California Electric Vehicle Registration EXECUTIVE SUMMARY

Introduction

In this notebook I will analyze electric vehicle registration in California. My hypothesis is that there will be higher rates of battery-powered vehicle registration in zip codes with higher median annual incomes. To do this, I acquired two datasets from the California state government. Below, we'll test my hypothesis and further explore what revelations this data reveals.

Data Explained

Link to first dataset: https://data.ca.gov/dataset/personal-income-tax-statistics-by-zip-code/resource/7091fcca-e695-49ab-aa44-6e0c6f49c9c1

Link to second dataset: https://data.ca.gov/dataset/vehicle-fuel-type-count-by-zip-code/resource/d304108a-06c1-462f-a144-981dd0109900

The first dataset provided data on vehicle registrations, make, and model; as well as type of fuel - including gas, diesel, hybrid, and battery-electric. The second dataset contained data on number of tax filings, annual gross income, total tax liability, etc. Both datasets had columns of data that were unnecessary for the analysis, like make/model, heavy/light duty, model year, etc., so those columns were dropped; and then the datasets were combined into a single frame. Once joined, because the median annual gross income (AGI) was not provided in either set, this was calculated with the AGI per tax filing, per zip code.

See data dictionary below:

In [23]:
```
df = pd.DataFrame(EVsAndIncome.dtypes,columns=['Type'])
df['Description']=['California Zip Code','Number of Tax Returns Filed','California Annual Gross Income','Total Tax Liability for Zip Code','Number of Electric Vehicles
df[['Description','Type']]
```

Out[23]:

	Description	Type
Zip Code	California Zip Code	int64
Returns	Number of Tax Returns Filed	int64
CA AGI	California Annual Gross Income	int64
Total Tax Liability	Total Tax Liability for Zip Code	int64
Battery Electric Vehicles	Number of Electric Vehicles	int64
Average AGI/TaxReturn	Average Annual Gross Income per Tax Return	float64

Results

In [21]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')

EVsAndIncome = pd.read_excel('EVsAndIncome.xlsx')
EVsAndIncome.head()
```

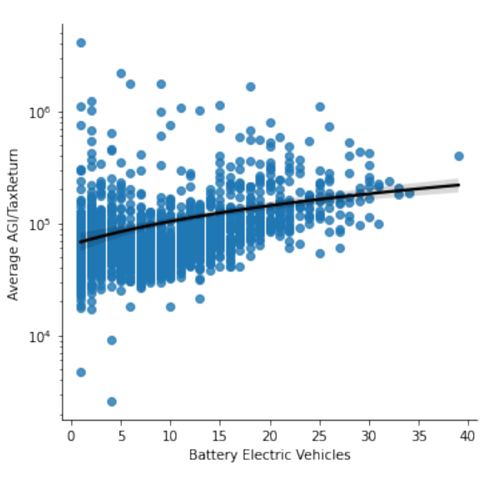
Out[21]:

	Zip Code	Returns	CA AGI	Total Tax Liability	Battery Electric Vehicles	Average AGI/TaxReturn
0	96047	297	16491335	558545	1	55526.38
1	92022	416	27534314	1314928	1	66188.25
2	95117	13881	1362064173	73703746	16	98124.36
3	95036	541	43632815	1982815	1	80652.15
4	95355	25579	1664582060	60683658	10	65076.12

The average annual gross income per tax return was calculated by dividing "CA AGI" by "Returns." As shown above, a new column featuring that metric was added to the dataset. Below, the first scatterplot reveals the result of testing the hypothesis that the number of registered electric vehicles (by zip code) would increase as average annual income increased. There is indeed a higher number of electric vehicles as incomes are higher, though perhaps not to the extent expected.

In [25]:
```
grid = sns.lmplot(data=EVsAndIncome,x = 'Battery Electric Vehicles',y = 'Average AGI/TaxReturn',line_kws={'color': 'black'})
grid.set(yscale="log")
```

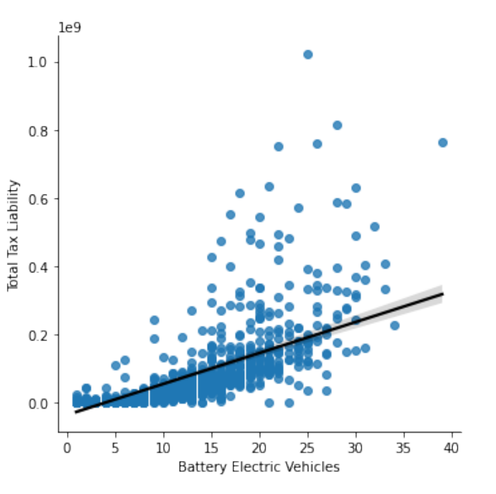
Out[25]: <seaborn.axisgrid.FacetGrid at 0x1acbf3bddc0>



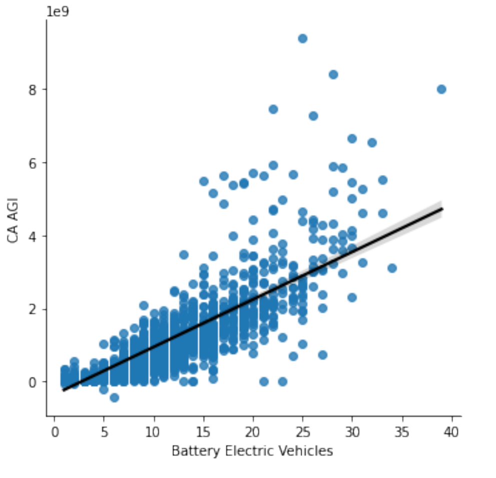
The two scatterplots below illustrate how the number of electric vehicles increases as total tax liabiilty, and annual gross income for a zip code increases. While these are related to the above plot, they show a more dramatic rise in electric vehicles. This could indicate that the overall wealth of a zip code has a more significant effect on the number of battery-powered vehicles than does average income.

In [26]:
```
sns.lmplot(data=EVsAndIncome,x = 'Battery Electric Vehicles',y = 'Total Tax Liability',line_kws={'color': 'black'})
```

Out[26]: <seaborn.axisgrid.FacetGrid at 0x1acbfd83880>



In [27]:
```
grid = sns.lmplot(data=EVsAndIncome,x = 'Battery Electric Vehicles',y = 'CA AGI',line_kws={'color': 'black'})
```

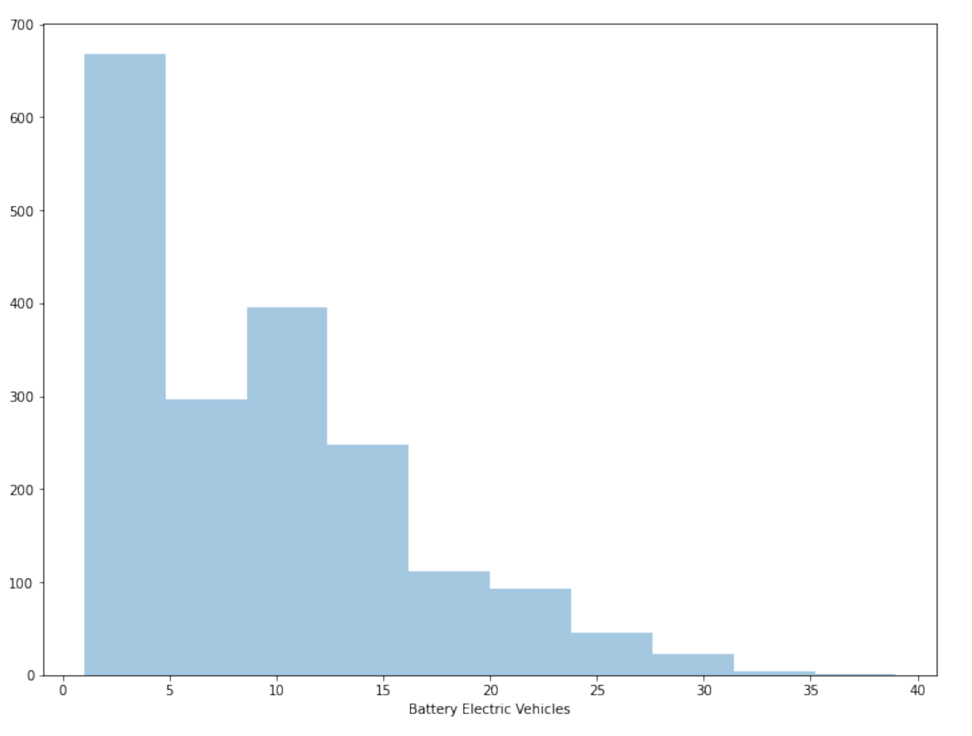


The below distribution plot represents totals of electric vehicles as bins, and reveals which bins are most common among zip codes. Each zip code had at least one electric vehicle: notice the x-axis "0" has no bar.

In [29]:
```
f, ax = plt.subplots(figsize=(12,9))

sns.distplot(EVsAndIncome['Battery Electric Vehicles'],kde=False,bins=10)
```

Out[29]: <AxesSubplot:xlabel='Battery Electric Vehicles'>



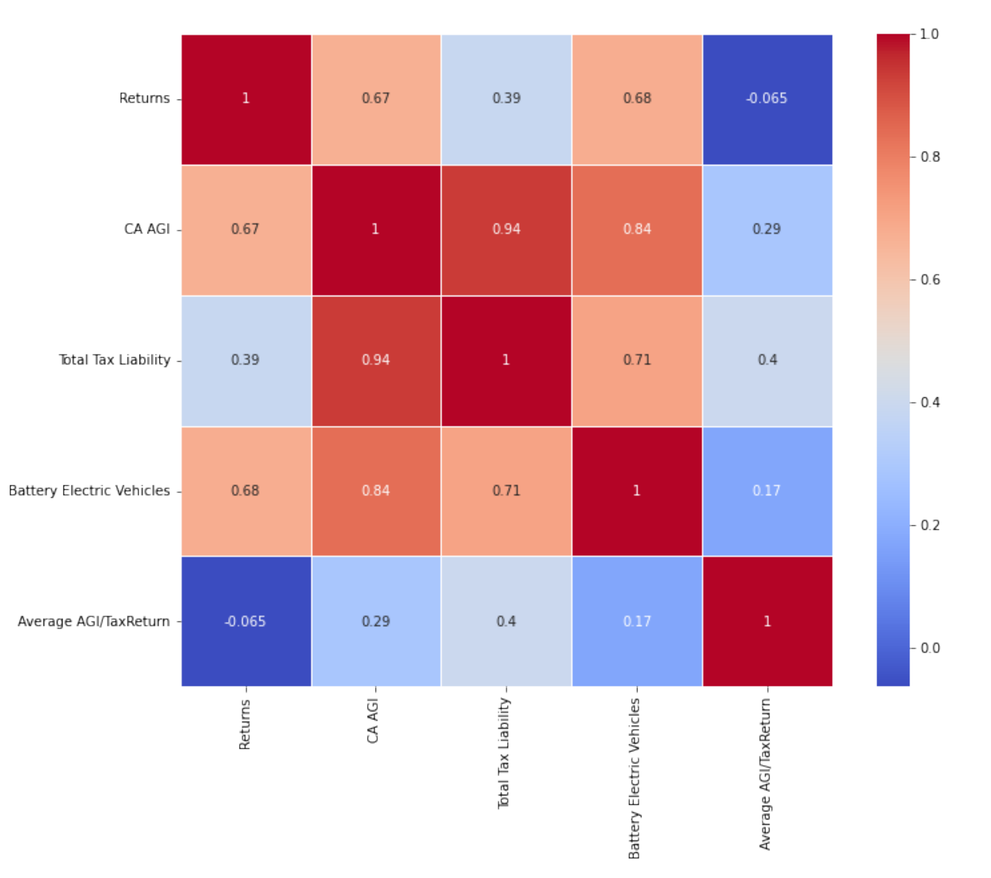
The below heat map reveals the strength and weakness of the correlations between the various types of data. It reinforces the second two scatterplots by showing hues of orange/red representing stronger correlations between battery electric vehicles and average annual income and total tax liability. The light blues to dark blues represent weaker correlations, though still some correlation.

In [28]:
```
columns = EVsAndIncome.columns[1:6]
df_corr = EVsAndIncome[columns]

corrmat = df_corr.corr()

f, ax = plt.subplots(figsize=(12,9))
sns.heatmap(corrmat,square=True,annot=True,cmap='coolwarm',linewidths=.5)
```

Out[28]: <AxesSubplot:>



The below code converts the zip codes into counties and the counties into FIPS, so that the data can be actually mapped to zip codes and for the creation of categorical data for use in a boxplot.

In [33]:
```
import addfips

from uszipcode import SearchEngine
search = SearchEngine()

def zco(x):
    city = search.by_zipcode(x).county
    return city if city else 'None'

def get_fips(x):
    af = addfips.AddFIPS()
    fips = af.get_county_fips(x, state='California')
    return fips

EVsAndIncome['Counties'] = EVsAndIncome['Zip Code'].apply(zco)
EVsAndIncome['FIPS']=EVsAndIncome['Counties'].apply(get_fips)

EVsAndIncome
```

Out[33]:

	Zip Code	Returns	CA AGI	Total Tax Liability	Battery Electric Vehicles	Average AGI/TaxReturn	Counties	FIPS
0	96047	297	16491335	558545	1	55526.38	Shasta County	06089
1	92022	416	27534314	1314928	1	66188.25	San Diego County	06073
2	95117	13881	1362064173	73703746	16	98124.36	Santa Clara County	06085
3	95036	541	43632815	1982815	1	80652.15	Santa Clara County	06085
4	95355	25579	1664582060	60683658	10	65076.12	Stanislaus County	06099
...	...	...	...	...	...	...	...	...
1881	90017	9933	747190649	45793835	15	75223.06	Los Angeles County	06037
1882	95692	2043	130131494	4553717	4	63696.28	Yuba County	06115
1883	92117	26357	1909543664	82407461	19	72449.20	San Diego County	06073
1884	94511	830	48899459	1779150	6	58915.01	Contra Costa County	06013
1885	95947	679	29684175	750943	4	43717.49	Plumas County	06063

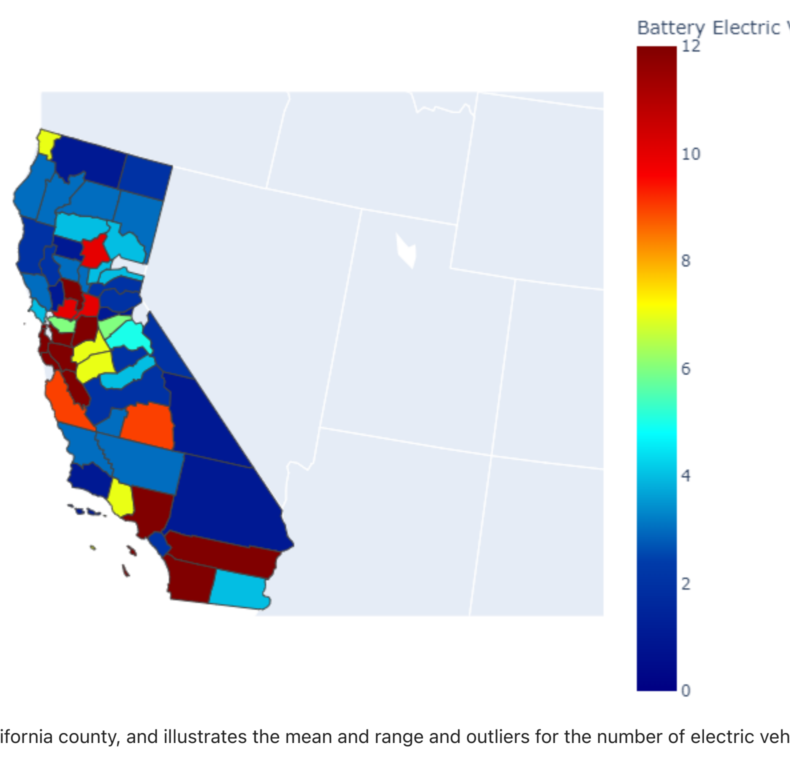
1886 rows × 8 columns

The below code is specifically what creates the mapping of battery electric vehicles to counties in California. The darker orange and red hues indicate higher numbers of electric vehicles, while yellows/greens/blues indicate lower numbers. As illustrated in the map, the highest concentration of electric vehicles is in the San Franciso Bay Area, The Los Angeles County area, and the San Diego area. As we look north and inland, the number of electric vehicles is comparatively low.

In [20]:
```
import plotly.express as px

from urllib.request import urlopen
import json
with urlopen('https://raw.githubusercontent.com/plotly/datasets/master/geojson-counties-fips.json') as response:
    counties = json.load(response)

fig = px.choropleth(EVsAndIncome, geojson=counties, locations='FIPS', color='Battery Electric Vehicles',
                           color_continuous_scale="Jet",
                           range_color=(0, 12),
                           scope="usa",
                           labels={'Counties':'Counties'}
                          )
fig.update_layout(margin={"r":0,"t":0,"l":0,"b":0})
fig.show()
```

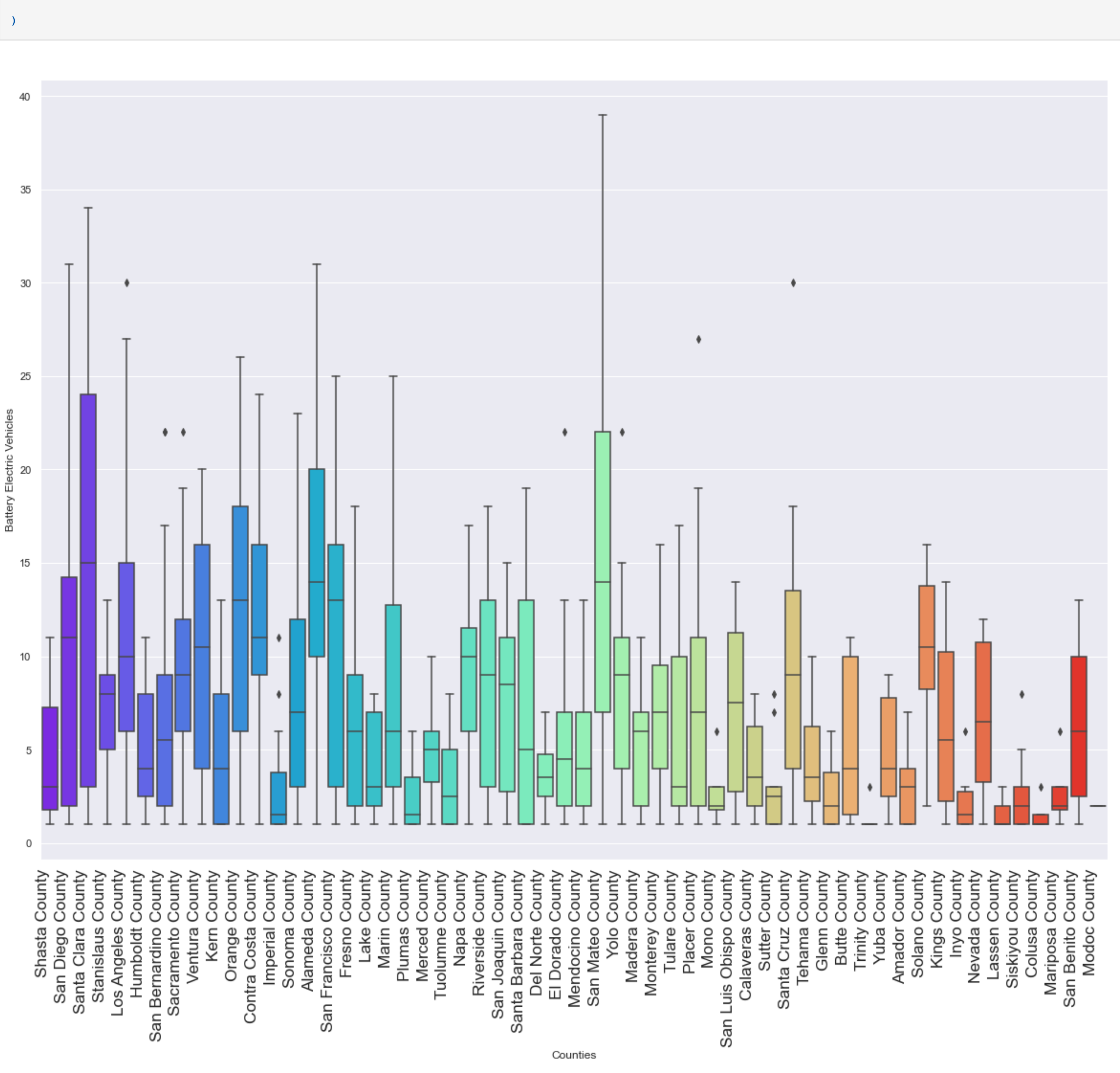


The below code creates a barplot for each California county, and illustrates the mean and range and outliers for the number of electric vehicles registered in each county.

In [24]:
```
sns.set(rc={'figure.figsize':(20,15)})
ax=sns.boxplot(x="Counties", y="Battery Electric Vehicles", data=EVsAndIncome,palette='rainbow')
ax.set_xticklabels(
    ax.get_xticklabels(),
    rotation=90,
    horizontalalignment='right',
    fontweight='light',
    fontsize='x-large'

)
```

Out[24]:



Summary

In all, the analysis did indeed reveal a correlation between income in an area, both zip code and county. While there was a positive correlation between average annual income (based on filed tax returns), it was perhaps not as strong as expected. There were stronger positive correlations between the number of registered electric vehicles and total tax liability, and annual gross income, for an entire zip code. This could indicate that wealthier areas have higher rates of electric vehicle adoption. However, further analysis may lead to more predictive results, as the plots here could also indicate a positive correlation between population density and the number of electric vehicles. Population density vs the number of battery-electric vehicle registrations would be my suggestion for future analysis.

Save to HTML

Save your notebook to HTML with the naming format of lastname_Executive_Summary.HTML

In [ ]: