Final Part 3 - Percent Extremely High Debt

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0.1 Final Part 3 - Percent Extremely High Debt

0.1.1 Load Libraries

[1]:
```
import pandas as pd
import numpy as np
import geopandas as gpd
import contextily as ctx
import esda
from esda.moran import Moran, Moran_Local
import splot
from splot.esda import moran_scatterplot, plot_moran,␣
↪lisa_cluster,plot_moran_simulation
import libpysal as lps
import matplotlib.pyplot as plt
import plotly.express as px
import seaborn as sns
```

```
/opt/conda/lib/python3.8/site-packages/geopandas/_compat.py:106: UserWarning:
The Shapely GEOS version (3.8.1-CAPI-1.13.3) is incompatible with the GEOS
version PyGEOS was compiled with (3.9.0-CAPI-1.16.2). Conversions between both
will be slow.
  warnings.warn(
```

0.1.2 Load Data

The same datasets I've been working with are below, except I have added a file with latitude and longitudes for the state of California so I can create a scatterplot of the zip codes to save some memory on my interactive maps/

[2]:
```
acs = pd.read_csv('../Data/Updated Bill Data 2_22.csv')

zips = gpd.read_file('../Data/ca_california_zip_codes_geo.min.json')

latlon = pd.read_csv('../Data/CA Zip Lat and Lon - Sheet1.csv')
```

0.1.3 Clean Data

From working with this data for several weeks now, I know there are N/A values I need to drop. The same general process for cleaning will take place.

[3]:
```
acs = acs.dropna()
```

Next, I only keep my columns of interest.

[4]:
```
refined_columns = ['Zip Codes',
 'Sum of Less than $100',
 'Sum of $100-$200',
 'Sum of $200-$300',
 'Sum of $300-$400',
 'Sum of $400-$500',
 'Sum of $500-$600',
 'Sum of $600-$700',
 'Sum of $700-$800',
 'Sum of $800-$900',
 'Sum of $900-$1000',
 'Sum of More than $1000',
 'Sum of Total number of delinquent residential accounts',
 'pop',
 'mhhi',
 'pct_nhw',
 'pct_black',
 'pct_hisp',
 'pct_asian',
 'pct_povt',
 'pct_overcrowded',
 'pct_no_veh_hh',
 'pct_broadband',
 'pct_no_broadband',
 'pct_uninsured_19_64',
 'pct_noncitizen',
 'pct_immigrants',
 'pct_lep_hh',
 'pct_no_hins',
 '% Renter Pop',
  '% Owner Pop']
```

Then I save these over the old dataframe.

[5]:
```
acs = acs[refined_columns]
```

0.1.4 Normalize the Data

Next, I use the for loops I created a few weeks ago to normalize my data so that my debt buckets are in percents and my demographic factors are multipled by 100 so they are in a more readable

percent format and not decimals

[6]:
```
acs['Percent Delinquent'] = acs['Sum of Total number of delinquent residential␣
↪accounts']/acs['pop']*100


pct_debt_buckets = ['Percent Less than $100', 'Percent $100-$200', 'Percent␣
↪$200-$300' ,
                'Percent $300-$400', 'Percent $400-$500', 'Percent $500-$600',␣
↪'Percent $600-$700',
                'Percent $700-$800', 'Percent $800-$900', 'Percent $900-$1000',␣
↪'Percent More than $1000']

debt_buckets =  ['Sum of Less than $100', 'Sum of $100-$200', 'Sum of␣
↪$200-$300' ,
                'Sum of $300-$400', 'Sum of $400-$500', 'Sum of $500-$600',␣
↪'Sum of $600-$700',
                'Sum of $700-$800', 'Sum of $800-$900', 'Sum of $900-$1000',␣
↪'Sum of More than $1000']

sum_total = 'Sum of Total number of delinquent residential accounts'

demographics = ['pct_nhw','pct_black',␣
↪'pct_hisp','pct_asian','pct_povt','pct_overcrowded','pct_no_veh_hh',
                'pct_broadband','pct_no_broadband',␣
↪'pct_uninsured_19_64','pct_noncitizen','pct_immigrants',
                'pct_lep_hh','pct_no_hins','% Renter Pop','% Owner Pop']

for pct, debt in zip(pct_debt_buckets, debt_buckets):
    acs[pct] = acs[debt] / acs[sum_total]*100

for dem in demographics:
    acs[dem] = acs[dem]*100
```

Now I drop the columns I no longer need (the sum columns, since I hasve now converted my columns of interest into percents)

[7]:
```
columns_drop = ['Sum of Less than $100',
 'Sum of $100-$200',
 'Sum of $200-$300',
 'Sum of $300-$400',
 'Sum of $400-$500',
 'Sum of $500-$600',
 'Sum of $600-$700',
 'Sum of $700-$800',
 'Sum of $800-$900',
 'Sum of $900-$1000',
```

```
 'Sum of More than $1000',
 'Sum of Total number of delinquent residential accounts']

acs = acs.drop(columns_drop, axis = 1)
```

Now that I've done these calculations, I want to make sure all new N/A values have also been dropped

[8]:
```
acs = acs.dropna()
```

Finally, I know from working with the data, that there are some outliers of over 100% that also need to be removed.

[9]:
```
acs.drop(acs[acs['Percent Delinquent'] > 100].index, inplace = True)
acs.drop(acs[acs['Percent $400-$500'] > 100].index, inplace = True)
```

Next, I need to clean up the zip code shapefile.

0.1.5 Clean Zip Codes and Merge

[10]:
```
zips_keep = ['ZCTA5CE10', 'geometry']
```

I know from working with this file a lot that my two columns of interest are ZCTA5CE10 and geometry

[11]:
```
zips = zips[zips_keep]
```

Now I will over-write these onto the orginial zips file

[12]:
```
zips.columns = ['Zip Codes', 'geometry']
```

Then I will rename ZCTA5CE to 'Zip Codes' so it can merge with my ACS file with the same column name.

[13]:
```
merged = acs.merge(zips,
                   on='Zip Codes')
```

I save this file as a geodataframe.

[14]:
```
merged = gpd.GeoDataFrame(merged, geometry='geometry')
```

Then I want to make sure my "Zip Codes" file is saved as an integer so I can merge with the Latitude and Longitude file.

[15]:
```
merged['Zip Codes'] = merged['Zip Codes'].astype(int)
```

0.1.6 Latitude and Longitude Data

Now I just need to merge latitude and longitude data to my merged data so I can plot zip code locations. First, I need to look at the data to get a sense of which columns to keep.

[16]:
```
latlon.head()
```

[16]:

	Zip	City	State	Latitude	Longitude	Timezone	Daylight savings time flag	geopoint
0	95717	Gold Run	CA	39.177026	-120.84510	-8	1	39.177026, -120.8451
1	94564	Pinole	CA	37.997509	-122.29208	-8	1	37.997509, -122.29208
2	91605	North Hollywood	CA	34.208142	-118.40110	-8	1	34.208142, -118.4011
3	91102	Pasadena	CA	33.786594	-118.29866	-8	1	33.786594, -118.298662
4	95019	Freedom	CA	36.935552	-121.77972	-8	1	36.935552, -121.77972

My columns of interest are Zip, Latitude, and Longitude

[17]:
```
latlon_keep = ['Zip', 'Latitude', 'Longitude']
```

Now I will over-write those columns on the original dataset.

[18]:
```
latlon = latlon[latlon_keep]
```

Now I change the column names so I can merge

[19]:
```
latlon.columns = ['Zip Codes', 'Latitude', 'Longitude']
```

And now my second merged column is merged_2

[20]:
```
merged_2 = merged.merge(latlon,
                        on='Zip Codes')
```

0.1.7 Maps: Percent Extreme Debt Indicators

Now, I am moving on to indicators of extreme debt (over $1000), as I think these serves as a good comparison against general percent delinquent. Extreme debt can cripple a household and cause many unintended consequences, so it is important to understand the risk factors a little better.

First, let's create a basemap of Percent More Than $1000 zip codes, to get a sense of the data spread.

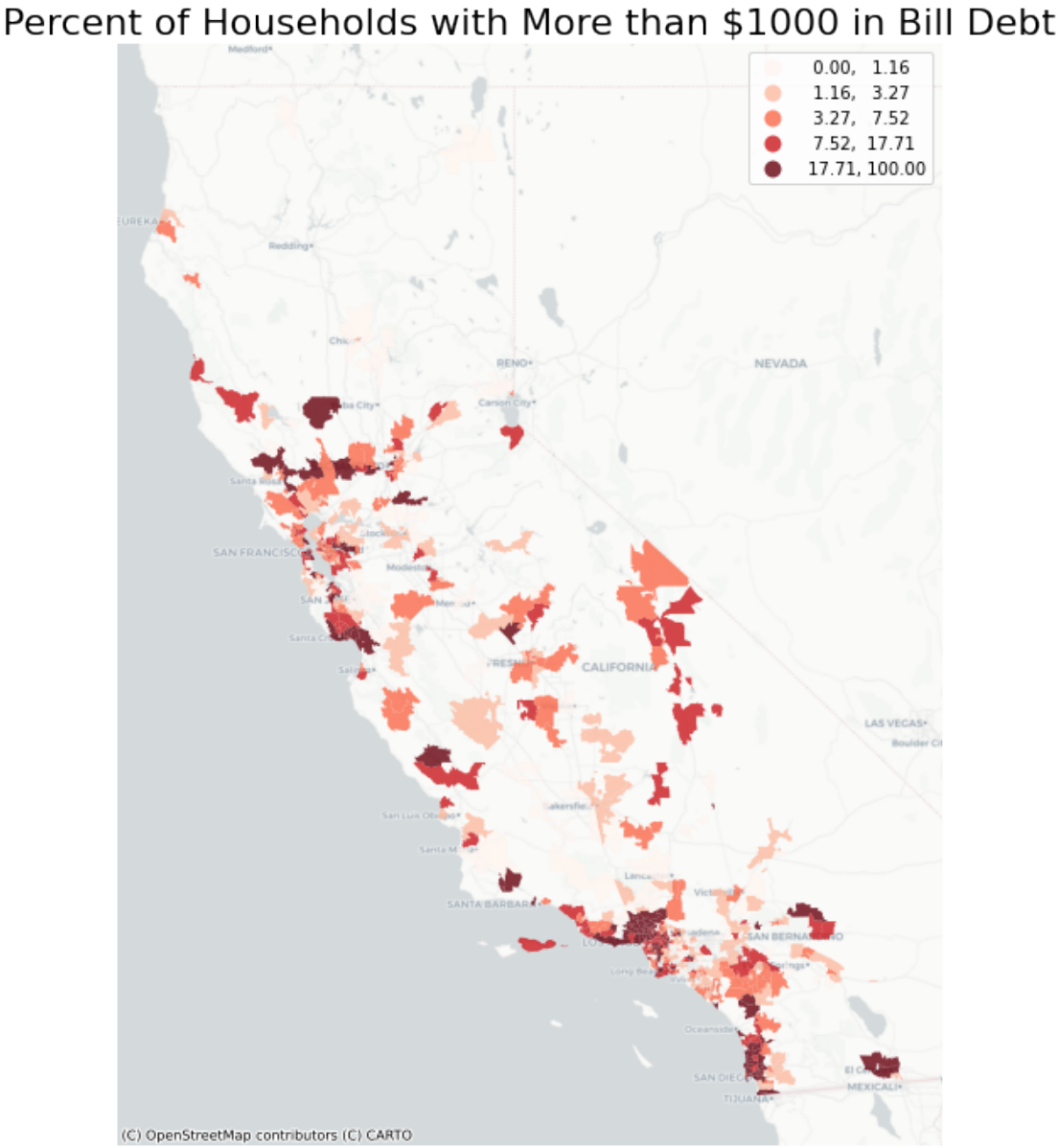
First, I need to get the web mercator projection.

[21]:
```
merged_2 = merged_2.to_crs(epsg=3857)
```

Then I plot the distribution of water bill debt in quantiles.

[22]:
```
fig,ax = plt.subplots(figsize=(12,12))
```

```
merged_2.plot(ax=ax,
        column='Percent More than $1000',
        legend=True,
        alpha=0.8,
        cmap='Reds',
        scheme='quantiles')

ax.axis('off')
ax.set_title('Percent of Households with More than $1000 in Bill␣
 ↪Debt',fontsize=22)
ctx.add_basemap(ax,source=ctx.providers.CartoDB.Positron)
```



We can see from the map there is a high contentration of extreme percent debt in/around LA and also closer to the Nevada border (sort of in the Death Valley area). Let's map the risk indicators and see if they also appear in those areas.

Next, let's take a look at the inidcators for extreme debt: Percent Poverty, Percent No Vehicle per Household, and Percent Immigrant. Each of these factors showed a positive, statistically significant relationship to the extreme debt bucket - as these demographic factors increase, so does the percent of households per zip code with extreme water bill debt over $1,000.

I want to map the zip codes that are most at risk of having water bill debt based on these demographic indicators, but to do this, I want to isolate the highest quartile for each indicator, thus, I will map the zip codes that are in the 75th percentile for each risk indicator

First, we want to create new colums in the dataset and print which quartile each zip code falls under for my variables of interest. I am interested in which zip codes have %black %overcrowded, and %immigrant in the 4th quartile or 75th percentile.

[23]:
```
merged_2['povt_quartile'] = pd.
↪qcut(merged_2['pct_povt'],4,labels=['Q1','Q2','Q3','Q4'])
```

[24]:
```
merged_2['noveh_quartile'] = pd.
↪qcut(merged_2['pct_no_veh_hh'],4,labels=['Q1','Q2','Q3','Q4'])
```

[25]:
```
merged_2['imm_quartile'] = pd.
↪qcut(merged_2['pct_immigrants'],4,labels=['Q1','Q2','Q3','Q4'])
```

[26]:
```
merged_2_quart = merged_2[(merged_2['povt_quartile']=='Q4') |
          (merged_2['noveh_quartile']=='Q4') |
          (merged_2['imm_quartile']=='Q4')
         ]
```

Now I have instructed my code to spit out Q1, 2, 3, and 4 based on the percent of each variable of interest.

I want to get a sense of how many zip codes fall into quartile 4 for at least 1 of my variables of interest.

[27]:
```
merged_2_quart.shape
```

[27]:
```
(379, 37)
```

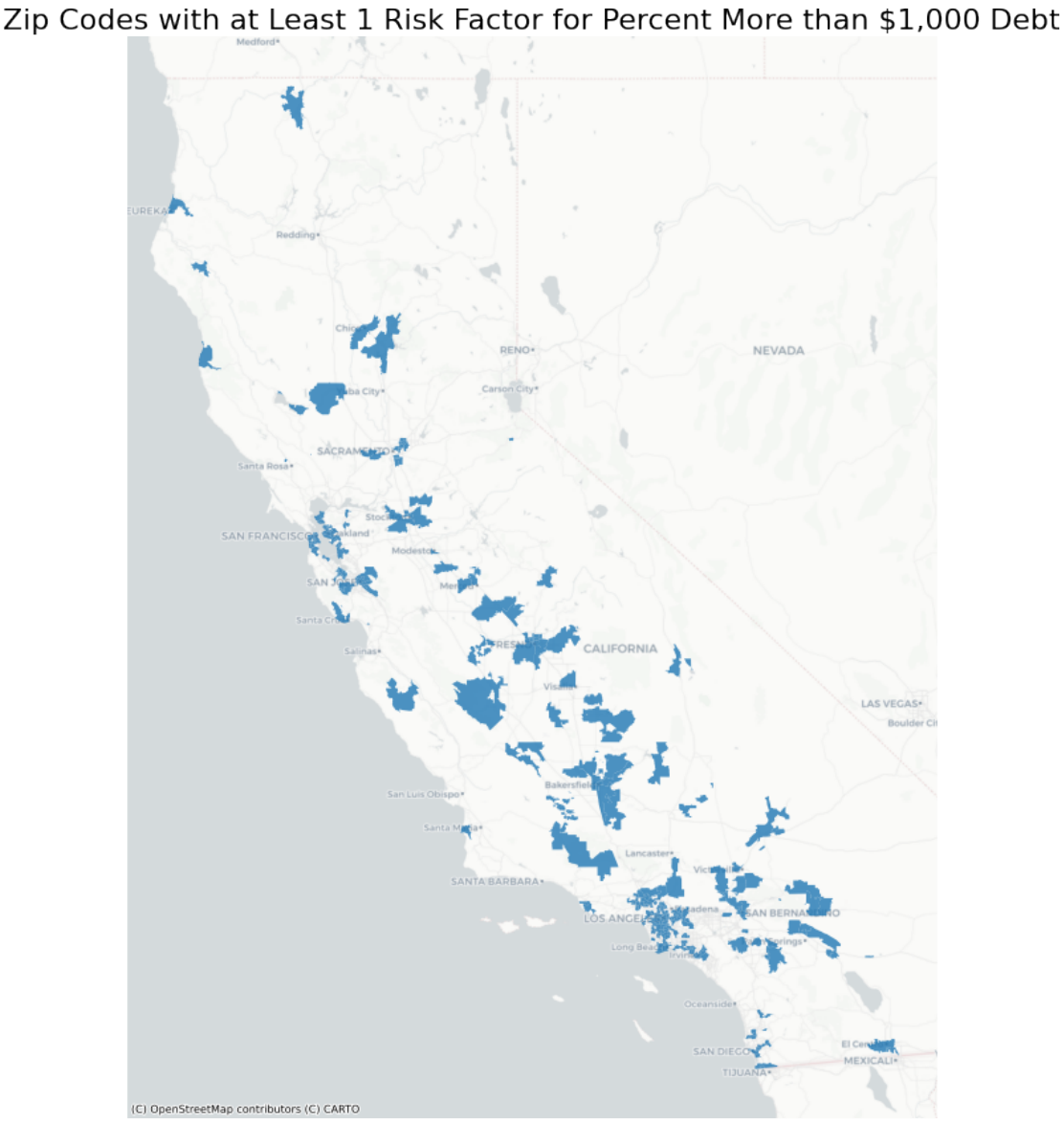
I see there are 398 zip codes in my dataset that have at least one of my 3 variables of interest (percent black, percent overcrowded, or percent immigrant) in the 75th percentile.

Now I want to map only those zip codes under my variables of interest that fall into the 75th percentile. First,I project to the web mercator.

[28]:
```
merged_2_quart=merged_2_quart.to_crs('epsg:3857')
```

Next, we plot the basemap.

[29]:
```
fig,ax = plt.subplots(figsize=(15,15))

merged_2_quart.plot(ax=ax,alpha=0.8)

ax.axis('off')
ax.set_title('Zip Codes with at Least 1 Risk Factor for Percent More than␣
 ↪$1,000 Debt',fontsize=22)

ctx.add_basemap(ax,source=ctx.providers.CartoDB.Positron)
```



Above, you'll see a basemap with each of the 398 zip codes of interest. There is a high concentration of zip codes in the 75th percentile for %black, %overcrowded, and %immigrant mostly around LA,

but a smattering up the coast.

The next thing I want better unsderstand is if there are certain zip codes that fall under 1 or more of these 75th percentile variables of interest. I am going to make an interactive map to better visualize this.

The first thing I do is define a new function, "color_code," and I create a function using numpy that sums up all the instances where %black, %overcrowded, and %immigrant is in the 4th Quartile for each zip code (or each line of data).

[30]:
```
def color_code(x):
    return np.sum([x['povt_quartile']=='Q4', x['noveh_quartile']=='Q4',␣
 ↪x['imm_quartile']=='Q4'])

merged_2_quart['color_code'] = merged_2_quart.apply(color_code, axis=1)
```

Once this function runs through all my data, I add it to my existing dataset, "merged_2_quart" as a new column, "color_code."

Next, I want to clean up the names.

[31]:
```
merged_2_quart = merged_2_quart.rename(columns={'povt_quartile': 'Percent␣
 ↪Poverty',
                                        'noveh_quartile': 'Percent No Vehicle␣
 ↪per Household',
                                        'imm_quartile': 'Percent Immigrant'})
```

I want the names of each of my variables of interest to appear a little cleaner on my map, so I changed the names to Percent Black, Percent Overcrowded, and Percent Immigrant

Next, I'll create the interactive map.

[32]:
```
fig = px.scatter_mapbox(merged_2_quart,
                        lat="Latitude",
                        lon="Longitude",
                        color="color_code",
                        hover_name = 'Zip Codes',
                        hover_data = {'Percent Poverty': True,
                                      'Percent No Vehicle per Household': True,
                                      'Percent Immigrant': True,
                                      'Latitude': False,
                                      'Longitude': False
                                     },
                        size = 'pop',
                        labels={'color_code':'Risk Level'}
                       )

fig.update_layout(mapbox_style="stamen-terrain")

fig.show()
```

[33]:
```
fig.write_html('../Final/highdebt.html')
```

You can see from the above map that I have color coded the zip codes that overlap with 1-3 of the 75th percentile variables of interest, and these Zip codes are labeled as Risk Level 1, 2, or 3. The size of the circles depends on the population of the zip code, which ideally helps better allocate resources to the majority of Californians who may live in an "at risk" area for high bill delinquency. When you hover over a circle, it will tell you which quartile the demograpgic variable of interst falls under and give you the zip code of that area.

0.1.8 Point Pattern Analysis

Next I want to do a point pattern analysis to see where the highest concentration of Zip Codes within each risk level exist.

[34]:
```
merged_2_quart = merged_2_quart.to_crs('EPSG:3857')
```

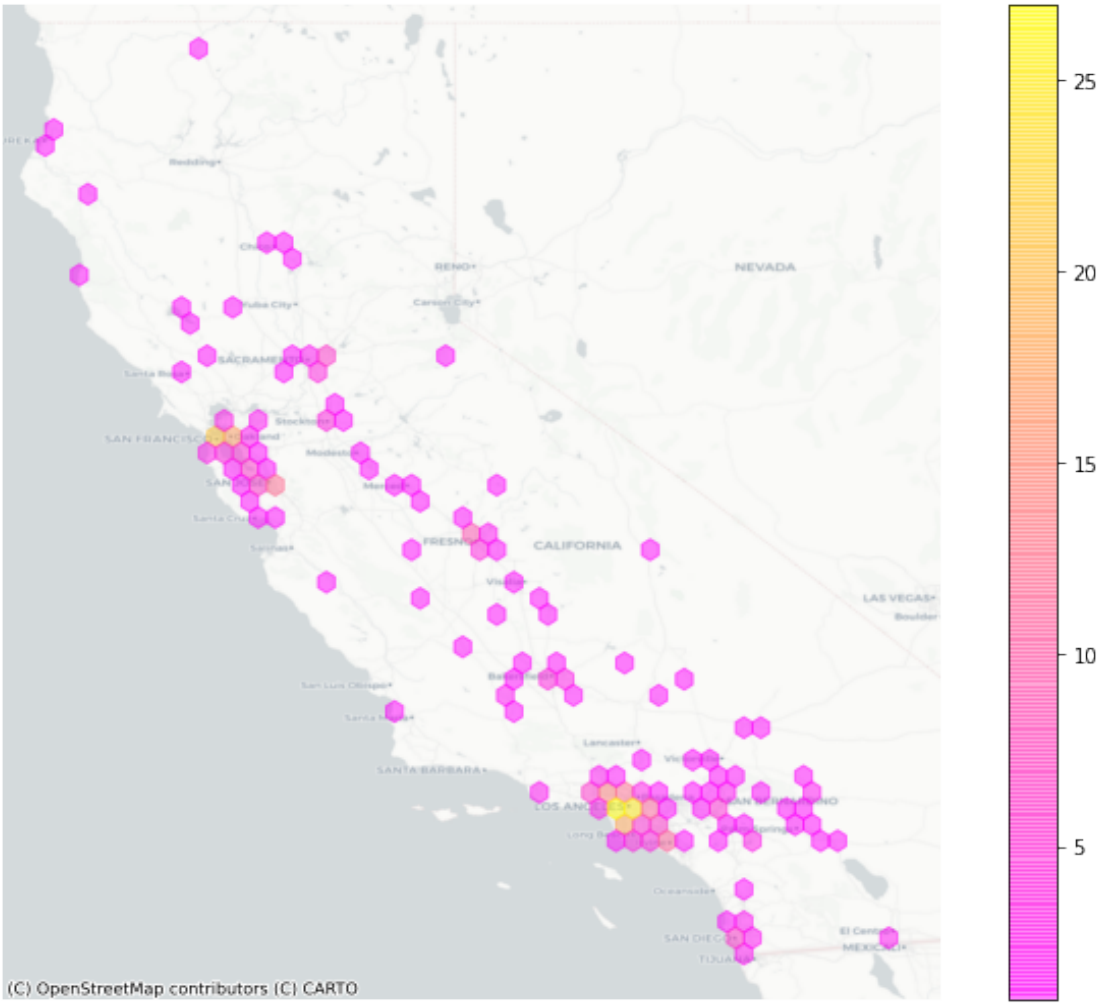
First I linked to the web mercator, and changed my Latitude and Longitude names.

[35]:
```
merged_2_quart = merged_2_quart.rename(columns={'Longitude': 'x',
                                        'Latitude': 'y',})
```

Then, I created some hex bins and added them to a base map.

[36]:
```
f, ax = plt.subplots(figsize=(12, 9))


hb = ax.hexbin(
    x = merged_2_quart['x'],
    y = merged_2_quart['y'],
    gridsize=50,
    linewidths=1,
    alpha=0.5,
    mincnt=1,
    cmap='spring'
)


ctx.add_basemap(
    ax,
    crs='epsg:4326',
    source=ctx.providers.CartoDB.Positron
)


plt.colorbar(hb)


ax.axis('off')
```

[36]: (-124.59344850951342, -115.08002149048657, 32.09661475, 42.20889825)



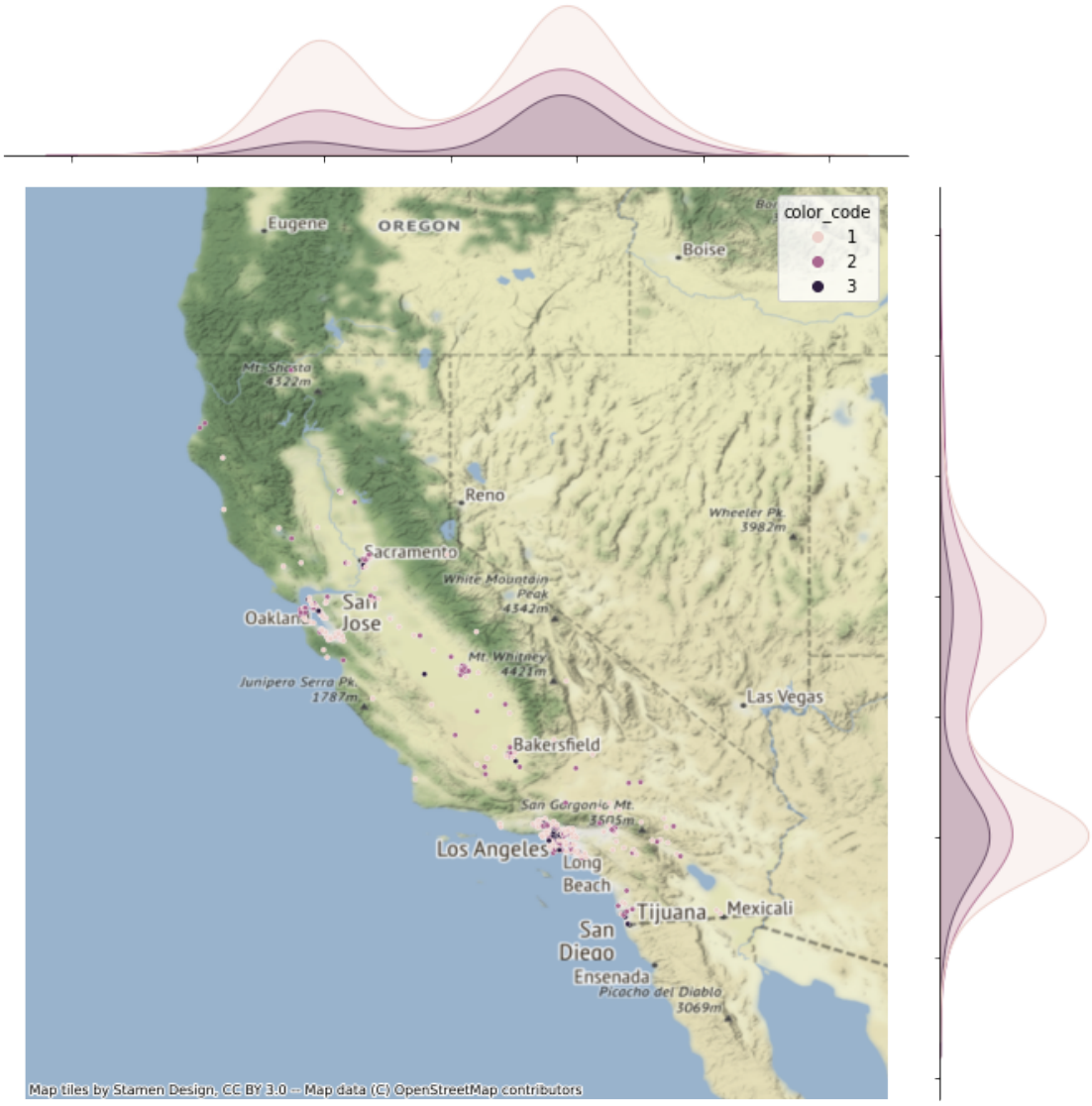
Much like the percent delinquent file, you can see a large concentration of extreme debt around LA, and slightly less around SF.

Next, I subsetted my data and mapped it.

[37]:
```
data_color = merged_2_quart[merged_2_quart.color_code.isin(['1','2','3'])]
```

[38]:
```
g = sns.jointplot(data = data_color,
                  x='x',
                  y='y',
                  hue='color_code',
                  s=10,
                  height=10)
```

```
g.ax_joint.set_axis_off()


ctx.add_basemap(g.ax_joint,
                crs='epsg:4326')
```



Based on this point pattern analysis, we see that most zip codes only have 1 risk indicator for extreme debt, which is an unexpected, but slightly conforting conclusion. Similarly to the last Point Pattern analysis, we see there is a concentration in LA and SF, but not as much variability as in the previous graph.

It looks like there are slightly more ar risk zip codes in LA, so if I were the water board, I would

prioritize those zip codes with 3 risk indicators, then 2, then 1.

[ ]: