INFO 2950 Final Project - Phase II

Research Question:

Question: Can we reliably predict future electric vehicle (EV) registration rates across US states over the next 5 years based on trends in renewable energy production, EV pricing, charging station availability, government incentives, and other relevant factors?

In this assignment, we collected and cleaned data on key variables relevant to our research question, such as renewable energy production, electric vehicle (EV) pricing, charging station availability, and government incentives. Our goal for this phase was to explore trends within these explanatory variables and analyze their correlation with our dependent variable—EV registration rates across all US states. For the final deliverable, we plan to employ a multivariable regression using these variables to build a predictive model.

While we've collected data across all states for this phase, we plan to narrow our focus for the final deliverable to the top 5, lowest 5, and middle 5 states based on EV registration rates. This will enable us to conduct a deeper, more focused analysis while refining our model. In our current exploration, we've observed significant differences among states; for example, Delaware shows minimized numbers compared to California. We also intend to explore additional variables that may enhance the accuracy of our final model.

Data Descriptions:

We collected 5 data tables for this phase: one pertaining to the variable we are aiming to predict, and four input variables for our model.

1. **Vehicle Registration Counts by State**
   - Data Source: US Department of Energy - Alternative Fuels Data Center (AFDC)
   - URL: https://afdc.energy.gov/vehicle-registration?year=2023

> Description: This page provides approximate light-duty vehicle registration counts derived by the National Renewable Energy Laboratory with data from Experian Information Solutions. Counts are rounded to the closest 100 vehicles and reflect the total number of light-duty registered vehicles through the selected year. Fuel types are based on vehicle identification numbers (VINs), which do not reflect aftermarket conversions to use different fuels or power sources.

2. **Renewable and Total Energy Production by State**
    - Data Source: US Energy Information Administration (EIA) – State Energy Data System (SEDS)
    - URL(s):
      Website - https://www.eia.gov/renewable/data.php
      File - https://www.eia.gov/state/seds/sep_prod/SEDS_Production_Report.pdf (pg 18-119)

    > Description: This report provides estimates of primary energy production (renewable and non-renewable) for all U.S. states from 1960 to 2022. Data is available in both physical units (e.g. short tons, cubic feet) and thermal units (British thermal units, Btu). The report includes various fuel types, including coal, natural gas, crude oil, fuel ethanol, biodiesel, and renewable diesel, offering a comprehensive view of energy production trends over time.

3. **EV Retail Prices by Models**
    - Data Source: US Department of Energy - Office of Energy efficiency & Renewable Energy
    - URL: https://www.fueleconomy.gov/feg/PowerSearch.do?
      action=noform&year1=2016&year2=2023&minmsrpsel=0&maxmsrpsel=0&city=0&hwy=0&comb=0&cbvtelectric=Electri
      2023&make=&mclass=&vfuel=&vtype=Electric&trany=&drive=&cyl=&MpgSel=000&sortBy=Comb&Units=&url=SearchSe

    > Description: This official website serves as a resource for consumers looking for detailed, fuel-related data about electric vehicles and allows them to compare EVs across various models and years in terms of price, fuel economy, and other specifications. This page specifically displays a list of electric vehicles (EVs) that match the search criteria set for model years between 2016 and 2023.

4. **EV Charge Stations**
    - Data Source: Open Charge Map
    - URL: https://openchargemap.org/site/develop/api#/

> Description: Open Charge Map's API provides access to a global database of electric vehicle charging locations. It offers a range of functionalities, including retrieving nearby charging stations, filtering stations by country, operator, or status, and contributing data such as new locations or updates. The API supports JSON and XML formats, allowing developers to integrate charging point information into apps, navigation systems, or research projects. The data is community-driven and free to use.

5. **State Incentives Related to Alternative Fuels and Vehicles**
    - Data Source: US Department of Energy - Alternative Fuels Data Center (AFDC)
    - URL: https://afdc.energy.gov/laws/state

> Description: The National Renewable Energy Laboratory (NREL) maintains a database of state and federal laws and incentives related to alternative fuels and vehicles, air quality, vehicle efficiency, and other transportation-related topics. State-level information is updated annually after each state's legislative session ends; necessary updates may be made independent of the legislative session schedule. Information for these updates is obtained from state legislative websites when the sites are deemed accurate and timely or by calling specific state offices directly. In addition, NREL maintains a resource list of the most useful websites and contacts for every state, as well as a list of search terms states routinely used in website searches.

Importing:

In [1]:
```
#pip install pdfplumber
```

In [2]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import requests
from bs4 import BeautifulSoup
import os
import re
import pdfplumber
import duckdb
from io import BytesIO
```

Data Scraping:

1. **Vehicle Registration Counts by State**
    - Data Source: US Department of Energy - Alternative Fuels Data Center (AFDC)
    - URL: https://afdc.energy.gov/vehicle-registration?year=2023

In [3]:
```
afdc_url = "https://afdc.energy.gov/vehicle-registration?year={}"
years = range(2016, 2024)

compiled_data = []

for year in years:
    url = afdc_url.format(year)
    afdc_result = requests.get(url)

    if afdc_result.status_code == 200:
        print(f"Scraping data for {year}...")

    page = BeautifulSoup(afdc_result.text, 'html.parser')

    table = page.find('table')

    if table:
        rows = table.find_all('tr')

        print(f"Found {len(rows)} rows in the table for {year}.")
```

```
        for row in rows[2:]:
            cols = row.find_all('td')
            cols = [col.text.strip() for col in cols]

            compiled_data.append([year] + cols)

    else:
        print(f"Failed to retrieve data for {year}: {afdc_result.status_code} - {afdc_result.reason}")


if table:
        header_row = table.find('tbody').find_all('tr')[0]
        headers = [td['headers'] for td in header_row.find_all('td')]
        clean_headers = []
        for header in headers:
            if header[0].isupper():
                    clean_headers.append(header[0].strip())
            else:
                    clean_headers.append(header[0].strip().capitalize())

        print(f"Headers found: {clean_headers}")

compiled_df = pd.DataFrame(compiled_data, columns=["Year"] + clean_headers)

print(compiled_df.head(n=5))
```

```
Scraping data for 2016...
Found 54 rows in the table for 2016.
Scraping data for 2017...
Found 54 rows in the table for 2017.
Scraping data for 2018...
Found 54 rows in the table for 2018.
Scraping data for 2019...
Found 54 rows in the table for 2019.
Scraping data for 2020...
Found 54 rows in the table for 2020.
Scraping data for 2021...
Found 54 rows in the table for 2021.
Scraping data for 2022...
Found 54 rows in the table for 2022.
Scraping data for 2023...
Found 54 rows in the table for 2023.
Headers found: ['State', 'Electric', 'PHEV', 'HEV', 'Biodiesel', 'Flex', 'CNG', 'Propane', 'Hydrogen', 'Met
hanol', 'Gas', 'Diesel', 'Unknown']
   Year       State Electric     PHEV      HEV Biodiesel       Flex     CNG  \
0  2016     Alabama      500      900   29,100         0    428,300  20,100
1  2016      Alaska      200      200    5,000         0     55,700   4,900
2  2016     Arizona    4,700    4,400   89,600         0    427,300  17,500
3  2016    Arkansas      200      500   19,100         0    320,500  12,600
4  2016  California  141,500  116,700  966,700         0  1,322,600  80,600

  Propane Hydrogen Methanol         Gas   Diesel  Unknown
0       0        0        0   3,777,300  126,500   53,900
1       0        0        0     525,900   44,800   19,400
2       0        0      100   4,805,000  179,500  112,800
3       0        0        0   2,097,800   96,800   22,200
4       0    1,300      400  27,241,000  710,400  115,500
```

2. **Renewable and Total Energy Production by State**
   - Data Source: US Energy Information Administration (EIA) – State Energy Data System (SEDS)
   - URL(s):

     Website - https://www.eia.gov/renewable/data.php

     File - https://www.eia.gov/state/seds/sep_prod/SEDS_Production_Report.pdf (pg 18-119)

In [4]:
```python
def extract_pdf(pdf_url, start_page, end_page):
    response = requests.get(pdf_url)
```

```
    if response.status_code == 200:
        file = BytesIO(response.content)

        with pdfplumber.open(file) as pdf:
            all_tables = []

            for i in range(start_page, end_page):
                one_page = []
                count = 0

                page = pdf.pages[i]
                text = page.extract_text()

                entries = re.findall(r'NA|\(s\)|\b\d{1,3}(?:,\d{3})*(?:\.\d+)?\b', text)

                cleaned_entries = [float(num.replace(',', '')) if num not in ['NA', '(s)'] else num for nur

                one_page.extend(cleaned_entries)
                count += len(cleaned_entries)

                one_page = one_page[:354]

                reshaped_data = np.array(one_page).reshape(59, 6)

                all_tables.append(reshaped_data)

            return all_tables

    else:
        return "Something went wrong"

pdf_url = 'https://www.eia.gov/state/seds/sep_prod/SEDS_Production_Report.pdf'

data = extract_pdf(pdf_url, 17, 119)
```

In [5]:
```
states = ["Alabama", "Alaska", "Arizona", "Arkansas",
          "California", "Colorado", "Connecticut",
          "Delaware", "District of Columbia", "Florida",
          "Georgia", "Hawaii", "Idaho", "Illinois",
          "Indiana", "Iowa", "Kansas", "Kentucky",
          "Louisiana", "Maine", "Maryland", "Massachusetts",
```

```
          "Michigan", "Minnesota", "Mississippi", "Missouri",
          "Montana", "Nebraska", "Nevada", "New Hampshire",
          "New Jersey", "New Mexico", "New York", "North Carolina",
          "North Dakota", "Ohio", "Oklahoma", "Oregon", "Pennsylvania",
          "Rhode Island", "South Carolina", "South Dakota", "Tennessee",
          "Texas", "Utah", "Vermont", "Virginia", "Washington",
          "West Virginia", "Wisconsin", "Wyoming"]

physical_units = []
thermal_units = []

for j in range(len(data)):
    df = pd.DataFrame(data[j])

    if j % 2 == 0:
        state_index = j//2
        df.insert(0, 'State', states[state_index])
        physical_units.append(df)

    else:
        state_index = (j-1)//2
        df.insert(0, 'State', states[state_index])
        thermal_units.append(df)


physical_units_df = pd.concat(physical_units, ignore_index=True)

physical_units_df.insert(1, 'Units', "Physical")
physical_units_df.rename(
    columns={
            0: 'Coal (K short tons)',
            1: 'Natural Gas (M cubic ft)',
            2: 'Crude Oil (K barrels)',
            3: 'Fuel Ethanol (K barrels)',
            4: 'Biodiesel (K barrels)',
            5: 'Renewable Diesel (K barrels)'
        }, inplace=True)


thermal_units_df = pd.concat(thermal_units, ignore_index=True)

thermal_units_df.insert(1, 'Units', "Thermal")
```

```
thermal_units_df.rename(
        columns={
            0: 'Coal (T Btu)',
            1: 'Natural Gas (T Btu)',
            2: 'Crude Oil (T Btu)',
            3: 'Fuel Ethanol (T Btu)',
            4: 'Biodiesel (T Btu)',
            5: 'Renewable Diesel (T Btu)'
        }, inplace=True)

display(physical_units_df)
display(thermal_units_df)
```

	State	Units	Coal (K short tons)	Natural Gas (M cubic ft)	Crude Oil (K barrels)	Fuel Ethanol (K barrels)	Biodiesel (K barrels)	Renewable Diesel (K barrels)
0	Alabama	Physical	13011.0	57.0	7329.0	NA	NA	NA
1	Alabama	Physical	14832.0	203.0	8064.0	NA	NA	NA
2	Alabama	Physical	14219.0	252.0	8030.0	NA	NA	NA
3	Alabama	Physical	15486.0	248.0	7348.0	NA	NA	NA
4	Alabama	Physical	16440.0	230.0	7635.0	NA	NA	NA
...	...	...	...	...	...	...	...	...
3004	Wyoming	Physical	304188.0	1637517.0	87.0	0.0	0.0	276912.0
3005	Wyoming	Physical	1488854.0	102.0	0.0	0.0	2.0	218556.0
3006	Wyoming	Physical	1206.0	89.0	0.0	0.0	2.0	238773.0
3007	Wyoming	Physical	1109.0	85.0	0.0	0.0	2289.0	244730.0
3008	Wyoming	Physical	1032634.0	90906.0	0.0	0.0	3320.0	NA

3009 rows × 8 columns

	State	Units	Coal (T Btu)	Natural Gas (T Btu)	Crude Oil (T Btu)	Fuel Ethanol (T Btu)	Biodiesel (T Btu)	Renewable Diesel (T Btu)
0	Alabama	Thermal	318.8	0.1	42.5	0.0	NA	45.7
1	Alabama	Thermal	21.0	428.0	363.4	0.3	46.8	0.0
2	Alabama	Thermal	NA	47.6	24.0	482.0	348.4	0.4
3	Alabama	Thermal	46.6	0.0	NA	49.1	23.0	468.0
4	Alabama	Thermal	379.5	0.4	42.6	0.0	NA	49.1
...	...	...	...	...	...	...	...	...
3004	Wyoming	Thermal	0.7	0.9	4.0	8989.0	7019.8	1811.9
3005	Wyoming	Thermal	300.3	0.0	0.7	2.4	6.0	9141.0
3006	Wyoming	Thermal	7740.0	1990.7	307.2	0.0	0.7	2.1
3007	Wyoming	Thermal	6.0	10046.0	7847.6	2231.3	313.9	0.0
3008	Wyoming	Thermal	0.7	2.3	5.0	10401.0	8087.4	2463.0

3009 rows × 8 columns

3. **EV Manufacturer Suggested Retail Prices and Annual Fuel Cost (by Models)**
    - Data Source: US Department of Energy - Office of Energy efficiency & Renewable Energy
    - URL: https://www.fueleconomy.gov/feg/PowerSearch.do?action=noform&year1=2016&year2=2023&minmsrpsel=0&maxmsrpsel=0&city=0&hwy=0&comb=0&cbvtelectric=Electri 2023&make=&mclass=&vfuel=&vtype=Electric&trany=&drive=&cyl=&MpgSel=000&sortBy=Comb&Units=&url=SearchSe

In [6]:
```
# List of URLs for multiple pages
urls = [
    'https://www.fueleconomy.gov/feg/PowerSearch.do?action=noform&year1=2016&year2=2023&minmsrpsel=0&maxms
    'https://www.fueleconomy.gov/feg/PowerSearch.do?action=noform&year1=2016&year2=2023&minmsrpsel=0&maxms
    'https://www.fueleconomy.gov/feg/PowerSearch.do?action=noform&year1=2016&year2=2023&minmsrpsel=0&maxms
]

# Initialize lists for data storage
```

```
years = []
models = []
annual_fuel_costs = []
msrp_prices = []

# Loop over each URL to fetch data from multiple pages
for url in urls:
    # Send request and parse HTML
    response = requests.get(url)
    soup = BeautifulSoup(response.content, 'html.parser')

    # Find all 'tr' tags with the 'ymm-row' class
    vehicle_rows = soup.find_all('tr', class_='ymm-row')

    # Loop over each 'ymm-row' and find the next row for cost and msrp
    for vehicle_row in vehicle_rows:
        # Get vehicle details
        vehicle_tag = vehicle_row.find('a')
        if vehicle_tag:
            vehicle_text = vehicle_tag.get_text(strip=True)
            year, model = vehicle_text.split(' ', 1)  # Split on the first space to separate year and mode
            years.append(year)
            models.append(model)
        else:
            years.append(np.nan)
            models.append(np.nan)

        # Find the next sibling row for cost and MSRP
        cost_row = vehicle_row.find_next_sibling('tr')
        if cost_row:
            fuel_cost_tag = cost_row.find('td', class_='ann-fuel-cost')
            msrp_tag = cost_row.find('td', class_='msrp')

            # Check if MSRP exists, else skip this entry
            if msrp_tag:
                # Process fuel cost
                if fuel_cost_tag:
                    fuel_cost_text = fuel_cost_tag.get_text(strip=True)
                    annual_fuel_costs.append(fuel_cost_text.replace('\r', '').replace('\n', '').replace('\
                else:
                    annual_fuel_costs.append(np.nan)
```

```
                # Process MSRP and clean up
                msrp_text = msrp_tag.get_text(strip=True)
                msrp_cleaned = msrp_text.replace('\r', '').replace('\n', '').replace('\t', '')
                msrp_prices.append(msrp_cleaned)
            else:
                # If MSRP is missing, skip this entry
                years.pop()  # Remove the last added item from years
                models.pop()  # Remove the last added item from models
        else:
            # If there's no next row, remove the last entry
            years.pop()
            models.pop()

# Create DataFrame
pricing_data = {
    'Year': years,
    'Model': models,
    'Annual Fuel Cost': annual_fuel_costs,
    'MSRP': msrp_prices
}
pricing_df = pd.DataFrame(pricing_data)

# Convert 'Year' to numeric for sorting, ignoring errors for NaN
pricing_df['Year'] = pd.to_numeric(pricing_df['Year'], errors='coerce')

# Sort by Year
pricing_df_sorted = pricing_df.sort_values(by='Year', ascending=True)

# Display the DataFrame
print(pricing_df_sorted)
```

```
     Year                                            Model Annual Fuel Cost  \
94   2016      Nissan Leaf (24 kW-hr battery pack)                 $650
29   2016                                      BMW i3 BEV                 $600
157  2016         smart fortwo electric drive coupe                 $700
156  2016   smart fortwo electric drive convertible                 $700
229  2016      Tesla Model S (60 kW-hr battery pack)                 $750
..    ...                                              ...                 ...
307  2023                          Volvo C40 Recharge twin                 $850
309  2023                                  Vinfast VF 8 Eco                 $850
310  2023   Nissan ARIYA PLAT Plus e-4ORCE 87kWh 20                 $850
314  2023     BMW i7 xDrive60 Sedan (21 inch wheels)                 $850
441  2023                               Lordstown Endurance               $1,600

                MSRP
94   $29,010- $36,790
29            $42,400
157
156
229           $66,000
..                ...
307  $55,300- $60,100
309           $49,000
310
314          $119,300
441

[442 rows x 4 columns]
```

4. **EV Charge Stations**
    - Data Source: Open Charge Map
    - Website URL: https://openchargemap.org/site/develop/api#
    - Data Description: Open Charge Map's API provides access to a global database of electric vehicle charging locations. It offers a range of functionalities, including retrieving nearby charging stations, filtering stations by country, operator, or status, and contributing data such as new locations or updates. The API supports JSON and XML formats, allowing developers to integrate charging point information into apps, navigation systems, or research projects. The data is community-driven and free to use.

`ocm_us_data.csv` contains charging station data in the US. This csv file was generated by using Open Charge Map's public API. Using Postman, we sent the following HTTPS GET request (API key is ommitted):

`https://api.openchargemap.io/v3/poi?key=apikey&countrycode=US&includecomments=false&maxresults=9999999&output=csv`

The `key` parameter sets our API key so we can call the API. The `countrycode` parameter filters for US charging stations only. The `include comments` parameter removes use comments from the returned data for efficiency. The `maxresults` parameter ensures all data on US charging stations is returned (100 is default, maxresults=9999999 returns the same data as maxresults=999999 so we know our upper limit is high enough). Finally, the `output` parameter ensures our returned data is in the form of a csv file.

Data Cleaning:

1. **EV Registration Data**

Since we want to predict the EV registration rate, we first need to convert the registration data into numeric types for future use.

In [7]:
```
def clean_regis(regis):
    if pd.isna(regis):
        return None
    regis = regis.replace(',', '').strip()
    return float(regis)

compiled_df['Electric'] = compiled_df['Electric'].apply(clean_regis)
print(compiled_df)
```

```
     Year          State   Electric       PHEV        HEV  Biodiesel  \
0    2016        Alabama      500.0        900     29,100          0   
1    2016         Alaska      200.0        200      5,000          0   
2    2016        Arizona     4700.0      4,400     89,600          0   
3    2016       Arkansas      200.0        500     19,100          0   
4    2016     California   141500.0    116,700    966,700          0   
..    ...            ...        ...        ...        ...        ...   
411  2023     Washington   152100.0     41,200    307,200     73,800   
412  2023  West Virginia     2800.0      1,800     22,400     17,300   
413  2023      Wisconsin    24900.0     12,500    123,600     52,900   
414  2023        Wyoming     1100.0        800      8,400     21,200   
415  2023  United States  3555900.0  1,307,200  7,392,300  2,803,600   

           Flex     CNG Propane Hydrogen Methanol          Gas     Diesel  \
0       428,300  20,100       0        0        0    3,777,300    126,500   
1        55,700   4,900       0        0        0      525,900     44,800   
2       427,300  17,500       0        0      100    4,805,000    179,500   
3       320,500  12,600       0        0        0    2,097,800     96,800   
4     1,322,600  80,600       0    1,300      400   27,241,000    710,400   
..          ...     ...     ...      ...      ...          ...        ...   
411     337,700     100     100        0        0    5,583,000    274,200   
412     123,400     100       0        0        0    1,281,500     46,400   
413     536,200     300       0        0        0    4,604,700    147,500   
414      57,700       0       0        0        0      489,100     60,900   
415  20,240,600  24,700   6,000   16,900        0  242,870,900  7,184,300   

       Unknown  
0       53,900  
1       19,400  
2      112,800  
3       22,200  
4      115,500  
..         ...  
411     46,700  
412     15,200  
413     26,400  
414     13,700  
415  1,694,100  

[416 rows x 14 columns]
```

2. **EV Manufacturer Suggested Retail Prices and Annual Fuel Cost (by Models)**

To look into the pricing data, we clean the MSRP column from our pricing dataset, which contain values in different formats (e.g., ranges, with dollar signs, commas, etc.). We also drop rows with missing prices.

In [8]:
```
# print(pricing_df_sorted['MSRP'])

# handle MSRP ranges and convert to numeric
def clean_msrp(msrp):
    if pd.isna(msrp) or msrp.strip() == '':  # Check for NaN or empty string
        return None
    msrp = msrp.replace('$', '').replace(',', '').strip()  # Remove $, commas, and spaces
    if '- ' in msrp:  # Handle price ranges
        low, high = msrp.split('-')
        return (float(low) + float(high)) / 2
    else:
        return float(msrp)  # Convert single price values to float

pricing_df_sorted['MSRP'] = pricing_df_sorted['MSRP'].apply(clean_msrp)

# drop rows where MSRP is NaN
pricing_df_sorted = pricing_df_sorted.dropna(subset=['MSRP'])

print(pricing_df_sorted)
```

```
     Year                               Model Annual Fuel Cost      MSRP
94   2016     Nissan Leaf (24 kW-hr battery pack)             $650   32900.0
29   2016                          BMW i3 BEV             $600   42400.0
229  2016   Tesla Model S (60 kW-hr battery pack)             $750   66000.0
237  2016   Tesla Model S (75 kW-hr battery pack)             $750   74500.0
240  2016             Tesla Model S AWD - P100D             $800  134500.0
..    ...                                 ...              ...       ...
73   2023                Kia EV6 Long Range RWD             $650   42600.0
306  2023  BMW i7 xDrive60 Sedan (19 inch wheels)             $850  119300.0
307  2023               Volvo C40 Recharge twin             $850   57700.0
309  2023                      Vinfast VF 8 Eco             $850   49000.0
314  2023  BMW i7 xDrive60 Sedan (21 inch wheels)             $850  119300.0

[323 rows x 4 columns]
```

3. **Electric Vehicle State Incentives**

In [9]:
```
# Get the current working directory instead of using __file__
current_dir = os.getcwd()

# Loading state incentives data
incentives_file_path = os.path.join(current_dir, 'csv_data_files', 'state_laws_and_incentives.csv')
# Read the CSV file into a DataFrame
state_incentives_df = pd.read_csv(incentives_file_path)

# Preview the data
display(state_incentives_df.head(20))
```

	Law Id	State	Title	Text	Enacted Date	Amended Date	Recent?	Sequence Number	Type	Agency	...	Archi D
0	284	US	Congestion Mitigation and Air Quality (CMAQ) I...	The CMAQ Program provides funding to state dep...	2005-08-10 00:00:00 UTC	2021-11-15 00:00:00 UTC	False	54.0	Incentives	U.S. Department of Transportation	...	
1	288	US	Clean Cities and Communities	The mission of Clean Cities and Communities is...	NaN	NaN	False	21.0	Programs	U.S. Department of Energy	...	
2	317	US	State Energy Program (SEP) Funding	The SEP provides grants to states to assist in...	NaN	2021-11-15 00:00:00 UTC	False	26.0	Incentives	U.S. Department of Energy	...	
3	323	US	Clean School Bus	The U.S. Environmental Protection Agency's (EP...	NaN	2021-11-15 00:00:00 UTC	False	33.0	Incentives	U.S. Environmental Protection Agency	...	
4	324	US	Clean Construction and Agriculture	Clean Construction is a voluntary program that...	NaN	NaN	False	34.0	Programs	U.S. Environmental Protection Agency	...	
5	325	US	Ports Initiative	The U.S. Environmental Protection Agency\'s (E...	NaN	NaN	False	34.0	Programs	U.S. Environmental Protection Agency	...	
6	383	US	Voluntary Airport Low Emission (VALE) Program	The goal of the VALE Program is to reduce grou...	2005-08-10 00:00:00 UTC	NaN	False	56.0	Programs	U.S. Department of Transportation	...	

	Law Id	State	Title	Text	Enacted Date	Amended Date	Recent?	Sequence Number	Type	Agency	...	Archi D
7	392	US	Electric Vehicle (EV) and Fuel Cell Electric V...	The U.S. Department of Energy (DOE) provides g...	2005-08-08 00:00:00 UTC	2022-08-16 00:00:00 UTC	False	27.0	Incentives	U.S. Department of Energy	...	
8	409	US	Electric Vehicle (EV) and Fuel Cell Electric V...	The Inflation Reduction Act of 2022 (Public La...	2008-10-03 00:00:00 UTC	2022-08-16 00:00:00 UTC	False	18.0	Incentives	U.S. Internal Revenue Service	...	
9	411	US	Advanced Technology Vehicle (ATV) and Alternat...	The U.S. Department of Energy's (DOE) Advanced...	2007-12-17 00:00:00 UTC	2021-08-16 00:00:00 UTC	False	NaN	Incentives	U.S. Department of Energy	...	
10	4178	AZ	Zero Emission Vehicle Emissions Test Exemption	Electric vehicles registered in Arizona are no...	2016-01-01 00:00:00 UTC	NaN	False	42.0	State Incentives	NaN	...	
11	4179	AZ	Reduced Alternative Fuel Vehicle (AFV) License...	The vehicle license tax for an AFV registered ...	2018-04-25 00:00:00 UTC	2019-06-07 00:00:00 UTC	False	30.0	State Incentives	NaN	...	
12	4219	CA	Employer Invested Emissions Reduction Funding ...	The South Coast Air Quality Management Distric...	NaN	NaN	False	80.0	State Incentives	NaN	...	
13	4241	CA	Electric Vehicle (EV) Charging Rate Reduction ...	The Sacramento Municipal Utility District (SMU...	NaN	NaN	False	149.0	Utility / Private Incentives	NaN	...	

	Law Id	State	Title	Text	Enacted Date	Amended Date	Recent?	Sequence Number	Type	Agency	...	Archi D
14	4272	CO	Alternative Fuel Vehicle (AFV) Weight Exemption	Gross vehicle weight rating limits for AFVs ar...	2016-05-04 00:00:00 UTC	NaN	False	35.0	State Incentives	NaN	...	
15	4378	IL	Fleet User Fee Exemption	Fleets with 10 or more vehicles located in def...	2004-08-12 00:00:00 UTC	NaN	False	60.0	State Incentives	NaN	...	
16	4684	OR	Alternative Fuel Loans	The Oregon Department of Energy administers th...	2005-06-14 00:00:00 UTC	2011-08-05 00:00:00 UTC	False	11.0	State Incentives	NaN	...	
17	4780	VA	High Occupancy Vehicle (HOV) Lane Exemption	Alternative fuel vehicles (AFVs) displaying th...	NaN	2012-04-18 00:00:00 UTC	False	25.0	State Incentives	NaN	...	
18	4781	VA	Alternative Fuel School Bus and Fueling Infras...	The Virginia Board of Education may use fundin...	NaN	NaN	False	40.0	Laws and Regulations	NaN	...	
19	4806	WA	Alternative Fuel Vehicle (AFV) Emissions Inspe...	AFVs powered exclusively by electricity, natur...	NaN	NaN	False	55.0	State Incentives	NaN	...	

20 rows × 22 columns

In [10]:
```
# Drop unecessary columns
incentives_cols_to_drop = ['Law Id', 'Text', 'Recent?', 'Sequence Number',
                           'Agency', 'Topic','Technology Categories', 'Archived Date',
```

```
                                'Amended Date', 'Repealed Date', 'User Categories',
                                'References', 'Status Date','Regulation Categories',
                                'Significant Update Date']
state_incentives_df = state_incentives_df.drop(columns=incentives_cols_to_drop)
```

In [11]:
```
# Drop rows that contain national-level data
state_incentives_df = state_incentives_df[state_incentives_df['State'] != 'US']

# Filter Type to only display state incentives
state_incentives_df = state_incentives_df[
state_incentives_df['Type'] == 'State Incentives']

# Sort data in alphabetical order by state and enacted date
state_incentives_df = state_incentives_df.sort_values(by=['State', 'Enacted Date'],
                                                      ascending=[True,True])
state_incentives_df.reset_index(drop=True, inplace=True)

state_incentives_df.head(20)
```

Out[11]:

	State	Title	Enacted Date	Type	Expired Date	Incentive Categories	Status
0	AK	Alaska's National Electric Vehicle Infrastruct...	NaN	State Incentives	NaN	GNT	NaN
1	AL	Electric Vehicle (EV) Charger and Medium- and ...	NaN	State Incentives	NaN	RBATE	NaN
2	AL	Electric Vehicle (EV) Chargers Grants	NaN	State Incentives	NaN	GNT	NaN
3	AL	Alabama's National Electric Vehicle Infrastruc...	NaN	State Incentives	NaN	GNT	NaN
4	AR	Arkansas' National Electric Vehicle Infrastruc...	NaN	State Incentives	NaN	GNT	NaN
5	AR	Diesel Emissions Reduction Grants	NaN	State Incentives	NaN	GNT	NaN
6	AR	Clean Fuels Program	NaN	State Incentives	NaN	GNT	NaN
7	AR	Bus Replacement Grants	NaN	State Incentives	NaN	GNT	NaN
8	AZ	Alternative Fuel Vehicle (AFV) Parking Incentive	2013-01-01 00:00:00 UTC	State Incentives	NaN	EXEM	enacted
9	AZ	Zero Emission Vehicle Emissions Test Exemption	2016-01-01 00:00:00 UTC	State Incentives	NaN	EXEM	enacted
10	AZ	Reduced Alternative Fuel Vehicle (AFV) License...	2018-04-25 00:00:00 UTC	State Incentives	NaN	TAX	amended
11	AZ	Alternative Fuel and Alternative Fuel Vehicle ...	NaN	State Incentives	NaN	EXEM|TAX	NaN
12	AZ	High Occupancy Vehicle (HOV) Lane Exemption	NaN	State Incentives	2025-09-30 00:00:00 UTC	EXEM	NaN
13	AZ	Arizona's National Electric Vehicle Infrastruc...	NaN	State Incentives	NaN	GNT	NaN

	State	Title	Enacted Date	Type	Expired Date	Incentive Categories	Status
14	CA	High Occupancy Vehicle (HOV) and High Occupanc...	2006-09-29 00:00:00 UTC	State Incentives	NaN	EXEM	amended
15	CA	Alternative Fuel and Vehicle Incentives	2007-10-14 00:00:00 UTC	State Incentives	NaN	GNT|LOANS	amended
16	CA	Low Emission Truck and Bus Purchase Vouchers	2010-02-01 00:00:00 UTC	State Incentives	NaN	OTHER|RBATE	enacted
17	CA	Advanced Transportation Tax Exclusion	2010-03-24 00:00:00 UTC	State Incentives	NaN	EXEM|TAX	amended
18	CA	Residential Electric Vehicle (EV) Charger Fina...	2014-09-26 00:00:00 UTC	State Incentives	NaN	LOANS	enacted
19	CA	Electric Vehicle (EV) Charger Incentives - San...	2015-10-01 00:00:00 UTC	State Incentives	NaN	GNT	enacted

In [12]:

```
# Convert each date column to the same datetime format
date_columns = ['Enacted Date', 'Expired Date']

for column in date_columns:
    state_incentives_df[column] = pd.to_datetime(state_incentives_df[column],
                                                 errors='coerce')
    # Extract the year directly
    state_incentives_df[column] = state_incentives_df[column].dt.year

# Check the resulting DataFrame
state_incentives_df.head(20)
state_incentives_df.shape
```

Out[12]: (306, 7)

In [13]:

```
# Drop rows with inactive state incentives
start_date = 2016
end_date = 2023
active_state_incentives_df = state_incentives_df[
    (state_incentives_df['Enacted Date'] <= end_date) &
    ((state_incentives_df['Expired Date'] >= start_date) |
     (state_incentives_df['Expired Date'].isna()))]
```

```
active_state_incentives_df.reset_index(drop=True, inplace=True)

# Dictionary to map state abbreviations to full names
state_abbreviation_to_name = {
    'AL': 'Alabama', 'AK': 'Alaska', 'AZ': 'Arizona', 'AR': 'Arkansas',
    'CA': 'California','CO': 'Colorado', 'CT': 'Connecticut', 'DE': 'Delaware',
    'FL': 'Florida', 'GA': 'Georgia','HI': 'Hawaii', 'ID': 'Idaho',
    'IL': 'Illinois', 'IN': 'Indiana', 'IA': 'Iowa', 'KS': 'Kansas',
    'KY': 'Kentucky', 'LA': 'Louisiana', 'ME': 'Maine', 'MD': 'Maryland',
    'MA': 'Massachusetts', 'MI': 'Michigan', 'MN': 'Minnesota',
    'MS': 'Mississippi', 'MO': 'Missouri', 'MT': 'Montana', 'NE': 'Nebraska',
    'NV': 'Nevada', 'NH': 'New Hampshire','NJ': 'New Jersey', 'NM': 'New Mexico',
    'NY': 'New York', 'NC': 'North Carolina', 'ND': 'North Dakota', 'OH': 'Ohio',
    'OK': 'Oklahoma', 'OR': 'Oregon', 'PA': 'Pennsylvania', 'RI': 'Rhode Island',
    'SC': 'South Carolina', 'SD': 'South Dakota', 'TN': 'Tennessee',
    'TX': 'Texas', 'UT': 'Utah', 'VT': 'Vermont', 'VA': 'Virginia',
    'WA': 'Washington', 'WV': 'West Virginia', 'WI': 'Wisconsin', 'WY': 'Wyoming'
}

active_state_incentives_df.loc[:, 'State'] = active_state_incentives_df['State'].map(state_abbreviation_to_
active_state_incentives_df
```

Out[13]:

	State	Title	Enacted Date	Type	Expired Date	Incentive Categories	Status
0	Arizona	Alternative Fuel Vehicle (AFV) Parking Incentive	2013.0	State Incentives	NaN	EXEM	enacted
1	Arizona	Zero Emission Vehicle Emissions Test Exemption	2016.0	State Incentives	NaN	EXEM	enacted
2	Arizona	Reduced Alternative Fuel Vehicle (AFV) License...	2018.0	State Incentives	NaN	TAX	amended
3	California	High Occupancy Vehicle (HOV) and High Occupanc...	2006.0	State Incentives	NaN	EXEM	amended
4	California	Alternative Fuel and Vehicle Incentives	2007.0	State Incentives	NaN	GNT|LOANS	amended
...	...	...	...	...	...	...	...
107	Washington	Alternative Fueling Infrastructure Grant Program	2015.0	State Incentives	NaN	GNT	amended
108	Washington	Green Transportation Grant Program	2019.0	State Incentives	NaN	GNT	enacted
109	Washington	Alternative Fuel Vehicle (AFV) Retail Sales an...	2019.0	State Incentives	2028.0	EXEM	enacted
110	Washington	Zero Emission Vehicle (ZEV) Carshare Grant	2022.0	State Incentives	NaN	GNT	enacted
111	Wisconsin	Alternative Fuel Tax Exemption	1993.0	State Incentives	NaN	EXEM|TAX	enacted

112 rows × 7 columns

4. **Electric Vehicle Charge Stations**

In [14]:

```
ocm_us_df = pd.read_csv("csv_data_files/ocm_us_data.csv", dtype={"DateLastConfirmed": 'string'})

#cleaning DateCreated column
ocm_us_df["DateCreated"] = pd.to_datetime(ocm_us_df['DateCreated'], format='%m/%d/%Y %H:%M:%S %p')
```

```
ocm_us_df["YearCreated"] = ocm_us_df["DateCreated"].dt.year

#cleaning StateOrProvince column
state_map = {
    'Alabama': 'AL', 'Alaska': 'AK', 'Arizona': 'AZ', 'Arkansas': 'AR', 'California': 'CA',
    'Colorado': 'CO', 'Connecticut': 'CT', 'Delaware': 'DE', 'Florida': 'FL', 'Georgia': 'GA',
    'Hawaii': 'HI', 'Idaho': 'ID', 'Illinois': 'IL', 'Indiana': 'IN', 'Iowa': 'IA',
    'Kansas': 'KS', 'Kentucky': 'KY', 'Louisiana': 'LA', 'Maine': 'ME', 'Maryland': 'MD',
    'Massachusetts': 'MA', 'Michigan': 'MI', 'Minnesota': 'MN', 'Mississippi': 'MS',
    'Missouri': 'MO', 'Montana': 'MT', 'Nebraska': 'NE', 'Nevada': 'NV', 'New Hampshire': 'NH',
    'New Jersey': 'NJ', 'New Mexico': 'NM', 'New York': 'NY', 'North Carolina': 'NC',
    'North Dakota': 'ND', 'Ohio': 'OH', 'Oklahoma': 'OK', 'Oregon': 'OR', 'Pennsylvania': 'PA',
    'Rhode Island': 'RI', 'South Carolina': 'SC', 'South Dakota': 'SD', 'Tennessee': 'TN',
    'Texas': 'TX', 'Utah': 'UT', 'Vermont': 'VT', 'Virginia': 'VA', 'Washington': 'WA',
    'West Virginia': 'WV', 'Wisconsin': 'WI', 'Wyoming': 'WY'
}
state_map.update({v: v for v in state_map.values()})

ocm_us_df["StateOrProvince"] = ocm_us_df["StateOrProvince"].map(state_map)
ocm_us_df = ocm_us_df[ocm_us_df["StateOrProvince"].isin(state_map.keys())]
ocm_us_df["State"] = ocm_us_df["StateOrProvince"]

ocm_us_df_grouped = duckdb.sql("SELECT State, YearCreated AS Year, \
COUNT(State) AS NewStationsCreated FROM ocm_us_df GROUP BY State, YearCreated ORDER BY Year ASC, State ASC'
ocm_us_df_grouped["TotalStations"] = ocm_us_df_grouped.groupby("State")["NewStationsCreated"].cumsum()

ocm_us_df_limited = ocm_us_df_grouped.loc[(ocm_us_df_grouped["Year"] > 2015) & (ocm_us_df_grouped["Year"] <
print(ocm_us_df_limited.shape)

#comparing with registered EV data
reg_data = pd.read_csv('csv_data_files/ev_registration_data.csv')
reg_data["State"] = reg_data["State"].map(state_map)

combined_df = duckdb.sql("SELECT reg_data.State, reg_data.Year, TotalStations, Electric \
FROM ocm_us_df_limited INNER JOIN reg_data ON reg_data.Year = ocm_us_df_limited.Year AND reg_data.State = o
combined_df["Electric"] = combined_df["Electric"].str.replace(",", "").astype(float)

print(combined_df.head())
print(combined_df.shape)
```

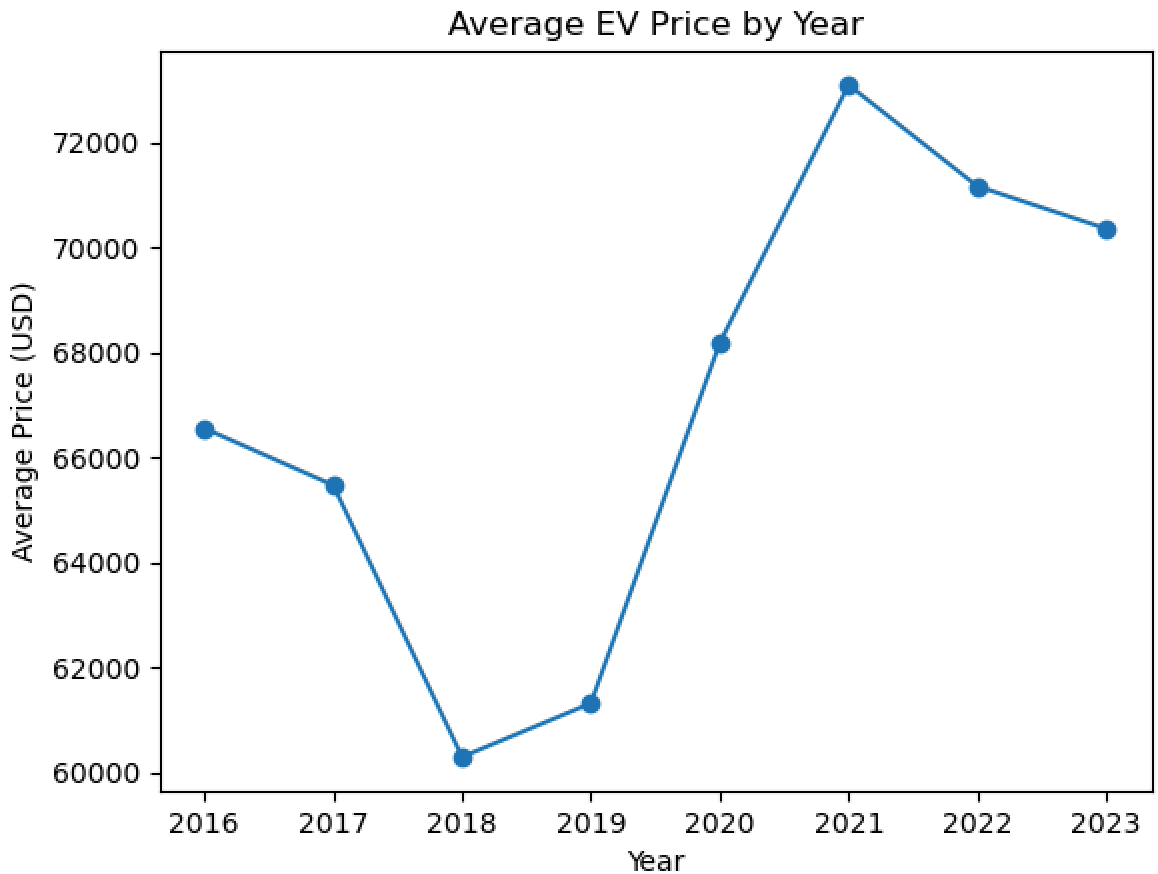
```
(372, 4)
  State  Year  TotalStations  Electric
0    AL  2016             49     500.0
1    AZ  2016             98    4700.0
2    AR  2016             24     200.0
3    CA  2016           1413  141500.0
4    CO  2016            222    5300.0
(372, 4)
```

Exploratory Data Analysis:

1. **EV Manufacturer Suggested Retail Prices (by Models)**

We want to explore the trend of average EV prices over the years. We first calculates the average EV price (MSRP) for each year. And we plots the trend of EV prices over time, providing insights into how EV prices have changed year over year.

In [15]:
```
# calculate the average MSRP by year
avg_prices_per_year = pricing_df_sorted.groupby('Year')['MSRP'].mean()

plt.plot(avg_prices_per_year.index, avg_prices_per_year.values, marker='o')
plt.title('Average EV Price by Year')
plt.xlabel('Year')
plt.ylabel('Average Price (USD)')
plt.show()
```

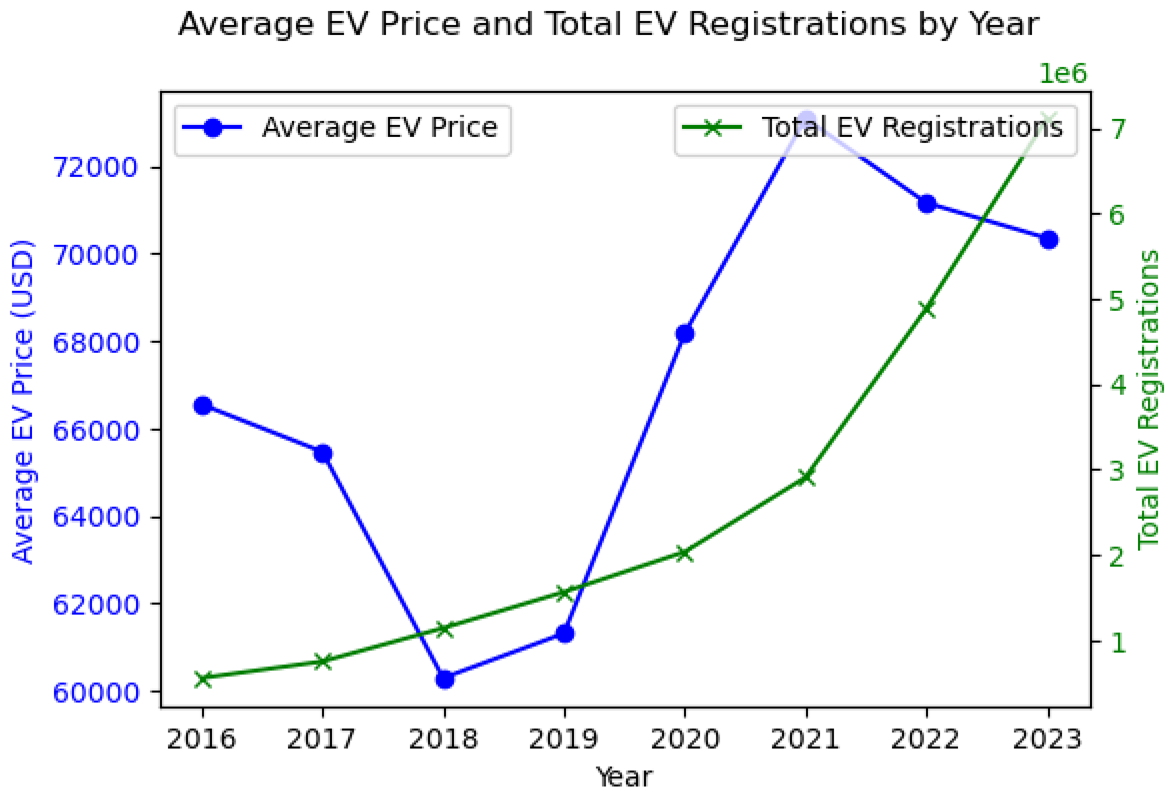


Here we compute the annual registration and visualize the relationship between the average EV price and total EV registrations over the years on a single chart.

In [16]:
```
annual_registrations = compiled_df.groupby('Year')['Electric'].sum()
print(annual_registrations.head())

# Create a figure and axis
fig, ax1 = plt.subplots(figsize=(6, 4))

# Plot the average EV price with ax1
ax1.set_xlabel('Year')
ax1.set_ylabel('Average EV Price (USD)', color='blue')
ax1.plot(avg_prices_per_year.index, avg_prices_per_year.values, label='Average EV Price', color='blue', ma
```

```
ax1.tick_params(axis='y', labelcolor='blue')

# Create a second y-axis for total EV registrations
ax2 = ax1.twinx()
ax2.set_ylabel('Total EV Registrations', color='green')
ax2.plot(annual_registrations.index, annual_registrations.values, label='Total EV Registrations', color='g
ax2.tick_params(axis='y', labelcolor='green')

# Add title and legends
fig.suptitle('Average EV Price and Total EV Registrations by Year')
ax1.legend(loc='upper left')
ax2.legend(loc='upper right')

plt.show()
```

```
Year
2016     560600.0
2017     754200.0
2018    1145200.0
2019    1567200.0
2020    2037800.0
Name: Electric, dtype: float64
```

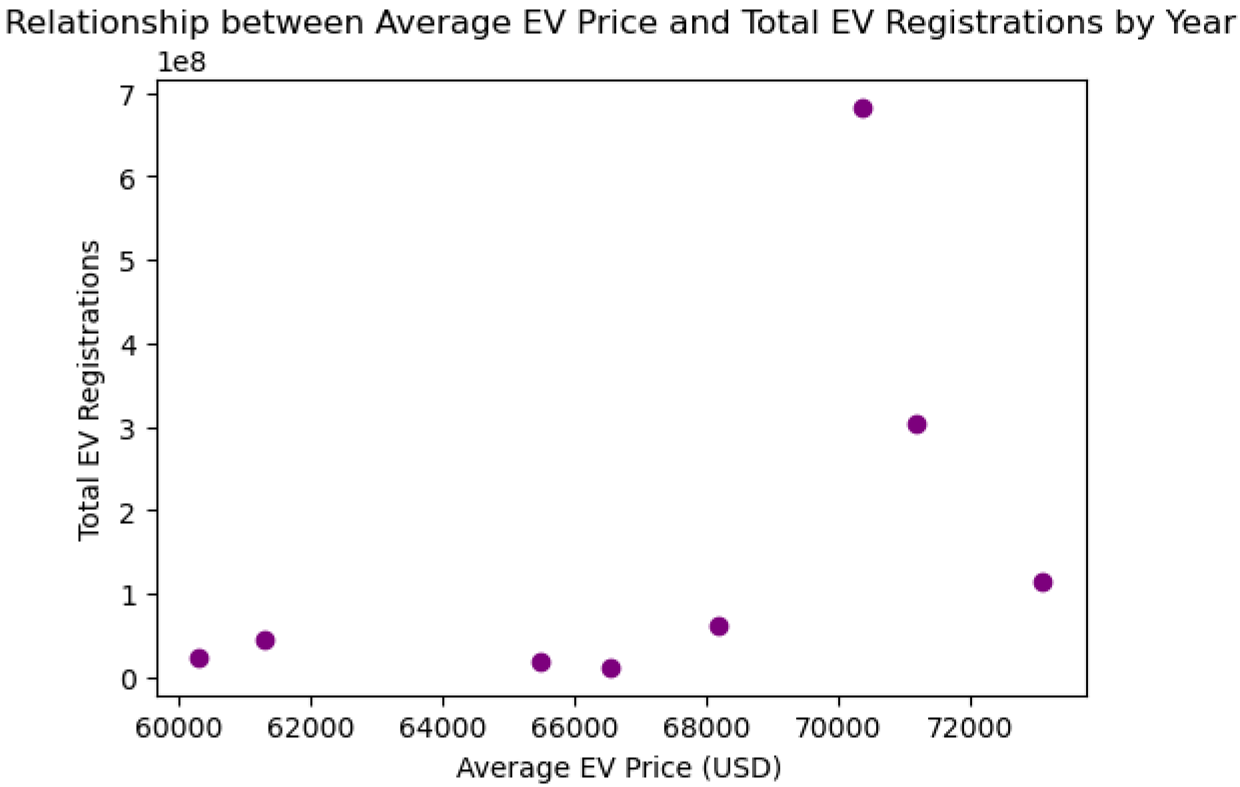


Now we want to see the relationship between average EV prices and total EV registrations over the years. A scatter plot is used because it can show whether there's any correlation between the two variables

In [17]:

```
registration_pricing_df = pd.merge(pricing_df_sorted, compiled_df, on='Year', how='inner')

# Group by Year to get the required aggregates
annual_data = registration_pricing_df.groupby('Year').agg({'Electric': 'sum', 'MSRP': 'mean'}).reset_index

# Plot the relationship using a scatter plot
plt.figure(figsize=(6, 4))
plt.scatter(annual_data['MSRP'], annual_data['Electric'], color='purple', marker='o')

# Add labels and title
plt.xlabel('Average EV Price (USD)')
plt.ylabel('Total EV Registrations')
plt.title('Relationship between Average EV Price and Total EV Registrations by Year')
```

```
plt.show()
```



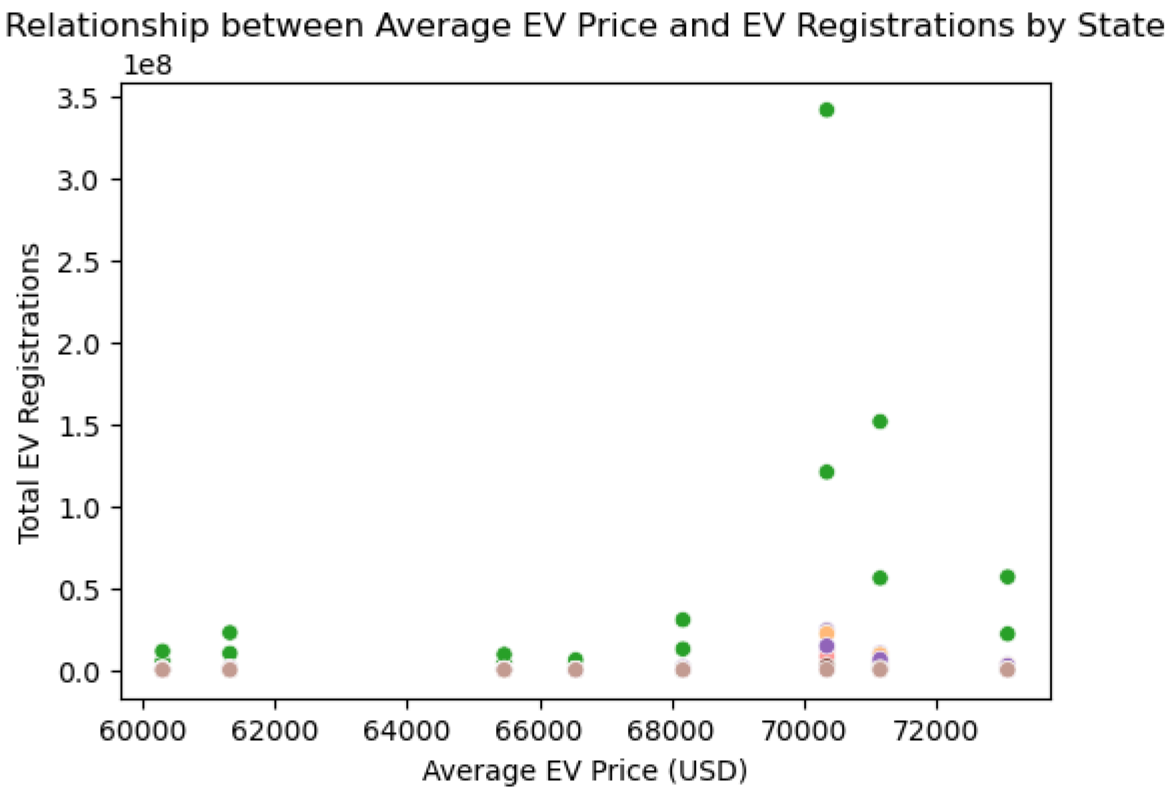
We also group the registration_pricing_df DataFrame by both 'Year' and 'State' to calculate aggregates for each state in each year. This leads to a scatter plot where we visualize the relationship between average EV price (MSRP) and total EV registrations (Electric) for each state

In [18]:

```
state_annual_data = registration_pricing_df.groupby(['Year', 'State']).agg({'Electric': 'sum', 'MSRP': 'mea

print(state_annual_data.head())

plt.figure(figsize=(6, 4))
sns.scatterplot(data=state_annual_data, x='MSRP', y='Electric', hue='State', palette='tab20', legend=False
plt.title('Relationship between Average EV Price and EV Registrations by State')
plt.xlabel('Average EV Price (USD)')
```

```
plt.ylabel('Total EV Registrations')
plt.show()
```

```
   Year       State   Electric          MSRP
0  2016     Alabama    11000.0  66551.136364
1  2016      Alaska     4400.0  66551.136364
2  2016     Arizona   103400.0  66551.136364
3  2016    Arkansas     4400.0  66551.136364
4  2016  California  3113000.0  66551.136364
```



2. **Electric Vehicle State Incentives**

In [19]:
```
regis_file_path = os.path.join(current_dir, 'csv_data_files', 'ev_registration_data.csv')
registration_df = pd.read_csv(regis_file_path)

def clean_regis(regis):
    if pd.isna(regis):
```

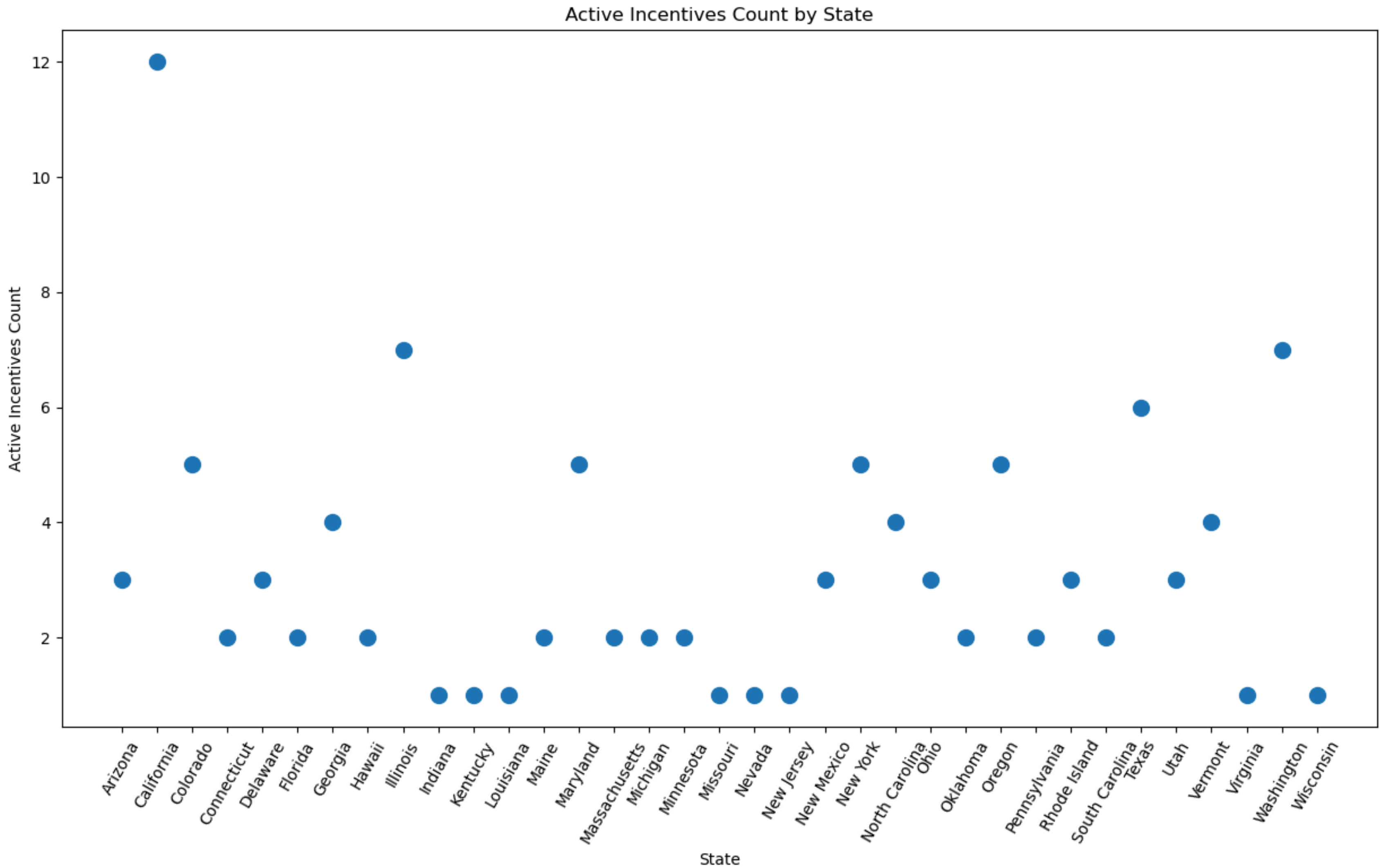
```
        return None
    regis = regis.replace(',', '').strip()
    return float(regis)

registration_df['Electric'] = registration_df['Electric'].apply(clean_regis)
```

We are counting how many active incentives for electric vehicles each state has and creates a scatter plot to show this. It then adds up the number of EV adoptions per state and year, combining this with the incentive counts. Finally, it keeps only the states with active incentives for further analysis.

In [20]:
```
# Count number of active incentives per state
active_incentives_count = active_state_incentives_df.groupby('State') \
.size().reset_index(name='Active Incentives Count')

print(active_incentives_count)

# Create dataframe with the provided data
incentives_states_df  = {
    'State': ['Arizona', 'California', 'Colorado', 'Connecticut', 'Delaware', 'Florida',
              'Georgia', 'Hawaii', 'Illinois', 'Indiana', 'Kentucky', 'Louisiana',
              'Maine', 'Maryland', 'Massachusetts', 'Michigan', 'Minnesota', 'Missouri',
              'Nevada', 'New Jersey', 'New Mexico', 'New York', 'North Carolina', 'Ohio',
              'Oklahoma', 'Oregon', 'Pennsylvania', 'Rhode Island', 'South Carolina',
              'Texas', 'Utah', 'Vermont', 'Virginia', 'Washington', 'Wisconsin'],
    'Active Incentives Count': [3, 12, 5, 2, 3, 2, 4, 2, 7, 1, 1, 1, 2, 5,
                                2, 2, 2, 1, 1, 1, 3, 5, 4, 3, 2, 5, 2,
                                3, 2, 6, 3, 4, 1, 7, 1]
}

adoption_incentives_df = pd.DataFrame(incentives_states_df )

# Create the scatter plot
# Define the figure size to improve readability
plt.figure(figsize=(15, 8))
plt.plot(adoption_incentives_df['State'], adoption_incentives_df['Active Incentives Count'], 'o', markersi

# Add titles and labels
plt.title('Active Incentives Count by State')
plt.xlabel('State')
plt.ylabel('Active Incentives Count')
```

```
# Rotate x-axis labels for better readability
plt.xticks(rotation=60)

# Show the plot
plt.show()

# # Sum EV adoptions per state and year from the registration_df
ev_adoptions_per_state = registration_df.groupby(['State', 'Year'])['Electric'] \
.sum().reset_index(name='EV Adoptions')

# Merge incentive counts with EV adoption data
adoptions_incentives_df = ev_adoptions_per_state.merge(active_incentives_count,
                                                       on='State', how='left')
# Filter to include only states with active incentives
adoptions_incentives_df = adoptions_incentives_df[
adoptions_incentives_df['Active Incentives Count'] > 0]
```

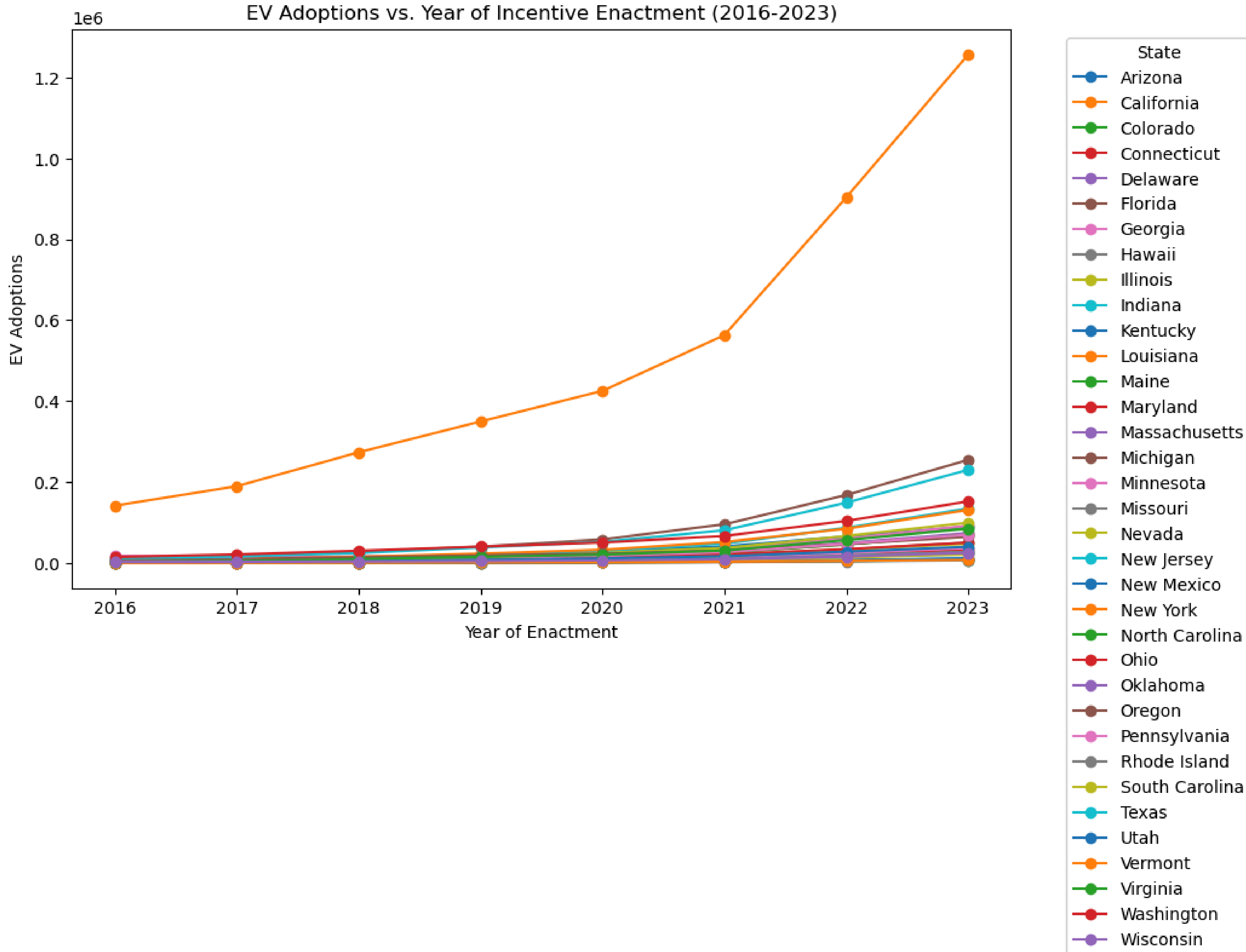
	State	Active Incentives Count
0	Arizona	3
1	California	12
2	Colorado	5
3	Connecticut	2
4	Delaware	3
5	Florida	2
6	Georgia	4
7	Hawaii	2
8	Illinois	7
9	Indiana	1
10	Kentucky	1
11	Louisiana	1
12	Maine	2
13	Maryland	5
14	Massachusetts	2
15	Michigan	2
16	Minnesota	2
17	Missouri	1
18	Nevada	1
19	New Jersey	1
20	New Mexico	3
21	New York	5
22	North Carolina	4
23	Ohio	3
24	Oklahoma	2
25	Oregon	5
26	Pennsylvania	2
27	Rhode Island	3
28	South Carolina	2
29	Texas	6
30	Utah	3
31	Vermont	4
32	Virginia	1
33	Washington	7
34	Wisconsin	1



A line plot is created that shows the number of EV adoptions for each state over the years 2016-2023. It loops through the data to draw separate lines for each state to make it easier to see trends over time. The plot also includes a legend that identifies each line by state.

In [21]:
```
# Create the line plot
plt.figure(figsize=(10, 6))

# Loop through each state to plot their line separately
```

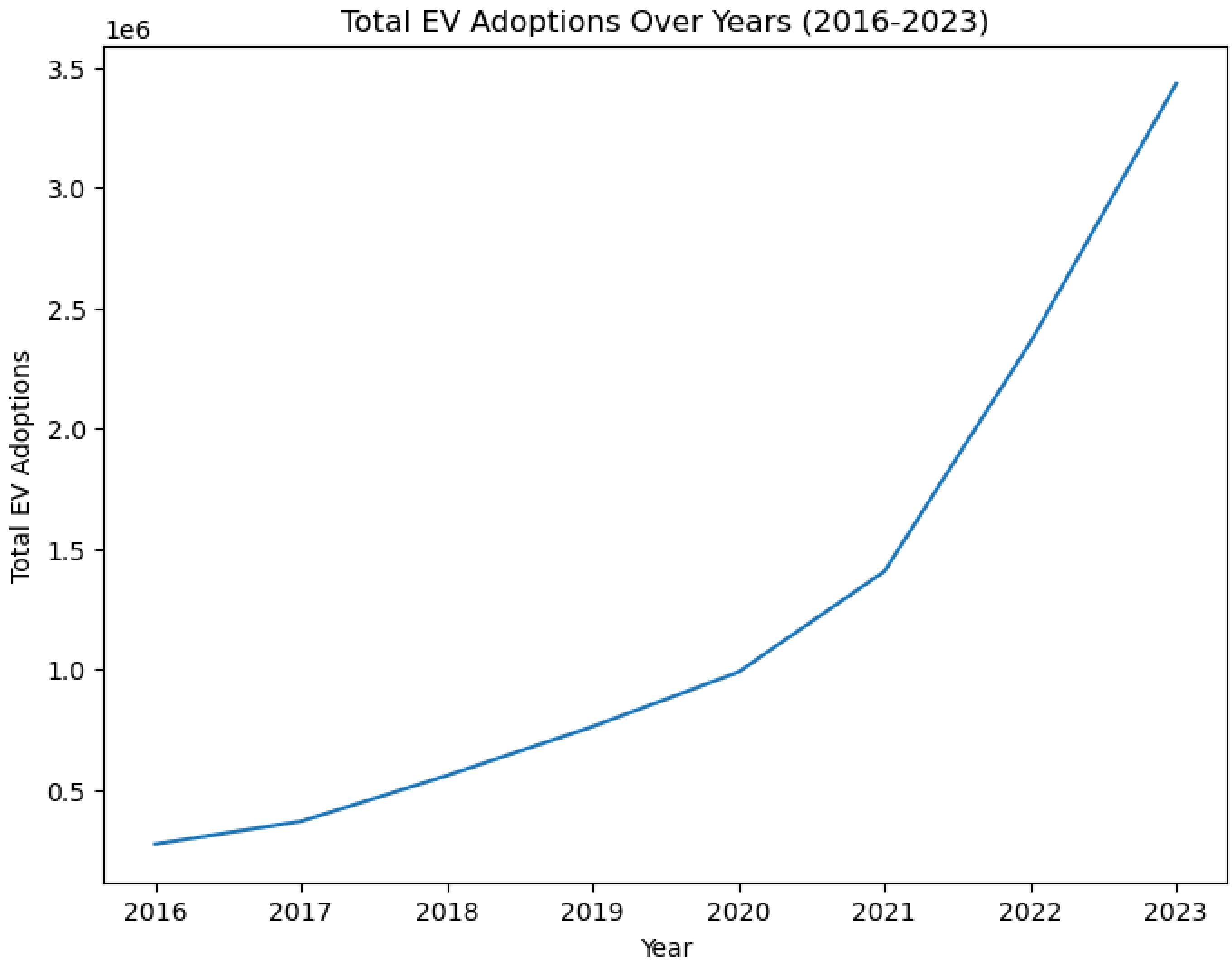
```
for state in adoptions_incentives_df['State'].unique():
    state_data = adoptions_incentives_df[adoptions_incentives_df['State'] == state]
    plt.plot(state_data['Year'], state_data['EV Adoptions'], marker='o', label=state)

# Add title and labels
plt.title('EV Adoptions vs. Year of Incentive Enactment (2016-2023)')
plt.xlabel('Year of Enactment')
plt.ylabel('EV Adoptions')

# Show legend
plt.legend(title='State', bbox_to_anchor=(1.05, 1), loc='upper left')

# Show the plot
plt.show()
```



We are interested in knowing the total number of EV adoptions per year from 2016 to 2023, particularly for active incentives. It first calculates the sum of EV adoptions for each year across states that have active incentives, then we use this data to plot the overall trend of EV adoption over time, which helps visualize how EV adoptions have changed year by year.

In [22]:

```
# Sum EV adoptions per year for states with active incentives
yearly_ev_adoptions = registration_df[registration_df['State'].
isin(adoptions_incentives_df['State'])].groupby(['Year'])['Electric'].sum().reset_index()

# Create the plot
plt.figure(figsize=(8, 6))
sns.lineplot(data=yearly_ev_adoptions, x='Year', y='Electric')
plt.title('Total EV Adoptions Over Years (2016-2023)')
plt.xlabel('Year')
plt.ylabel('Total EV Adoptions')
plt.show()
```

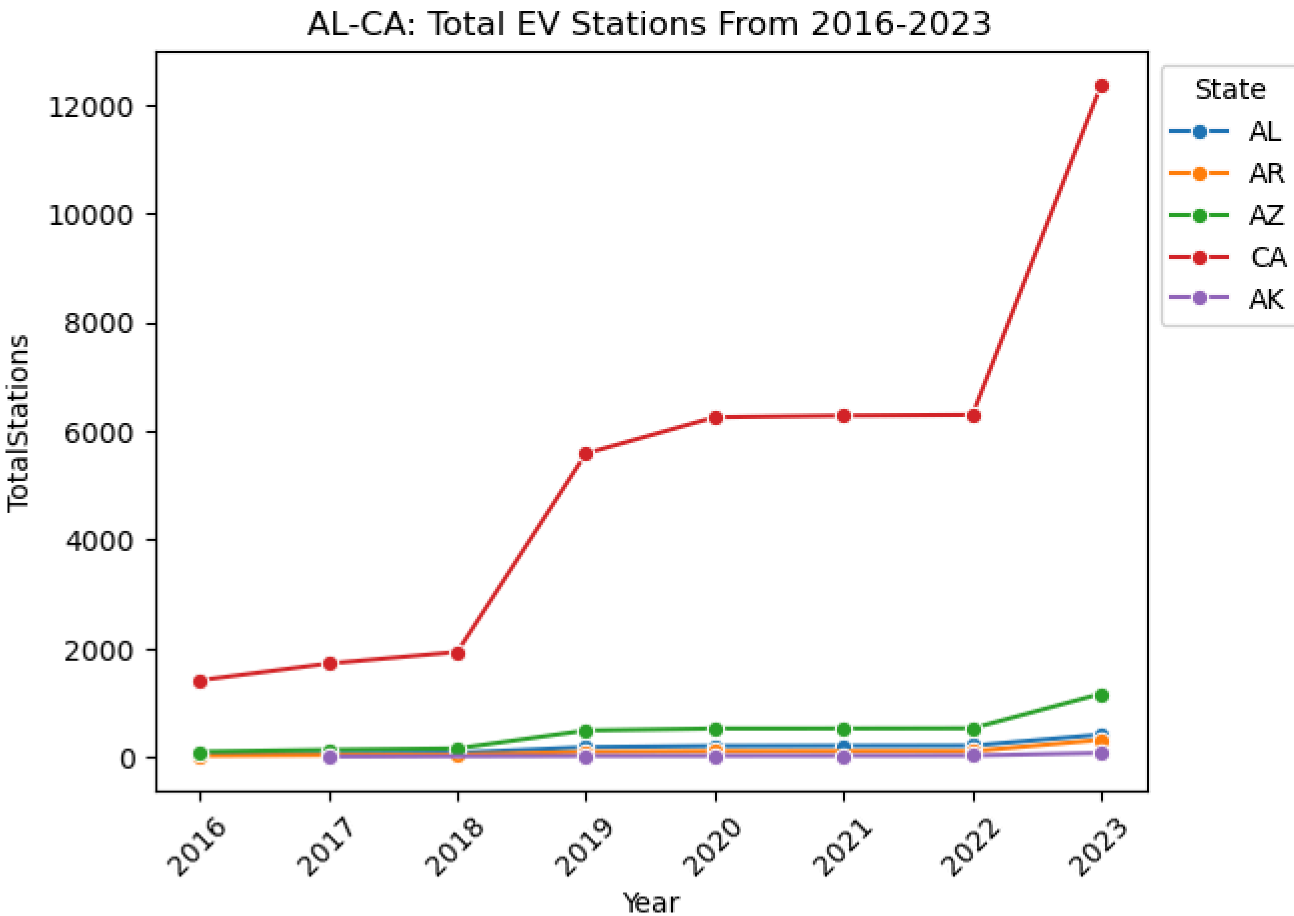


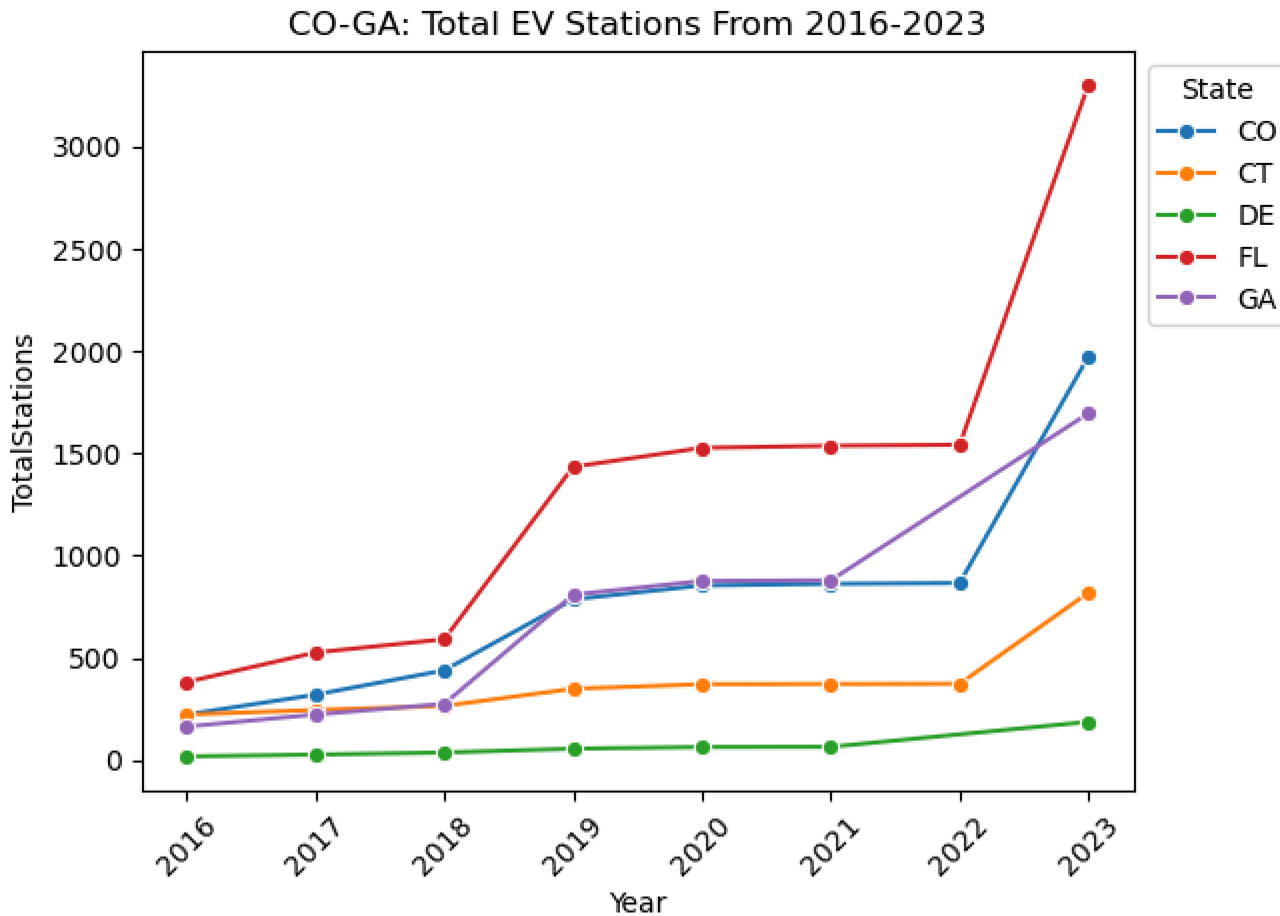
4. **Electric Vehicle Charge Stations**

Since 50 states is a lot of data to look at on one graph, let's split into groups of 5 and plot total EV charge stations over time.

In [23]:
```
#splitting df to groups of states for plotting
states_to_filter = ['AL', 'AK', 'AZ', 'AR', 'CA']
ocm_us_df_limited_5 = ocm_us_df_limited[ocm_us_df_limited["State"].isin(states_to_filter)]
```

```
s = sns.lineplot(data = ocm_us_df_limited_5, \
x = "Year", y = "TotalStations", marker = "o", hue = "State")
sns.move_legend(s, "upper left", bbox_to_anchor=(1, 1))
plt.xticks(rotation = 45)
plt.title("AL-CA: Total EV Stations From 2016-2023")
plt.show()

states_to_filter = ['CO', 'CT', 'DE', 'FL', 'GA']
ocm_us_df_limited_10 = ocm_us_df_limited[ocm_us_df_limited["State"].isin(states_to_filter)]
s = sns.lineplot(data = ocm_us_df_limited_10, \
x = "Year", y = "TotalStations", marker = "o", hue = "State")
sns.move_legend(s, "upper left", bbox_to_anchor=(1, 1))
plt.title("CO-GA: Total EV Stations From 2016-2023")
plt.xticks(rotation = 45)
plt.show()
```


AL-CA: Total EV Stations From 2016-2023
TotalStations
12000
10000
8000
6000
4000
2000
0
2016
2017
2018
2019
2020
2021
2022
2023
Year
State
AL
AR
AZ
CA
AK

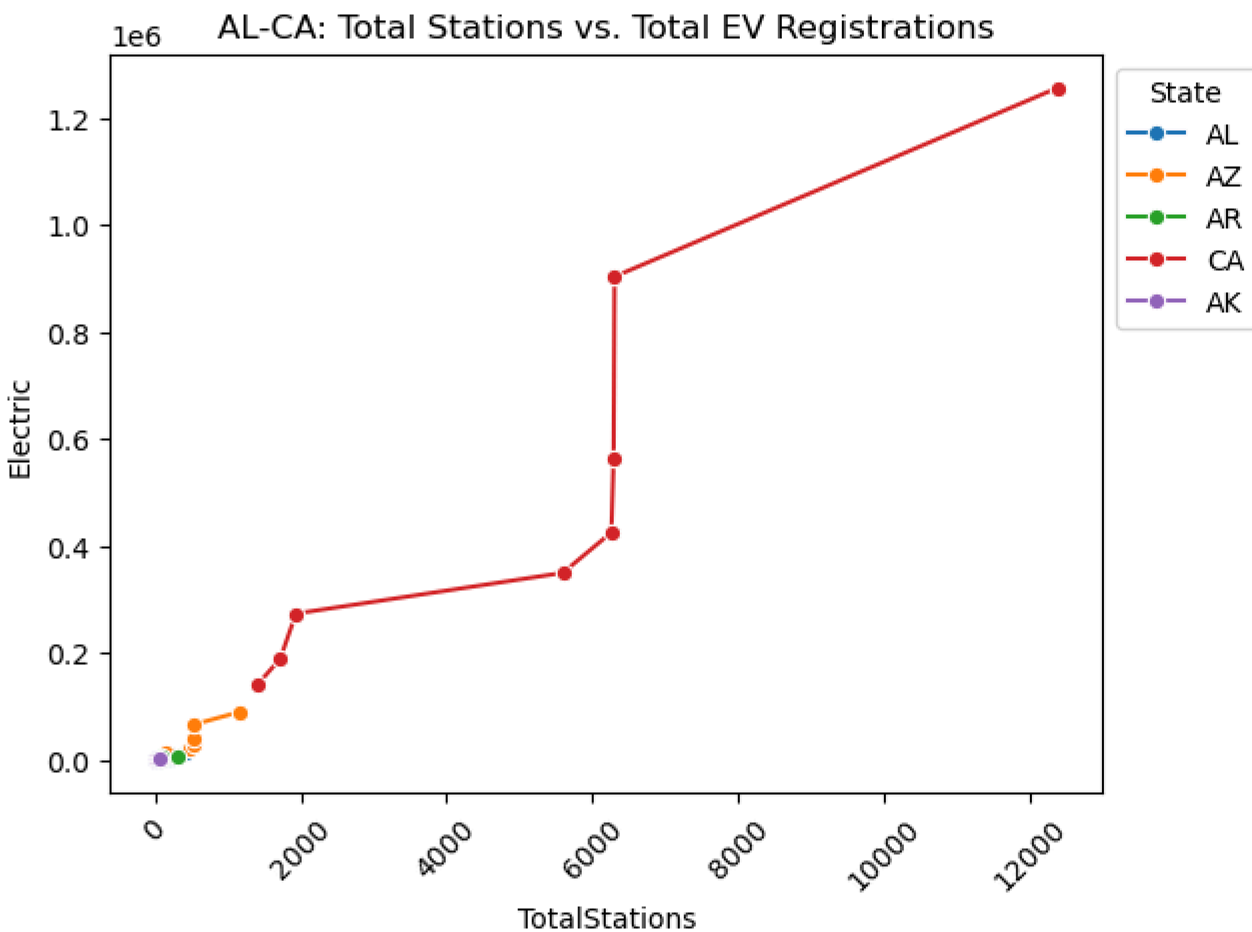


For now, we won't plot every state. Now let's look at TotalStations vs. Total EV Registrations per state.

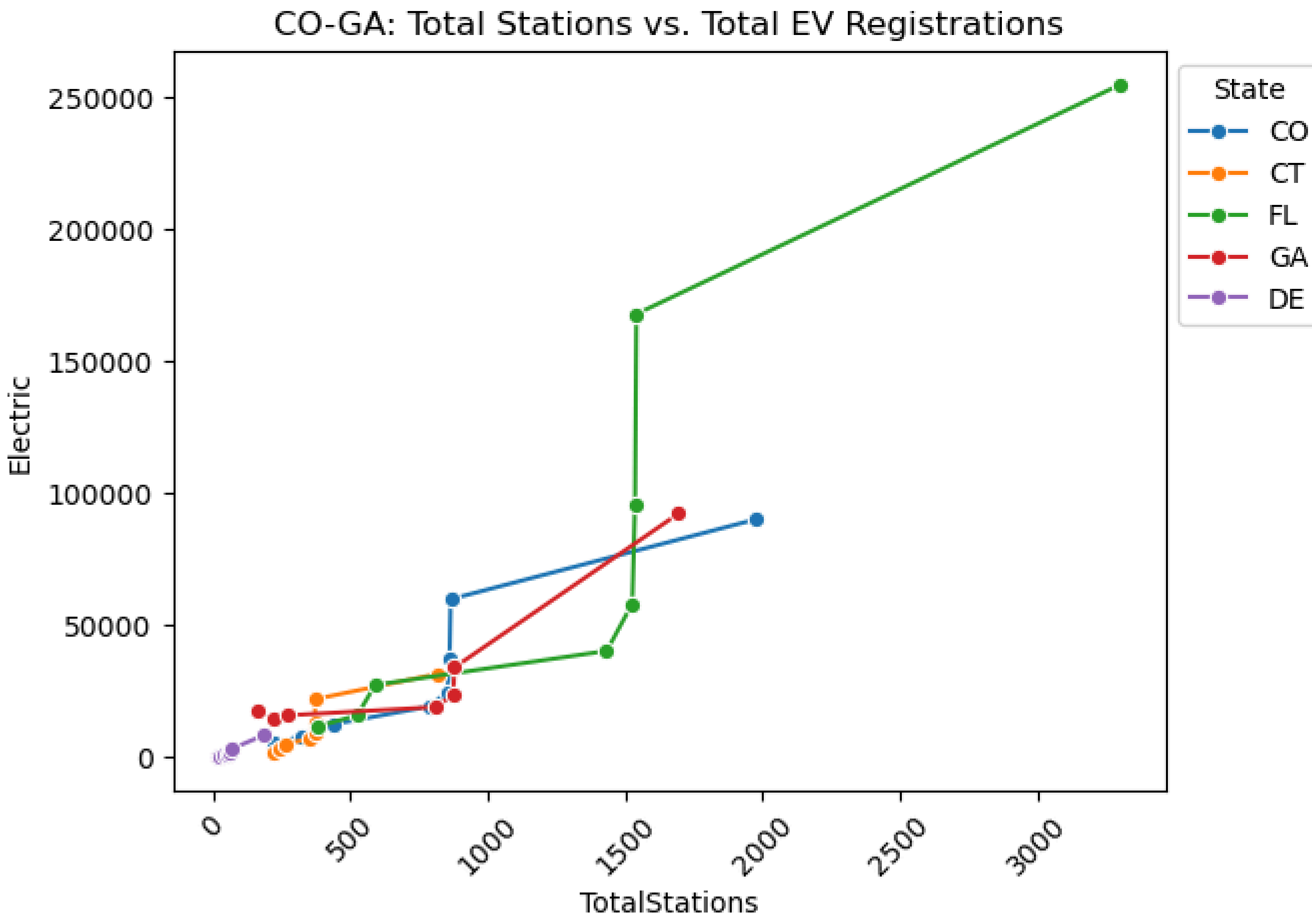
In [24]:
```
#splitting df to groups of states for plotting
states_to_filter = ['AL', 'AK', 'AZ', 'AR', 'CA']
combined_df_5 = combined_df[combined_df["State"].isin(states_to_filter)]
print(combined_df_5["Electric"].dtype)
s = sns.lineplot(data = combined_df_5, \
x = "TotalStations", y = "Electric", marker = "o", hue = "State")
sns.move_legend(s, "upper left", bbox_to_anchor=(1, 1))
plt.xticks(rotation = 45)
plt.title("AL-CA: Total Stations vs. Total EV Registrations")
plt.show()
```

```
#splitting df to groups of states for plotting
states_to_filter = ['CO', 'CT', 'DE', 'FL', 'GA']
combined_df_10 = combined_df[combined_df["State"].isin(states_to_filter)]
print(combined_df_10["Electric"].dtype)
s = sns.lineplot(data = combined_df_10, \
x = "TotalStations", y = "Electric", marker = "o", hue = "State")
sns.move_legend(s, "upper left", bbox_to_anchor=(1, 1))
plt.xticks(rotation = 45)
plt.title("CO-GA: Total Stations vs. Total EV Registrations")
plt.show()

#etc, etc
```

```
float64
```



```
float64
```



Data Limitations:

There are a few limitations in the data we've collected:

1. The current dataset only includes information from 2016 to 2023. This relatively narrow time range may hinder our ability to develop a reliable predictive model over a longer horizon. We are exploring additional sources to obtain data from earlier years, which may become more manageable once we narrow our focus to specific states.
2. The dataset is missing information for the year 2023. We are actively looking into potential sources that could help fill this gap.

3. Data only includes charge stations listed on open charge map, which might not include all the charging stations in the US. Data is limited for certain smaller states like Alaska or Delaware, leading to some missed data rows.
4. Based on the incentives dataset, not all dates provide incentives for electric vehicles, which limits our analysis if we were to consider all states. Additionally, there are missing values in the date columns that could lead to gaps in identifying active incentives.

Questions For Reviewers:

- Do we need to explain any external sources referenced like we do in Homework assignments? (e.g. I had to scrape data from a pdf file, which was not covered in class.)
- In the scrapped EV pricing data, some EV model prices are displayed as a range. Currently, I'm calculating the median of the range and using that as the price for the corresponding model. Do you think this is a valid approach, or would you recommend a better method for handling range data?
- Should states without incentives be factored differently in our comparative analysis?
- How do we handle missing data? E.g. if data is missing for Alaska for a year, should we not build a model at all for Alaska?