Final Project: Opioid prescription

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Prescription opioid overdose has become a national epidemic which impacts the health and economic well being of millions of Americans. Over-prescribing opioids certainly contributes to the misuse of the drug. This project will investigate how opioid prescriptions are related to the practioners' field, geography, local income, as well as how opioid overdose death are related to the prescription rate.

The key dataset is a Socrata API. It contains information about prescribers name, practice address, practice type, as well as opioid prescribing rates. I combined it with census api on income per capita in 2016 by zipcode and state, as well as opioid overdose death data from opendatasoft.com by state.

The project will answer the following questions:

- How does prescription opioid overdose death change over the years? (In the late 1990s, pharmaceutical companies begin advertising prescription painkillers as non-addicting, the subsequent widespread prescription and addiction was attributed to this period.)
- Who are prescribing opioids?
- Is prescription rate related to local per capita income? (Possible chanel: 1)Bad economy lead to depression which lead to drug abuse. 2)Poor places has less regulated healthcare industry which lead medical personale to abuse their power)
- Does more prescription lead to more overdose death?

Packages Used

In [90]:
```
import pandas as pd
from sodapy import Socrata #for prescrition data
import numpy  as np
import matplotlib as mpl
import matplotlib.pyplot as plt
from census import Census
from us import states
import requests
import json
from IPython.display import display, Image
import os
import fiona # Needed for geopandas to run
import geopandas as gpd # this is the main geopandas
from shapely.geometry import Point, Polygon # also needed
from mpl_toolkits.axes_grid1.inset_locator import zoomed_inset_axes
from mpl_toolkits.axes_grid1.inset_locator import mark_inset
import statsmodels.api as sm
import statsmodels.formula.api as smf
```

Prescription data

Grabbing the data

In [91]:
```
client = Socrata("data.cms.gov", 'jwf3Ur2ya3N6XrQBYjgV4vdXw',username=
"sw2804@nyu.edu",
                 password="mW@ng4*0o!")
```

In [92]:
```
results = client.get("3hwr-y534", limit=1072997)
```

In [93]:
```
results_df = pd.DataFrame.from_records(results)
```

In [94]:
```
results_df.head()
```

Out[94]:

	npi	nppes_provider_first_name	nppes_provider_last_org_name	nppes_pro
0	1831127620	FRED	BRESSLER	TX
1	1588095855	REID	BREWSTER	CA
2	1144293044	BRUCE	BRIDEWELL	FL
3	1255428645	THOMAS	BRIDGMAN	WA
4	1619082526	MARTIN	BRIGGS	LA

Cleaning the data

In [95]:
```
opioid = results_df.dropna()
```

In [96]:
```
opioid.rename(columns={'nppes_provider_zip5':'zipcode'}, inplace=True)
opioid
```

```
/Applications/anaconda3/lib/python3.6/site-packages/pandas/core/fram
e.py:3027: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/panda
s-docs/stable/indexing.html#indexing-view-versus-copy
  return super(DataFrame, self).rename(**kwargs)
```

Out[96]:

	npi	nppes_provider_first_name	nppes_provider_last_org_name	npp
7	1326336751	LOUIS	BRITT	TN
14	1841342003	CHARLES	BROWN	CA
15	1811325749	KARA	BROWN	OR
26	1194710434	JILL	BUCK	IN
31	1417264565	RYAN	BURKE	NM
34	1235186511	MARY	BURTON	UT
54	1265506067	LARISA	CANTER	CA
60	1164418778	BRENDA	CARRELL	MO
68	1649243320	RAYMOND	CAST	FL

72	1639395957	KIMBERLY	CERTA	VA
76	1982036091	JAMMIE	CHANG	TX
81	1346370509	HAI-SOU	CHEN	CA
86	1528247590	SUMA	CHERUKURI	MI
88	1013024538	SIV	CHHAY	TX
102	1629278502	PIER	CIPRIANI	PA
118	1134141542	SARAH	FRYE	MO
154	1033220991	PAUL	GOLDEN	CA
166	1508970039	AZIZ	GOPALANI	PA
182	1639368749	ELLEN	GREENE	NY
183	1346351533	JAMES	GREENE	GA
202	1518933571	STEVEN	KIRKHAM	OH
225	1578614061	KIMBERLY	KRON	OH
227	1174810360	LAURA	KRUTER	NY
235	1861649527	SUMEET	KUMAR	TX
238	1295929586	PRASAD	KURELLA	OH
245	1700871191	CHRISTINA	LANNOM	TN
251	1235290594	JULIE	LARSON	CO
257	1225041262	ALEX	LAU	CA
269	1619984705	SARA	MOBASSERI	GA
270	1962437491	ELLEN	MODELL	WA
...	...	...	...	...
1072967	1326013780	ARMANDO	WYATT	VA
1072968	1629041298	DAVID	GIRDANY	PA
1072969	1639313158	MARGARET	RODENBECK	IN
1072970	1679534564	TIMOTHY	MARTIN	PA
1072971	1124149190	ELIZABETH	SHARP	AR
1072972	1235225780	CLAUDE	FORTIN	IL
1072973	1891892626	DAVID	BENDER	WV

1072974	1801850995	SHELBY	BAILEY	AL
1072975	1134221062	MICHAEL	MAROULES	NJ
1072976	1669676714	MEERA	REDDY	CA
1072977	1194739508	STEVEN	GUTTENBERG	DC
1072978	1639126824	REGULO	TOBIAS	KY
1072979	1780600338	JAY	STIEFEL	NJ
1072980	1700996659	WILLIAM	MOSS	LA
1072981	1275700528	MEENA	SINGH	KS
1072982	1154765816	ALEXANDRA	DRESSEN	MA
1072983	1073574497	DARIUS	CLARKE	TX
1072984	1639102031	PERRY	WYNER	NY
1072985	1538276472	THOMAS	KRUPITZER	OH
1072986	1023178506	STEVEN	CHANDLER	AL
1072987	1285613653	MICHAEL	HOUSE	TX
1072988	1932272887	CHARLES	WHITEHILL	CA
1072989	1083601033	MALCOLM	SCHWARTZ	NJ
1072990	1497774723	DAVID	FRANK	WA
1072991	1497735096	HOWARD	SANDER	NY
1072992	1346419918	THANH	NGUYEN	CA
1072993	1841356219	CHRISTINE	PREBLICK	NY
1072994	1982609103	GORDON	SIEGEL	IL
1072995	1891880902	NORA	MEANEY-ELMAN	NY
1072996	1538507330	NUJUD	DAHAM	MA

753998 rows × 9 columns

Income Data by Zipcode

Now grabbing income per capita at zipcode level in 2016 data from census

In [97]:
```
my_api_key = '34caee0abc641aead3785ea57203c35b70def3ee'
c = Census(my_api_key)
code = ("NAME","B19301_001E")
#PER CAPITA INCOME IN THE PAST 12 MONTHS (IN 2016 INFLATION-ADJUSTED D
OLLARS)
state_wealth = c.acs5.get(code, {'for': 'state:* '})
state_wealth = pd.DataFrame(state_wealth)
state_wealth.rename(columns={'NAME':'State','B19301_001E':'state_per_c
apita_income'},
                    inplace=True)
state_wealth.drop('state',axis=1,inplace=True)
state_wealth.describe()
```

Out[97]:

	state_per_capita_income
count	52.000000
mean	29367.096154
std	5522.679835
min	11688.000000
25%	26092.500000
50%	28475.500000
75%	32177.750000
max	48781.000000

In [98]:
```
zipcode = pd.DataFrame(c.acs5.get(code,
                                                        {'for': 'zip code tabulation
area: *'}))

zipcode.head()
```

Out[98]:

	B19301_001E	NAME	zip code tabulation area
0	30430.0	ZCTA5 01001	01001
1	26072.0	ZCTA5 01002	01002
2	3829.0	ZCTA5 01003	01003
3	32169.0	ZCTA5 01005	01005
4	36359.0	ZCTA5 01007	01007

Making the data frame more readable by changing column names

In [99]:
```
zipcode.rename(columns={'zip code tabulation area':
                        'zipcode','B19301_001E':'per_capita_income'},i
nplace=True)
```

Merging these two datasets together by zipcode

In [100]:
```
combo = pd.merge(opioid, zipcode,
                 on='zipcode',
                 how='left',
                 indicator=True)

combo.rename(columns={'nppes_provider_state':'Abbreviation',
                      'nppes_provider_first_name':'first_name',
                      'nppes_provider_last_org_name':'last_name'}, inp
lace=True)
combo[combo["_merge"] == "left_only"]
```

Out[100]:

	npi	first_name	last_name	Abbreviation	zipcode	opioid_clain
80	1720139348	SCOTT	ZAMVIL	CA	94143	0
120	1306067921	ROCHELLE	AASER	TN	37933	0
175	1205096609	MOHAMED	ABAZEED	OH	44195	0

182	1538509062	ELHAM	ABBAS	KS	66160	0
192	1790756179	UME	ABBAS	OH	44195	0
194	1689881781	FARHA	ABBASI	MI	48824	0
258	1346276573	RICHARD	ABBOTT	CA	94143	0
306	1164693008	KHALED	ABDEL-KADER	TN	37232	0
308	1518181239	AHMED	ABDEL-LATIF	KY	40536	0
312	1982620340	MAY	ABDEL-WAHAB	OH	44195	0
392	1366509804	IBRAHIM	ABDULLAH	NE	68198	0
393	1558504142	LUBNA	ABDULLAH	MD	21287	0
446	1659690337	OLIVER	ABELA	MI	48824	0
469	1942263975	TOM	ABELSON	OH	44195	0
487	1093009219	MAC	ABERNATHY	SC	29425	0
555	1558415067	THOMAS	ABLEMAN	VA	22908	0
558	1770528192	ARTHUR	ABLIN	CA	94143	0
592	1144427766	NUHAD	ABOU ZEID	NC	27157	0
600	1063617470	HIBA	ABOUASSI	NC	27710	0
601	1265450233	NABIL	ABOUCHALA	ND	58122	0
608	1164715272	NAEL	ABOUL-HOSN	KY	40536	0
629	1720242464	ANU	ABRAHAM	UT	84132	0
647	1073660916	FENOTE	ABRAHAM	MD	20889	0
660	1831486182	JULIE	ABRAHAM	OH	44195	0
683	1740456144	SHINY	ABRAHAM	OH	44195	0
687	1467427096	THEODORE	ABRAHAM	MD	21287	0
814	1912081308	PAUL	ABRINKO	CA	94143	0
834	1366784902	DENEEN	ABSTON	OH	44195	0

838	1073546016	CHRISTINE	ABT	IL	60122	0
846	1720375785	AMAL	ABU LIBDEH	VA	22908	0
...	...	...	...	...	...	...
753691	1366436214	ANITHA	KUCHIPUDI	NH	3076	28
753708	1033313747	STEFAN	HOLUBAR	NH	3756	30
753721	1225384951	KRISTIN	MIKKELSEN	ME	4005	12
753726	1538143052	LYNN	TANOUE	CT	6519	15
753731	1538326640	MELISSA	MONAGHAN	NJ	7740	40
753748	1003840836	GAIL	LEE	MA	2111	25
753754	1841220829	YAN	LUPYAN	NJ	8816	119
753777	1023349503	SWATHI	ELURI	MD	21287	23
753780	1407859069	ANTONELLA	MAIETTA	NJ	7801	15
753792	1467476044	RAMON	MENDEZ-SEXTO	PR	966	84
753806	1477598928	NANCY	SCANGARELLO	NJ	7102	32
753810	1578990388	BERNADENE	LAWRENCE-PHILLIP	CT	6810	19
753811	1568590487	DOUGLASS	BIBULD	MA	2301	27
753820	1093857476	GERARD	GRAHAM	CT	6001	11
753830	1790787323	PAUL	BARLOW	NH	3038	119
753832	1245280270	GRISELLE	GERENA RAMIREZ	PR	754	338
753838	1861619967	DEBORAH	APPLEYARD	VI	820	77
753856	1124133657	DANIEL	BROWN	MA	1960	37
753861	1124002365	DAWN	HOGAN	RI	2863	58
753876	1407881915	MICHAEL	VIRATA	CT	6511	73

753897	1225041965	PAUL	FONTANAZZA	NJ	7029	11
753910	1992080212	EDUARDO	SALGUERO	PR	727	26
753931	1871852954	ANDREA	WHITE	TX	77555	18
753934	1417212192	JASON	POCO	NJ	8873	169
753940	1851310726	RAASHAN	WILLIAMS	NJ	7087	22
753976	1134221062	MICHAEL	MAROULES	NJ	7013	117
753980	1780600338	JAY	STIEFEL	NJ	8096	58
753983	1154765816	ALEXANDRA	DRESSEN	MA	2148	12
753990	1083601033	MALCOLM	SCHWARTZ	NJ	7090	28
753997	1538507330	NUJUD	DAHAM	MA	2111	12

94195 rows × 12 columns

In [101]:
```
combo.dropna(inplace=True)
combo.drop('_merge',axis=1,inplace=True)
```

Adding full state name to the dataframe

In [102]:
```
state=pd.read_csv('https://github.com/jasonong/List-of-US-States/raw/master/states.csv')
```

In [103]:
```
combo2=pd.merge(combo,state,on='Abbreviation',how='left',indicator=True)
combo2[combo2["_merge"] == "left_only"]
combo2.dropna(inplace=True)
combo2.drop('_merge',axis=1,inplace=True)
```

Opioid overdose data

In [104]:
```
url='https://data.opendatasoft.com/api/records/1.0/search/?dataset=prescription-opioid-overdose-deaths-and-death-rate-per-100000-population-age-adj%40public&rows=867&facet=prescription_opioid_overdose_deaths_missing_reason&facet=footnotes&facet=location&facet=year'
```

In [105]:
```
r=requests.get(url)
```

In [106]:
```
print(r.headers["content-type"])
```

```
application/json; charset=utf-8
```

In [107]:
```
data= json.loads(r.content.decode("utf-8"))
```

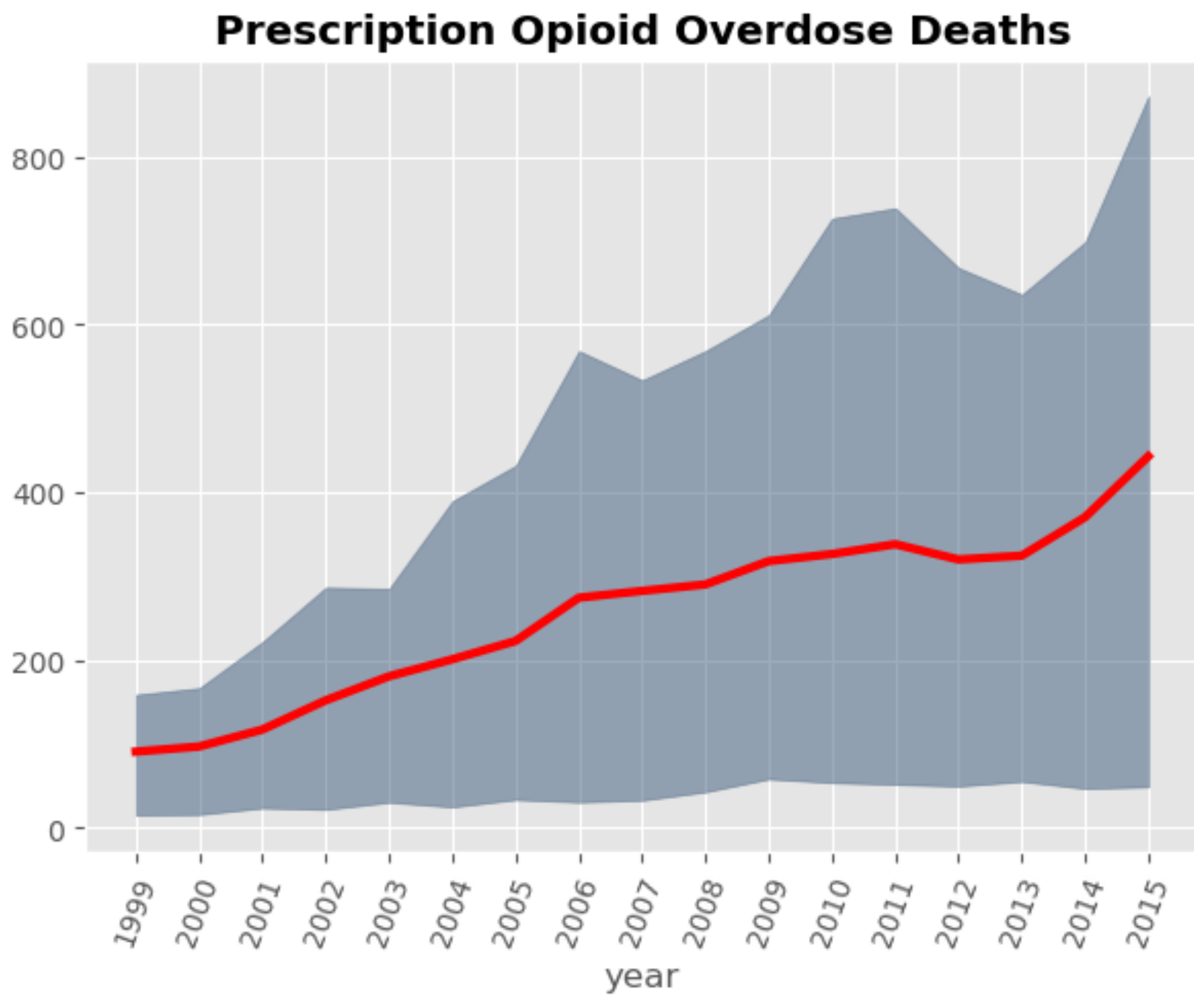
In [108]:
```
df=pd.DataFrame(data['records'])
dff=pd.DataFrame(df['fields'].tolist())
dff.drop('prescription_opioid_overdose_deaths_missing_reason',axis=1,i
nplace=True)
death=dff.set_index('year').loc['2015']
death.rename(columns={'location':'State'}, inplace=True)
death.describe()
```

Out[108]:

	prescription_opioid_overdose_deaths
count	51.000000
mean	443.098039
std	417.159454
min	21.000000
25%	124.500000
50%	340.000000
75%	616.000000
max	1800.000000

Opioid Overdose Death Trend

In [109]:
```
plt.style.use('ggplot')
fig, ax  = plt.subplots(figsize = (7,5))

dff_mean=dff.groupby('year').mean()
dff_q90=dff.groupby('year').prescription_opioid_overdose_deaths.quanti
le(0.90)
dff_q10=dff.groupby('year').prescription_opioid_overdose_deaths.quanti
le(0.10)

dff_mean.plot(ax = ax, color = "red", lw = 3, figsize = (7,5),label="M
ean")

ax.fill_between(dff_mean.index, dff_q10, dff_q90, color = "#3F5D7D",al
pha=0.5)

ax.set_title('Prescription Opioid Overdose Deaths',fontweight = "bold"
)
ax.set_xticklabels(range(1999,2016))
ax.tick_params(axis='x', rotation=70)

ax.legend().set_visible(False)
```



The mean prescription opioid overdoes death, represented by the red line, increased dramatically after the late 1990s. In addition, the variations in state-level opioid overdose death also increase over the years, mainly due to the increase in the upper quantile.

Final Data Frame

Adding state-level income data first

In [110]:
```
combo3=pd.merge(combo2,death,on='State',how='left',indicator=True)
combo3.drop(['NAME','_merge'],axis=1,inplace=True)
```

Final Data Frame

In [111]:
```
final_df=pd.merge(combo3,state_wealth,on='State',how='left')
final_df
```

Out[111]:

	npi	first_name	last_name	Abbreviation	zipcode	opioid_clai
0	1326336751	LOUIS	BRITT	TN	38018	0
1	1841342003	CHARLES	BROWN	CA	92618	0
2	1811325749	KARA	BROWN	OR	97015	0
3	1194710434	JILL	BUCK	IN	46143	0
4	1417264565	RYAN	BURKE	NM	87106	0
5	1235186511	MARY	BURTON	UT	84105	0
6	1265506067	LARISA	CANTER	CA	92660	0
7	1164418778	BRENDA	CARRELL	MO	65804	0
8	1649243320	RAYMOND	CAST	FL	32209	0
9	1639395957	KIMBERLY	CERTA	VA	22192	0
10	1982036091	JAMMIE	CHANG	TX	75034	0
11	1346370509	HAI-SOU	CHEN	CA	91776	0
12	1528247590	SUMA	CHERUKURI	MI	49525	0
13	1013024538	SIV	CHHAY	TX	75052	0
14	1629278502	PIER	CIPRIANI	PA	18940	0
15	1134141542	SARAH	FRYE	MO	65804	0
16	1033220991	PAUL	GOLDEN	CA	95350	0
17	1508970039	AZIZ	GOPALANI	PA	15017	0
18	1639368749	ELLEN	GREENE	NY	10016	0
19	1346351533	JAMES	GREENE	GA	30329	0
20	1518933571	STEVEN	KIRKHAM	OH	43302	0
21	1578614061	KIMBERLY	KRON	OH	44646	0
22	1174810360	LAURA	KRUTER	NY	11795	0

23	1861649527	SUMEET	KUMAR	TX	78229	0
24	1295929586	PRASAD	KURELLA	OH	44718	0
25	1700871191	CHRISTINA	LANNOM	TN	37067	0
26	1235290594	JULIE	LARSON	CO	81505	0
27	1225041262	ALEX	LAU	CA	94063	0
28	1619984705	SARA	MOBASSERI	GA	30309	0
29	1962437491	ELLEN	MODELL	WA	98026	0
...	...	...	...	...	...	...
659211	1033181821	CHRISTOPHER	THOMAS	FL	33484	329
659212	1700852092	ARTHUR	OZOLIN	WA	98405	88
659213	1376503623	SUSANNE	JOHNSON	TX	75093	38
659214	1538176011	ROBERT	PADILLA	CA	95350	11
659215	1366456584	DOROTHY	TANNER	IN	47274	1539
659216	1326013780	ARMANDO	WYATT	VA	23510	91
659217	1629041298	DAVID	GIRDANY	PA	15501	70
659218	1639313158	MARGARET	RODENBECK	IN	46845	23
659219	1679534564	TIMOTHY	MARTIN	PA	15024	268
659220	1124149190	ELIZABETH	SHARP	AR	72703	111
659221	1235225780	CLAUDE	FORTIN	IL	62702	523
659222	1891892626	DAVID	BENDER	WV	26354	1345
659223	1801850995	SHELBY	BAILEY	AL	35661	42
659224	1669676714	MEERA	REDDY	CA	91367	198

659225	1194739508	STEVEN	GUTTENBERG	DC	20006	26
659226	1639126824	REGULO	TOBIAS	KY	40207	148
659227	1700996659	WILLIAM	MOSS	LA	70601	116
659228	1275700528	MEENA	SINGH	KS	66216	34
659229	1073574497	DARIUS	CLARKE	TX	78701	83
659230	1639102031	PERRY	WYNER	NY	11570	61
659231	1538276472	THOMAS	KRUPITZER	OH	44256	228
659232	1023178506	STEVEN	CHANDLER	AL	35601	450
659233	1285613653	MICHAEL	HOUSE	TX	76201	78
659234	1932272887	CHARLES	WHITEHILL	CA	94611	302
659235	1497774723	DAVID	FRANK	WA	98101	46
659236	1497735096	HOWARD	SANDER	NY	10016	15
659237	1346419918	THANH	NGUYEN	CA	95340	98
659238	1841356219	CHRISTINE	PREBLICK	NY	10003	14
659239	1982609103	GORDON	SIEGEL	IL	60611	21
659240	1891880902	NORA	MEANEY-ELMAN	NY	14221	52

659241 rows × 13 columns

In [112]:
```
final_df.opioid_claim_count = final_df.opioid_claim_count.astype(float
)
final_df.opioid_rate = final_df.opioid_rate.astype(float)
final_df.total_claim_count = final_df.total_claim_count.astype(float)
```

In [113]:
```
final_df.dtypes
```

Out[113]:
```
npi                                    object
first_name                             object
last_name                              object
Abbreviation                           object
zipcode                                object
opioid_claim_count                    float64
opioid_rate                           float64
specialty_desc                         object
total_claim_count                     float64
per_capita_income                     float64
State                                  object
prescription_opioid_overdose_deaths   float64
state_per_capita_income               float64
dtype: object
```

Prescription by Specialty

In [114]:
```
g_spec=final_df.groupby('specialty_desc')
```

In [115]:
```
m_spec=g_spec.mean()
```

In [116]:
```
m_spec.sort_values('opioid_rate',ascending=False).head(10)
```

Out[116]:

	opioid_claim_count	opioid_rate	total_claim_count	per_capita_income
specialty_desc				
Hand Surgery	99.608365	0.601982	176.333650	-8.836863e+06
Interventional Pain Management	1394.197080	0.542010	2480.824818	-4.831844e+06
Assistant, Podiatric	9.333333	0.526984	28.666667	3.104533e+04
Pain Management	1174.977382	0.518620	2077.787526	-3.164060e+06
Orthopedic Surgery	176.789409	0.508211	369.021772	-4.123252e+06
Denturist	114.000000	0.476987	239.000000	3.150600e+04
Neurosurgery	126.880944	0.441513	288.808114	-6.174456e+06
Surgical Oncology	42.040189	0.390584	157.205674	-2.202946e+07
Sports Medicine	95.676471	0.382460	324.223982	3.336064e+04
General Surgery	54.846896	0.377302	278.526271	-6.160003e+06

The specialties contained in this dataset is too detailed. Therefore, I mainly looked at 7 categories investigated in this NIH study ('https://www.ncbi.nlm.nih.gov/pubmed/25896191'). I combined small branches of surgeries into overarching "surgery" by the following code:

In [117]:
```
surgery=m_spec.filter(regex='Surgery',axis='index')
surgery_s=surgery.opioid_claim_count.sum()
```

In [118]:
```
pain=m_spec.filter(regex='Pain',axis='index') # I did the same for pai
n management
pain_s=pain.opioid_claim_count.sum()
```

In [119]:
```
dent=m_spec.filter(regex='Dent',axis='index') # and for dentistry
dent_s=dent.opioid_claim_count.sum()
```

I noticed non-physician prescribers like students and assitants also appeared a lot in the dataset, therefore, I lumped them into one specialty as "non-physician".

In [120]:
```
assistant=m_spec.filter(regex='Assistant',axis='index')
tech=m_spec.filter(regex='Tech',axis='index')
student=m_spec.filter(regex='Student',axis='index')
non_physician=assistant.opioid_claim_count.sum()+tech.opioid_claim_cou
nt.sum()
+student.opioid_claim_count.sum()
non_physician_s=non_physician
```

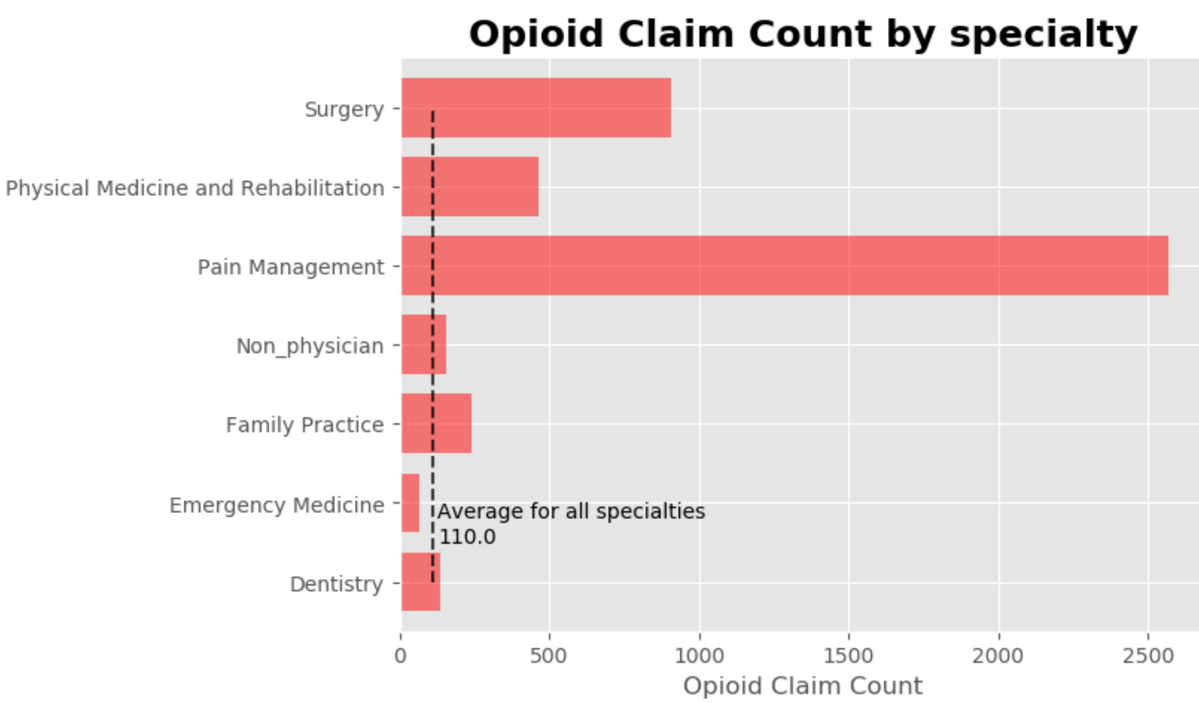
In [121]:
```
specialty={'Surgery':[surgery_s],'Pain Management':[pain_s],'Dentistry
':[dent_s],
          'Non_physician':[non_physician_s],
           'Physical Medicine and Rehabilitation':[463.715237],
           'Emergency Medicine':[69.022202],'Family Practice':[241.814
089]}
specialty_df=pd.DataFrame(specialty)
specialty_df
```

Out[121]:

	Dentistry	Emergency Medicine	Family Practice	Non_physician	Pain Management	Physical Medicine and Rehabilitation	
0	134.126081	69.022202	241.814089	156.319471	2569.174462	463.715237	9

In [122]:
```
fig, ax = plt.subplots(figsize = (7,5))
specialty_df.T.plot(kind='barh',ax=ax,color='r',alpha=0.5, width=0.75,
legend=False)
ax.set_xlabel("Opioid Claim Count")

ax.set_title("Opioid Claim Count by specialty",fontsize = 18, fontweig
ht = "bold")

ax.spines["right"].set_visible(False)
ax.spines["top"].set_visible(False)

avg=final_df.opioid_claim_count.mean()
message="Average for all specialties\n" + str(round(avg,-1))
ax.vlines(avg,0,6,linestyle="--",color="black",alpha=0.75)
ax.text(avg + 15,
        0.5,
        message,
        horizontalalignment='left')
```

Out[122]:
```
Text(127.46,0.5,'Average for all specialties\n110.0')
```



Since prescription opioids are mainly used to relieve pain, pain management prescribes the most opioid, followed by surgery. However, Family practice and Non-physician also make above average amount of opioid prescription, which are surprising, since they are less transparent and in some case less experienced. They should be expected to handle less sensitive drugs.

State-level Income and Overdose Death Map

I want to visualize the distribution of state-level income and overdose death, and compare them side by side to see if there are any patterns.

In [123]:
```
cwd = os.getcwd()

regions_shape = cwd + "/shape_files/cb_2017_us_state_500k"
```

In [124]:
```
us_map = gpd.read_file(regions_shape)
```

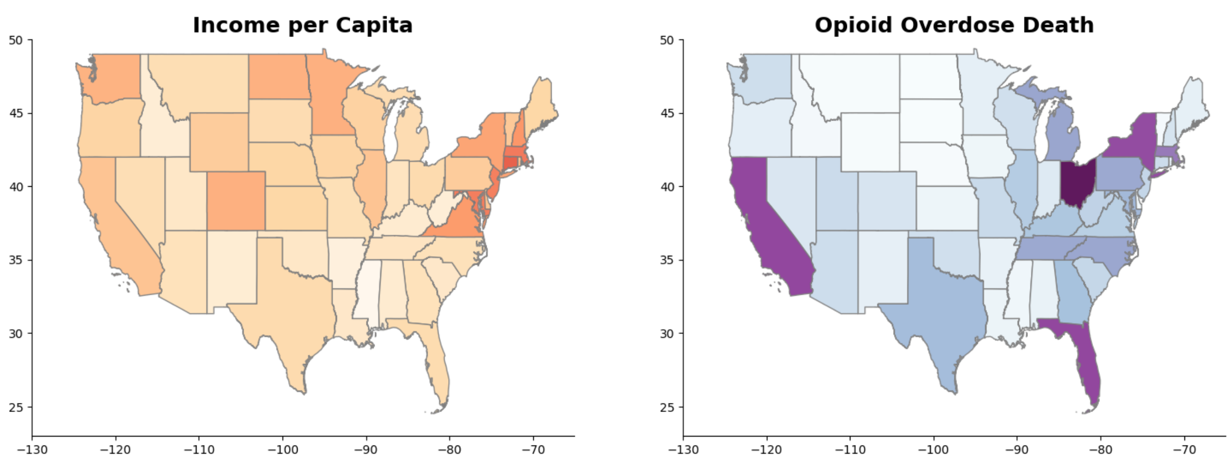
In [125]:
```
death_map=death.set_index('State')
```

In [126]:
```
us_map.rename(columns={'NAME':'State'},inplace=True)
us_map=us_map.merge(state_wealth,on='State',how='inner')
us_map=us_map.join(death_map,on='State',how='inner')
```

In [127]:
```
us_map.dtypes
```

Out[127]:
```
STATEFP                                 object
STATENS                                 object
AFFGEOID                                object
GEOID                                   object
STUSPS                                  object
State                                   object
LSAD                                    object
ALAND                                    int64
AWATER                                   int64
geometry                                object
state_per_capita_income                float64
prescription_opioid_overdose_deaths    float64
dtype: object
```

In [128]:
```
plt.style.use('default')
fig, ax = plt.subplots(1,2,sharex=True, figsize = (18,6))

us_map.plot(ax = ax[0],
            edgecolor='tab:grey', # Tell it the edge color
            column='state_per_capita_income', #it says color it based
on this column
            cmap='OrRd',
            alpha = 0.9) # Transparent

us_map.plot(ax = ax[1],
            edgecolor='tab:grey',
            column='prescription_opioid_overdose_deaths',
            cmap='BuPu',
            alpha = 0.9)

ax_length = range(0,2)

for var in ax_length:
    ax[var].spines["right"].set_visible(False)
    ax[var].spines["top"].set_visible(False)

ax[var].set_ylim(23,50)
ax[var].set_xlim(-130,-65)
ax[0].set_ylim(23,50)

ax[0].set_title('Income per Capita',fontsize = 18, fontweight = "bold"
)
ax[1].set_title('Opioid Overdose Death',fontsize = 18, fontweight = "b
old")

plt.show()
```



Northeast region is the richest. Ohio, New York, California and Florida seem to have the most opioid overdose death. There is no apparent correlation. But state averages may have masked a lot of vriations, therefore I want to look at data by zipcode.

Regression of opioid prescription on income by zipcode

In [129]:
```
g_zip=final_df.groupby('zipcode')
```

In [130]:
```
m_zip=g_zip.mean()
m_zip.per_capita_income=m_zip.per_capita_income*0.000001
m_zip_clean=m_zip[m_zip['per_capita_income'] > 0]
```

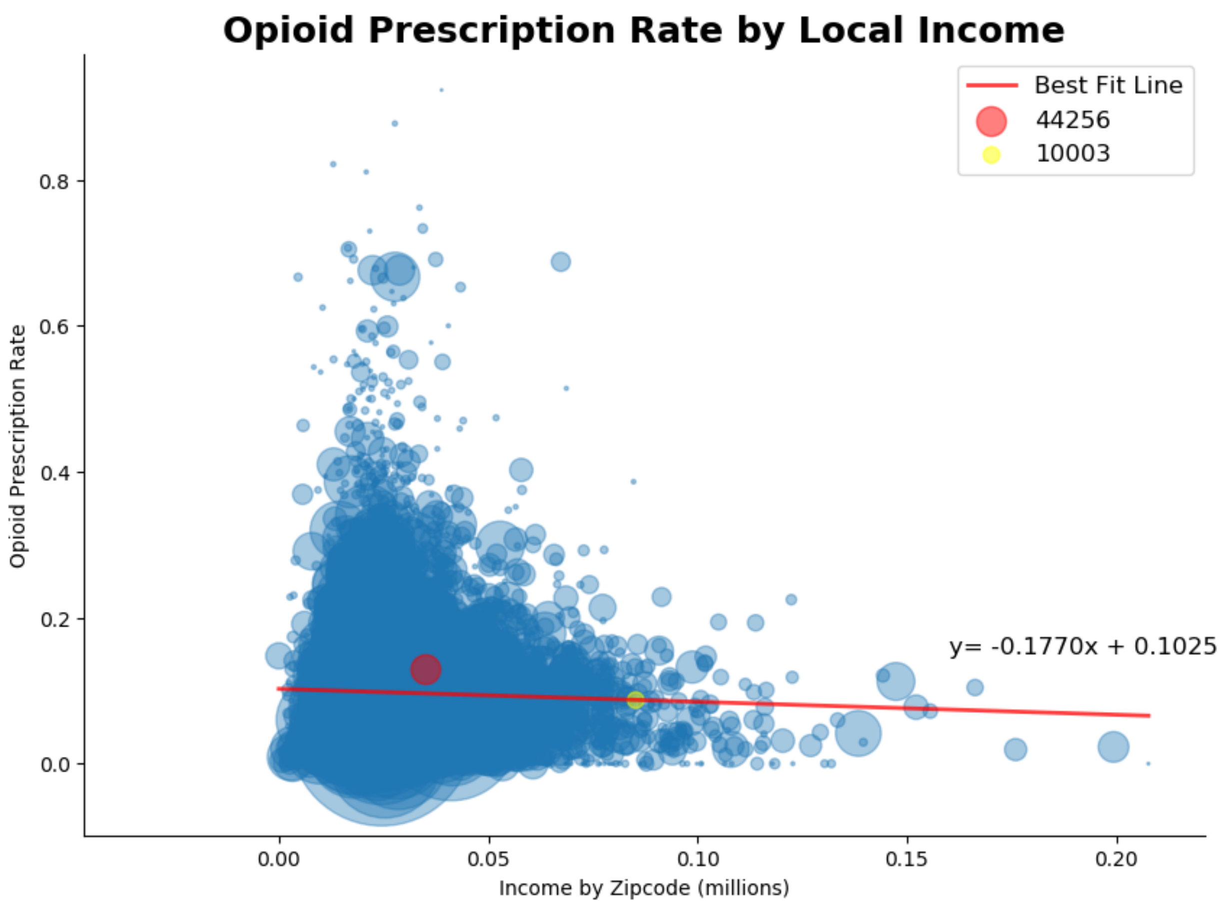
In [131]:
```
results = smf.ols('opioid_rate ~ per_capita_income',
                  data=m_zip_clean).fit()
type(results)

print(results.summary())
```

```
                            OLS Regression Results
====================================================================
==========
Dep. Variable:            opioid_rate   R-squared:
0.001
Model:                            OLS   Adj. R-squared:
0.001
Method:                 Least Squares   F-statistic:
15.54
Date:                Sat, 12 May 2018   Prob (F-statistic):
8.13e-05
Time:                        22:23:06   Log-Likelihood:
19101.
No. Observations:               16217   AIC:
-3.820e+04
Df Residuals:                   16215   BIC:
-3.818e+04
Df Model:                           1
Covariance Type:            nonrobust
====================================================================
=================
                        coef    std err          t      P>|t|      [
0.025      0.975]
--------------------------------------------------------------------
-----------------
Intercept             0.1025      0.001     72.786      0.000
0.100       0.105
per_capita_income    -0.1770      0.045     -3.942      0.000      -
0.265      -0.089
====================================================================
==========
Omnibus:                     8908.312   Durbin-Watson:
1.810
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
116815.596
Skew:                           2.366   Prob(JB):
0.00
Kurtosis:                      15.267   Cond. No.
76.8
====================================================================
==========

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

The coefficient is negative and significant, confirming our hypothesis that poorer places have more opioid prescriptions. However, R square is small, indicating linear model may not be the best fit.

In [132]:
```
plt.style.use('default')
###Ploting the scatter plot:
pred = results.predict(exog = m_zip_clean["per_capita_income"].sort_va
lues())

fig, ax = plt.subplots(figsize = (10,7))
m_zip_clean.plot('per_capita_income','opioid_rate',kind='scatter',
                 s=m_zip_clean['total_claim_count']*0.1,
                 ax=ax,alpha=0.4)

###Plotting the best fit line
ax.plot(m_zip_clean["per_capita_income"].sort_values(), pred , color =
'r',
        linewidth = 2.0,alpha=0.75,
        label = "Best Fit Line")


###Indicating two places of interest:
ax.scatter(m_zip_clean.loc['44256']["per_capita_income"], #Ohio
           m_zip_clean.loc['44256']["opioid_rate"],
            s=m_zip_clean.loc['44256']['total_claim_count']*0.1,
            alpha= 0.50,color='red',label='44256')

ax.scatter(m_zip_clean.loc['10003']["per_capita_income"], #New York
           m_zip_clean.loc['10003']["opioid_rate"],
            s=m_zip_clean.loc['10003']['total_claim_count']*0.1,
            alpha= 0.50,color='yellow',label='10003')

###Polishing the graph:
ax.set_title("Opioid Prescription Rate by Local Income",fontsize = 18,
fontweight = "bold")

ax.spines["right"].set_visible(False)
ax.spines["top"].set_visible(False)

ax.set_xlabel("Income by Zipcode (millions)")
ax.set_ylabel("Opioid Prescription Rate")

ax.legend(fontsize=12)
equation="y= -0.1770x + 0.1025"
ax.text(0.16,0.15,equation,fontsize=12,
        horizontalalignment='left')
```

```
Out[132]: Text(0.16,0.15,'y= -0.1770x + 0.1025')
```



The scatterplot definitly show an negtive relationship between opioid prescription rate and local income. However the shape shows that the relationship is likely non-linear.

Regression of Opioid Overdose death on opioid prescription rate

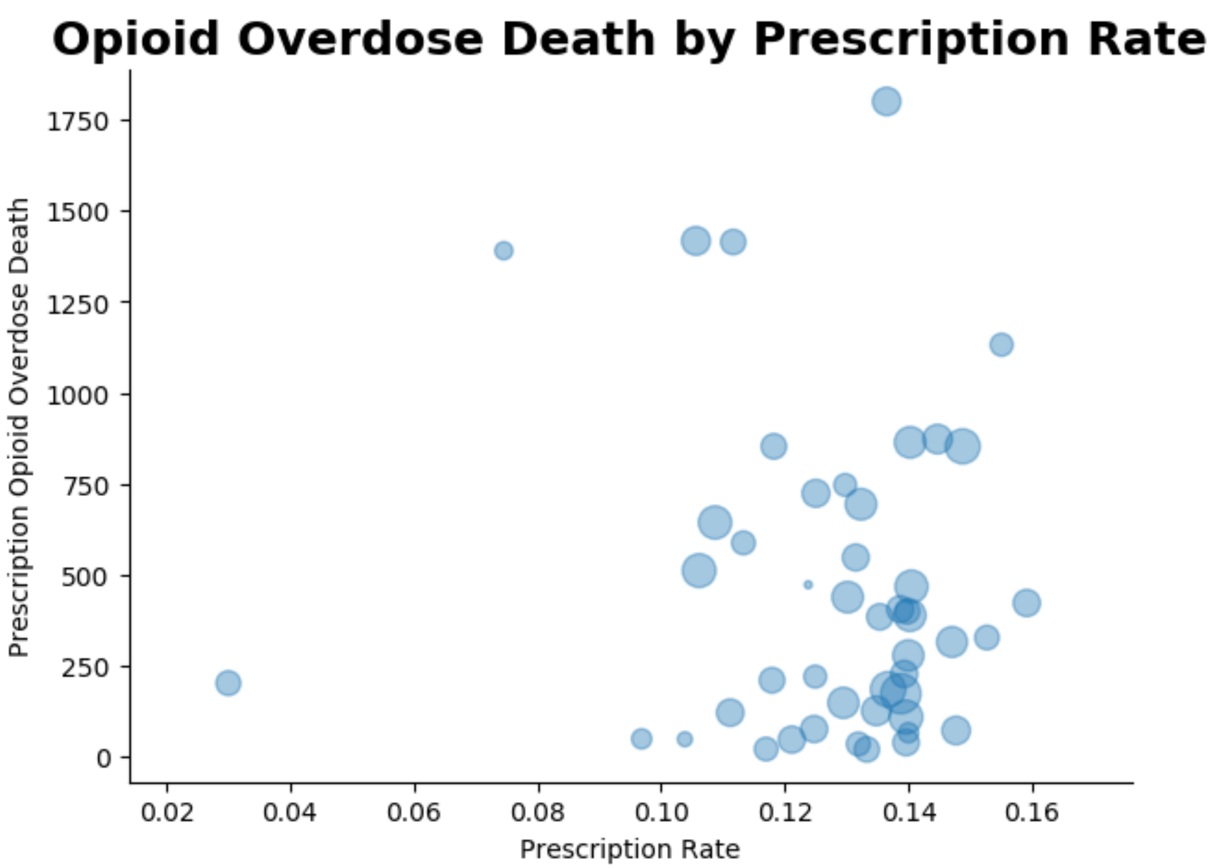
```
In [133]: g_state=final_df.groupby('State').mean()

          results2 = smf.ols('prescription_opioid_overdose_deaths ~ opioid_rate'
          ,
                             data=g_state).fit()

          type(results2)

          print(results2.summary())
```

```
                                    OLS Regression Results
==================================================================================
==========================
Dep. Variable:     prescription_opioid_overdose_deaths   R-squared:
0.004
Model:                                             OLS   Adj. R-squa
red:                 -0.018
Method:                                  Least Squares   F-statistic
:                     0.2009
Date:                                 Sat, 12 May 2018   Prob (F-sta
tistic):               0.656
Time:                                         22:23:09   Log-Likelih
ood:                 -351.00
No. Observations:                                   47   AIC:
706.0
Df Residuals:                                       45   BIC:
709.7
Df Model:                                            1
Covariance Type:                             nonrobust
==================================================================================
===========
                  coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------------------
-----------
Intercept     625.2814    376.289      1.662      0.104    -132.604
1383.166
opioid_rate -1304.9239   2911.091     -0.448      0.656   -7168.162
4558.314
==================================================================================
==========
Omnibus:                       13.655   Durbin-Watson:
2.030
Prob(Omnibus):                  0.001   Jarque-Bera (JB):
14.388
Skew:                           1.242   Prob(JB):
0.000751
Kurtosis:                       4.086   Cond. No.
46.8
==================================================================================
==========

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

The correlation is surprisingly not significant. However, it maybe because overdose death data is state-level. The average masked a lot of variation.

In [134]:
```
plt.style.use('default')
fig, ax = plt.subplots(figsize = (7,5))

g_state.plot('opioid_rate','prescription_opioid_overdose_deaths',kind=
'scatter',
             s=g_state['opioid_claim_count'],
                 ax=ax,alpha=0.4)

ax.set_title("Opioid Overdose Death by Prescription Rate",fontsize = 1
8, fontweight = "bold")

ax.spines["right"].set_visible(False)
ax.spines["top"].set_visible(False)

ax.set_xlabel("Prescription Rate")
ax.set_ylabel("Prescription Opioid Overdose Death")
```

Out[134]: Text(0,0.5,'Prescription Opioid Overdose Death')



Consitent with the regression, the scatterplot looked fairly random.

Conclusion

In this project, we have visualized opioid overdose death increase in both numbers and variations since the late 1990s. Looking at specialties, an outstanding number of prescription from pain management, and above avaerage counts for non-physicians and family practices were found. More investigation should be done on whether these specialties are prescribing opioid reasonably. we have also visualized state-level income per capita and opioid overdose death on a map. Importantly, a significant correlation between local (by zipcode)income and opioid prescription rate was found. Indicating poor places have either higher demand for opioids or inadequate prescription regulation. However, the correlation between opioid prescription rate and overdose death is not significant. Data for zipcode-level overdose death may give better result. Policy maker should focus on poor neighborhoods to solve the opioid crisis.

Reference

Opioid Overdose Crisis ('https://www.drugabuse.gov/drugs-abuse/opioids/opioid-overdose-crisis')