MA_opioid_overdose_death_rate_and_partD_drug_match_by_town

September 24, 2019

1 Goals:

- 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

1.0.1 Outputs:

- /data/tidy_data/medicare_partD_opioid_prescriber_all_years_no_ziptown_duplicates.csv"
- /data/tidy_data/acs_medicare_opioid_stats_death_rate.csv

[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/
 ↪death_count_norm_to_pop_and_acs_town_demographics_merge.csv")
opi_pres_13 = pd.read_csv("../../../data/tidy_data/
 ↪medicare_partD_opioid_prescriber_2013_w_zip_MAtown_v1.csv").drop('Unnamed:␣
 ↪0', axis=1)
opi_pres_14 = pd.read_csv("../../../data/tidy_data/
 ↪medicare_partD_opioid_prescriber_2014_w_zip_MAtown_v1.csv").drop('Unnamed:␣
 ↪0', axis=1)
opi_pres_15 = pd.read_csv("../../../data/tidy_data/
 ↪medicare_partD_opioid_prescriber_2015_w_zip_MAtown_v1.csv").drop('Unnamed:␣
 ↪0', axis=1)
opi_pres_16 = pd.read_csv("../../../data/tidy_data/
 ↪medicare_partD_opioid_prescriber_2016_w_zip_MAtown_v1.csv").drop('Unnamed:␣
 ↪0', axis=1)
```

```
opi_pres_17 = pd.read_csv("../../../data/tidy_data/
↪medicare_partD_opioid_prescriber_2017_w_zip_MAtown_v1.csv").drop('Unnamed:␣
↪0', axis=1)
```

[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]:
```
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]:
```
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)
```

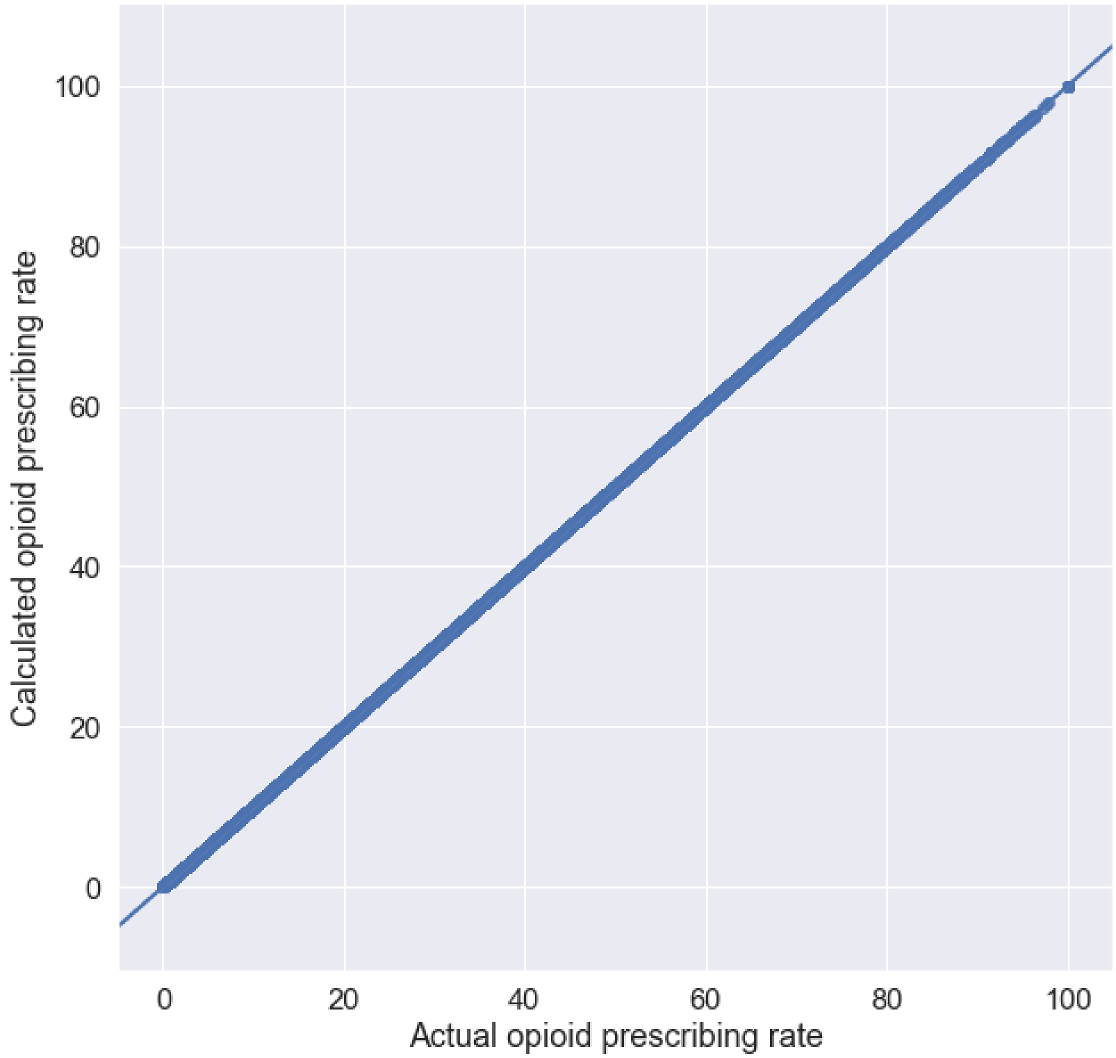
```
(34086, 11)
(34734, 11)
(35416, 11)
(36357, 11)
(37069, 11)
(177662, 11)
```

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

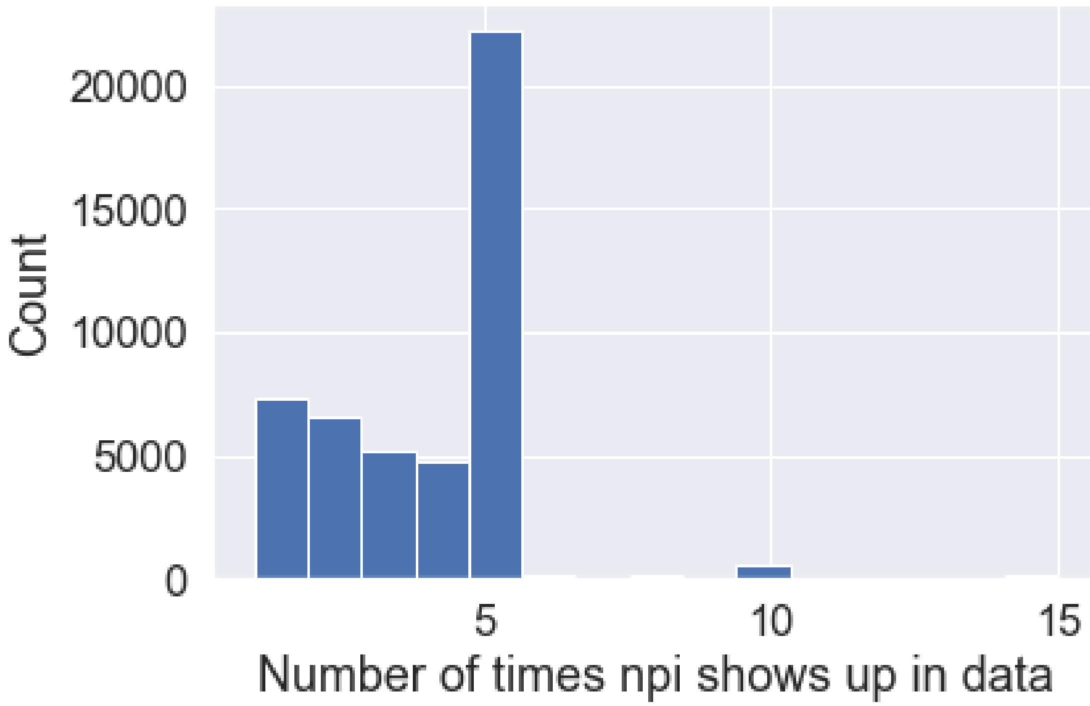
[11]:
```
          npi nppes_provider_last_name nppes_provider_first_name  \
0  1003002312                  hopkins                  patricia
1  1003083270                   kabadi                    mitesh
2  1003834433                     nair                      anil
3  1003895269                 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]:
```python
# was the opioid prescribing rate calculated as I expected?
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
```



[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]:
```
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
```

[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
```

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

[18]:
```
177662
```

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

[20]:
```
print(len(l))
print(len(set(l)))
```

```
177662
177662
```

[21]:
```
opi_pres_all['sort_index'] = l
```

[22]:
```
opi_pres_all.head()
```

[22]:
```
          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       12157
1                             0.0  2013          0.000000        2384
2                             NaN  2013          0.410846       65671
3                             0.0  2013          0.000000       81143
4                             0.0  2013         13.513514       26778
```

[27]:
```
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))
```

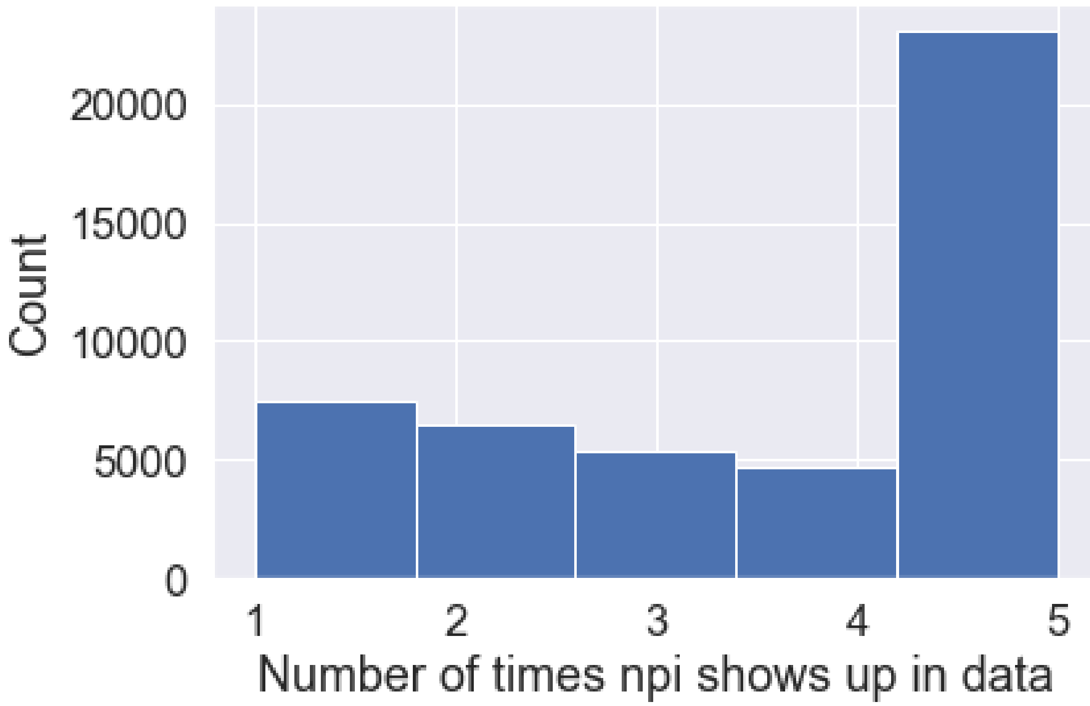
```
47875
47160
170744
170744
```

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

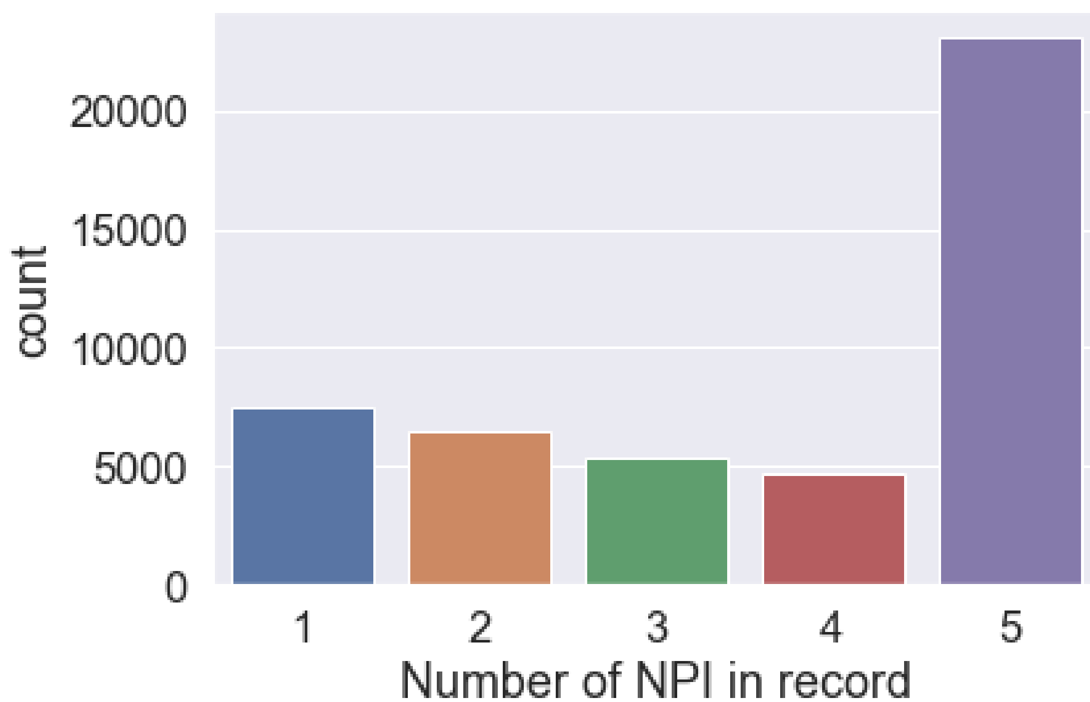
[28]:
```
opi_pres_no_zip_dup = opi_pres_all.sort_values(['npi', 'year', 'sort_index']).
 ↪drop_duplicates(subset=['npi', 'year', 'nppes_provider_last_name',␣
 ↪'nppes_provider_first_name'], keep='last')
print(opi_pres_no_zip_dup.shape)
```

```
(170744, 13)
```

[29]:
```
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()
```



[30]:
```
sns.countplot(x="npi", data=npi_counts_updt)
plt.xlabel('Number of NPI in record')
plt.show()
```



[31]:
```
opi_pres_no_zip_dup.columns
```

[31]:
```
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')
```

[32]:
```
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()
```

[32]:
```
               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
```

[33]:
```
# 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')
```

[34]:
```
death_and_acs_data
```

[34]:
```
    city_death  tot_pop_17  over_65_count  over_65_prop  med_house_inc  \
0     abington       16275           2469      0.151705   87156.000000
1        acton       23455           4001      0.170582  139890.466667
2     acushnet       10443           2431      0.232788   69624.714286
3        adams        8211           1764      0.214834   48445.400000
4      agawam       27769           6195      0.223090   65490.125000
..         ...         ...            ...           ...            ...
342   winthrop       18462           4114      0.222836   75567.000000
```

```
343     woburn      39500         7595      0.192278   84871.428571
344  worcester     184743        26267      0.142181   52213.955556
345   wrentham      11597         1814      0.156420  109280.000000
346   yarmouth      23459         7897      0.336630   66455.380952

     mean_house_inc  mean_med_inc_desp   drop_out  less_than_hs_ed  \
0      98809.035505       11653.035505   3.452855         5.405643
1     156680.203867       16789.737200   1.219512         2.456531
2      80333.175842       10708.461556  10.992908        18.297315
3      60968.594660       12523.194660   6.906907        11.862182
4      79464.234446       13974.109446   0.000000         7.748863
..              ...                ...        ...              ...
342    95947.051705       20380.051705   2.687412         5.598220
343    98642.691942       13771.263371   3.173804         5.676144
344    65734.403488       14222.791135   2.574476        15.274429
345   133462.931270       24182.931270   3.359173         3.251092
346    79616.747798       13195.409916   0.000000         5.042380

     at_or_below_pov_prop  pop_struggling_prop town_status urb_v_rur  \
0                0.035754             0.100408       grown     rural
1                0.038315             0.041747       grown     rural
2                0.040828             0.178406       grown     rural
3                0.110854             0.144597      shrunk     rural
4                0.094819             0.142656      shrunk     rural
..                    ...                  ...         ...       ...
342              0.082171             0.111967       grown     rural
343              0.059830             0.108290       grown     rural
344              0.217695             0.196946       grown     urban
345              0.050582             0.058336       grown     rural
346              0.068643             0.133892      shrunk     rural

     death_rate_12  death_rate_13  death_rate_14  death_rate_15  \
0         0.622361       1.241520       0.000000       3.705501
1         0.894397       0.000000       0.438618       0.868901
2         1.933675       0.000000       0.000000       3.845045
3         1.189525       1.195090       2.401413       3.619130
4         0.354022       1.065671       0.356434       0.715304
..             ...            ...            ...            ...
342       3.938622       1.116659       0.000000       1.099730
343       1.557864       1.549930       1.285064       0.255717
344       1.317946       2.354489       4.695396       6.532872
345       0.897793       0.000000       0.883247       1.752300
346       1.265953       2.959849       0.847381       1.273646

     death_rate_16  death_rate_17  death_rate_18
0         0.616007       1.843318       3.064396
1         1.291084       0.000000       0.422409
```

```
2          1.918833       3.830317       0.000000
3          1.212100       0.000000       4.894848
4          0.000000       1.440455       2.890860
..              ...            ...            ...
342        0.545728       4.874878       1.075277
343        2.289910       2.531646       2.015258
344        5.917008       6.387251       7.232637
345        0.869166       1.724584       0.855526
346        2.552462       3.410205       1.708578

[347 rows x 20 columns]
```

[35]:
```python
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
```

[36]:
```python
set(opi_pres_no_zip_dup['town']) - set(death_and_acs_data['city_death'])
```

[36]:
```
{'manchester by the sea', 'monroe', 'worthington'}
```

[37]:
```python
set(death_and_acs_data['city_death']) - set(opi_pres_no_zip_dup['town'])
```

[37]:
```
{'acushnet',
 'alford',
 'aquinnah',
 'ashby',
 'becket',
 'blandford',
 'cheshire',
 'chesterfield',
 'clarksburg',
 'colrain',
 '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',
 'plainfield',
 'plympton',
 'rowe',
 'royalston',
 'russell',
 'sandisfield',
 'savoy',
 'tolland',
 'tyringham',
 'wales',
 'warwick',
 'washington',
 'wendell',
 'westhampton'}
```

[38]:
```
opi_pres_no_zip_dup['town'] = opi_pres_no_zip_dup['town'].str.
 ↪replace('manchester by the sea', 'manchester')
```

[39]:
```
set(opi_pres_no_zip_dup['town']) - set(death_and_acs_data['city_death'])
```

[39]:
```
{'monroe', 'worthington'}
```

[40]:
```
#opi_pres_no_zip_dup.to_csv("../../../data/tidy_data/
 ↪medicare_partD_opioid_prescriber_all_years_no_ziptown_duplicates.csv",␣
 ↪index=False)
```

[41]:
```
opi_pres_no_zip_dup.head()
```

[41]:
```
              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
```

[47]:
```
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()
```

[47]:
```
       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
```

[49]:
```
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()
```

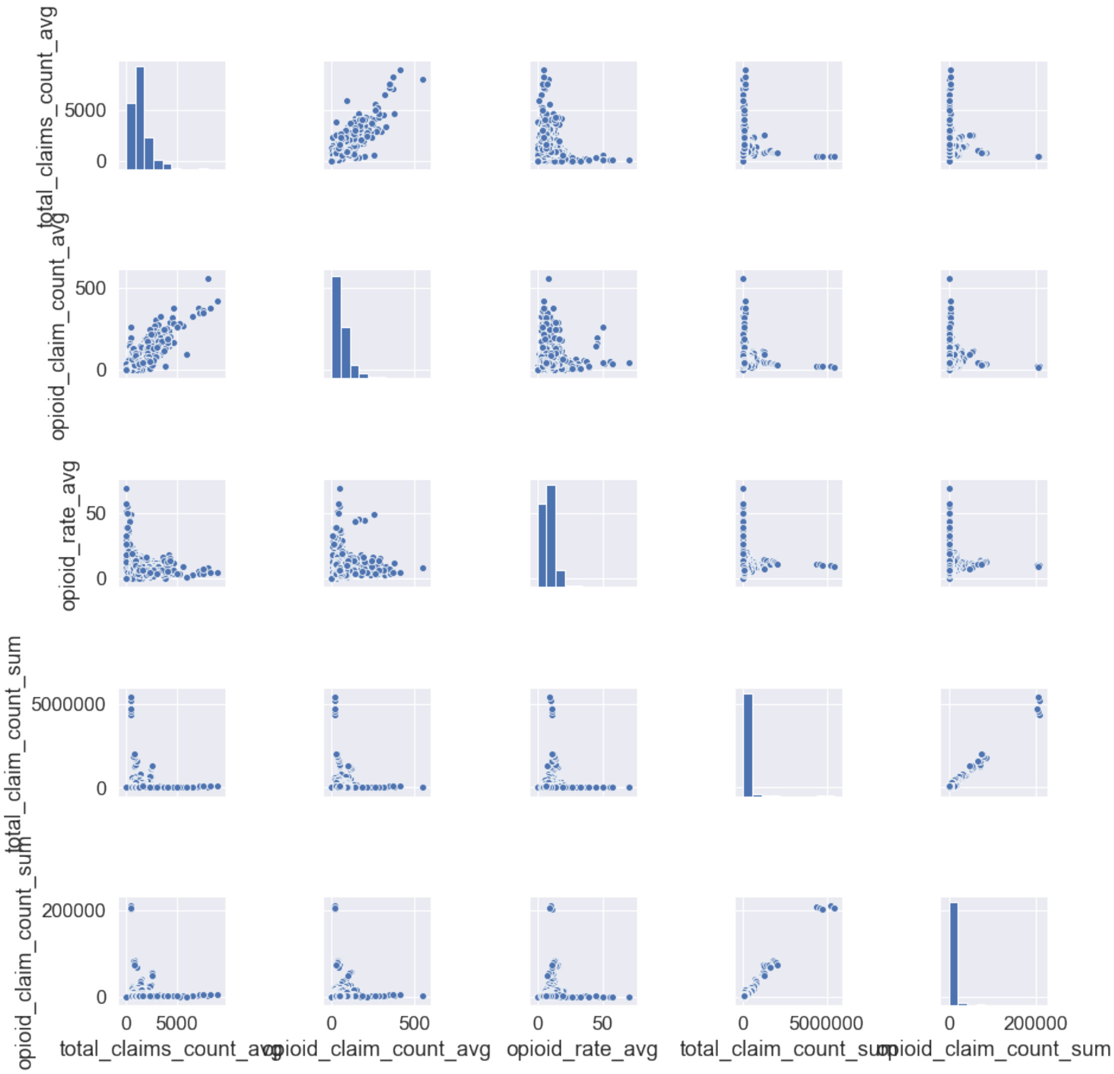
[49]:
```
       town  year  total_claim_count_sum  opioid_claim_count_sum
0  abington  2013                  52298                  2152.0
1  abington  2014                  38507                  1594.0
2  abington  2015                  57814                  1537.0
3  abington  2016                  60309                  1519.0
4  abington  2017                  57473                  1551.0
```

[52]:
```
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
```

[54]:
```
sns.pairplot(opi_pres_stats.drop(['town', 'year'], axis=1))
```

[54]:
```
<seaborn.axisgrid.PairGrid at 0x2274422f9e8>
```



[61]:
```
opi_pres_stats[opi_pres_stats['total_claim_count_sum'] > 2000000]
```

[61]:
```
           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
```

[82]:
```
year_dict = {'death_rate_12': 2011, 'death_rate_13': 2012, 'death_rate_14':␣
 ↪2013, 'death_rate_15': 2014,
    'death_rate_16': 2015, 'death_rate_17': 2016, 'death_rate_18': 2017}
city_year_death_long = pd.melt(death_and_acs_data, id_vars=['city_death'],␣
 ↪value_vars=[
    'death_rate_12', 'death_rate_13', 'death_rate_14', 'death_rate_15',
    'death_rate_16', 'death_rate_17', 'death_rate_18'
]).replace({"variable": year_dict})
city_year_death_long.columns = ['city_death', 'year', 'death_rate_per10k']
display(city_year_death_long.head())
```

```
  city_death  year  death_rate_per10k
0   abington  2011           0.622361
1      acton  2011           0.894397
2   acushnet  2011           1.933675
3      adams  2011           1.189525
4     agawam  2011           0.354022
```

[83]:
```
print(city_year_death_long.shape)
print(death_and_acs_data.shape)
death_and_acs_long = city_year_death_long.merge(death_and_acs_data.
 ↪drop(['death_rate_12', 'death_rate_13', 'death_rate_14', 'death_rate_15',␣
 ↪'death_rate_16', 'death_rate_17', 'death_rate_18'], axis=1), on="city_death")
print(death_and_acs_long.shape)
death_and_acs_long.head()
```

```
(2429, 3)
(347, 20)
(2429, 15)
```

[83]:
```
  city_death  year  death_rate_per10k  tot_pop_17  over_65_count  \
0   abington  2011           0.622361       16275           2469
1   abington  2012           1.241520       16275           2469
2   abington  2013           0.000000       16275           2469
3   abington  2014           3.705501       16275           2469
4   abington  2015           0.616007       16275           2469

   over_65_prop  med_house_inc  mean_house_inc  mean_med_inc_desp  drop_out  \
0      0.151705        87156.0    98809.035505       11653.035505  3.452855
1      0.151705        87156.0    98809.035505       11653.035505  3.452855
```

```
2      0.151705        87156.0     98809.035505       11653.035505  3.452855
3      0.151705        87156.0     98809.035505       11653.035505  3.452855
4      0.151705        87156.0     98809.035505       11653.035505  3.452855

   less_than_hs_ed  at_or_below_pov_prop  pop_struggling_prop town_status  \
0         5.405643              0.035754             0.100408       grown
1         5.405643              0.035754             0.100408       grown
2         5.405643              0.035754             0.100408       grown
3         5.405643              0.035754             0.100408       grown
4         5.405643              0.035754             0.100408       grown

  urb_v_rur
0     rural
1     rural
2     rural
3     rural
4     rural
```

[84]:
```
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, 21)

  city_death  year  death_rate_per10k  tot_pop_17  over_65_count  \
0   abington  2013           0.000000       16275           2469
1   abington  2014           3.705501       16275           2469
2   abington  2015           0.616007       16275           2469
3   abington  2016           1.843318       16275           2469
4   abington  2017           3.064396       16275           2469

   over_65_prop  med_house_inc  mean_house_inc  mean_med_inc_desp  drop_out  \
0      0.151705        87156.0     98809.035505       11653.035505  3.452855
1      0.151705        87156.0     98809.035505       11653.035505  3.452855
2      0.151705        87156.0     98809.035505       11653.035505  3.452855
3      0.151705        87156.0     98809.035505       11653.035505  3.452855
4      0.151705        87156.0     98809.035505       11653.035505  3.452855

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

```
       town total_claims_count_avg  opioid_claim_count_avg  opioid_rate_avg  \
0  abington            2179.083333               89.666667         7.123603
1  abington            1925.350000               79.700000         7.807532
2  abington            2408.916667               64.041667         6.627004
3  abington            2871.857143               72.333333         4.429928
4  abington            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

[5 rows x 21 columns]


              year  death_rate_per10k     tot_pop_17  over_65_count  \
count  1428.000000        1428.000000    1428.000000    1428.000000
mean   2014.995098           1.733554   23269.595938    4087.070728
std       1.413462           2.079226   44840.436313    6014.409427
min    2013.000000           0.000000     446.000000      96.000000
25%    2014.000000           0.000000    7117.000000    1419.000000
50%    2015.000000           1.101811   13855.000000    2692.000000
75%    2016.000000           2.466260   26823.000000    5009.000000
max    2017.000000          15.974441  668541.000000   85040.000000

       over_65_prop  med_house_inc  mean_house_inc  mean_med_inc_desp  \
count   1428.000000    1428.000000     1428.000000        1428.000000
mean       0.202919   91050.875142   112834.042914       21783.683044
std        0.065342   30176.605424    41695.447804       15913.157560
min        0.086886   38909.750000    50750.537570        2129.112803
25%        0.165207   70220.250000    86561.728307       12725.573046
50%        0.188014   86875.000000   102959.957747       17116.689304
75%        0.222270  106846.681818   128540.605810       24222.601387
max        0.473703  203026.750000   316351.858774      113325.108774

          drop_out  less_than_hs_ed  at_or_below_pov_prop  \
count  1428.000000      1428.000000           1428.000000
mean      2.393748         6.597659              0.073977
std       3.748634         4.993370              0.049453
min       0.000000         0.354019              0.005354
25%       0.000000         3.135615              0.042231
50%       1.006923         5.363993              0.059686
75%       3.278689         8.302169              0.094519
max      30.000000        32.336132              0.332260
```

```
       pop_struggling_prop  total_claims_count_avg  opioid_claim_count_avg  \
count          1428.000000             1428.000000             1428.000000
mean              0.102210             1370.942198               60.941325
std               0.052502             1034.683050               56.786610
min               0.010566               11.000000                0.000000
25%               0.063789              789.810225               26.999220
50%               0.090870             1229.965190               48.634430
75%               0.130955             1714.009832               75.919167
max               0.304869             8922.636364              555.500000

       opioid_rate_avg  total_claim_count_sum  opioid_claim_count_sum
count      1428.000000           1.428000e+03             1428.000000
mean          8.823179           1.129176e+05             4747.203081
std           6.174974           3.424591e+05            14594.418466
min           0.000000           1.100000e+01                0.000000
25%           5.312575           1.080225e+04              415.750000
50%           8.071573           3.400650e+04             1405.000000
75%          10.989267           9.939450e+04             4237.750000
max          69.696970           5.442227e+06           209604.000000
```

[85]:
```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()
```

[85]:
```
       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
```

[86]:
```python
acs_death_and_opi_pres.columns
```

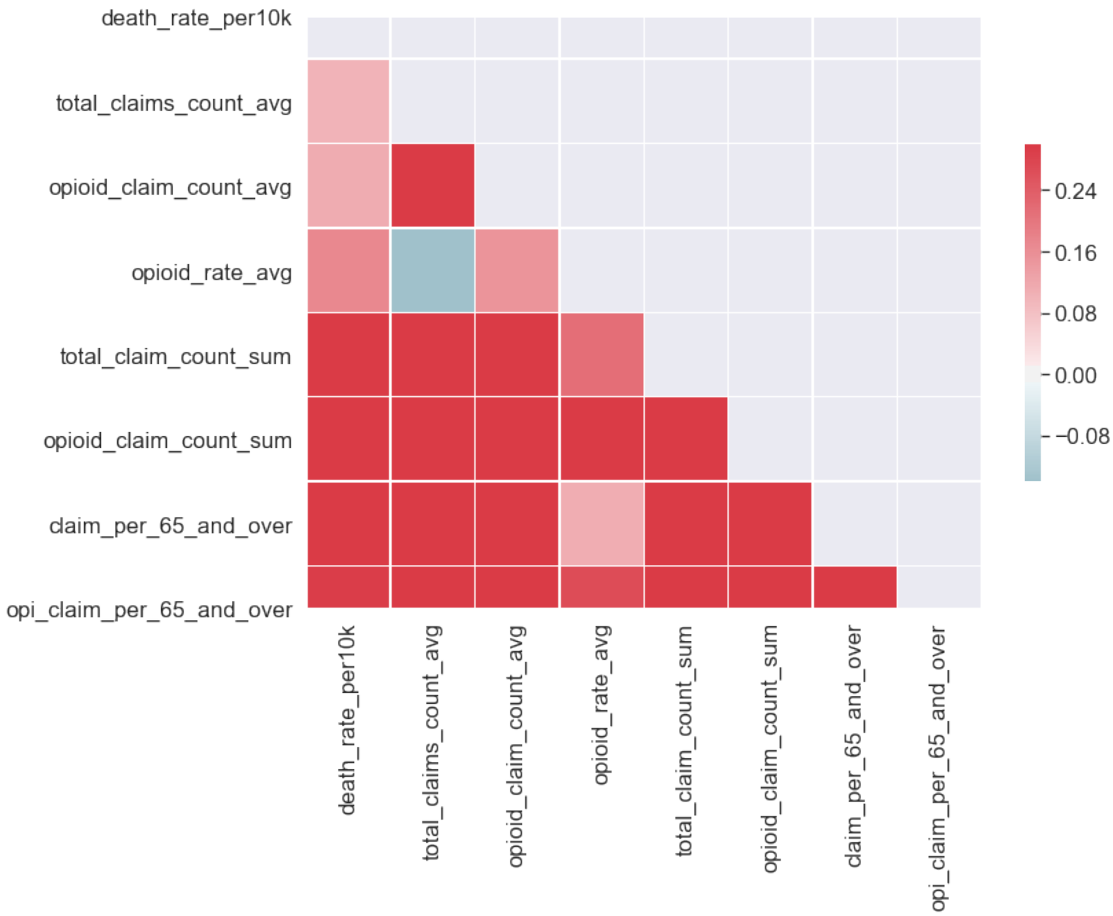
[86]:
```
Index(['city_death', 'year', 'death_rate_per10k', 'tot_pop_17',
       'over_65_count', 'over_65_prop', 'med_house_inc', 'mean_house_inc',
       'mean_med_inc_desp', 'drop_out', 'less_than_hs_ed',
       'at_or_below_pov_prop', 'pop_struggling_prop', 'town_status',
       'urb_v_rur', 'town', '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')
```

[89]:
```
opi_and_death_stats = acs_death_and_opi_pres[['city_death', 'year',␣
↪'death_rate_per10k', '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']].copy()
opi_and_death_stats.head()
```

[89]:
```
  city_death  year  death_rate_per10k  total_claims_count_avg  \
0   abington  2013           0.000000             2179.083333
1   abington  2014           3.705501             1925.350000
2   abington  2015           0.616007             2408.916667
3   abington  2016           1.843318             2871.857143
4   abington  2017           3.064396             2498.826087

   opioid_claim_count_avg  opioid_rate_avg  total_claim_count_sum  \
0               89.666667         7.123603                  52298
1               79.700000         7.807532                  38507
2               64.041667         6.627004                  57814
3               72.333333         4.429928                  60309
4               67.434783         5.274131                  57473

   opioid_claim_count_sum  claim_per_65_and_over  opi_claim_per_65_and_over
0                  2152.0              21.181855                   0.871608
1                  1594.0              15.596193                   0.645606
2                  1537.0              23.415958                   0.622519
3                  1519.0              24.426488                   0.615229
4                  1551.0              23.277845                   0.628190
```

[93]:
```
opi_death_rate_corr = opi_and_death_stats.drop(['city_death', 'year'], axis=1).
↪corr(method="spearman")
# Generate a mask for the upper triangle
mask = np.zeros_like(opi_death_rate_corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

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

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

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



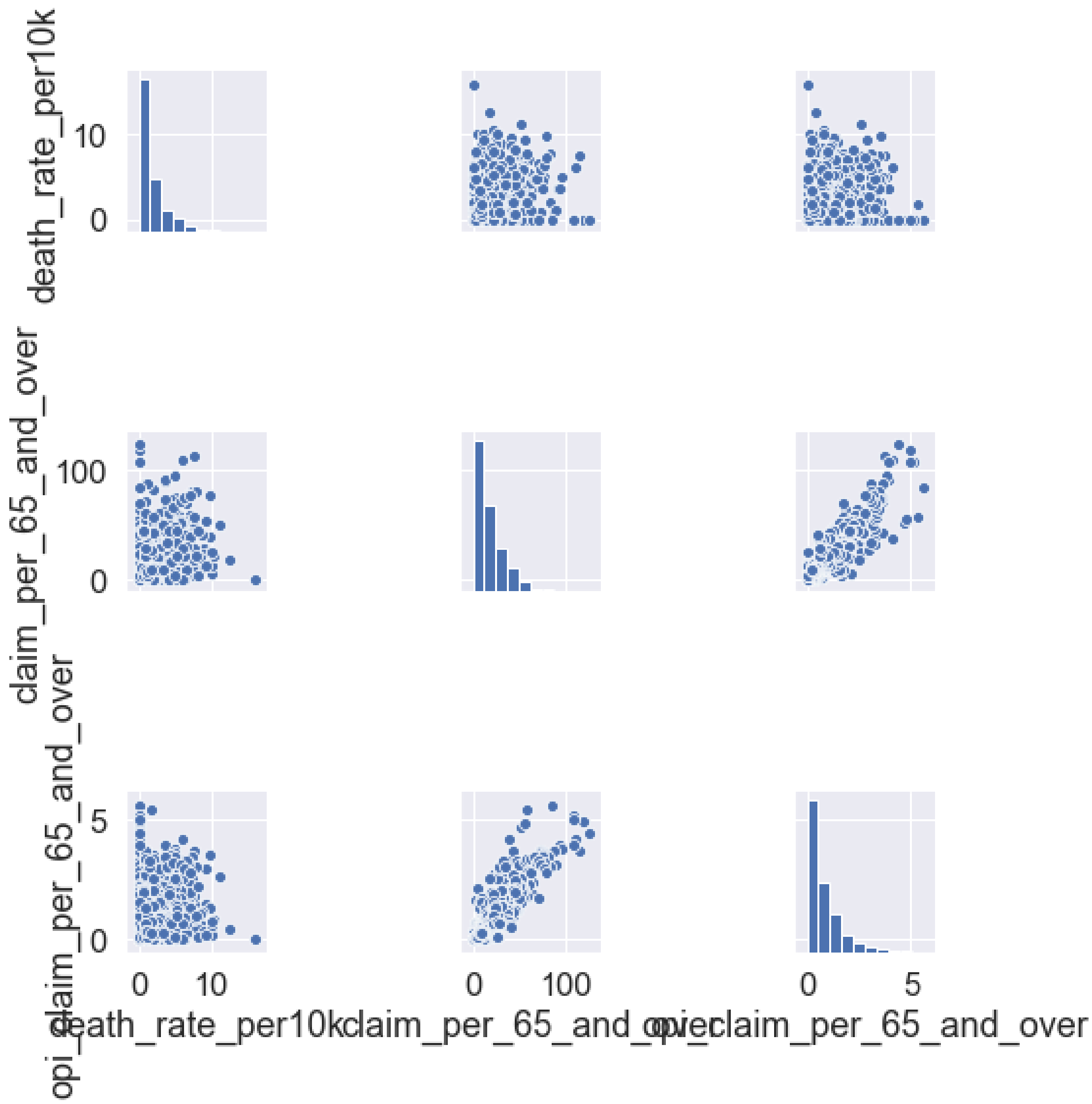
[96]:
```
opi_death_rate_corr[['death_rate_per10k']]
```

[96]:

	death_rate_per10k
death_rate_per10k	1.000000
total_claims_count_avg	0.102671
opioid_claim_count_avg	0.113558
opioid_rate_avg	0.173038
total_claim_count_sum	0.432325
opioid_claim_count_sum	0.430813
claim_per_65_and_over	0.310250
opi_claim_per_65_and_over	0.294367

[106]:
```
sns.pairplot(opi_and_death_stats[['death_rate_per10k', 'claim_per_65_and_over',␣
↪'opi_claim_per_65_and_over']])
```

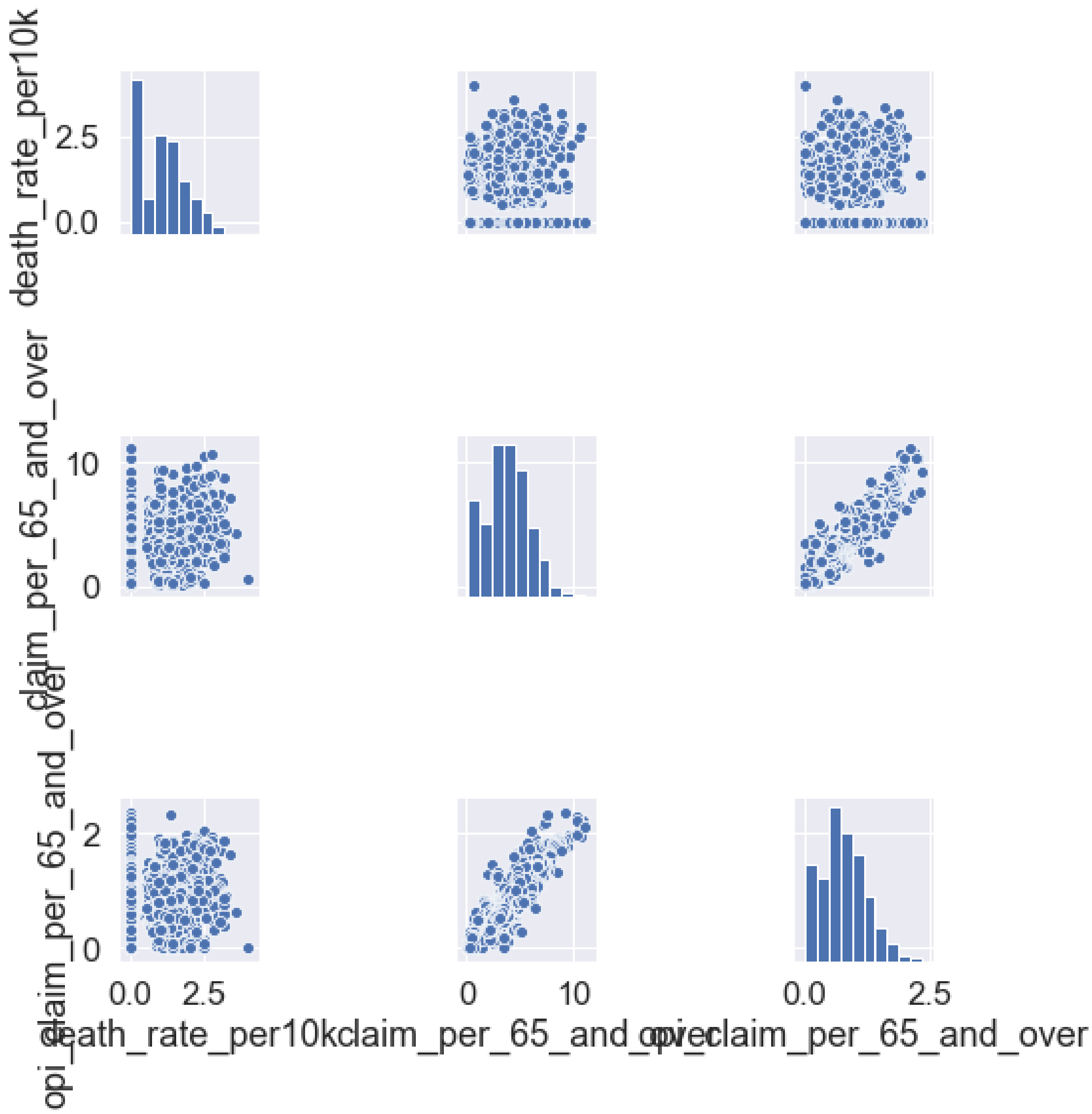
[106]:
```
<seaborn.axisgrid.PairGrid at 0x2274b98eef0>
```



[108]:
```
sns.pairplot(opi_and_death_stats[['death_rate_per10k', 'claim_per_65_and_over',␣
↪'opi_claim_per_65_and_over']].apply(np.sqrt))
```

[108]: <seaborn.axisgrid.PairGrid at 0x2274c710c88>

```
<Figure size 1008x1008 with 0 Axes>
```



[110]:
```
acs_death_and_opi_pres.head()
```

[110]:
```
  city_death  year  death_rate_per10k  tot_pop_17  over_65_count  \
0   abington  2013           0.000000       16275           2469
1   abington  2014           3.705501       16275           2469
2   abington  2015           0.616007       16275           2469
3   abington  2016           1.843318       16275           2469
4   abington  2017           3.064396       16275           2469

   over_65_prop  med_house_inc  mean_house_inc  mean_med_inc_desp  drop_out  \
0      0.151705        87156.0    98809.035505       11653.035505  3.452855
1      0.151705        87156.0    98809.035505       11653.035505  3.452855
2      0.151705        87156.0    98809.035505       11653.035505  3.452855
```

```
3      0.151705        87156.0    98809.035505       11653.035505  3.452855
4      0.151705        87156.0    98809.035505       11653.035505  3.452855

   ...  town_status  urb_v_rur      town total_claims_count_avg  \
0  ...        grown      rural  abington            2179.083333
1  ...        grown      rural  abington            1925.350000
2  ...        grown      rural  abington            2408.916667
3  ...        grown      rural  abington            2871.857143
4  ...        grown      rural  abington            2498.826087

  opioid_claim_count_avg opioid_rate_avg  total_claim_count_sum  \
0              89.666667        7.123603                  52298
1              79.700000        7.807532                  38507
2              64.041667        6.627004                  57814
3              72.333333        4.429928                  60309
4              67.434783        5.274131                  57473

   opioid_claim_count_sum  claim_per_65_and_over  opi_claim_per_65_and_over
0                  2152.0              21.181855                   0.871608
1                  1594.0              15.596193                   0.645606
2                  1537.0              23.415958                   0.622519
3                  1519.0              24.426488                   0.615229
4                  1551.0              23.277845                   0.628190

[5 rows x 23 columns]
```

[113]:
```
acs_death_and_opi_pres.drop('town', axis=1, inplace=True)
```

[114]:
```
#acs_death_and_opi_pres.to_csv("../../../data/tidy_data/
↪acs_medicare_opioid_stats_death_rate.csv", index=False)
```