notebook_6_ma_opioid_overdose_death_and_acs_and_partD_drug_m

October 20, 2019

1 MA opioid overdose death, ACS, and Medicare part D data merge

1.0.1 Goals:

- Resolve NPI prescribers being assigned to more than one town (zip code matched to more than one town most likely)
- Fill in missing opioid prescription rates
- associate towns (opioid overdose death rates + acs) and medicare drug spending/claim counts
- EDA on potential relationship between opioid overdose deaths and opioid or benzo claims

1.0.2 Outputs:

- `data/tidy_data/medicare_partD_opioid_prescriber_all_years_no_ziptown_duplicates.csv` - concatenated (rows) of opioid prescribers, with zip codes assigned to only one town (using random removal)
- `data/tidy_data/overdose_death_count_acs_merge_long_format.csv` - reformatted overdose death count and ACS merged data from wide format to long format (death counts and total population columns)
- `data/tidy_data/acs_medicare_opioid_stats_death_count_merge.csv` - opioid overdose death counts, ACS data, and opioid prescription patterns summarized and merged
- pdf report (in case notebook won't run): `products/notebook_6_ma_opioid_overdose_death_and_acs_and`

[1]:
```
import random
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_and_acs_data = pd.read_csv("../../../data/tidy_data/
↪overdose_death_count_acs_merge.csv")
opi_pres_13 = pd.read_csv("../../../data/tidy_data/
↪medicare_partD_opioid_prescriber_2013_w_zip_MAtown_v1.csv")
```

```
opi_pres_14 = pd.read_csv("../../../data/tidy_data/
 ↪medicare_partD_opioid_prescriber_2014_w_zip_MAtown_v1.csv")
opi_pres_15 = pd.read_csv("../../../data/tidy_data/
 ↪medicare_partD_opioid_prescriber_2015_w_zip_MAtown_v1.csv")
opi_pres_16 = pd.read_csv("../../../data/tidy_data/
 ↪medicare_partD_opioid_prescriber_2016_w_zip_MAtown_v1.csv")
opi_pres_17 = pd.read_csv("../../../data/tidy_data/
 ↪medicare_partD_opioid_prescriber_2017_w_zip_MAtown_v1.csv")
```

[3]:
```
opi_pres_13.head()
```

[3]:
```
          npi nppes_provider_last_name nppes_provider_first_name  \
0  1003002312                  hopkins                  patricia
1  1003083270                   kabadi                    mitesh
2  1003834433                     nair                      anil
3  1003895269                 angelini                   domenic
4  1003992397                  carolan                  patricia

   nppes_provider_zip_code    town nppes_provider_state specialty_description  \
0                     2169  quincy                   MA     internal medicine
1                     2169  quincy                   MA            cardiology
2                     2169  quincy                   MA             neurology
3                     2169  quincy                   MA               dentist
4                     2169  quincy                   MA               dentist

   total_claim_count  opioid_claim_count  opioid_prescribing_rate  \
0               4139               522.0                    12.61
1                 40                 0.0                     0.00
2               1217                 NaN                      NaN
3                 14                 0.0                     0.00
4                 37                 NaN                      NaN

   long-acting_opioid_claim_count  year
0                           104.0  2013
1                             0.0  2013
2                             NaN  2013
3                             0.0  2013
4                             0.0  2013
```

[4]:
```
opi_pres_df = [opi_pres_13, opi_pres_14, opi_pres_15, opi_pres_16, opi_pres_17]
```

[5]:
```
for x in opi_pres_df:
    print(x['nppes_provider_state'].value_counts())
for x in opi_pres_df:
    x.drop('nppes_provider_state', axis=1, inplace=True)
```

```
MA    34086
Name: nppes_provider_state, dtype: int64
MA    34734
```

```
Name: nppes_provider_state, dtype: int64
MA    35416
Name: nppes_provider_state, dtype: int64
MA    36357
Name: nppes_provider_state, dtype: int64
MA    37069
Name: nppes_provider_state, dtype: int64
```

[6]:
```
opi_pres_13.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 34086 entries, 0 to 34085
Data columns (total 11 columns):
npi                                 34086 non-null int64
nppes_provider_last_name            34085 non-null object
nppes_provider_first_name           34002 non-null object
nppes_provider_zip_code             34086 non-null int64
town                                34086 non-null object
specialty_description               34086 non-null object
total_claim_count                   34086 non-null int64
opioid_claim_count                  22667 non-null float64
opioid_prescribing_rate             22667 non-null float64
long-acting_opioid_claim_count      28188 non-null float64
year                                34086 non-null int64
dtypes: float64(3), int64(4), object(4)
memory usage: 2.9+ MB
```

[7]:
```
# fix the zip codes again - some kind of issue related to importing it
for x in opi_pres_df:
    x['nppes_provider_zip_code'] = x['nppes_provider_zip_code'].astype(str).str.
 ↪zfill(5)
```

[8]:
```
opi_pres_13.head()
```

[8]:
```
          npi nppes_provider_last_name nppes_provider_first_name  \
0  1003002312                  hopkins                  patricia
1  1003083270                   kabadi                    mitesh
2  1003834433                     nair                      anil
3  1003895269                 angelini                   domenic
4  1003992397                  carolan                  patricia

  nppes_provider_zip_code    town specialty_description  total_claim_count  \
0                   02169  quincy     internal medicine               4139
1                   02169  quincy            cardiology                 40
2                   02169  quincy             neurology               1217
3                   02169  quincy               dentist                 14
4                   02169  quincy               dentist                 37
```

```
   opioid_claim_count  opioid_prescribing_rate  \
0               522.0                    12.61
1                 0.0                     0.00
2                 NaN                      NaN
3                 0.0                     0.00
4                 NaN                      NaN

   long-acting_opioid_claim_count  year
0                           104.0  2013
1                             0.0  2013
2                             NaN  2013
3                             0.0  2013
4                             0.0  2013
```

[9]:
```
# concatenate all rows for all years together
opi_pres_all = pd.concat(opi_pres_df, axis=0, ignore_index=True)
```

[10]:
```
for x in opi_pres_df:
    print(x.shape)
print(opi_pres_all.shape)
```

```
(34086, 11)
(34734, 11)
(35416, 11)
(36357, 11)
(37069, 11)
(177662, 11)
```

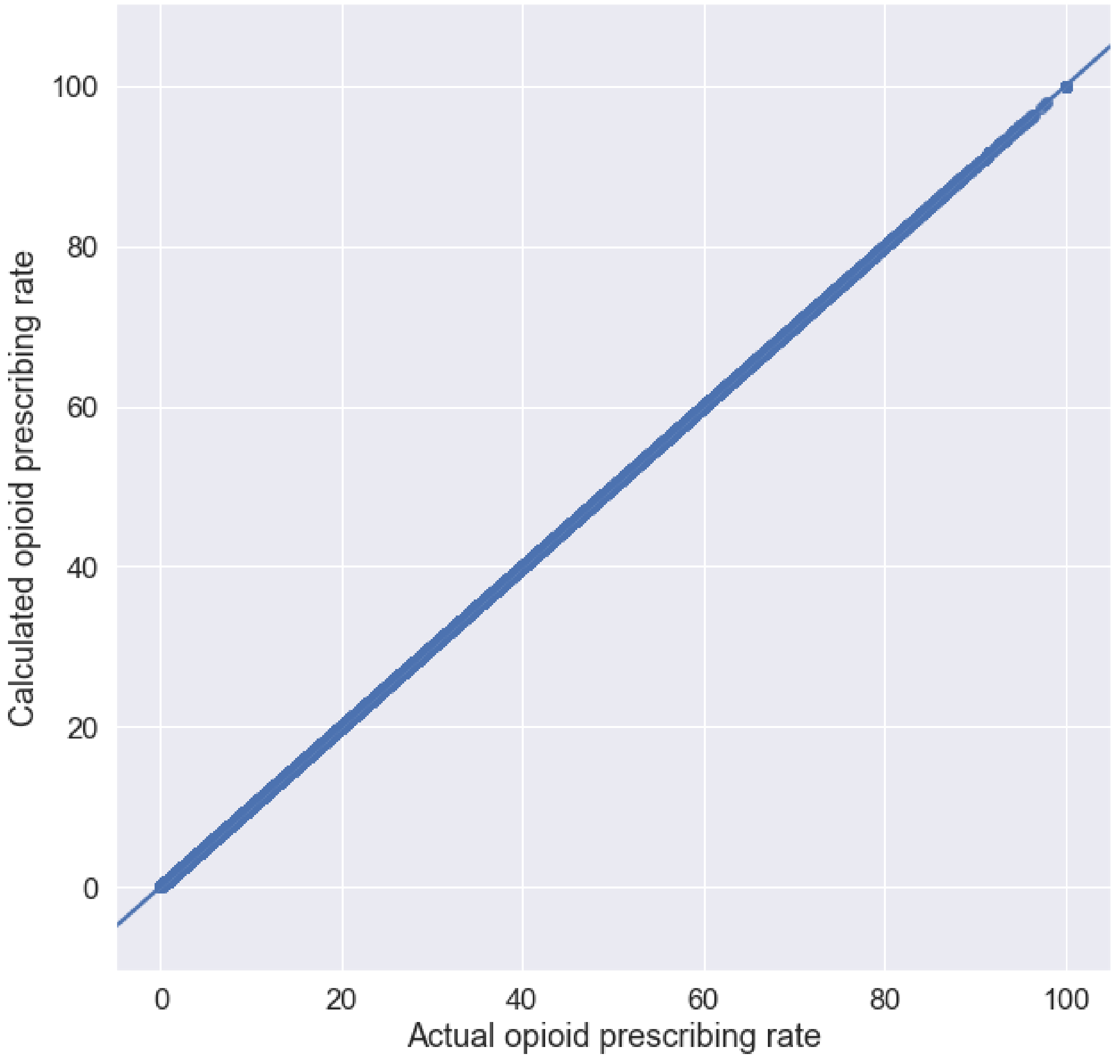
[11]:
```
# according to documentation, opioid claims are redacted if claim count is␣
 ↪between 1-10 (not zero - reveals if 0)
# replace missing claim with 5
opi_pres_all['opioid_claim_count'] = opi_pres_all['opioid_claim_count'].
 ↪fillna(value=5.0)
# calculate rate with replaced values
opi_pres_all['calc_opioid_rate'] = (opi_pres_all['opioid_claim_count'] /␣
 ↪opi_pres_all['total_claim_count']) * 100
opi_pres_all.head()
```

[11]:
```
          npi nppes_provider_last_name nppes_provider_first_name  \
0  1003002312                  hopkins                  patricia
1  1003083270                   kabadi                    mitesh
2  1003834433                     nair                      anil
3  1003895269                 angelini                   domenic
4  1003992397                  carolan                  patricia

  nppes_provider_zip_code    town specialty_description  total_claim_count  \
0                   02169  quincy     internal medicine               4139
1                   02169  quincy            cardiology                 40
```

```
2                  02169  quincy             neurology              1217
3                  02169  quincy               dentist                14
4                  02169  quincy               dentist                37

   opioid_claim_count  opioid_prescribing_rate  \
0               522.0                    12.61
1                 0.0                     0.00
2                 5.0                      NaN
3                 0.0                     0.00
4                 5.0                      NaN

   long-acting_opioid_claim_count  year  calc_opioid_rate
0                           104.0  2013         12.611742
1                             0.0  2013          0.000000
2                             NaN  2013          0.410846
3                             0.0  2013          0.000000
4                             0.0  2013         13.513514
```

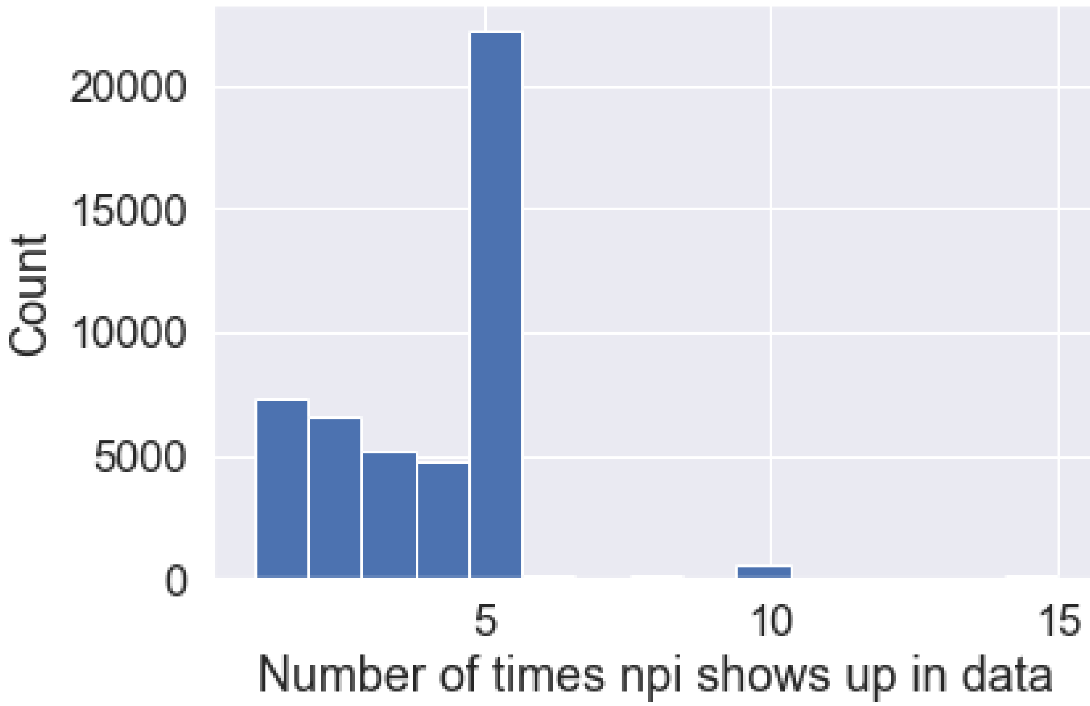
[12]:

```
# was the opioid prescribing rate calculated as I expected?
# compare calculated rate with actual rate where it is not missing
plt.figure(figsize=(10,10))
sns.regplot(x='opioid_prescribing_rate', y='calc_opioid_rate',␣
 ↪data=opi_pres_all.dropna())
plt.xlabel('Actual opioid prescribing rate')
plt.ylabel('Calculated opioid prescribing rate')
plt.show()
# A: yes
```



Now for the prescribers that were associated with more than 1 town per year:

[13]:
```
npi_counts = opi_pres_all['npi'].value_counts().reset_index()
npi_counts['npi'].hist(bins=15)
plt.xlabel('Number of times npi shows up in data')
plt.ylabel('Count')
plt.show()
```



[14]:
```
npi_counts.head()
```

[14]:
```
        index  npi
0  1801868161   15
1  1417060989   15
2  1265650162   15
3  1205096583   15
4  1760446140   15
```

[15]:
```
# where is the problem coming from?
opi_pres_all[opi_pres_all['npi'] == npi_counts.iloc[0,0]].sort_values('year')
```

[15]:
```
               npi nppes_provider_last_name nppes_provider_first_name  \
20515   1801868161                    costa                    joseph
20516   1801868161                    costa                    joseph
20517   1801868161                    costa                    joseph
55159   1801868161                    costa                    joseph
55160   1801868161                    costa                    joseph
55161   1801868161                    costa                    joseph
90560   1801868161                    costa                    joseph
90561   1801868161                    costa                    joseph
90562   1801868161                    costa                    joseph
128212  1801868161                    costa                    joseph
128213  1801868161                    costa                    joseph
128214  1801868161                    costa                    joseph
166060  1801868161                    costa                    joseph
```

```
166061  1801868161                     costa                    joseph
166062  1801868161                     costa                    joseph

       nppes_provider_zip_code       town specialty_description  \
20515                    02467  brookline               dentist
20516                    02467     boston               dentist
20517                    02467     newton               dentist
55159                    02467  brookline               dentist
55160                    02467     boston               dentist
55161                    02467     newton               dentist
90560                    02467  brookline               dentist
90561                    02467     boston               dentist
90562                    02467     newton               dentist
128212                   02467  brookline               dentist
128213                   02467     boston               dentist
128214                   02467     newton               dentist
166060                   02467  brookline               dentist
166061                   02467     boston               dentist
166062                   02467     newton               dentist

        total_claim_count  opioid_claim_count  opioid_prescribing_rate  \
20515                  18                 5.0                      NaN
20516                  18                 5.0                      NaN
20517                  18                 5.0                      NaN
55159                  25                 5.0                      NaN
55160                  25                 5.0                      NaN
55161                  25                 5.0                      NaN
90560                  22                 5.0                      NaN
90561                  22                 5.0                      NaN
90562                  22                 5.0                      NaN
128212                 14                 0.0                      0.0
128213                 14                 0.0                      0.0
128214                 14                 0.0                      0.0
166060                 18                 0.0                      0.0
166061                 18                 0.0                      0.0
166062                 18                 0.0                      0.0

        long-acting_opioid_claim_count  year  calc_opioid_rate
20515                              0.0  2013         27.777778
20516                              0.0  2013         27.777778
20517                              0.0  2013         27.777778
55159                              0.0  2014         20.000000
55160                              0.0  2014         20.000000
55161                              0.0  2014         20.000000
90560                              0.0  2015         22.727273
90561                              0.0  2015         22.727273
90562                              0.0  2015         22.727273
```

```
128212                                   0.0  2016          0.000000
128213                                   0.0  2016          0.000000
128214                                   0.0  2016          0.000000
166060                                   0.0  2017          0.000000
166061                                   0.0  2017          0.000000
166062                                   0.0  2017          0.000000
```

Same zip code is being associated with multiple towns per year - the same prescriber appears in triplicate for each year with the same prescription numbers.

Try to understand the problem a little bit more.

What if some prescribers are not in all 5 datasets, but their zip code is associated with more than 1 town for the years that they do appear - number of npi appearances might be less than 5, but their information appears 2x/3x?

[16]:
```
npi_counts[npi_counts['npi'] > 5]
```

[16]:
```
           index  npi
0     1801868161   15
1     1417060989   15
2     1265650162   15
3     1205096583   15
4     1760446140   15
...          ...  ...
1197  1033269782    6
1198  1205277761    6
1199  1609250406    6
1200  1154736007    6
1201  1790044303    6

[1202 rows x 2 columns]
```

[17]:
```
opi_pres_all[opi_pres_all['npi'] == 1790044303]
```

[17]:
```
              npi nppes_provider_last_name nppes_provider_first_name  \
24564  1790044303                   agnoli                    alicia
24565  1790044303                   agnoli                    alicia
59258  1790044303                   agnoli                    alicia
59259  1790044303                   agnoli                    alicia
94296  1790044303                   agnoli                    alicia
94297  1790044303                   agnoli                    alicia

      nppes_provider_zip_code    town  \
24564                   02148  malden
24565                   02148  revere
59258                   02148  malden
59259                   02148  revere
94296                   02148  malden
94297                   02148  revere

                                  specialty_description  total_claim_count  \
```

```
24564  student in an organized health care education/...                  87
24565  student in an organized health care education/...                  87
59258  student in an organized health care education/...                 369
59259  student in an organized health care education/...                 369
94296  student in an organized health care education/...                 470
94297  student in an organized health care education/...                 470

       opioid_claim_count  opioid_prescribing_rate  \
24564                 5.0                      NaN
24565                 5.0                      NaN
59258                29.0                     7.86
59259                29.0                     7.86
94296                25.0                     5.32
94297                25.0                     5.32

       long-acting_opioid_claim_count  year  calc_opioid_rate
24564                             NaN  2013          5.747126
24565                             NaN  2013          5.747126
59258                             NaN  2014          7.859079
59259                             NaN  2014          7.859079
94296                             NaN  2015          5.319149
94297                             NaN  2015          5.319149
```

Working through these would take too long, but duplicates per year should be removed. Luckily this is a problem for a relatively small number out of the total prescribers. Will resolve this by randomly dropping duplicates per year.

[18]:
```
len(opi_pres_all.index)
```

[18]:
```
177662
```

[19]:
```
# generate random index order
l = random.sample(range(0,177662), 177662)
```

[20]:
```
opi_pres_all['sort_index'] = l
opi_pres_all.head()
```

[20]:
```
          npi nppes_provider_last_name nppes_provider_first_name  \
0  1003002312                  hopkins                  patricia
1  1003083270                   kabadi                    mitesh
2  1003834433                     nair                      anil
3  1003895269                 angelini                   domenic
4  1003992397                  carolan                  patricia

  nppes_provider_zip_code    town specialty_description  total_claim_count  \
0                   02169  quincy     internal medicine               4139
1                   02169  quincy            cardiology                 40
2                   02169  quincy             neurology               1217
3                   02169  quincy               dentist                 14
4                   02169  quincy               dentist                 37
```

```
   opioid_claim_count  opioid_prescribing_rate  \
0               522.0                    12.61
1                 0.0                     0.00
2                 5.0                      NaN
3                 0.0                     0.00
4                 5.0                      NaN

   long-acting_opioid_claim_count  year  calc_opioid_rate  sort_index
0                           104.0  2013         12.611742      172909
1                             0.0  2013          0.000000       59056
2                             NaN  2013          0.410846       29246
3                             0.0  2013          0.000000      111291
4                             0.0  2013         13.513514      107657
```

[21]:
```
print(len(opi_pres_all[['npi', 'nppes_provider_last_name',␣
↪'nppes_provider_first_name']].drop_duplicates().index))
print(len(opi_pres_all[['npi']].drop_duplicates().index))
print(len(opi_pres_all[['npi', 'year']].drop_duplicates().index))
print(len(opi_pres_all[['npi', 'year', 'nppes_provider_last_name',␣
↪'nppes_provider_first_name']].drop_duplicates().index))
```

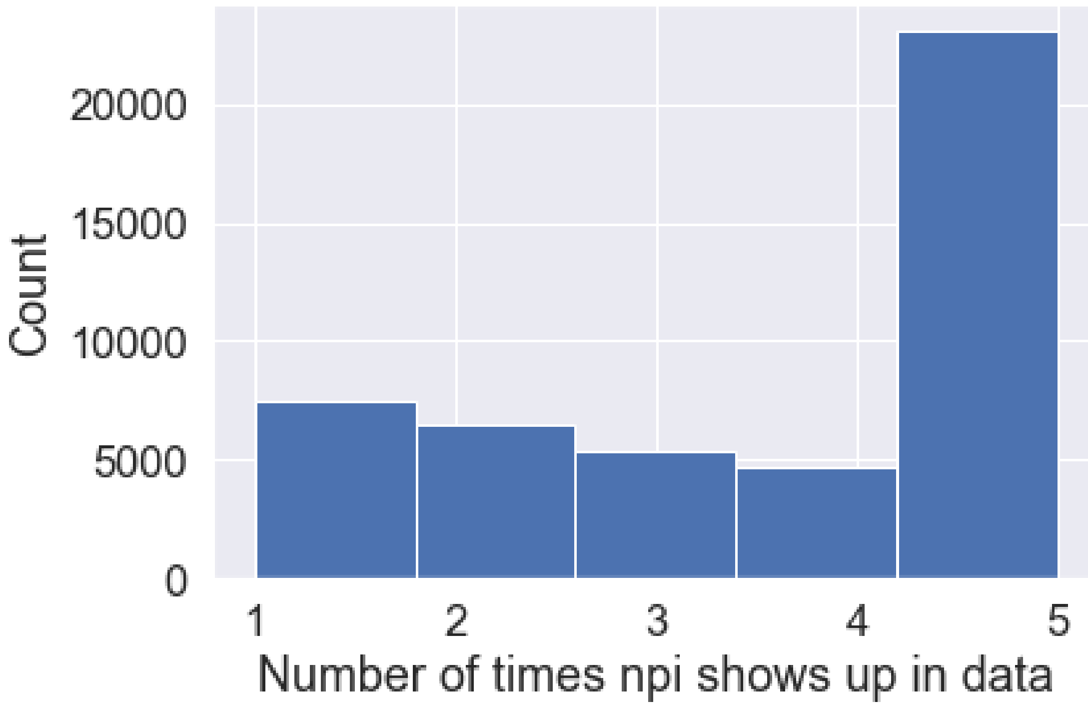
```
47875
47160
170744
170744
```

Not sure what's going on with the npi/name combos

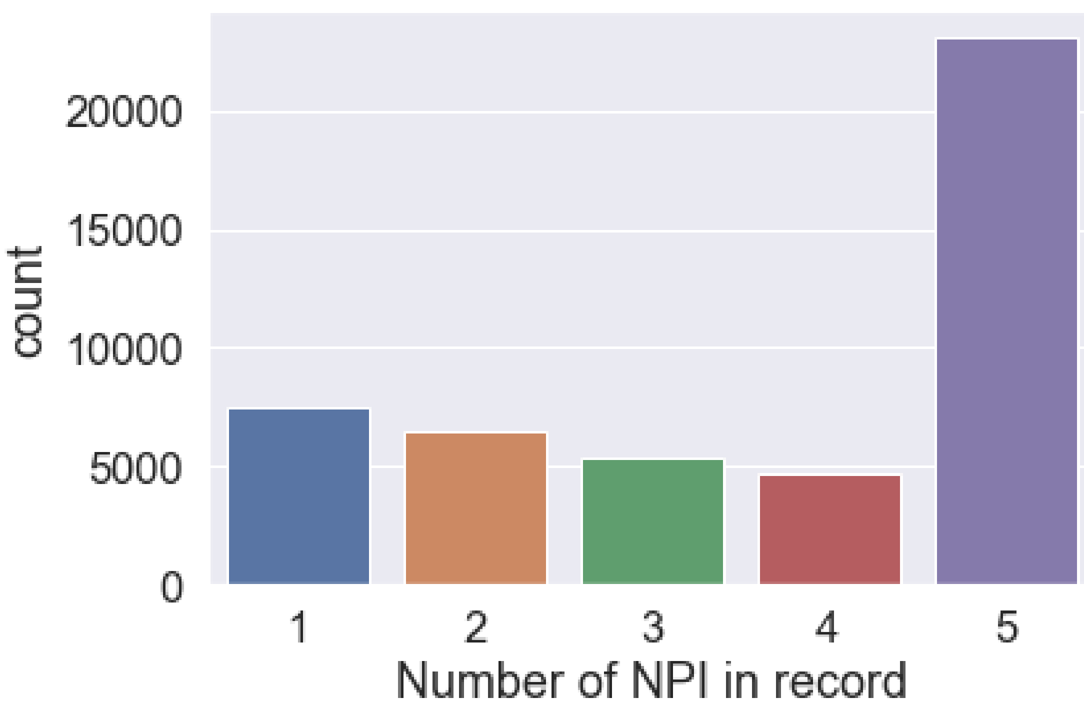
[22]:
```
opi_pres_no_zip_dup = opi_pres_all.sort_values(['npi', 'year', 'sort_index']).
↪drop_duplicates(subset=['npi', 'year', 'nppes_provider_last_name',␣
↪'nppes_provider_first_name'], keep='last')
print(opi_pres_no_zip_dup.shape)
```

```
(170744, 13)
```

[23]:
```
npi_counts_updt = opi_pres_no_zip_dup['npi'].value_counts().reset_index()
npi_counts_updt['npi'].hist(bins=5)
plt.xlabel('Number of times npi shows up in data')
plt.ylabel('Count')
plt.show()
```



[24]:
```
sns.countplot(x="npi", data=npi_counts_updt)
plt.xlabel('Number of NPI in record')
plt.show()
```



Although not the best solution, the problem is resolved quickly at least.
Prepare for export:

[25]:
```
opi_pres_no_zip_dup.columns
```

[25]:
```
Index(['npi', 'nppes_provider_last_name', 'nppes_provider_first_name',
       'nppes_provider_zip_code', 'town', 'specialty_description',
       'total_claim_count', 'opioid_claim_count', 'opioid_prescribing_rate',
       'long-acting_opioid_claim_count', 'year', 'calc_opioid_rate',
       'sort_index'],
      dtype='object')
```

[26]:
```
opi_pres_no_zip_dup.drop(['long-acting_opioid_claim_count',␣
↪'opioid_prescribing_rate', 'sort_index'], axis=1, inplace=True)
opi_pres_no_zip_dup.head()
```

[26]:
```
               npi nppes_provider_last_name nppes_provider_first_name  \
34086   1003001660                   newton                    robert
0       1003002312                  hopkins                  patricia
34365   1003002312                  hopkins                  patricia
68820   1003002312                  hopkins                  patricia
104236  1003002312                  hopkins                  patricia

       nppes_provider_zip_code       town specialty_description  \
34086                    02446  brookline               urology
0                        02169     quincy     internal medicine
34365                    02169     quincy     internal medicine
68820                    02169     quincy     internal medicine
104236                   02169     quincy          rheumatology

        total_claim_count  opioid_claim_count  year  calc_opioid_rate
34086                  12                 0.0  2014          0.000000
0                    4139               522.0  2013         12.611742
34365                4467               542.0  2014         12.133423
68820                4183               495.0  2015         11.833612
104236               4634               593.0  2016         12.796720
```

[27]:
```
# to keep zeroes in zipcode when writing
opi_pres_no_zip_dup['nppes_provider_zip_code'] =␣
↪opi_pres_no_zip_dup['nppes_provider_zip_code'].astype('str')
```

[28]:
```
print(death_and_acs_data.shape)
death_and_acs_data.head()
```

```
(347, 20)
```

[28]:
```
  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
```

Towns missing from one dataset or another:

[29]:
```
print(len(set(death_and_acs_data['city_death']) -␣
 ↪set(opi_pres_no_zip_dup['town'])))
print(len(set(opi_pres_no_zip_dup['town']) -␣
 ↪set(death_and_acs_data['city_death'])))
```

```
54
3
```

[30]:
```
set(opi_pres_no_zip_dup['town']) - set(death_and_acs_data['city_death'])
```

[30]:
```
{'manchester by the sea', 'monroe', 'worthington'}
```

[31]:
```
set(death_and_acs_data['city_death']) - set(opi_pres_no_zip_dup['town'])
```

[31]:
```
{'acushnet',
 'alford',
 'aquinnah',
 'ashby',
 'becket',
 'blandford',
 'cheshire',
 'chesterfield',
 'clarksburg',
```

```
'colrain',
'cummington',
'dunstable',
'east brookfield',
'erving',
'florida',
'gill',
'gosnold',
'granby',
'granville',
'hancock',
'hawley',
'heath',
'hinsdale',
'holland',
'leyden',
'manchester',
'middlefield',
'millville',
'montgomery',
'mount washington',
'nahant',
'new ashford',
'new braintree',
'new marlborough',
'new salem',
'northfield',
'oakham',
'pelham',
'peru',
'petersham',
'phillipston',
'plympton',
'rowe',
'royalston',
'russell',
'sandisfield',
'savoy',
'tolland',
'tyringham',
'wales',
'warwick',
'washington',
'wendell',
'westhampton'}
```

[32]:
```
opi_pres_no_zip_dup['town'] = opi_pres_no_zip_dup['town'].str.
↪replace('manchester by the sea', 'manchester')
```

[33]:
```
set(opi_pres_no_zip_dup['town']) - set(death_and_acs_data['city_death'])
```

[33]:
```
{'monroe', 'worthington'}
```

[34]:
```
opi_pres_no_zip_dup.head()
```

[34]:
```
               npi nppes_provider_last_name nppes_provider_first_name  \
34086   1003001660                   newton                    robert
0       1003002312                  hopkins                  patricia
34365   1003002312                  hopkins                  patricia
68820   1003002312                  hopkins                  patricia
104236  1003002312                  hopkins                  patricia

       nppes_provider_zip_code       town specialty_description  \
34086                    02446  brookline               urology
0                        02169     quincy     internal medicine
34365                    02169     quincy     internal medicine
68820                    02169     quincy     internal medicine
104236                   02169     quincy          rheumatology

        total_claim_count  opioid_claim_count  year  calc_opioid_rate
34086                  12                 0.0  2014          0.000000
0                    4139               522.0  2013         12.611742
34365                4467               542.0  2014         12.133423
68820                4183               495.0  2015         11.833612
104236               4634               593.0  2016         12.796720
```

1.0.3 File disclaimer:

Generating the 1 index is random - forgot to set seed - when rerunning the notebook the output will probably change. I'm going to use the file that I created when this notebook was first run. There may be minor differences in prescriber assignment to town if the notebook is run again.

[35]:
```
#opi_pres_no_zip_dup.to_csv("../../../data/tidy_data/
↪medicare_partD_opioid_prescriber_all_years_no_ziptown_duplicates.csv",␣
↪index=False)
```

1.0.4 Now to merge the opioid overdose deaths and the opioid prescription data together:

[3]:
```
opi_pres_no_zip_dup = pd.read_csv("../../../data/tidy_data/
↪medicare_partD_opioid_prescriber_all_years_no_ziptown_duplicates.csv")
```

[4]:
```
opi_pres_no_zip_dup.head()
opi_pres_no_zip_dup.drop('nppes_provider_zip_code', axis=1, inplace=True)
```

[5]:
```

```

```
# summarize the prescription data by town and year (average of rates)
opi_pres_mean_stats = opi_pres_no_zip_dup.groupby(['town', 'year']).mean().
↪reset_index().drop('npi', axis=1)
opi_pres_mean_stats.columns = ['town', 'year', 'total_claims_count_avg',␣
↪'opioid_claim_count_avg', 'opioid_rate_avg']
opi_pres_mean_stats.head()
```

[5]:

```
       town  year  total_claims_count_avg  opioid_claim_count_avg  \
0  abington  2013             2179.083333               89.666667
1  abington  2014             1925.350000               79.700000
2  abington  2015             2408.916667               64.041667
3  abington  2016             2871.857143               72.333333
4  abington  2017             2498.826087               67.434783

   opioid_rate_avg
0         7.123603
1         7.807532
2         6.627004
3         4.429928
4         5.274131
```

[6]:

```
# summarize the prescription data by town and year (sum of counts)
opi_pres_sum_stats = opi_pres_no_zip_dup.groupby(['town', 'year']).sum().
↪reset_index().drop(['npi', 'calc_opioid_rate'], axis=1)
opi_pres_sum_stats.columns = ['town', 'year', 'total_claim_count_sum',␣
↪'opioid_claim_count_sum']
opi_pres_sum_stats.head()
```

[6]:

```
       town  year  total_claim_count_sum  opioid_claim_count_sum
0  abington  2013                  52298                  2152.0
1  abington  2014                  38507                  1594.0
2  abington  2015                  57814                  1537.0
3  abington  2016                  60309                  1519.0
4  abington  2017                  57473                  1551.0
```

[7]:

```
print(opi_pres_mean_stats.shape)
print(opi_pres_sum_stats.shape)
opi_pres_stats = opi_pres_mean_stats.merge(opi_pres_sum_stats, on=['town',␣
↪'year'], how='inner')
print(opi_pres_stats.shape)
display(opi_pres_stats.head())
display(opi_pres_stats.describe())
```

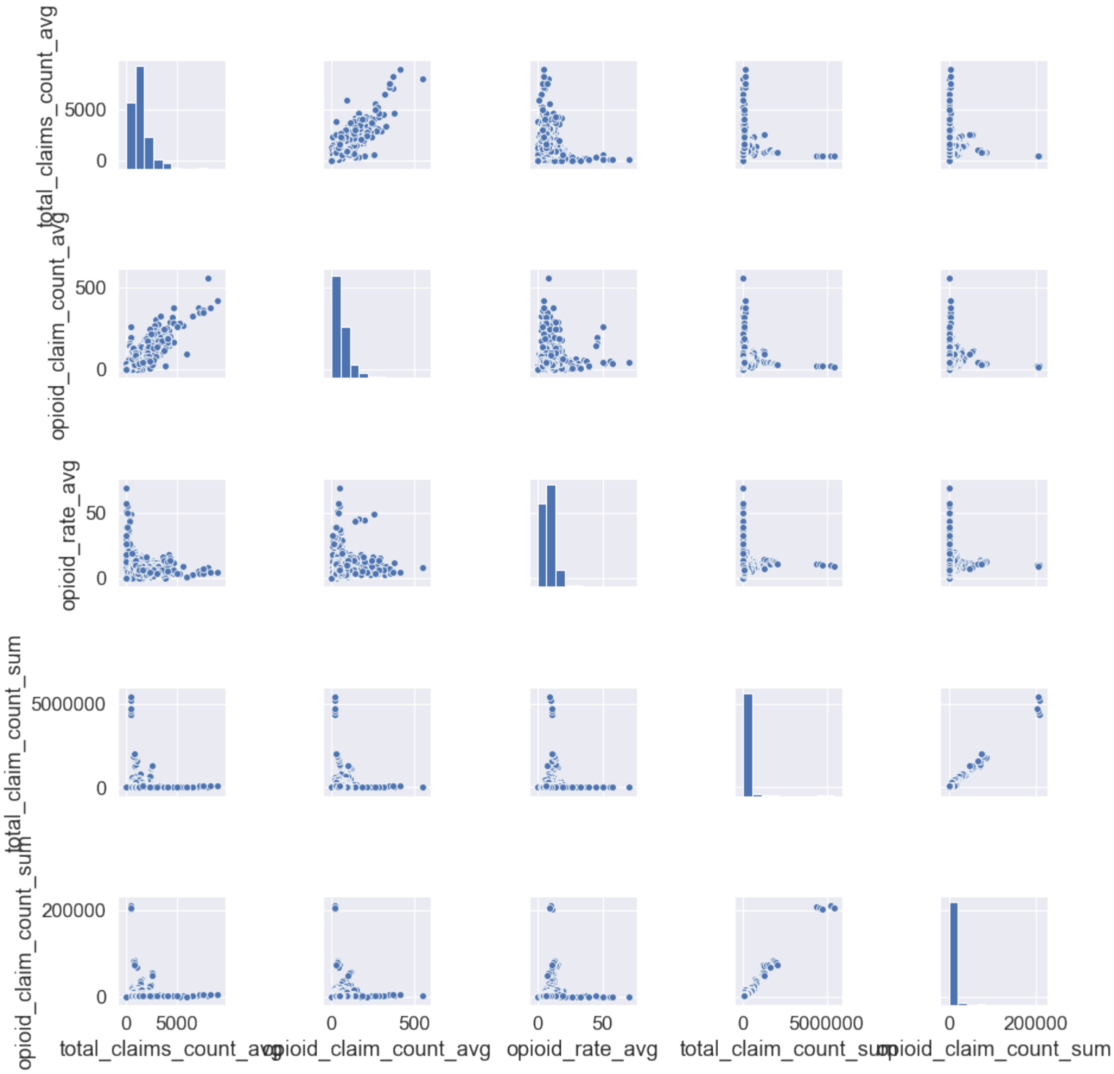
```
(1438, 5)
(1438, 4)
(1438, 7)
```

```
       town  year  total_claims_count_avg  opioid_claim_count_avg  \
0  abington  2013             2179.083333               89.666667
```

```
1  abington  2014            1925.350000             79.700000
2  abington  2015            2408.916667             64.041667
3  abington  2016            2871.857143             72.333333
4  abington  2017            2498.826087             67.434783

   opioid_rate_avg  total_claim_count_sum  opioid_claim_count_sum
0         7.123603                  52298                  2152.0
1         7.807532                  38507                  1594.0
2         6.627004                  57814                  1537.0
3         4.429928                  60309                  1519.0
4         5.274131                  57473                  1551.0


              year  total_claims_count_avg  opioid_claim_count_avg  \
count  1438.000000             1438.000000             1438.000000
mean   2014.995132             1368.366165               61.048364
std       1.413467             1031.772994               56.621581
min    2013.000000               11.000000                0.000000
25%    2014.000000              790.629670               27.251136
50%    2015.000000             1226.000000               48.902206
75%    2016.000000             1707.300826               76.386719
max    2017.000000             8922.636364              555.500000

       opioid_rate_avg  total_claim_count_sum  opioid_claim_count_sum
count      1438.000000           1.438000e+03             1438.000000
mean          8.856701           1.122620e+05             4723.317803
std           6.175832           3.413563e+05            14546.384508
min           0.000000           1.100000e+01                0.000000
25%           5.325307           1.087675e+04              420.250000
50%           8.091398           3.376600e+04             1396.500000
75%          11.058857           9.881100e+04             4184.000000
max          69.696970           5.442227e+06           209604.000000
```

[8]:
```
sns.pairplot(opi_pres_stats.drop(['town', 'year'], axis=1))
```

[8]:
```
<seaborn.axisgrid.PairGrid at 0x18f084f55f8>
```



Claim count features are very skewed - not surprising, probably depends on population:

[9]:
```
# where were the highest claims?
opi_pres_stats[opi_pres_stats['total_claim_count_sum'] > 2000000]
```

[9]:
```
           town  year  total_claims_count_avg  opioid_claim_count_avg  \
144      boston  2013              436.120317               20.636274
145      boston  2014              447.212293               20.033951
146      boston  2015              453.524232               19.308529
147      boston  2016              474.821885               19.145415
148      boston  2017              479.280229               18.064465
1422  worcester  2017              806.286672               29.255915

      opioid_rate_avg  total_claim_count_sum  opioid_claim_count_sum
144         11.472438                4400454                208220.0
145         11.057803                4583926                205348.0
```

```
146           10.666161                     4753841                   202392.0
147           10.180812                     5198350                   209604.0
148            9.217205                     5442227                   205122.0
1422          10.768587                     2044743                    74193.0
```

[10]:

```
death_and_acs_data
```

[10]:

```
      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
..           ...   ...   ...   ...   ...   ...            ...            ...
342     winthrop     0     2     1     9     2   17910.571429   18048.428571
343       woburn     5     1     9    10     8   38711.428571   38908.571429
344    worcester    86   120   109   118   134  182629.857143  183158.142857
345     wrentham     1     2     1     2     1   11230.142857   11321.857143
346     yarmouth     2     3     6     8     4   23649.857143   23602.142857

        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
..             ...            ...         ...            ...           ...
342   18186.285714   18324.142857       18462           4114      0.222836
343   39105.714286   39302.857143       39500           7595      0.192278
344  183686.428571  184214.714286      184743          26267      0.142181
345   11413.571429   11505.285714       11597           1814      0.156420
346   23554.428571   23506.714286       23459           7897      0.336630

     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
..             ...             ...              ...                   ...
342   75567.000000    95947.051705         5.598220              0.082171
343   84871.428571    98642.691942         5.676144              0.059830
344   52213.955556    65734.403488        15.274429              0.217695
345  109280.000000   133462.931270         3.251092              0.050582
346   66455.380952    79616.747798         5.042380              0.068643

     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
..                    ...       ...         ...
342              0.111967     rural       grown
343              0.108290     rural       grown
344              0.196946     urban       grown
345              0.058336     rural       grown
346              0.133892     rural      shrunk

[347 rows x 20 columns]
```

[11]:

```
city_year_death_long = pd.melt(death_and_acs_data, id_vars=['city_death'],␣
 ↪value_vars=[
    '2014', '2015', '2016', '2017', '2018'
])
city_year_death_long.columns = ['city_death', 'year', 'death_count']
display(city_year_death_long.head())
```

```
  city_death  year  death_count
0   abington  2014            0
1      acton  2014            1
2   acushnet  2014            0
3      adams  2014            2
4     agawam  2014            1
```

[12]:

```
pop_year_dict = {'tot_pop_13': 2013, 'tot_pop_14': 2014, 'tot_pop_15': 2015,␣
 ↪'tot_pop_16': 2016,
    'tot_pop_17': 2017}
city_year_pop_long = pd.melt(death_and_acs_data, id_vars=['city_death'],␣
 ↪value_vars=[
    'tot_pop_13', 'tot_pop_14', 'tot_pop_15', 'tot_pop_16', 'tot_pop_17'
]).replace({"variable": pop_year_dict})
city_year_pop_long.columns = ['city_death', 'year', 'tot_pop']
display(city_year_pop_long.head())
```

```
  city_death  year       tot_pop
0   abington  2013  16109.285714
1      acton  2013  22580.142857
2   acushnet  2013  10363.000000
3      adams  2013   8367.571429
4     agawam  2013  27684.428571
```

[13]:

```
display(city_year_death_long.info())
display(city_year_pop_long.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1735 entries, 0 to 1734
Data columns (total 3 columns):
city_death     1735 non-null object
year           1735 non-null object
death_count    1735 non-null int64
dtypes: int64(1), object(2)
memory usage: 40.8+ KB

None
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1735 entries, 0 to 1734
Data columns (total 3 columns):
city_death    1735 non-null object
year          1735 non-null int64
tot_pop       1735 non-null float64
dtypes: float64(1), int64(1), object(1)
memory usage: 40.8+ KB

None
```

[14]:
```python
city_year_death_long['year'] = city_year_death_long['year'].astype(int) - 1
city_year_death_long.columns = ['city_death', 'year', 'death_count_next_year']
city_year_death_long.head()
```

[14]:

	city_death	year	death_count_next_year
0	abington	2013	0
1	acton	2013	1
2	acushnet	2013	0
3	adams	2013	2
4	agawam	2013	1

[15]:
```python
city_year_long_merge = city_year_death_long.merge(city_year_pop_long,␣
 ↪how="inner", on=["city_death", "year"])
print(city_year_death_long.shape)
print(city_year_pop_long.shape)
print(city_year_long_merge.shape)
city_year_long_merge.head()
```

```
(1735, 3)
(1735, 3)
(1735, 4)
```

[15]:

	city_death	year	death_count_next_year	tot_pop
0	abington	2013	0	16109.285714
1	acton	2013	1	22580.142857

```
2   acushnet  2013                          0   10363.000000
3      adams  2013                          2    8367.571429
4    agawam  2013                          1   27684.428571
```

[16]:
```python
death_and_acs_for_merge = death_and_acs_data.drop(['2014', '2015', '2016',␣
 ↪'2017', '2018',
                                                    'tot_pop_13', 'tot_pop_14',␣
 ↪'tot_pop_15', 'tot_pop_16', 'tot_pop_17'],
                                                   axis=1)
death_and_acs_for_merge.head()
```

[16]:
```
  city_death  over_65_count  over_65_prop  med_house_inc  mean_house_inc  \
0   abington           2469      0.151705   87156.000000    98809.035505
1      acton           4001      0.170582  139890.466667   156680.203867
2   acushnet           2431      0.232788   69624.714286    80333.175842
3      adams           1764      0.214834   48445.400000    60968.594660
4    agawam           6195      0.223090   65490.125000    79464.234446

   less_than_hs_ed  at_or_below_pov_prop  pop_struggling_prop urb_v_rur  \
0         5.405643              0.035754             0.100408     rural
1         2.456531              0.038315             0.041747     rural
2        18.297315              0.040828             0.178406     rural
3        11.862182              0.110854             0.144597     rural
4         7.748863              0.094819             0.142656     rural

  town_status
0       grown
1       grown
2       grown
3      shrunk
4       grown
```

This isn't perfect - but will merge 2017 ACS data for all years - assume some of these don't change?

Problematic assumption

[17]:
```python
print(city_year_long_merge.shape)
print(death_and_acs_for_merge.shape)
death_and_acs_long = city_year_long_merge.merge(death_and_acs_for_merge,␣
 ↪on="city_death")
print(death_and_acs_long.shape)
death_and_acs_long.head()
```

```
(1735, 4)
(347, 10)
(1735, 13)
```

[17]:
```
  city_death  year  death_count_next_year       tot_pop  over_65_count  \
0   abington  2013                      0  16109.285714           2469
```

```
1   abington  2014                       6  16150.714286          2469
2   abington  2015                       1  16192.142857          2469
3   abington  2016                       3  16233.571429          2469
4   abington  2017                       5  16275.000000          2469

   over_65_prop  med_house_inc  mean_house_inc  less_than_hs_ed  \
0      0.151705        87156.0    98809.035505         5.405643
1      0.151705        87156.0    98809.035505         5.405643
2      0.151705        87156.0    98809.035505         5.405643
3      0.151705        87156.0    98809.035505         5.405643
4      0.151705        87156.0    98809.035505         5.405643

   at_or_below_pov_prop  pop_struggling_prop urb_v_rur town_status
0              0.035754             0.100408     rural       grown
1              0.035754             0.100408     rural       grown
2              0.035754             0.100408     rural       grown
3              0.035754             0.100408     rural       grown
4              0.035754             0.100408     rural       grown
```

[18]:
```python
# unique number of towns at this point
len(set(death_and_acs_long['city_death']))
```

[18]:
```
347
```

[60]:
```python
# write for plotting purposes
#death_and_acs_long.to_csv("../../../data/tidy_data/
↪overdose_death_count_acs_merge_long_format.csv", index=False)
```

Now join this reshaped file with the opioid prescription data:

[19]:
```python
print(opi_pres_stats.shape)
acs_death_and_opi_pres = death_and_acs_long.merge(opi_pres_stats, how="inner",␣
↪left_on=["city_death", "year"], right_on=["town", "year"])
print(acs_death_and_opi_pres.shape)
display(acs_death_and_opi_pres.head())
display(acs_death_and_opi_pres.describe())
```

```
(1438, 7)
(1428, 19)

  city_death  year  death_count_next_year       tot_pop  over_65_count  \
0   abington  2013                      0  16109.285714           2469
1   abington  2014                      6  16150.714286           2469
2   abington  2015                      1  16192.142857           2469
3   abington  2016                      3  16233.571429           2469
4   abington  2017                      5  16275.000000           2469

   over_65_prop  med_house_inc  mean_house_inc  less_than_hs_ed  \
0      0.151705        87156.0    98809.035505         5.405643
1      0.151705        87156.0    98809.035505         5.405643
```

2	0.151705	87156.0	98809.035505	5.405643
3	0.151705	87156.0	98809.035505	5.405643
4	0.151705	87156.0	98809.035505	5.405643

	at_or_below_pov_prop	pop_struggling_prop	urb_v_rur	town_status	town
0	0.035754	0.100408	rural	grown	abington
1	0.035754	0.100408	rural	grown	abington
2	0.035754	0.100408	rural	grown	abington
3	0.035754	0.100408	rural	grown	abington
4	0.035754	0.100408	rural	grown	abington

	total_claims_count_avg	opioid_claim_count_avg	opioid_rate_avg
0	2179.083333	89.666667	7.123603
1	1925.350000	79.700000	7.807532
2	2408.916667	64.041667	6.627004
3	2871.857143	72.333333	4.429928
4	2498.826087	67.434783	5.274131

	total_claim_count_sum	opioid_claim_count_sum
0	52298	2152.0
1	38507	1594.0
2	57814	1537.0
3	60309	1519.0
4	57473	1551.0

	year	death_count_next_year	tot_pop	over_65_count
count	1428.000000	1428.000000	1428.000000	1428.000000
mean	2014.995098	6.378151	23030.576431	4087.070728
std	1.413462	18.881139	44019.836836	6014.409427
min	2013.000000	0.000000	447.571429	96.000000
25%	2014.000000	0.000000	7057.535714	1419.000000
50%	2015.000000	1.000000	13794.714286	2692.000000
75%	2016.000000	4.000000	26566.142857	5009.000000
max	2017.000000	279.000000	668541.000000	85040.000000

	over_65_prop	med_house_inc	mean_house_inc	less_than_hs_ed
count	1428.000000	1428.000000	1428.000000	1428.000000
mean	0.202919	91050.875142	112834.042914	6.597659
std	0.065342	30176.605424	41695.447804	4.993370
min	0.086886	38909.750000	50750.537570	0.354019
25%	0.165207	70220.250000	86561.728307	3.135615
50%	0.188014	86875.000000	102959.957747	5.363993
75%	0.222270	106846.681818	128540.605810	8.302169
max	0.473703	203026.750000	316351.858774	32.336132

	at_or_below_pov_prop	pop_struggling_prop	total_claims_count_avg
count	1428.000000	1428.000000	1428.000000

```
mean                0.073977          0.102210          1370.942198
std                 0.049453          0.052502          1034.683050
min                 0.005354          0.010566            11.000000
25%                 0.042231          0.063789           789.810225
50%                 0.059686          0.090870          1229.965190
75%                 0.094519          0.130955          1714.009832
max                 0.332260          0.304869          8922.636364

       opioid_claim_count_avg  opioid_rate_avg  total_claim_count_sum  \
count             1428.000000      1428.000000           1.428000e+03
mean                60.941325         8.823179           1.129176e+05
std                 56.786610         6.174974           3.424591e+05
min                  0.000000         0.000000           1.100000e+01
25%                 26.999220         5.312575           1.080225e+04
50%                 48.634430         8.071573           3.400650e+04
75%                 75.919167        10.989267           9.939450e+04
max                555.500000        69.696970           5.442227e+06

       opioid_claim_count_sum
count             1428.000000
mean              4747.203081
std              14594.418466
min                  0.000000
25%                415.750000
50%               1405.000000
75%               4237.750000
max             209604.000000
```

[20]:
```python
# number of towns to predict on:
len(set(acs_death_and_opi_pres['city_death']))
```

[20]: 294

Some feature engineering:

[21]:
```python
acs_death_and_opi_pres['claim_per_65_and_over'] =␣
 ↪acs_death_and_opi_pres['total_claim_count_sum'] /␣
 ↪acs_death_and_opi_pres['over_65_count']
acs_death_and_opi_pres['opi_claim_per_65_and_over'] =␣
 ↪acs_death_and_opi_pres['opioid_claim_count_sum'] /␣
 ↪acs_death_and_opi_pres['over_65_count']
acs_death_and_opi_pres[['claim_per_65_and_over', 'opi_claim_per_65_and_over']].
 ↪describe()
```

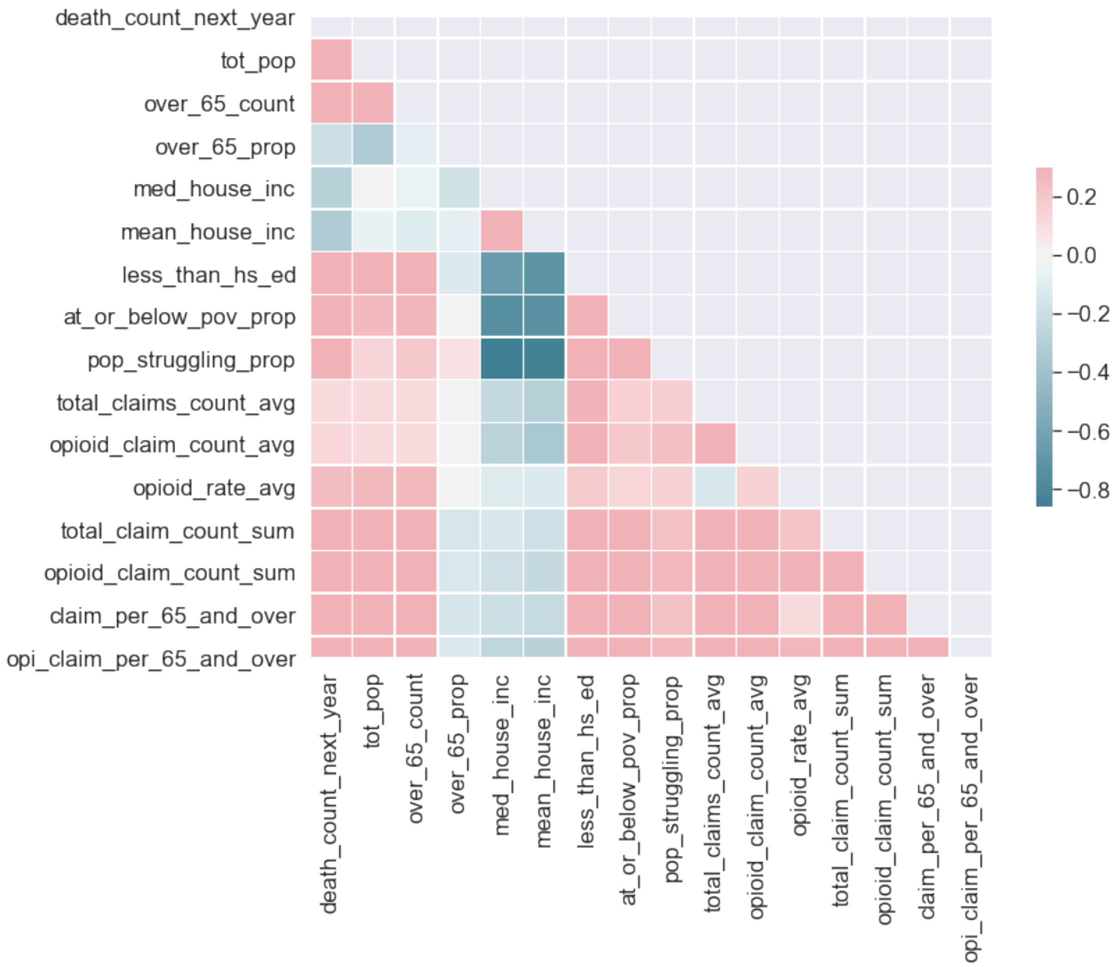
[21]:
```
       claim_per_65_and_over  opi_claim_per_65_and_over
count            1428.000000                1428.000000
mean               18.366112                   0.804856
std                17.571084                   0.840314
min                 0.010885                   0.000000
```

```
25%                5.762441                  0.208941
50%               13.827601                  0.530764
75%               26.006282                  1.132716
max              123.727848                  5.591346
```

[22]:
```
acs_death_and_opi_pres.columns
```

[22]:
```
Index(['city_death', 'year', 'death_count_next_year', 'tot_pop',
       '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', 'town', 'total_claims_count_avg',
       'opioid_claim_count_avg', 'opioid_rate_avg', 'total_claim_count_sum',
       'opioid_claim_count_sum', 'claim_per_65_and_over',
       'opi_claim_per_65_and_over'],
      dtype='object')
```

[23]:
```
opi_death_rate_corr = acs_death_and_opi_pres.drop(['city_death', 'year',␣
 ↪'urb_v_rur', 'town_status'], axis=1).corr(method="spearman")
mask = np.zeros_like(opi_death_rate_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(opi_death_rate_corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
plt.show()
```

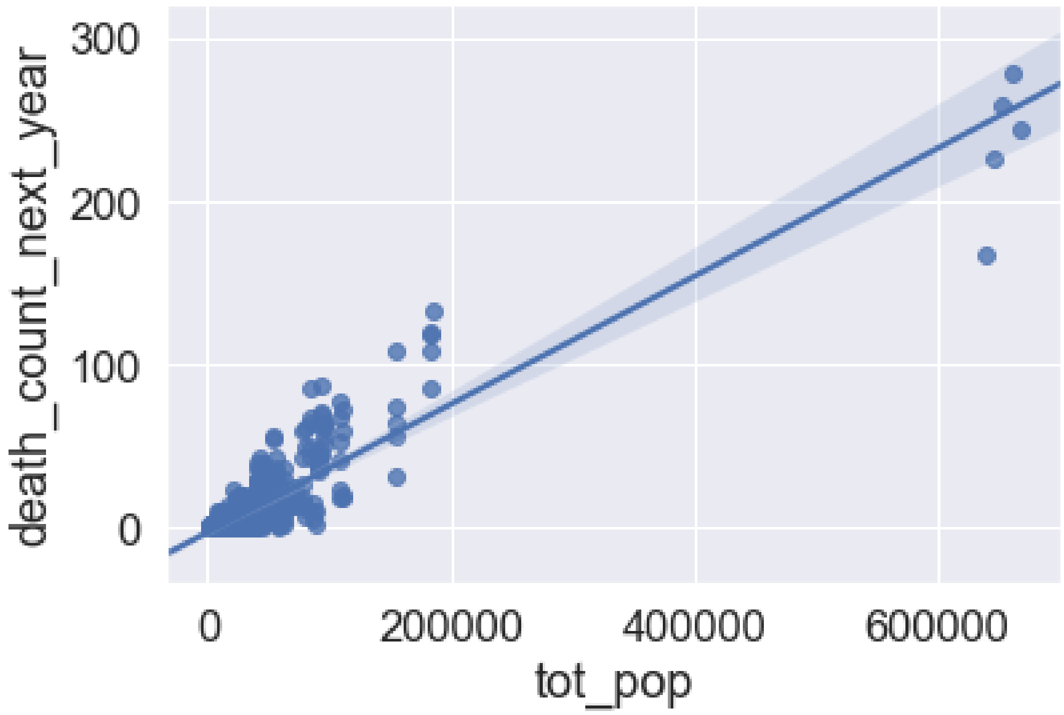


[24]:
```
opi_death_rate_corr[['death_count_next_year']].
↪sort_values('death_count_next_year', ascending=False)
```

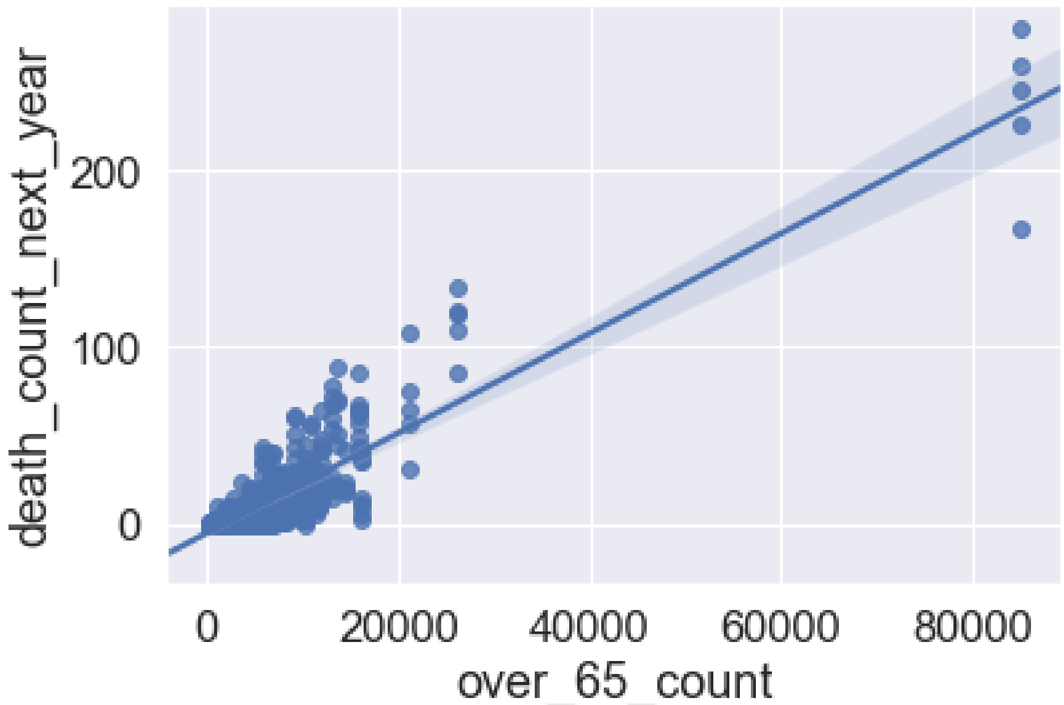
[24]:
```
                           death_count_next_year
death_count_next_year                   1.000000
tot_pop                                 0.723126
over_65_count                           0.715564
total_claim_count_sum                   0.650890
opioid_claim_count_sum                  0.641590
less_than_hs_ed                         0.463468
at_or_below_pov_prop                    0.427273
claim_per_65_and_over                   0.418149
opi_claim_per_65_and_over               0.390337
pop_struggling_prop                     0.370075
opioid_rate_avg                         0.250391
opioid_claim_count_avg                  0.126282
total_claims_count_avg                  0.107456
over_65_prop                           -0.195283
```

```
med_house_inc                          -0.291439
mean_house_inc                         -0.324288
```

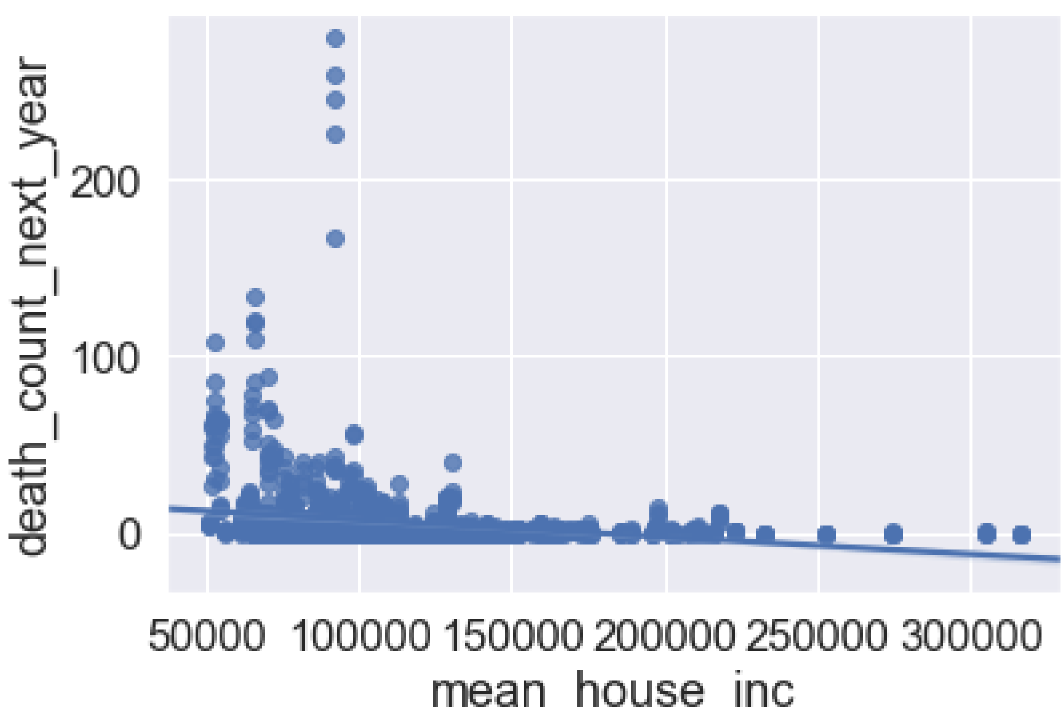
[29]:
```
sns.regplot(x='tot_pop', y='death_count_next_year', data=acs_death_and_opi_pres)
plt.show()
```



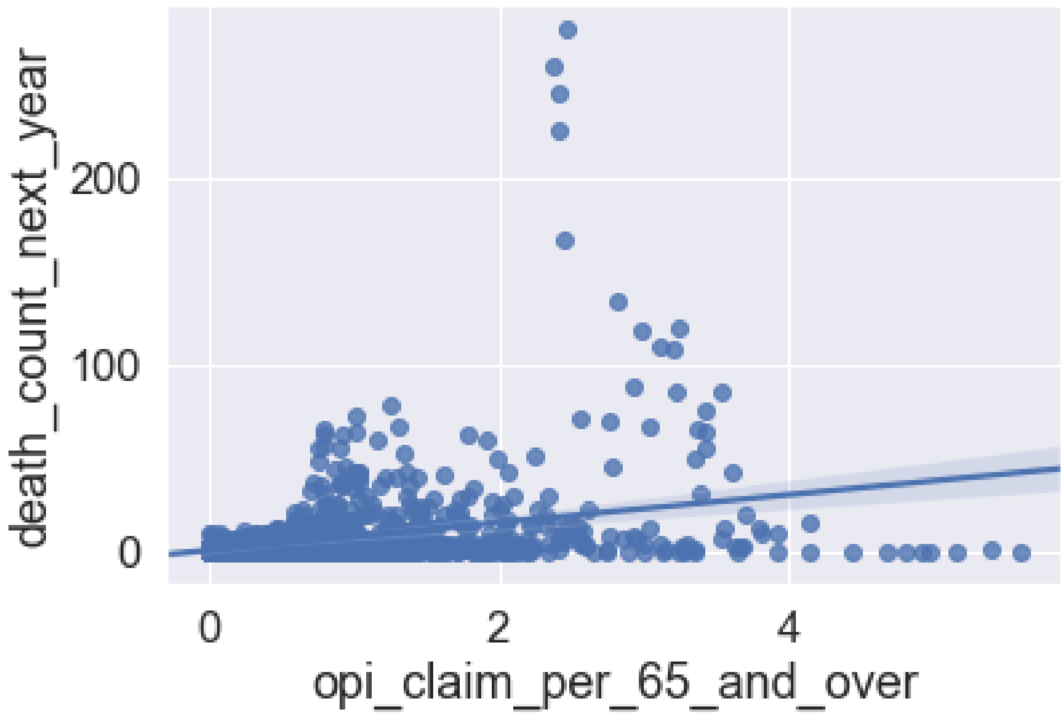
[28]:
```
sns.regplot(x='over_65_count', y='death_count_next_year',␣
 ↪data=acs_death_and_opi_pres)
plt.show()
```



[26]:
```
sns.regplot(x='mean_house_inc', y='death_count_next_year',␣
    ↪data=acs_death_and_opi_pres)
plt.show()
```



```
[27]: sns.regplot(x='opi_claim_per_65_and_over', y='death_count_next_year',␣
       ↪data=acs_death_and_opi_pres)
      plt.show()
```



Of course, these plots aren't very meaningful, because when I will model, the geospatial/time/total population components will also be in the model - that will likely change these relationships

```
[70]: #acs_death_and_opi_pres.to_csv("../../../data/tidy_data/
       ↪acs_medicare_opioid_stats_death_count_merge.csv", index=False)
```