('Relationship between 2010 population estimate error (from the␣
 ↪town-block merge)\nand the change from 2010 to 2017 in population')
plt.show()
```

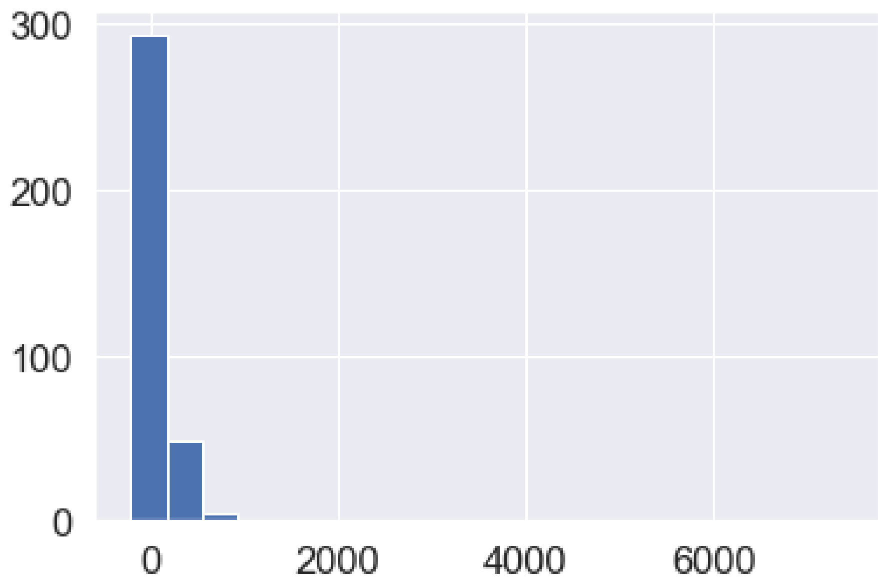


[37]:
```
print(sum(full_merge['pop_change_10_to_17_est'] == 0))
print(sum(full_merge['pop_change_10_to_17'] == 0))
```

```
0
0
```

Will use 2010 estimate derived from the town - census block merge vs 2017 estimate derived from merge to estimate growth rate (hopefully the error made from census blocks-town assignment means a similar error for both estimates)

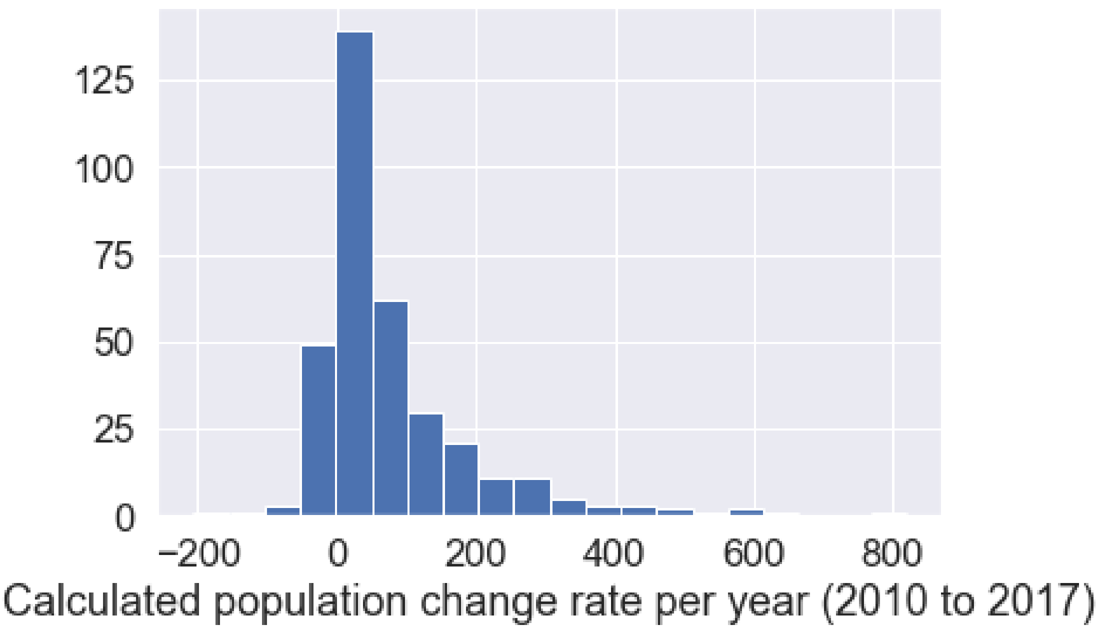
[38]:
```
full_merge['pop_change_rate'] = full_merge['pop_change_10_to_17_est'] / (2017 -␣
↪2010)
full_merge['pop_change_rate'].hist(bins=20)
plt.xlabel('Calculated population change rate per year (2010 to 2017)')
plt.show()
```



[39]:
```
full_merge[full_merge['pop_change_rate'] > 1000]
```

[39]:
```
   city_death  tot_pop_17  over_65_count  town_actual_2010_pop  \
35     boston      668541          85040              617594.0

    block_est_2010_pop  count_error  percent_error   pop_density  \
35            616852.0       -742.0       0.120144  27786.891612

    med_house_inc  mean_house_inc  ...  at_or_below_pov_prop  \
35   71196.049505    92167.940523  ...              0.205154

    pop_struggling_prop  2014  2015  2016  2017  2018  pop_change_10_to_17  \
35             0.158644   167   226   259   279   245              50947.0

    pop_change_10_to_17_est  pop_change_rate
35                  51689.0      7384.142857

[1 rows x 22 columns]
```

[40]:
```
# remove extreme point (Boston)
full_merge[full_merge['pop_change_rate'] < 1000]['pop_change_rate'].
 ↪hist(bins=20)
plt.xlabel('Calculated population change rate per year (2010 to 2017)')
plt.show()
```



[41]:
```
full_merge[(full_merge['pop_change_rate'] > -10) &␣
↪(full_merge['pop_change_rate'] < 10)]
```

[41]:
```
      city_death  tot_pop_17  over_65_count  town_actual_2010_pop  \
29   bernardston        1074            261                2129.0
33     blandford        1259            306                1233.0
36        bourne       19832           4614               19754.0
41      brewster        9856           3274                9820.0
45    brookfield        3406            791                3390.0
..           ...         ...            ...                   ...
307       warren        5199            554                5135.0
309   washington         499            158                 538.0
315      wendell         864            204                 848.0
336  williamsburg       2481            578                2482.0
341      windsor         909            184                 899.0

     block_est_2010_pop  count_error  percent_error  pop_density  \
29               1018.0      -1111.0      52.184124    86.640560
33               1233.0          0.0       0.000000    24.411060
36              19776.0         22.0       0.111370  1009.739420
41               9820.0          0.0       0.000000   491.873789
45               3390.0          0.0       0.000000   237.359100
..                  ...          ...            ...          ...
307              5135.0          0.0       0.000000   279.391975
309               538.0          0.0       0.000000    13.137440
315               848.0          0.0       0.000000    27.134650
336              2482.0          0.0       0.000000   119.907030
```

```
341            899.0         0.0      0.000000   25.976800

     med_house_inc  mean_house_inc  ...  at_or_below_pov_prop  \
29    70500.000000    82633.333333  ...              0.035382
33    62875.000000    78223.844732  ...              0.070691
36    69166.937500    91659.357901  ...              0.068506
41    71159.111111    93807.274446  ...              0.048019
45    63971.333333    86589.528959  ...              0.091930
..             ...             ...  ...                   ...
307   68332.000000    70051.858136  ...              0.112906
309   86389.000000    91221.120690  ...              0.028169
315   42750.000000    65966.497462  ...              0.175581
336   74244.500000    95587.601080  ...              0.108021
341   81875.000000   110717.195767  ...              0.055006

     pop_struggling_prop  2014  2015  2016  2017  2018  pop_change_10_to_17  \
29              0.220670     0     0     0     0     0              -1055.0
33              0.155679     0     0     0     0     0                 26.0
36              0.112949     2     4     6     1     4                 78.0
41              0.122623     0     1     1     1     0                 36.0
45              0.110553     0     0     0     2     1                 16.0
..                   ...   ...   ...   ...   ...   ...                  ...
307             0.205424     1     0     0     0     1                 64.0
309             0.072435     0     0     0     0     0                -39.0
315             0.172093     0     0     0     0     0                 16.0
336             0.077791     0     0     0     0     1                 -1.0
341             0.063806     0     0     0     0     0                 10.0

     pop_change_10_to_17_est  pop_change_rate
29                      56.0         8.000000
33                      26.0         3.714286
36                      56.0         8.000000
41                      36.0         5.142857
45                      16.0         2.285714
..                       ...              ...
307                     64.0         9.142857
309                    -39.0        -5.571429
315                     16.0         2.285714
336                     -1.0        -0.142857
341                     10.0         1.428571

[62 rows x 22 columns]
```

[42]:
```
# number of towns with negative growth rate
full_merge[full_merge['pop_change_rate'] < 0].shape
```

[42]:
```
(60, 22)
```

- Tried to pull in more years of ACS data, but it was challenging to find and extract the data
- Will use rough estimates to guess population changes

[43]:
```
# rough estimates of yearly population
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.head()
```

[43]:

	city_death	tot_pop_17	over_65_count	town_actual_2010_pop	\
0	abington	16275	2469	15985.0	
1	acton	23455	4001	21924.0	
2	acushnet	10443	2431	10303.0	
3	adams	8211	1764	8485.0	
4	agawam	27769	6195	28438.0	

	block_est_2010_pop	count_error	percent_error	pop_density	med_house_inc	\
0	15985.0	0.0	0.000000	1932.969130	87156.000000	
1	21924.0	0.0	0.000000	1257.583593	139890.466667	
2	10303.0	0.0	0.000000	1152.357871	69624.714286	
3	8485.0	0.0	0.000000	1982.318840	48445.400000	
4	27621.0	-817.0	2.872917	1897.273569	65490.125000	

	mean_house_inc	...	2016	2017	2018	pop_change_10_to_17	\
0	98809.035505	...	1	3	5	290.0	
1	156680.203867	...	3	0	1	1531.0	
2	80333.175842	...	2	4	0	140.0	
3	60968.594660	...	1	0	4	-274.0	
4	79464.234446	...	0	4	8	-669.0	

	pop_change_10_to_17_est	pop_change_rate	tot_pop_16	tot_pop_15	\
0	290.0	41.428571	16233.571429	16192.142857	
1	1531.0	218.714286	23236.285714	23017.571429	
2	140.0	20.000000	10423.000000	10403.000000	
3	-274.0	-39.142857	8250.142857	8289.285714	
4	148.0	21.142857	27747.857143	27726.714286	

	tot_pop_14	tot_pop_13
0	16150.714286	16109.285714
1	22798.857143	22580.142857
2	10383.000000	10363.000000
3	8328.428571	8367.571429
4	27705.571429	27684.428571

[5 rows x 26 columns]

[44]:
```
# classify a town as shrining or growing based on the rate of population change
full_merge['town_status'] = ['grown' if x > 10 else 'shrunk' if x < -10 else␣
 ↪'uncertain' for x in full_merge['pop_change_rate']]
full_merge['town_status'].value_counts()
```

[44]:
```
grown        252
uncertain     62
shrunk        33
Name: town_status, dtype: int64
```

[45]:
```
# simple definition of urban vs rural
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()
```

[45]:
```
rural    322
urban     25
Name: urb_v_rur, dtype: int64
```

I want to experiment with converting the death count to a death rate by normalizing it to the population estimate

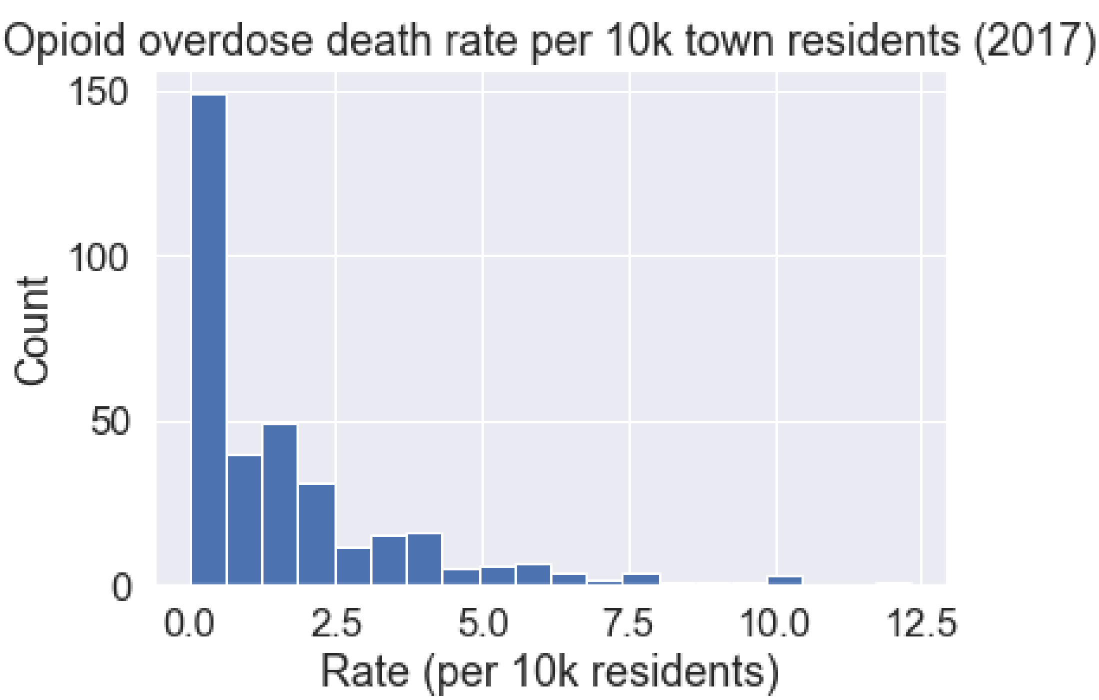
- will it change the distribution? (the count data is very skewed)
- what is the relationship between the death rate and some of the other variables pulled out from the 2017 ACS?

[46]:
```
# calculate opioid overdose death rate per 10k residents (so that numbers␣
 ↪aren't just small decimals)
rate_exp = full_merge.copy()
rate_exp['death_rate_17'] = (rate_exp['2017'] / rate_exp['tot_pop_17']) * 10000
rate_exp.head()
```

[46]:
```
  city_death  tot_pop_17  over_65_count  town_actual_2010_pop  \
0   abington       16275           2469               15985.0
1      acton       23455           4001               21924.0
2   acushnet       10443           2431               10303.0
3      adams        8211           1764                8485.0
4     agawam       27769           6195               28438.0

   block_est_2010_pop  count_error  percent_error  pop_density  med_house_inc  \
0             15985.0          0.0       0.000000  1932.969130   87156.000000
1             21924.0          0.0       0.000000  1257.583593  139890.466667
2             10303.0          0.0       0.000000  1152.357871   69624.714286
3              8485.0          0.0       0.000000  1982.318840   48445.400000
4             27621.0       -817.0       2.872917  1897.273569   65490.125000

   mean_house_inc  ...  pop_change_10_to_17  pop_change_10_to_17_est  \
0    98809.035505  ...                290.0                    290.0
```

```
1   156680.203867  ...               1531.0                      1531.0
2    80333.175842  ...                140.0                       140.0
3    60968.594660  ...               -274.0                      -274.0
4    79464.234446  ...               -669.0                       148.0

   pop_change_rate    tot_pop_16    tot_pop_15    tot_pop_14    tot_pop_13  \
0        41.428571  16233.571429  16192.142857  16150.714286  16109.285714
1       218.714286  23236.285714  23017.571429  22798.857143  22580.142857
2        20.000000  10423.000000  10403.000000  10383.000000  10363.000000
3       -39.142857   8250.142857   8289.285714   8328.428571   8367.571429
4        21.142857  27747.857143  27726.714286  27705.571429  27684.428571

   town_status  urb_v_rur  death_rate_17
0        grown      rural       1.843318
1        grown      rural       0.000000
2        grown      rural       3.830317
3       shrunk      rural       0.000000
4        grown      rural       1.440455

[5 rows x 29 columns]
```

[47]:
```
rate_exp['death_rate_17'].hist(bins=20)
plt.xlabel('Rate (per 10k residents)')
plt.ylabel('Count')
plt.title('Opioid overdose death rate per 10k town residents (2017)')
plt.show()
```



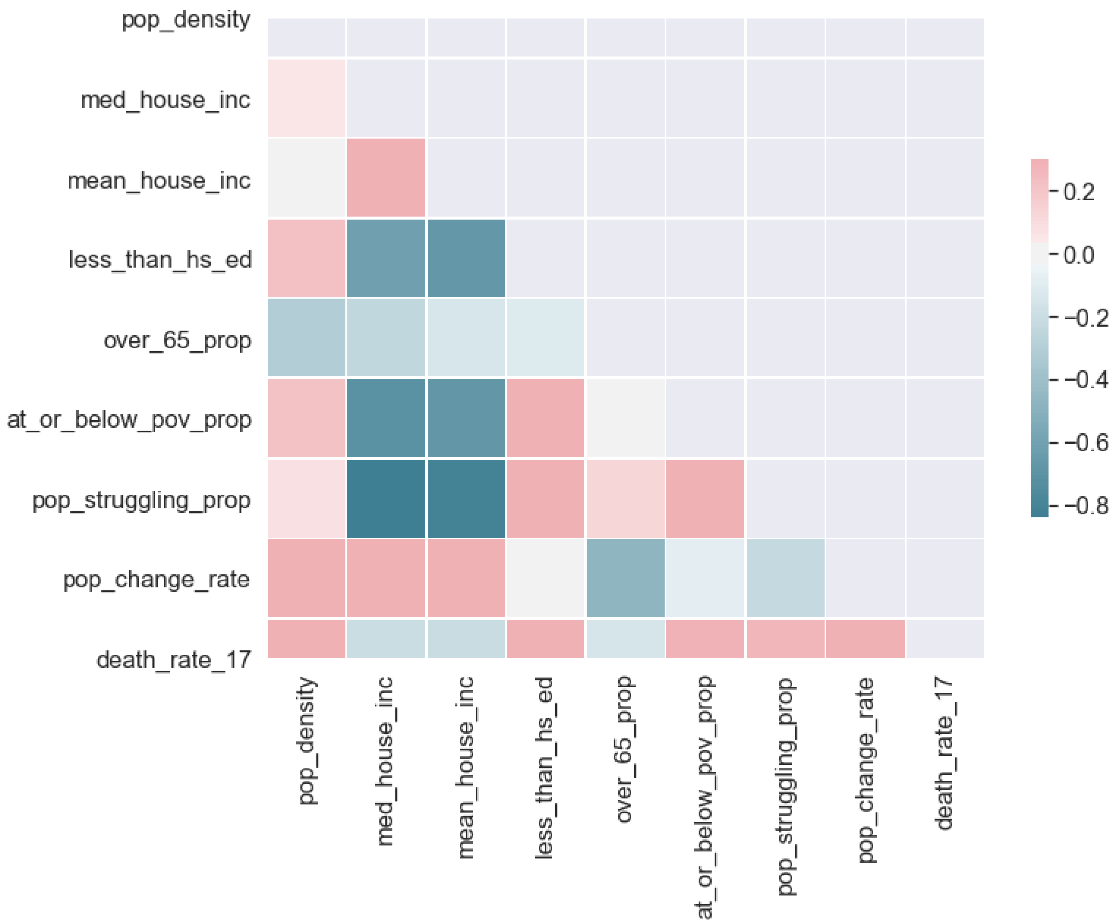
[48]:
```
rate_exp.columns
```

[48]:
```
Index(['city_death', 'tot_pop_17', 'over_65_count', 'town_actual_2010_pop',
       'block_est_2010_pop', 'count_error', 'percent_error', 'pop_density',
       'med_house_inc', 'mean_house_inc', 'less_than_hs_ed', 'over_65_prop',
       'at_or_below_pov_prop', 'pop_struggling_prop', '2014', '2015', '2016',
       '2017', '2018', 'pop_change_10_to_17', 'pop_change_10_to_17_est',
       'pop_change_rate', 'tot_pop_16', 'tot_pop_15', 'tot_pop_14',
       'tot_pop_13', 'town_status', 'urb_v_rur', 'death_rate_17'],
      dtype='object')
```

[49]:
```
rate_exp_columns = list(rate_exp.columns)
rate_exp_col_sub = rate_exp_columns[0:1] + rate_exp_columns[7:14] +␣
↪rate_exp_columns[21:22] + rate_exp_columns[26:]
rate_exp_sub = rate_exp[rate_exp_col_sub].copy()
rate_exp_sub.head()
```

[49]:
```
  city_death  pop_density  med_house_inc  mean_house_inc  less_than_hs_ed  \
0  abington   1932.969130   87156.000000    98809.035505         5.405643
1     acton   1257.583593  139890.466667   156680.203867         2.456531
2  acushnet   1152.357871   69624.714286    80333.175842        18.297315
3     adams   1982.318840   48445.400000    60968.594660        11.862182
4    agawam   1897.273569   65490.125000    79464.234446         7.748863

   over_65_prop  at_or_below_pov_prop  pop_struggling_prop  pop_change_rate  \
0      0.151705              0.035754             0.100408        41.428571
1      0.170582              0.038315             0.041747       218.714286
2      0.232788              0.040828             0.178406        20.000000
3      0.214834              0.110854             0.144597       -39.142857
4      0.223090              0.094819             0.142656        21.142857

  town_status urb_v_rur  death_rate_17
0       grown     rural       1.843318
1       grown     rural       0.000000
2       grown     rural       3.830317
3      shrunk     rural       0.000000
4       grown     rural       1.440455
```

[50]:
```
rate_exp_sub_corr = rate_exp_sub.drop(['city_death', 'town_status',␣
↪'urb_v_rur'], axis=1).dropna().corr(method='spearman')
mask = np.zeros_like(rate_exp_sub_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(rate_exp_sub_corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
plt.show()
```



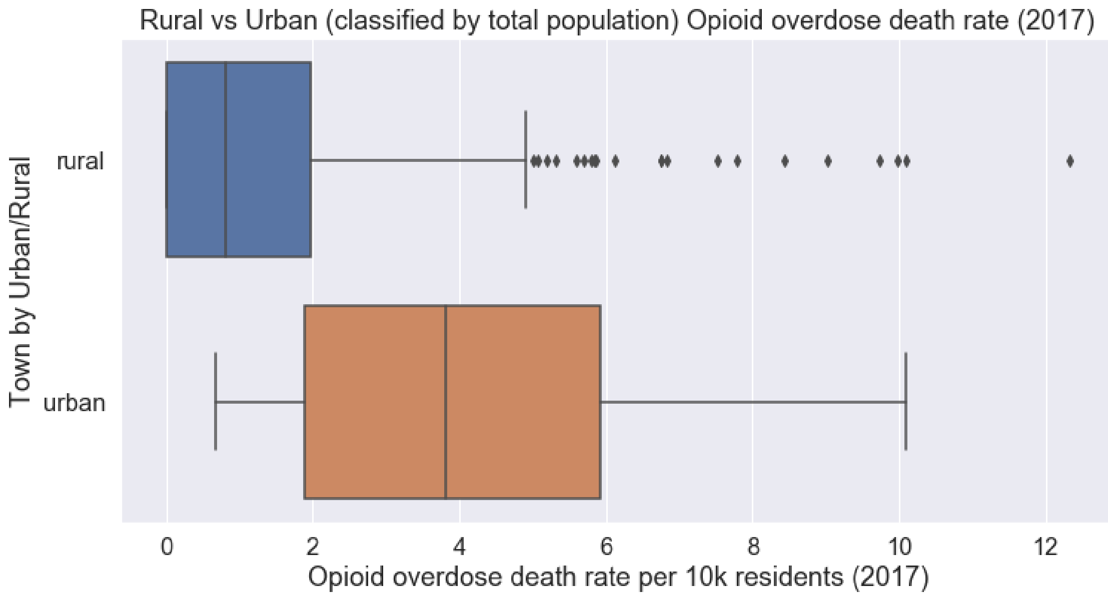
[51]:
```
rate_exp_sub_corr.sort_values('death_rate_17', ascending=False)['death_rate_17']
```

[51]:
```
death_rate_17            1.000000
pop_density              0.577145
pop_change_rate          0.375721
less_than_hs_ed          0.353322
at_or_below_pov_prop     0.290039
pop_struggling_prop      0.270851
over_65_prop            -0.145125
med_house_inc           -0.198810
mean_house_inc          -0.204348
Name: death_rate_17, dtype: float64
```

Looks like there are some weak positive and negative correlations * pop_density correlation surprisingly high - think it has to do with urban/rural (city vs urban)

[52]:
```
plt.figure(figsize=(12, 6))
sns.boxplot(y='urb_v_rur', x='death_rate_17', orient='h', data=rate_exp_sub)
plt.ylabel('Town by Urban/Rural')
plt.xlabel('Opioid overdose death rate per 10k residents (2017)')
```

```
plt.title('Rural vs Urban (classified by total population) Opioid overdose␣
 ↪death rate (2017)')
plt.show()
```



[53]:
```
# mean overdose death rate for 2017
print(round(rate_exp_sub['death_rate_17'].mean(), 2))
# standard error of the mean (sem) the rate:
print(round(rate_exp_sub[['death_rate_17']].sem(axis=0), 2))
rate_exp_sub[['urb_v_rur', 'death_rate_17']].groupby('urb_v_rur').mean()
```

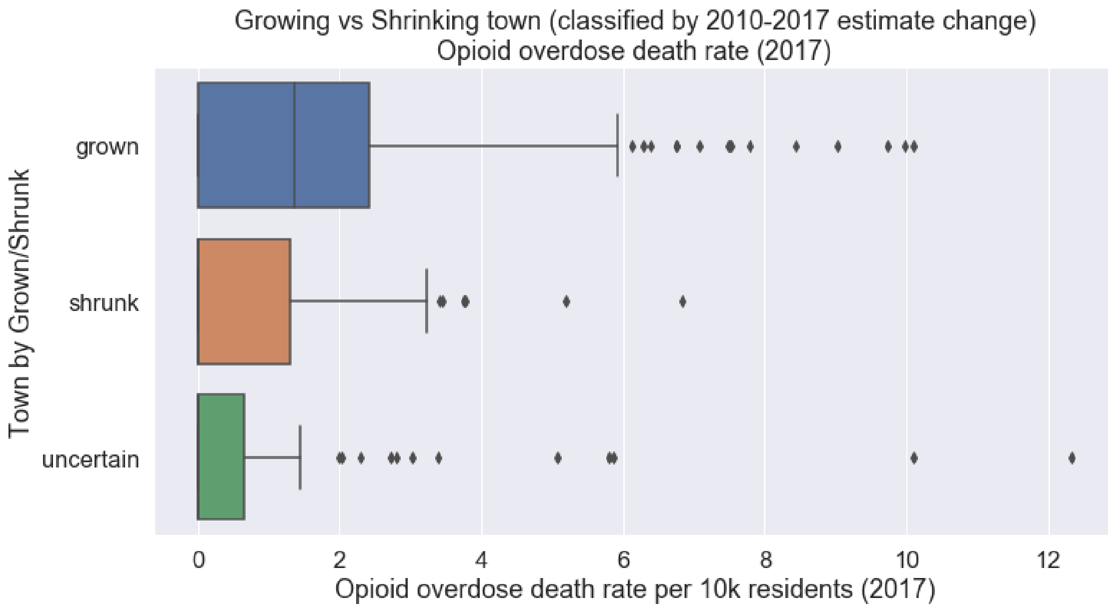
```
1.63
death_rate_17    0.12
dtype: float64
```

[53]:

urb_v_rur	death_rate_17
rural	1.441318
urban	4.020464

"Urban" (high population area) rate seems to be much higher than low population areas

[54]:
```
plt.figure(figsize=(12, 6))
sns.boxplot(y='town_status', x='death_rate_17', orient='h', data=rate_exp_sub)
plt.ylabel('Town by Grown/Shrunk')
plt.xlabel('Opioid overdose death rate per 10k residents (2017)')
plt.title('Growing vs Shrinking town (classified by 2010-2017 estimate␣
 ↪change)\nOpioid overdose death rate (2017)')
plt.show()
```



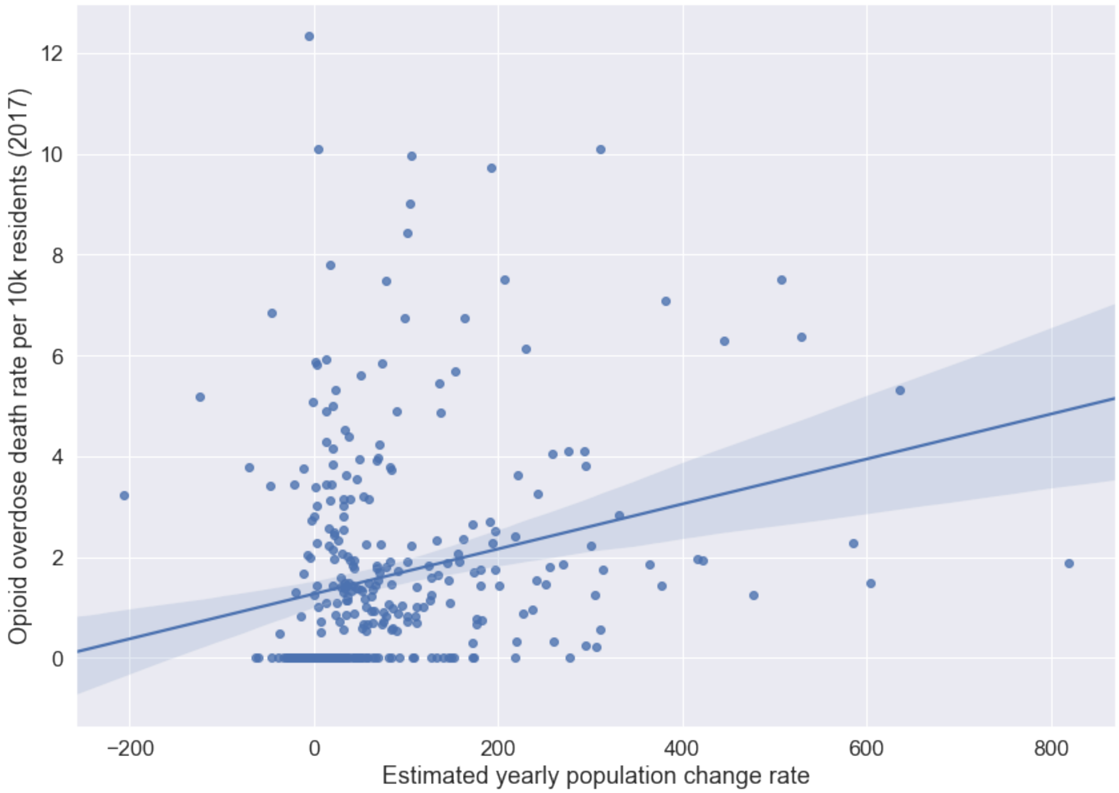
[55]:
```
rate_exp_sub[['town_status', 'death_rate_17']].groupby('town_status').mean()
```

[55]:

	death_rate_17
town_status	
grown	1.858204
shrunk	1.029335
uncertain	1.006140

Small difference with large errors/outliers? - may not be meaningful

[56]:
```
plt.figure(figsize=(14, 10))
sns.regplot(x='pop_change_rate', y='death_rate_17',␣
↪data=rate_exp_sub[rate_exp_sub['pop_change_rate'] < 1000])
plt.xlabel('Estimated yearly population change rate')
plt.ylabel('Opioid overdose death rate per 10k residents (2017)')
plt.show()
```



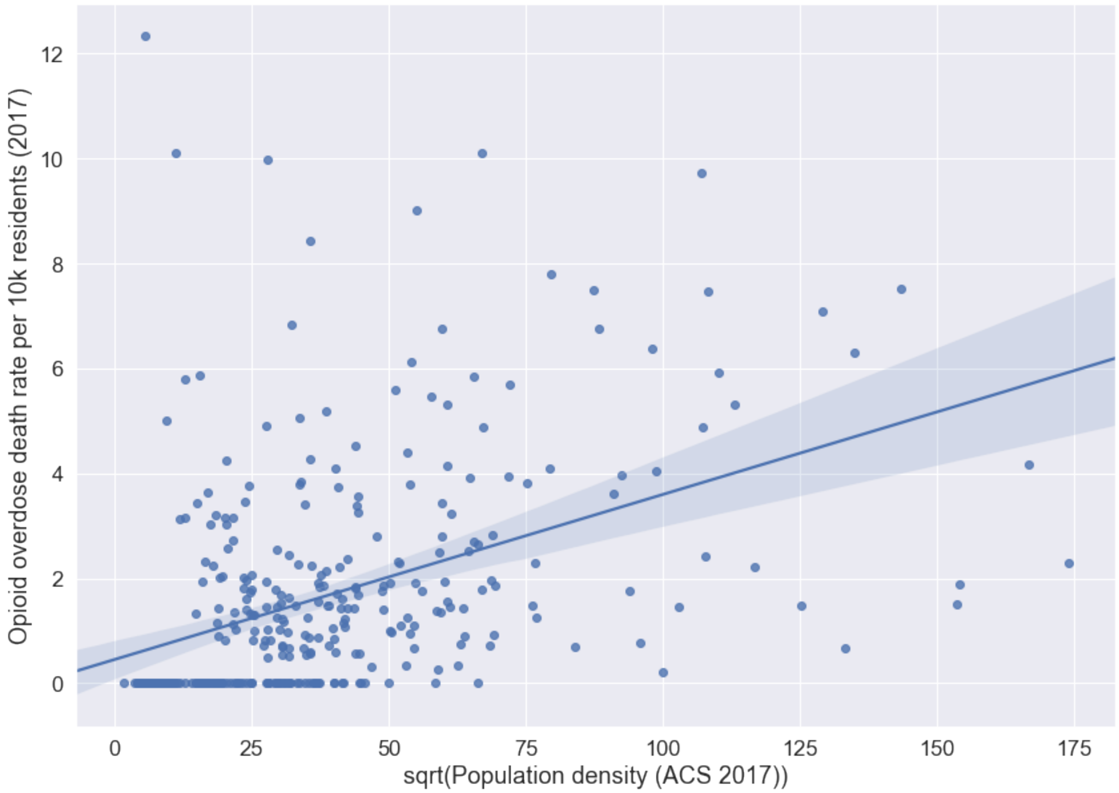
Think the estimated population change will probably not be useful, also most likely these two variables are confounded because population estimates for each year were calculated using the population change rate.

Population density probably related to the urban/rural difference seen earlier - what's the relationship of this variable to the death rate?

[57]:
```
plt.figure(figsize=(14, 10))
sns.regplot(x='pop_density', y='death_rate_17', data=rate_exp_sub)
plt.xlabel('Population density (ACS 2017)')
plt.ylabel('Opioid overdose death rate per 10k residents (2017)')
plt.show()
```

Data too noisy to tell if there is a true relationship - this is probably not a useful metric, but what if I try to take the square root of the density (maybe it's too skewed?)

[58]:
```python
rate_exp_sub['pop_den_sqrt'] = np.sqrt(rate_exp_sub['pop_density'])
plt.figure(figsize=(14, 10))
sns.regplot(x='pop_den_sqrt', y='death_rate_17', data=rate_exp_sub)
plt.xlabel('sqrt(Population density (ACS 2017))')
plt.ylabel('Opioid overdose death rate per 10k residents (2017)')
plt.show()
```



There might be a positive relationship - but still a lot of noise

1.1 Prep for export

Note: I had originally planned to predict/model the death rates instead of the raw counts - but that didn't go well and I switched focus to trying to model the counts instead (but included the total population estimates in the model as a way to account for differences in counts based on population)

[59]:
```
full_merge.columns
```

[59]:
```
Index(['city_death', 'tot_pop_17', 'over_65_count', 'town_actual_2010_pop',
       'block_est_2010_pop', 'count_error', 'percent_error', 'pop_density',
       'med_house_inc', 'mean_house_inc', 'less_than_hs_ed', 'over_65_prop',
       'at_or_below_pov_prop', 'pop_struggling_prop', '2014', '2015', '2016',
       '2017', '2018', 'pop_change_10_to_17', 'pop_change_10_to_17_est',
       'pop_change_rate', 'tot_pop_16', 'tot_pop_15', 'tot_pop_14',
       'tot_pop_13', 'town_status', 'urb_v_rur'],
      dtype='object')
```

[94]:
```
full_merge_cols = list(full_merge.columns)
full_merge_select = full_merge_cols[0:3] + full_merge_cols[8:19] +␣
 ↪full_merge_cols[22:]
print(full_merge_select)
```

```
print(len(full_merge_select))
print(len(set(full_merge_select)))
full_merge_reorder = full_merge_select[:1] + full_merge_select[9:14] +␣
↪full_merge_select[17:13:-1] + full_merge_select[1:2] + full_merge_select[2:
↪3] + full_merge_select[6:7] + full_merge_select[3:6] + full_merge_select[7:
↪9] + full_merge_select[-1:-3:-1]
print(full_merge_reorder)
print(len(full_merge_reorder))
# make sure no columns were doubl copied
print(len(set(full_merge_reorder)))
```

```
['city_death', 'tot_pop_17', 'over_65_count', 'med_house_inc', 'mean_house_inc',
'less_than_hs_ed', 'over_65_prop', 'at_or_below_pov_prop',
'pop_struggling_prop', '2014', '2015', '2016', '2017', '2018', 'tot_pop_16',
'tot_pop_15', 'tot_pop_14', 'tot_pop_13', 'town_status', 'urb_v_rur']
20
20
['city_death', '2014', '2015', '2016', '2017', '2018', 'tot_pop_13',
'tot_pop_14', 'tot_pop_15', 'tot_pop_16', 'tot_pop_17', 'over_65_count',
'over_65_prop', 'med_house_inc', 'mean_house_inc', 'less_than_hs_ed',
'at_or_below_pov_prop', 'pop_struggling_prop', 'urb_v_rur', 'town_status']
20
20
```

[95]:
```
full_merge_for_csv = full_merge[full_merge_reorder].copy()
full_merge_for_csv.head()
```

[95]:

	city_death	2014	2015	2016	2017	2018	tot_pop_13	tot_pop_14	\
0	abington	0	6	1	3	5	16109.285714	16150.714286	
1	acton	1	2	3	0	1	22580.142857	22798.857143	
2	acushnet	0	4	2	4	0	10363.000000	10383.000000	
3	adams	2	3	1	0	4	8367.571429	8328.428571	
4	agawam	1	2	0	4	8	27684.428571	27705.571429	

	tot_pop_15	tot_pop_16	tot_pop_17	over_65_count	over_65_prop	\
0	16192.142857	16233.571429	16275	2469	0.151705	
1	23017.571429	23236.285714	23455	4001	0.170582	
2	10403.000000	10423.000000	10443	2431	0.232788	
3	8289.285714	8250.142857	8211	1764	0.214834	
4	27726.714286	27747.857143	27769	6195	0.223090	

	med_house_inc	mean_house_inc	less_than_hs_ed	at_or_below_pov_prop	\
0	87156.000000	98809.035505	5.405643	0.035754	
1	139890.466667	156680.203867	2.456531	0.038315	
2	69624.714286	80333.175842	18.297315	0.040828	
3	48445.400000	60968.594660	11.862182	0.110854	
4	65490.125000	79464.234446	7.748863	0.094819	

```
   pop_struggling_prop urb_v_rur town_status
0             0.100408     rural       grown
1             0.041747     rural       grown
2             0.178406     rural       grown
3             0.144597     rural      shrunk
4             0.142656     rural       grown
```

[96]:
```
# final file:
#full_merge_for_csv.to_csv("../../data/tidy_data/overdose_death_count_acs_merge.
↪csv", index=False)
```

Old files derived from this notebook (to keep track to reorganize other notebooks - can ignore otherwise)

[ ]:
```
#full_merge.to_csv("../../data/tidy_data/
↪death_count_norm_to_pop_and_acs_town_demographics_merge_all_cols.csv",␣
↪index=False)
#full_merge_for_csv.to_csv("../../data/tidy_data/
↪death_count_norm_to_pop_and_acs_town_demographics_merge.csv", index=False)
```