Final Project Code - EV Analysis

Jennifer Zhuang

Our Original Data

In [1]:
```
import pandas as pd
df = pd.read_csv('NY_gasoline_data.csv')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 402 entries, 0 to 401
Data columns (total 51 columns):
 #   Column                                                   Non-Null Count  Dtype  
---  ------                                                   --------------  -----  
 0   Date                                                     402 non-null    object 
 1   New York State Average ($/gal)                           402 non-null    float64
 2   Albany Average ($/gal)                                   402 non-null    float64
 3   Batavia Average ($/gal)                                  400 non-null    float64
 4   Binghamton Average ($/gal)                               402 non-null    float64
 5   Buffalo Average ($/gal)                                  402 non-null    float64
 6   Dutchess Average ($/gal)                                 402 non-null    float64
 7   Elmira Average ($/gal)                                   402 non-null    float64
 8   Glens Falls Average ($/gal)                              402 non-null    float64
 9   Ithaca Average ($/gal)                                   402 non-null    float64
 10  Kingston Average ($/gal)                                 402 non-null    float64
 11  Nassau Average ($/gal)                                   402 non-null    float64
 12  New York City Average ($/gal)                            402 non-null    float64
 13  Rochester Average ($/gal)                                402 non-null    float64
 14  Syracuse Average ($/gal)                                 402 non-null    float64
 15  Utica Average ($/gal)                                    402 non-null    float64
 16  Watertown Average ($/gal)                                402 non-null    float64
 17  White Plains Average ($/gal)                             402 non-null    float64
 18  East Coast Production of Gasoline (Thousand Barrels per Day)  401 non-null    float64
 19  East Coast Production of Jet Fuel (Thousand Barrels per Day)  401 non-null    float64
 20  U.S. Production of Gasoline (Thousand Barrels per Day)   401 non-null    float64
 21  U.S. Gasoline Demand (Thousand Barrels per Day)          401 non-null    float64
 22  U.S. Production of Jet Fuel (Thousand Barrels per Day)   401 non-null    float64
 23  NY Conventional Gasoline Spot Price ($/gal)              402 non-null    float64
 24  NY Ultra-Low Sulfur Diesel Spot Price ($/gal)            402 non-null    float64
 25  WTI Crude Oil Spot Price ($/barrel)                      402 non-null    float64
 26  Brent Crude Oil Spot Price ($/barrel)                    402 non-null    float64
 27  Mid-Atlantic ULS Diesel Stocks (Thousand Barrels)        401 non-null    float64
 28  Mid-Atlantic Gasoline Stocks (Thousand Barrels)          401 non-null    float64
 29  East Coast Gasoline Stocks (Thousand Barrels)            401 non-null    float64
 30  East Coast Ethanol Stocks  (Thousand Barrels)            401 non-null    float64
 31  East Coast Jet Fuels Stocks (Thousand Barrels)           401 non-null    float64
 32  U.S. Gasoline Stocks (Thousand Barrels)                  401 non-null    float64
 33  U.S. Crude Oil Stocks (Thousand Barrels)                 401 non-null    float64
 34  New York State Average ($/gal)Diesel                     402 non-null    float64
 35  Albany Average ($/gal)Diesel                             402 non-null    float64
 36  Batavia Average ($/gal)Diesel                            402 non-null    float64
 37  Binghamton Average ($/gal)Diesel                         402 non-null    float64
 38  Buffalo Average ($/gal)Diesel                            402 non-null    float64
 39  Dutchess Average ($/gal)Diesel                           402 non-null    float64
 40  Elmira Average ($/gal)Diesel                             402 non-null    float64
 41  Glens Falls Average ($/gal)Diesel                        402 non-null    float64
 42  Ithaca Average ($/gal)Diesel                             402 non-null    float64
 43  Kingston Average ($/gal)Diesel                           402 non-null    float64
 44  Nassau Average ($/gal)Diesel                             402 non-null    float64
 45  New York City Average ($/gal)Diesel                      402 non-null    float64
 46  Rochester Average ($/gal)Diesel                          402 non-null    float64
 47  Syracuse Average ($/gal)Diesel                           402 non-null    float64
 48  Utica Average ($/gal)Diesel                              402 non-null    float64
 49  Watertown Average ($/gal)Diesel                          402 non-null    float64
 50  White Plains Average ($/gal)Diesel                       402 non-null    float64
dtypes: float64(50), object(1)
memory usage: 160.3+ KB
```

- The first step is to break apart our dataset and create three new columns:
    - Region
    - Region Gas Cost $/gal
    - Region Diesel Cost $/gal

In [2]:
```
# Define gasoline and diesel columns
gasoline_columns = [
    "Albany Average ($/gal)",
    "Batavia Average ($/gal)",
    "Binghamton Average ($/gal)",
    "Buffalo Average ($/gal)",
    "Dutchess Average ($/gal)",
    "Elmira Average ($/gal)",
    "Glens Falls Average ($/gal)",
    "Ithaca Average ($/gal)",
    "Kingston Average ($/gal)",
    "Nassau Average ($/gal)",
    "New York City Average ($/gal)",
    "Rochester Average ($/gal)",
    "Syracuse Average ($/gal)",
    "Utica Average ($/gal)",
    "Watertown Average ($/gal)",
    "White Plains Average ($/gal)"
]

diesel_columns = [
    "Albany Average ($/gal)Diesel",
    "Batavia Average ($/gal)Diesel",
    "Binghamton Average ($/gal)Diesel",
    "Buffalo Average ($/gal)Diesel",
    "Dutchess Average ($/gal)Diesel",
    "Elmira Average ($/gal)Diesel",
    "Glens Falls Average ($/gal)Diesel",
    "Ithaca Average ($/gal)Diesel",
    "Kingston Average ($/gal)Diesel",
    "Nassau Average ($/gal)Diesel",
    "New York City Average ($/gal)Diesel",
    "Rochester Average ($/gal)Diesel",
    "Syracuse Average ($/gal)Diesel",
    "Utica Average ($/gal)Diesel",
    "Watertown Average ($/gal)Diesel",
    "White Plains Average ($/gal)Diesel"
]

# Melt gasoline columns
gasoline_melted = df.melt(
    id_vars=[col for col in df.columns if col not in gasoline_columns + diesel_columns],  # Keep other columns
    value_vars=gasoline_columns,
    var_name="Region",
    value_name="Region Gas Cost ($/gal)"
)
gasoline_melted["Region"] = gasoline_melted["Region"].str.replace(" Average \\(\\$/gal\\)", "", regex=True)

# Melt diesel columns
diesel_melted = df.melt(
    id_vars=[col for col in df.columns if col not in gasoline_columns + diesel_columns],  # Keep other columns
    value_vars=diesel_columns,
    var_name="Region",
    value_name="Region Diesel Cost ($/gal)"
)
diesel_melted["Region"] = diesel_melted["Region"].str.replace(" Average \\(\\$/gal\\)Diesel", "", regex=True)

# Merge gasoline and diesel costs directly
result = pd.merge(
    gasoline_melted,
    diesel_melted,
    on=["Date", "Region"] + [col for col in df.columns if col not in gasoline_columns + diesel_columns],
    how="outer"
)

# Drop any duplicated or unnecessary columns if needed
```

```python
result = result.loc[:, ~result.columns.duplicated()]

# Display result
print(result.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6432 entries, 0 to 6431
Data columns (total 22 columns):
 #   Column                                                    Non-Null Count  Dtype  
---  ------                                                    --------------  -----  
 0   Date                                                      6432 non-null   object 
 1   New York State Average ($/gal)                            6432 non-null   float64
 2   East Coast Production of Gasoline (Thousand Barrels per Day) 6416 non-null   float64
 3   East Coast Production of Jet Fuel (Thousand Barrels per Day) 6416 non-null   float64
 4   U.S. Production of Gasoline (Thousand Barrels per Day)    6416 non-null   float64
 5   U.S. Gasoline Demand (Thousand Barrels per Day)           6416 non-null   float64
 6   U.S. Production of Jet Fuel (Thousand Barrels per Day)    6416 non-null   float64
 7   NY Conventional Gasoline Spot Price ($/gal)               6432 non-null   float64
 8   NY Ultra-Low Sulfur Diesel Spot Price ($/gal)             6432 non-null   float64
 9   WTI Crude Oil Spot Price ($/barrel)                       6432 non-null   float64
 10  Brent Crude Oil Spot Price ($/barrel)                     6432 non-null   float64
 11  Mid-Atlantic ULS Diesel Stocks (Thousand Barrels)         6416 non-null   float64
 12  Mid-Atlantic Gasoline Stocks (Thousand Barrels)           6416 non-null   float64
 13  East Coast Gasoline Stocks (Thousand Barrels)             6416 non-null   float64
 14  East Coast Ethanol Stocks  (Thousand Barrels)             6416 non-null   float64
 15  East Coast Jet Fuels Stocks (Thousand Barrels)            6416 non-null   float64
 16  U.S. Gasoline Stocks (Thousand Barrels)                   6416 non-null   float64
 17  U.S. Crude Oil Stocks (Thousand Barrels)                  6416 non-null   float64
 18  New York State Average ($/gal)Diesel                      6432 non-null   float64
 19  Region                                                    6432 non-null   object 
 20  Region Gas Cost ($/gal)                                   6430 non-null   float64
 21  Region Diesel Cost ($/gal)                                6432 non-null   float64
dtypes: float64(20), object(2)
memory usage: 1.1+ MB
None
```

In [3]:
```python
result.head()
```

Out[3]:

	Date	New York State Average ($/gal)	East Coast Production of Gasoline (Thousand Barrels per Day)	East Coast Production of Jet Fuel (Thousand Barrels per Day)	U.S. Production of Gasoline (Thousand Barrels per Day)	U.S. Gasoline Demand (Thousand Barrels per Day)	U.S. Production of Jet Fuel (Thousand Barrels per Day)	NY Conventional Gasoline Spot Price ($/gal)	NY Ultra-Low Sulfur Diesel Spot Price ($/gal)	WTI Crude Oil Spot Price ($/barrel)	...	Mid-Atlantic Gasoline Stocks (Thousand Barrels)
0	1/2/17	2.52	NaN	NaN	NaN	NaN	NaN	0.00	0.00	53.60	...	NaN
1	1/9/17	2.54	2830.0	78.0	9666.0	8470.0	1707.0	1.69	1.67	53.34	...	35086.0
2	1/16/17	2.54	2883.0	69.0	8953.0	8069.0	1621.0	1.63	1.62	52.07	...	36289.0
3	1/23/17	2.53	2960.0	72.0	8825.0	8039.0	1650.0	1.61	1.61	51.82	...	36639.0
4	1/30/17	2.51	2886.0	87.0	9101.0	8310.0	1637.0	1.57	1.59	52.74	...	39686.0

5 rows × 22 columns

In [4]:
```python
result['Region'].unique()
```

Out[4]:
```
array(['Albany', 'Batavia', 'Binghamton', 'Buffalo', 'Dutchess', 'Elmira',
       'Glens Falls', 'Ithaca', 'Kingston', 'Nassau', 'New York City',
       'Rochester', 'Syracuse', 'Utica', 'Watertown', 'White Plains'],
      dtype=object)
```

Region / County Data

- Some of the datasets have county instead of Region
- We create a mapping of all 62 counties in New York State to a Region

In [5]:
```python
county_to_area = [
    ("Madison", "Syracuse"),
```

```
    ("Onondaga", "Syracuse"),
    ("Queens", "New York City"),
    ("Westchester", "White Plains"),
    ("New York", "New York City"),
    ("Herkimer", "Utica"),
    ("Oneida", "Utica"),
    ("Monroe", "Rochester"),
    ("Wayne", "Rochester"),
    ("Suffolk", "New York City"),
    ("Orange", "Dutchess"),
    ("Nassau", "Nassau"),
    ("Erie", "Buffalo"),
    ("Kings", "New York City"),
    ("Tompkins", "Ithaca"),
    ("Albany", "Albany"),
    ("Broome", "Binghamton"),
    ("Ontario", "Rochester"),
    ("Ulster", "Kingston"),
    ("Saratoga", "Glens Falls"),
    ("Cayuga", "Syracuse"),
    ("Oswego", "Syracuse"),
    ("Bronx", "New York City"),
    ("Jefferson", "Watertown"),
    ("Warren", "Glens Falls"),
    ("Dutchess", "Dutchess"),
    ("Putnam", "White Plains"),
    ("Rockland", "White Plains"),
    ("Columbia", "Albany"),
    ("Schenectady", "Albany"),
    ("Steuben", "Elmira"),
    ("Yates", "Rochester"),
    ("Richmond", "New York City"),
    ("Niagara", "Buffalo"),
    ("Cattaraugus", "Buffalo"),
    ("Cortland", "Binghamton"),
    ("Lewis", "Watertown"),
    ("St. Lawrence", "Watertown"),
    ("Chautauqua", "Buffalo"),
    ("Sullivan", "Kingston"),
    ("Rensselaer", "Albany"),
    ("Tioga", "Binghamton"),
    ("Essex", "Glens Falls"),
    ("Chemung", "Elmira"),
    ("Seneca", "Rochester"),
    ("Otsego", "Utica"),
    ("Schoharie", "Albany"),
    ("Delaware", "Binghamton"),
    ("Livingston", "Rochester"),
    ("Orleans", "Buffalo"),
    ("Washington", "Glens Falls"),
    ("Schuyler", "Elmira"),
    ("Allegany", "Elmira"),
    ("Genesee", "Batavia"),
    ("Chenango", "Binghamton"),
    ("Greene", "Albany"),
    ("Fulton", "Albany"),
    ("Montgomery", "Albany"),
    ("Clinton", "Glens Falls"),
    ("Franklin", "Glens Falls"),
    ("Wyoming", "Buffalo"),
    ("Hamilton", "Glens Falls")
]
```

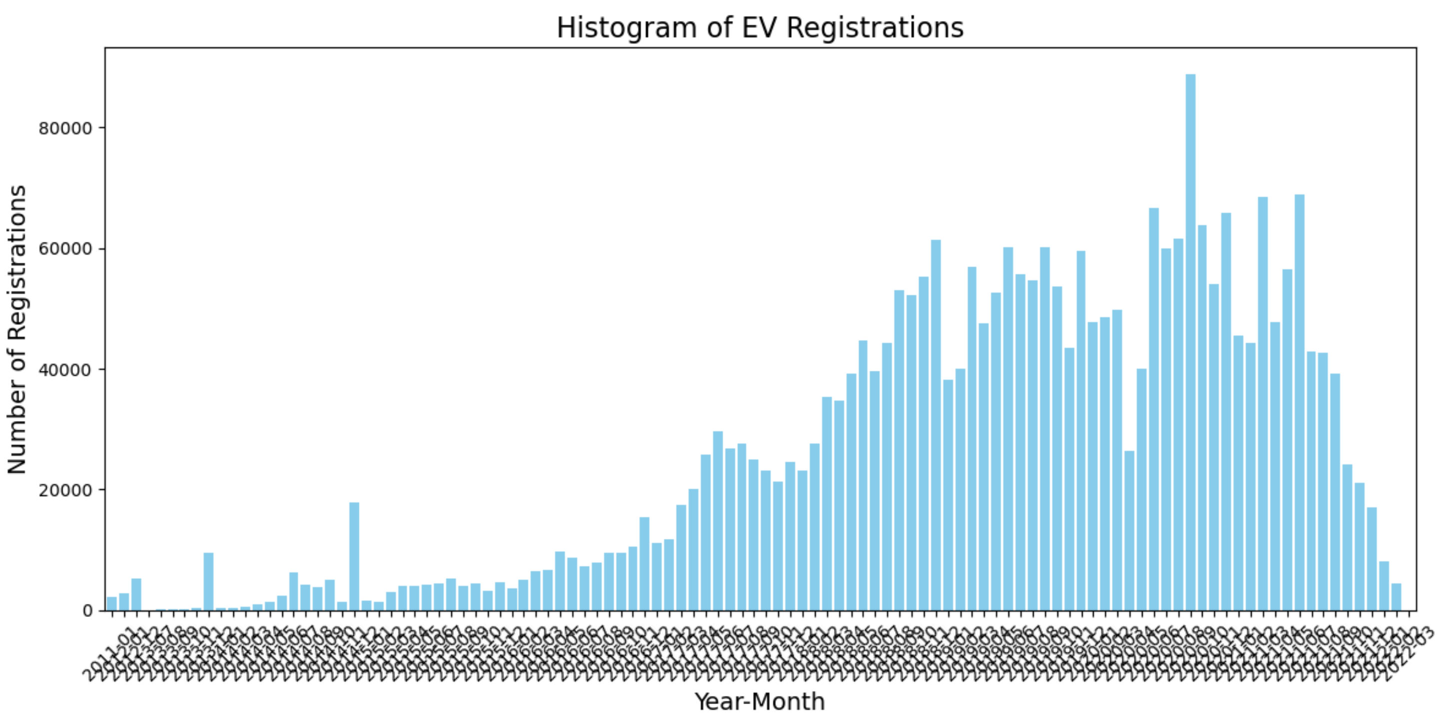
New York EV Registrations

From New York State Energy Research and Development Authority (NYSERDA) and their EValuateNY dataset: (https://www.nyserda.ny.gov/All-Programs/Drive-Clean-Rebate-For-Electric-Cars-Program/About-Electric-Cars/Data-on-Electric-Vehicles-and-Charging-Stations)

In [6]:
```
registration_df = pd.read_csv('ny_ev_registrations.csv')
registration_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2810091 entries, 0 to 2810090
Data columns (total 6 columns):
 #   Column                  Dtype 
---  ------                  ----- 
 0   ZIP Code                int64 
 1   Registration Valid Date  object
 2   DMV ID                  int64 
 3   Registration            object
 4   VIN Prefix              object
 5   Vehicle ID              int64 
dtypes: int64(3), object(3)
memory usage: 128.6+ MB
```

In [7]:
```python
import pandas as pd
import matplotlib.pyplot as plt

# Convert Submitted Date to datetime
registration_df['Registration Valid Date'] = pd.to_datetime(registration_df['Registration Valid Date'])

# Group by month
registration_df['YearMonth'] = registration_df['Registration Valid Date'].dt.to_period('M')
submission_counts = registration_df.groupby('YearMonth').size()

# Plot the histogram
plt.figure(figsize=(12, 6))
submission_counts.plot(kind='bar', width=0.8, color='skyblue')
plt.title('Histogram of EV Registrations', fontsize=16)
plt.xlabel('Year-Month', fontsize=14)
plt.ylabel('Number of Registrations', fontsize=14)
plt.xticks(rotation=45, fontsize=10)
plt.tight_layout()
plt.show()
```



> We need a way to translate zip code info into county info (https://data.ny.gov/Government-Finance/New-York-State-ZIP-Codes-County-FIPS-Cross-Referen/juva-r6g2/data)

In [8]:
```python
region_county_df = pd.read_csv('NY_ZIP_County_Cross-Reference.csv')
region_county_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2543 entries, 0 to 2542
Data columns (total 6 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   County Name  2543 non-null   object
 1   State FIPS   2543 non-null   int64 
 2   County Code  2543 non-null   int64 
 3   County FIPS  2543 non-null   int64 
 4   ZIP Code     2543 non-null   int64 
 5   File Date    2543 non-null   object
dtypes: int64(4), object(2)
memory usage: 119.3+ KB
```

In [9]:
```
registration_df = registration_df.merge(
    region_county_df[['ZIP Code', 'County Code', 'County Name']],
    on='ZIP Code',
    how='left'
)
print(registration_df.head())
```

```
   ZIP Code Registration Valid Date  DMV ID Registration  VIN Prefix  \
0     13104              2020-10-01      62     Original  YV4BR0DL7M   
1     13104              2020-10-01      62     Original  YV4BR0DL7M   
2     13104              2020-10-01      48     Original  YV4BR0DL7M   
3     13104              2020-10-01      48     Original  YV4BR0DL7M   
4     13104              2020-10-01      46     Original  YV4BR0DL7M   

   Vehicle ID YearMonth  County Code County Name  
0    18096911   2020-10         53.0     Madison  
1    18096911   2020-10         67.0    Onondaga  
2    18096911   2020-10         53.0     Madison  
3    18096911   2020-10         67.0    Onondaga  
4    18096911   2020-10         53.0     Madison  
```

In [10]:
```
county_to_region = dict(county_to_area)
registration_df['Region'] = registration_df['County Name'].map(county_to_region)
```

In [11]:
```
registration_df.head()
```

Out[11]:

	ZIP Code	Registration Valid Date	DMV ID	Registration	VIN Prefix	Vehicle ID	YearMonth	County Code	County Name	Region
0	13104	2020-10-01	62	Original	YV4BR0DL7M	18096911	2020-10	53.0	Madison	Syracuse
1	13104	2020-10-01	62	Original	YV4BR0DL7M	18096911	2020-10	67.0	Onondaga	Syracuse
2	13104	2020-10-01	48	Original	YV4BR0DL7M	18096911	2020-10	53.0	Madison	Syracuse
3	13104	2020-10-01	48	Original	YV4BR0DL7M	18096911	2020-10	67.0	Onondaga	Syracuse
4	13104	2020-10-01	46	Original	YV4BR0DL7M	18096911	2020-10	53.0	Madison	Syracuse

Combining with our Transportation Fuel Dataset:

Use datetimes to join the two tables

In [12]:
```
registration_df['Registration Valid Date'] = pd.to_datetime(registration_df['Registration Valid Date'])
registration_df['Formatted Registration Valid Date'] = registration_df['Registration Valid Date'].dt.strftime('%m/
registration_df['Week_start'] = registration_df['Registration Valid Date'] - pd.to_timedelta(registration_df['Regi
registration_df['Week_start'] = registration_df['Week_start'].dt.strftime('%m/%d/%Y')
registration_df.head()
```

Out[12]:

	ZIP Code	Registration Valid Date	DMV ID	Registration	VIN Prefix	Vehicle ID	YearMonth	County Code	County Name	Region	Formatted Registration Valid Date	Week_
0	13104	2020-10-01	62	Original	YV4BR0DL7M	18096911	2020-10	53.0	Madison	Syracuse	10/01/2020	09/28/
1	13104	2020-10-01	62	Original	YV4BR0DL7M	18096911	2020-10	67.0	Onondaga	Syracuse	10/01/2020	09/28/
2	13104	2020-10-01	48	Original	YV4BR0DL7M	18096911	2020-10	53.0	Madison	Syracuse	10/01/2020	09/28/
3	13104	2020-10-01	48	Original	YV4BR0DL7M	18096911	2020-10	67.0	Onondaga	Syracuse	10/01/2020	09/28/
4	13104	2020-10-01	46	Original	YV4BR0DL7M	18096911	2020-10	53.0	Madison	Syracuse	10/01/2020	09/28/

In [13]:

```python
registration_df['Week_start'] = pd.to_datetime(registration_df['Week_start'], format='%m/%d/%Y')
result['Date'] = pd.to_datetime(result['Date'], format='%m/%d/%y')

# Step 2: Aggregate registration_df by Week_start and Region
aggregated_df = (
    registration_df.groupby(['Week_start', 'Region'])
    .size()  # Count the number of registrations per group
    .reset_index(name='Registration Count')  # Reset index and name the count column
)

# Step 3: Perform an inner join to retain only matching rows
merged_df = pd.merge(
    result,
    aggregated_df,
    left_on=['Date', 'Region'],  # Use 'Date' and 'Region' from result
    right_on=['Week_start', 'Region'],  # Use 'Week_start' and 'Region' from aggregated_df
    how='inner'  # Use inner join to keep only matching rows
)

# Step 4: Drop redundant Week_start column (optional)
merged_df.drop(columns=['Week_start'], inplace=True)
merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 978 entries, 0 to 977
Data columns (total 23 columns):
 #   Column                                                Non-Null Count  Dtype         
---  ------                                                --------------  -----         
 0   Date                                                  978 non-null    datetime64[ns]
 1   New York State Average ($/gal)                        978 non-null    float64       
 2   East Coast Production of Gasoline (Thousand Barrels per Day)  978 non-null    float64       
 3   East Coast Production of Jet Fuel (Thousand Barrels per Day)  978 non-null    float64       
 4   U.S. Production of Gasoline (Thousand Barrels per Day)  978 non-null    float64       
 5   U.S. Gasoline Demand (Thousand Barrels per Day)       978 non-null    float64       
 6   U.S. Production of Jet Fuel (Thousand Barrels per Day)  978 non-null    float64       
 7   NY Conventional Gasoline Spot Price ($/gal)           978 non-null    float64       
 8   NY Ultra-Low Sulfur Diesel Spot Price ($/gal)         978 non-null    float64       
 9   WTI Crude Oil Spot Price ($/barrel)                   978 non-null    float64       
 10  Brent Crude Oil Spot Price ($/barrel)                 978 non-null    float64       
 11  Mid-Atlantic ULS Diesel Stocks (Thousand Barrels)     978 non-null    float64       
 12  Mid-Atlantic Gasoline Stocks (Thousand Barrels)       978 non-null    float64       
 13  East Coast Gasoline Stocks (Thousand Barrels)         978 non-null    float64       
 14  East Coast Ethanol Stocks  (Thousand Barrels)         978 non-null    float64       
 15  East Coast Jet Fuels Stocks (Thousand Barrels)        978 non-null    float64       
 16  U.S. Gasoline Stocks (Thousand Barrels)               978 non-null    float64       
 17  U.S. Crude Oil Stocks (Thousand Barrels)              978 non-null    float64       
 18  New York State Average ($/gal)Diesel                  978 non-null    float64       
 19  Region                                                978 non-null    object        
 20  Region Gas Cost ($/gal)                               978 non-null    float64       
 21  Region Diesel Cost ($/gal)                            978 non-null    float64       
 22  Registration Count                                    978 non-null    int64         
dtypes: datetime64[ns](1), float64(20), int64(1), object(1)
memory usage: 175.9+ KB
```

In [14]:

```python
merged_df.head()
```

Out[14]:

	Date	New York State Average ($/gal)	East Coast Production of Gasoline (Thousand Barrels per Day)	East Coast Production of Jet Fuel (Thousand Barrels per Day)	U.S. Production of Gasoline (Thousand Barrels per Day)	U.S. Gasoline Demand (Thousand Barrels per Day)	U.S. Production of Jet Fuel (Thousand Barrels per Day)	NY Conventional Gasoline Spot Price ($/gal)	NY Ultra-Low Sulfur Diesel Spot Price ($/gal)	WTI Crude Oil Spot Price ($/barrel)	...	East Coast Gasoline Stocks (Thousand Barrels)
0	2017-01-30	2.51	2886.0	87.0	9101.0	8310.0	1637.0	1.57	1.59	52.74	...	73540.0
1	2017-02-27	2.47	3129.0	71.0	9456.0	8686.0	1562.0	1.53	1.63	54.03	...	75041.0
2	2017-03-27	2.42	3107.0	76.0	10028.0	9524.0	1731.0	1.49	1.50	47.28	...	65648.0
3	2017-05-01	2.54	3267.0	108.0	9783.0	9156.0	1738.0	1.53	1.52	49.12	...	67206.0
4	2017-05-29	2.51	3376.0	87.0	10430.0	9822.0	1701.0	1.61	1.58	50.21	...	68426.0

5 rows × 23 columns

In [45]:

```
merged_df['Region'].unique()
```

Out[45]:

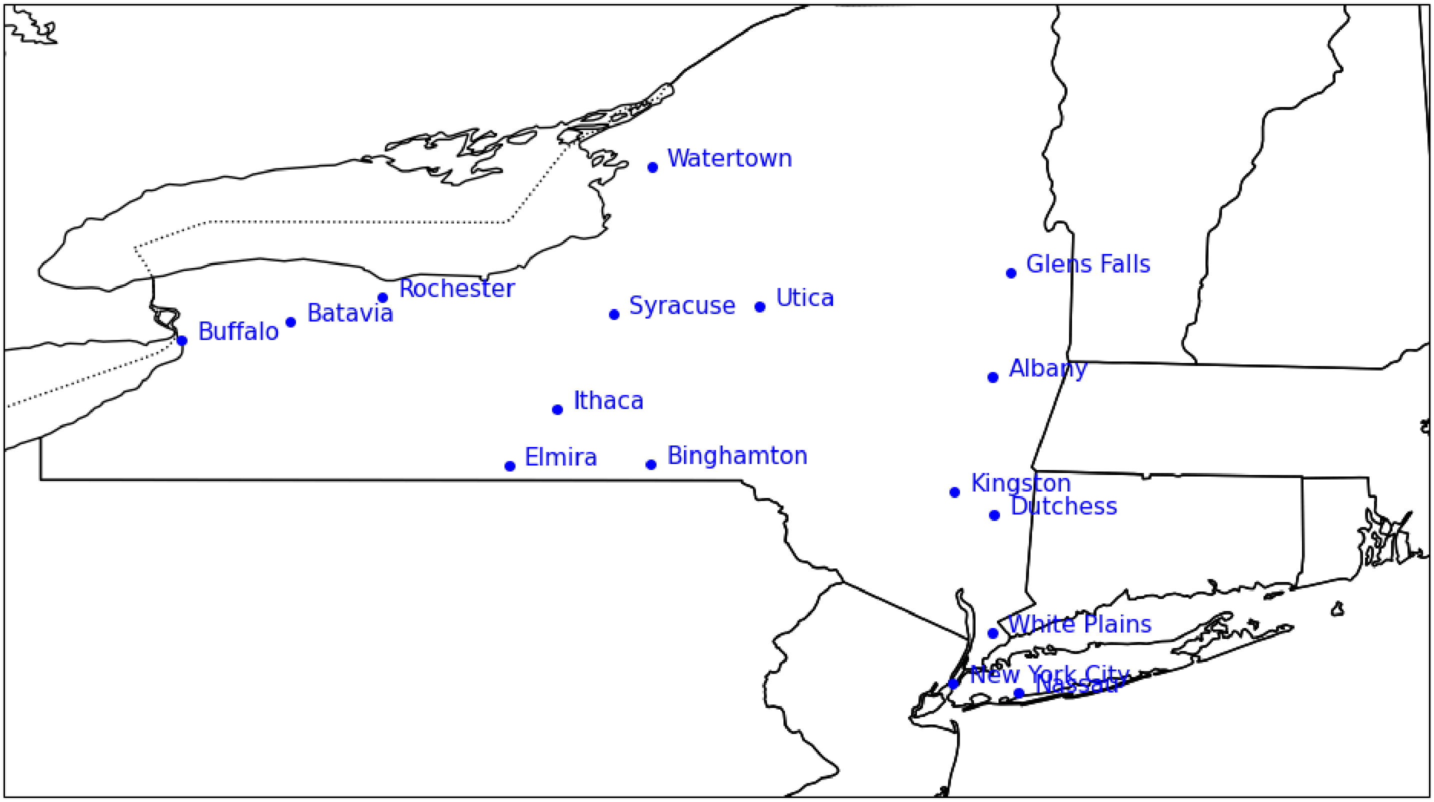
```
array(['Albany', 'Batavia', 'Binghamton', 'Buffalo', 'Dutchess', 'Elmira',
       'Glens Falls', 'Ithaca', 'Kingston', 'Nassau', 'New York City',
       'Rochester', 'Syracuse', 'Utica', 'Watertown', 'White Plains'],
      dtype=object)
```

In [55]:

```
import matplotlib.pyplot as plt
import cartopy.crs as ccrs
import cartopy.feature as cfeature

# Approximate locations of the regions
region_locations = {
    'Albany': (-73.7562, 42.6526),
    'Batavia': (-78.1875, 42.9981),
    'Binghamton': (-75.9180, 42.0987),
    'Buffalo': (-78.8784, 42.8864),
    'Dutchess': (-73.7489, 41.7784),
    'Elmira': (-76.8098, 42.0898),
    'Glens Falls': (-73.6441, 43.3095),
    'Ithaca': (-76.5019, 42.4437),
    'Kingston': (-73.9974, 41.9270),
    'Nassau': (-73.5894, 40.6546),
    'New York City': (-74.0060, 40.7128),
    'Rochester': (-77.6109, 43.1566),
    'Syracuse': (-76.1474, 43.0481),
    'Utica': (-75.2268, 43.1009),
    'Watertown': (-75.9108, 43.9748),
    'White Plains': (-73.7629, 41.0330)
}

# Set up the map with Cartopy
fig, ax = plt.subplots(figsize=(12, 12), subplot_kw={'projection': ccrs.PlateCarree()})
ax.set_extent([-80, -71, 40, 45], crs=ccrs.PlateCarree())  # Bounding box for New York State

# Add map features
ax.add_feature(cfeature.BORDERS, linestyle=':')
ax.add_feature(cfeature.COASTLINE)
ax.add_feature(cfeature.STATES, edgecolor='black')

# Plot region points
for name, (lon, lat) in region_locations.items():
    ax.plot(lon, lat, marker='o', color='blue', markersize=4, transform=ccrs.PlateCarree())
    ax.text(lon + 0.1, lat, name, transform=ccrs.PlateCarree(), fontsize=11, color='blue')
```

```python
# Title and layout
ax.set_title('Regions in New York State', fontsize=16)
plt.show()
```

Regions in New York State



NYSERDA Electric Vehicle Drive Clean Rebate Data: Beginning 2017

https://data.ny.gov/Energy-Environment/NYSERDA-Electric-Vehicle-Drive-Clean-Rebate-Data-B/thd2-fu8y/data

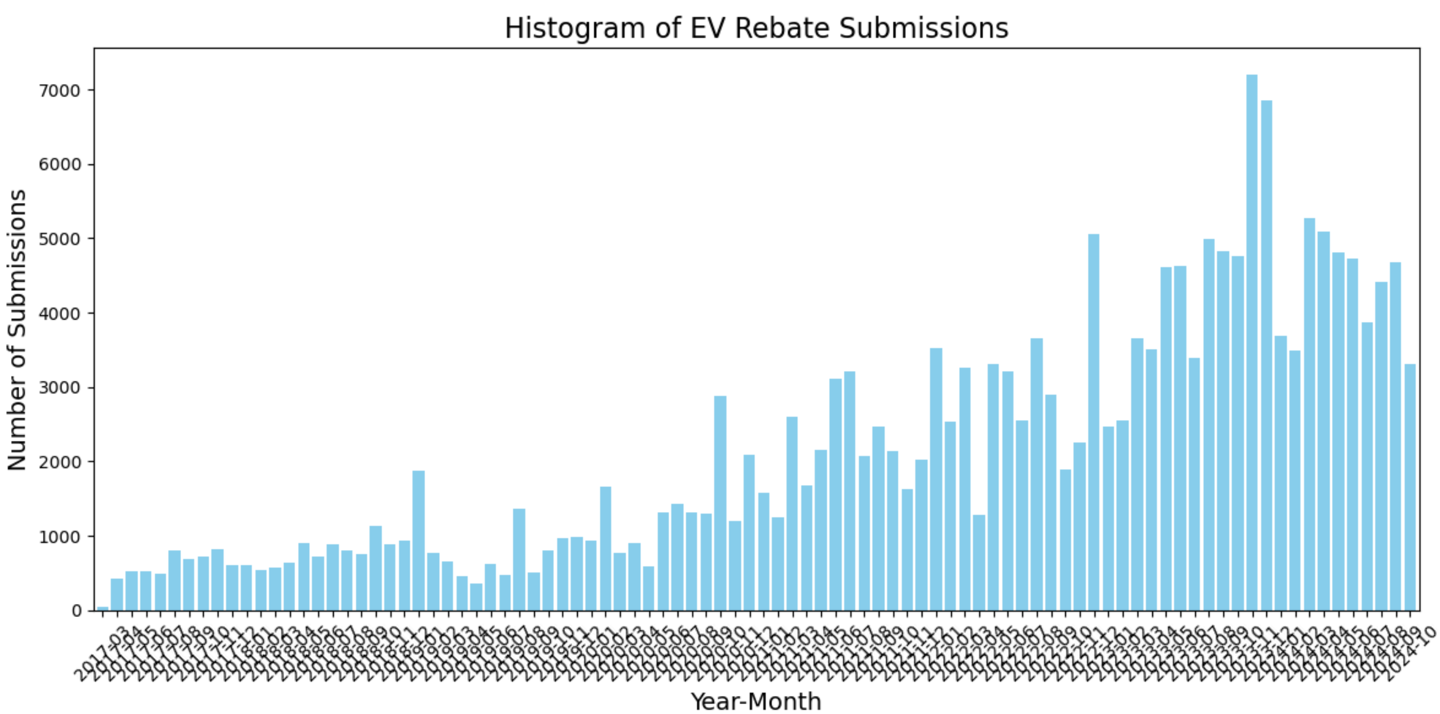
```
    New York State’s Charge NY initiative offers electric car buyers the Drive Clean Rebate of
up to $2,000 for new car purchases or leases. The rebate amount depends on the battery-only
range of each vehicle. Dealers enrolled in the program deduct the eligible amount from the
vehicle price at the point of sale and then submit a rebate application with NYSERDA. This
dataset includes all completed rebate applications as of the data through date.
```

In [15]:
```python
ev_df = pd.read_csv('NY_EV_data.csv')
ev_df = pd.merge(
    ev_df,
    region_county_df[['ZIP Code', 'County Code', 'County Name']],
    left_on='ZIP',
    right_on='ZIP Code',
    how='left'
)
ev_df.drop(columns=['ZIP Code'], inplace=True)
ev_df['Region'] = ev_df['County Name'].map(county_to_region)
print(ev_df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 199280 entries, 0 to 199279
Data columns (total 14 columns):
 #   Column                                   Non-Null Count   Dtype  
---  ------                                   --------------   -----  
 0   Data through Date                        199280 non-null  object 
 1   Submitted Date                           199280 non-null  object 
 2   Make                                     199280 non-null  object 
 3   Model                                    199278 non-null  object 
 4   County                                   199274 non-null  object 
 5   ZIP                                      199279 non-null  float64
 6   EV Type                                  199280 non-null  object 
 7   Transaction Type                         199274 non-null  object 
 8   Annual GHG Emissions Reductions (MT CO2e)  199280 non-null  float64
 9   Annual Petroleum Reductions (gallons)    199280 non-null  float64
 10  Rebate Amount (USD)                      199280 non-null  int64  
 11  County Code                              199279 non-null  float64
 12  County Name                              199279 non-null  object 
 13  Region                                   199279 non-null  object 
dtypes: float64(4), int64(1), object(9)
memory usage: 21.3+ MB
None
```

In [16]:
```python
ev_df['Submitted Date'] = pd.to_datetime(ev_df['Submitted Date'])
ev_df['Formatted Submitted Date'] = ev_df['Submitted Date'].dt.strftime('%-m/%-d/%y')
```

In [17]:
```python
ev_df['YearMonth'] = ev_df['Submitted Date'].dt.to_period('M')
submission_counts = ev_df.groupby('YearMonth').size()

# Plot the histogram
plt.figure(figsize=(12, 6))
submission_counts.plot(kind='bar', width=0.8, color='skyblue')
plt.title('Histogram of EV Rebate Submissions', fontsize=16)
plt.xlabel('Year-Month', fontsize=14)
plt.ylabel('Number of Submissions', fontsize=14)
plt.xticks(rotation=45, fontsize=10)
plt.tight_layout()
plt.show()
```



In [18]:
```python
ev_df['Submitted Date'] = pd.to_datetime(ev_df['Submitted Date'])
ev_df['Formatted Submitted Date'] = ev_df['Submitted Date'].dt.strftime('%m/%d/%Y')
ev_df['Week_start'] = ev_df['Submitted Date'] - pd.to_timedelta(ev_df['Submitted Date'].dt.dayofweek, unit='d')
ev_df['Week_start'] = ev_df['Week_start'].dt.strftime('%m/%d/%Y')
ev_df.head()
```

Out[18]:

	Data through Date	Submitted Date	Make	Model	County	ZIP	EV Type	Transaction Type	Annual GHG Emissions Reductions (MT CO2e)	Annual Petroleum Reductions (gallons)	Rebate Amount (USD)	County Code	
0	10/31/2024	2020-05-28	Tesla	Model Y	NaN	10509.0	BEV	Purchase	3.093	592.890	2000	79.0	
1	10/31/2024	2020-05-28	Tesla	Model Y	NaN	10509.0	BEV	Purchase	3.093	592.890	2000	119.0	W
2	10/31/2024	2023-08-30	Chevrolet	Bolt	NaN	NaN	BEV	Purchase	3.018	592.890	2000	NaN	
3	10/31/2024	2023-11-08	Jeep	Grand Cherokee	NaN	13647.0	PHEV	Lease	0.089	247.229	500	89.0	
4	10/31/2024	2024-06-10	Cadillac	Lyriq	NaN	13669.0	BEV	Purchase	2.418	592.890	500	89.0	

In [19]:

```
aggregated_ev_df = (
    ev_df.groupby(['Region', 'Week_start'], as_index=False)
    .agg(
        ev_rebate_count=('Rebate Amount (USD)', 'count'),  # Count of EV registrations
        avg_ghg_reductions=('Annual GHG Emissions Reductions (MT CO2e)', 'mean'),  # Average GHG reductions
        avg_petroleum_reductions=('Annual Petroleum Reductions (gallons)', 'mean'),  # Average petroleum reduction
        avg_rebate_amount=('Rebate Amount (USD)', 'mean')  # Average rebate amount
    )
)

print(aggregated_ev_df.head())
```

```
   Region  Week_start  ev_rebate_count  avg_ghg_reductions  \
0  Albany  01/01/2018                7            2.582286   
1  Albany  01/01/2024               55            2.250436   
2  Albany  01/02/2023               43            2.193302   
3  Albany  01/03/2022               50            2.842180   
4  Albany  01/04/2021               14            2.286714   

   avg_petroleum_reductions  avg_rebate_amount  
0                472.925571        1400.000000  
1                507.228345         636.363636  
2                493.283558         883.720930  
3                575.159340         610.000000  
4                421.077857        1207.142857  
```

In [20]:

```
aggregated_ev_df['Week_start'] = pd.to_datetime(aggregated_ev_df['Week_start'], format='%m/%d/%Y')
merged_df['Date'] = pd.to_datetime(merged_df['Date'], format='%m/%d/%Y')
final_df = pd.merge(
    merged_df,
    aggregated_ev_df,
    left_on=['Date', 'Region'],
    right_on=['Week_start', 'Region'],
    how='inner'
)
final_df.drop(columns=['Week_start'], inplace=True)
print(final_df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 881 entries, 0 to 880
Data columns (total 27 columns):
 #   Column                                                 Non-Null Count  Dtype
---  ------                                                 --------------  -----
 0   Date                                                   881 non-null    datetime64[ns]
 1   New York State Average ($/gal)                         881 non-null    float64
 2   East Coast Production of Gasoline (Thousand Barrels per Day)  881 non-null    float64
 3   East Coast Production of Jet Fuel (Thousand Barrels per Day)  881 non-null    float64
 4   U.S. Production of Gasoline (Thousand Barrels per Day)  881 non-null    float64
 5   U.S. Gasoline Demand (Thousand Barrels per Day)        881 non-null    float64
 6   U.S. Production of Jet Fuel (Thousand Barrels per Day)  881 non-null    float64
 7   NY Conventional Gasoline Spot Price ($/gal)            881 non-null    float64
 8   NY Ultra-Low Sulfur Diesel Spot Price ($/gal)          881 non-null    float64
 9   WTI Crude Oil Spot Price ($/barrel)                    881 non-null    float64
 10  Brent Crude Oil Spot Price ($/barrel)                  881 non-null    float64
 11  Mid-Atlantic ULS Diesel Stocks (Thousand Barrels)      881 non-null    float64
 12  Mid-Atlantic Gasoline Stocks (Thousand Barrels)        881 non-null    float64
 13  East Coast Gasoline Stocks (Thousand Barrels)          881 non-null    float64
 14  East Coast Ethanol Stocks  (Thousand Barrels)          881 non-null    float64
 15  East Coast Jet Fuels Stocks (Thousand Barrels)         881 non-null    float64
 16  U.S. Gasoline Stocks (Thousand Barrels)                881 non-null    float64
 17  U.S. Crude Oil Stocks (Thousand Barrels)               881 non-null    float64
 18  New York State Average ($/gal)Diesel                   881 non-null    float64
 19  Region                                                 881 non-null    object
 20  Region Gas Cost ($/gal)                                881 non-null    float64
 21  Region Diesel Cost ($/gal)                             881 non-null    float64
 22  Registration Count                                     881 non-null    int64
 23  ev_rebate_count                                        881 non-null    int64
 24  avg_ghg_reductions                                     881 non-null    float64
 25  avg_petroleum_reductions                               881 non-null    float64
 26  avg_rebate_amount                                      881 non-null    float64
dtypes: datetime64[ns](1), float64(23), int64(2), object(1)
memory usage: 186.0+ KB
None
```

In [21]:
```
final_df.head()
```

Out[21]:

	Date	New York State Average ($/gal)	East Coast Production of Gasoline (Thousand Barrels per Day)	East Coast Production of Jet Fuel (Thousand Barrels per Day)	U.S. Production of Gasoline (Thousand Barrels per Day)	U.S. Gasoline Demand (Thousand Barrels per Day)	U.S. Production of Jet Fuel (Thousand Barrels per Day)	NY Conventional Gasoline Spot Price ($/gal)	NY Ultra-Low Sulfur Diesel Spot Price ($/gal)	WTI Crude Oil Spot Price ($/barrel)	...	U.S. Crude Oil Stocks (Thousand Barrels)
0	2017-03-27	2.42	3107.0	76.0	10028.0	9524.0	1731.0	1.49	1.50	47.28	...	533977.0
1	2017-05-01	2.54	3267.0	108.0	9783.0	9156.0	1738.0	1.53	1.52	49.12	...	527772.0
2	2017-05-29	2.51	3376.0	87.0	10430.0	9822.0	1701.0	1.61	1.58	50.21	...	509912.0
3	2017-06-26	2.45	3342.0	106.0	10334.0	9538.0	1775.0	1.39	1.37	43.09	...	509213.0
4	2017-07-31	2.44	3371.0	103.0	10295.0	9842.0	1781.0	1.61	1.59	48.27	...	481888.0

5 rows × 27 columns

EV Charging Stations / Infrastructure

- Electric Vehicle Charging Stations in New York: https://data.ny.gov/Energy-Environment/Electric-Vehicle-Charging-Stations-in-New-York/7rrd-248n/about_data

In [22]:
```
charge_df = pd.read_csv('EV_Charging_Stations_NY.csv')

charge_df = pd.merge(
    charge_df,
    region_county_df[['ZIP Code', 'County Code', 'County Name']],
    left_on='ZIP',
    right_on='ZIP Code',
    how='left'
)
charge_df.drop(columns=['ZIP Code'], inplace=True)
charge_df['Region'] = charge_df['County Name'].map(county_to_region)
print(charge_df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5341 entries, 0 to 5340
Data columns (total 34 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Fuel Type Code           5341 non-null   object 
 1   Station Name             5341 non-null   object 
 2   Street Address           5341 non-null   object 
 3   Intersection Directions  1347 non-null   object 
 4   City                     5340 non-null   object 
 5   State                    5341 non-null   object 
 6   ZIP                      5341 non-null   int64  
 7   Plus4                    0 non-null      float64
 8   Station Phone            5314 non-null   object 
 9   Status Code              5341 non-null   object 
 10  Expected Date            0 non-null      float64
 11  Groups With Access Code  5341 non-null   object 
 12  Access Days Time         4758 non-null   object 
 13  Cards Accepted           605 non-null    object 
 14  EV Level1 EVSE Num       9 non-null      float64
 15  EV Level2 EVSE Num       4863 non-null   float64
 16  EV DC Fast Count         563 non-null    float64
 17  EV Other Info            0 non-null      float64
 18  EV Network               5341 non-null   object 
 19  EV Network Web           5005 non-null   object 
 20  Geocode Status           5341 non-null   object 
 21  Latitude                 5341 non-null   float64
 22  Longitude                5341 non-null   float64
 23  Date Last Confirmed      5335 non-null   object 
 24  ID                       5341 non-null   int64  
 25  Updated At               5341 non-null   object 
 26  Owner Type Code          1373 non-null   object 
 27  Federal Agency ID        1 non-null      float64
 28  Federal Agency Name      1 non-null      object 
 29  Open Date                5323 non-null   object 
 30  EV Connector Types       5341 non-null   object 
 31  County Code              5330 non-null   float64
 32  County Name              5330 non-null   object 
 33  Region                   5330 non-null   object 
dtypes: float64(10), int64(2), object(22)
memory usage: 1.4+ MB
None
```

In [23]:
```
charge_df.head()
```

Out[23]:

	Fuel Type Code	Station Name	Street Address	Intersection Directions	City	State	ZIP	Plus4	Station Phone	Status Code	...	ID	Updated At	Owner Type Code	Fe Ag
0	ELEC	BRUNSWICK HD BRUNSWICK HD2	1130 Hoosick Rd	NaN	Troy	NY	12180	NaN	888-758-4389	E	...	150341	2024-12-06 01:36:38	NaN	
1	ELEC	Salamanca City Hall	225 Wildwood Ave	NaN	Salamanca	NY	14779	NaN	716-945-4620	E	...	157959	2024-03-14 18:02:10	P	
2	ELEC	CITY OF GENEVA CITY HALL #1	47 Castle St	At the rear of the building	Geneva	NY	14456	NaN	888-758-4389	E	...	164639	2024-12-06 01:42:27	NaN	
3	ELEC	CITY OF GENEVA CITY HALL #1	47 Castle St	At the rear of the building	Geneva	NY	14456	NaN	888-758-4389	E	...	164639	2024-12-06 01:42:27	NaN	
4	ELEC	CITY OF GENEVA CITY HALL #1	47 Castle St	At the rear of the building	Geneva	NY	14456	NaN	888-758-4389	E	...	164639	2024-12-06 01:42:27	NaN	

5 rows × 34 columns

In [24]:

```
charge_df['Open Date'] = pd.to_datetime(charge_df['Open Date'], format='%m/%d/%Y')
charge_df['Formatted Open Date'] = charge_df['Open Date'].dt.strftime('%m/%d/%Y')
charge_df['Week_start'] = charge_df['Open Date'] - pd.to_timedelta(charge_df['Open Date'].dt.dayofweek, unit='d')
charge_df['Week_start'] = charge_df['Week_start'].dt.strftime('%m/%d/%Y')
print(charge_df.head())
```

```
  Fuel Type Code                 Station Name     Street Address  \
0           ELEC   BRUNSWICK HD BRUNSWICK HD2   1130 Hoosick Rd   
1           ELEC          Salamanca City Hall  225 Wildwood Ave   
2           ELEC  CITY OF GENEVA CITY HALL #1      47 Castle St   
3           ELEC  CITY OF GENEVA CITY HALL #1      47 Castle St   
4           ELEC  CITY OF GENEVA CITY HALL #1      47 Castle St   

       Intersection Directions       City State    ZIP  Plus4 Station Phone  \
0                          NaN       Troy    NY  12180    NaN  888-758-4389   
1                          NaN  Salamanca    NY  14779    NaN  716-945-4620   
2  At the rear of the building     Geneva    NY  14456    NaN  888-758-4389   
3  At the rear of the building     Geneva    NY  14456    NaN  888-758-4389   
4  At the rear of the building     Geneva    NY  14456    NaN  888-758-4389   

  Status Code  ...  Owner Type Code Federal Agency ID Federal Agency Name  \
0           E  ...              NaN               NaN                 NaN   
1           E  ...                P               NaN                 NaN   
2           E  ...              NaN               NaN                 NaN   
3           E  ...              NaN               NaN                 NaN   
4           E  ...              NaN               NaN                 NaN   

   Open Date  EV Connector Types  County Code  County Name     Region  \
0 2019-12-19               J1772         83.0   Rensselaer     Albany   
1 2020-05-15               J1772          9.0  Cattaraugus    Buffalo   
2 2020-07-30               J1772         69.0      Ontario  Rochester   
3 2020-07-30               J1772         99.0       Seneca  Rochester   
4 2020-07-30               J1772        123.0        Yates  Rochester   

  Formatted Open Date  Week_start  
0          12/19/2019  12/16/2019  
1          05/15/2020  05/11/2020  
2          07/30/2020  07/27/2020  
3          07/30/2020  07/27/2020  
4          07/30/2020  07/27/2020  

[5 rows x 36 columns]
```

In [25]:

```
aggregated_charge_df = (
    charge_df.groupby(['Week_start', 'Region'], as_index=False)
```

```
    .agg(
        stations_opened_count=('Station Name', 'nunique'),  # Count unique stations
        unique_connector_types=('EV Connector Types', 'nunique'),  # Count unique connector types
        first_open_date=('Open Date', 'min')  # Get the earliest open date
    )
)
aggregated_charge_df['first_open_date'] = aggregated_charge_df['first_open_date'].dt.strftime('%m/%d/%Y')
```

In [26]:

```
final_df['Date'] = pd.to_datetime(final_df['Date'], format='%m/%d/%Y')
aggregated_charge_df['Week_start'] = pd.to_datetime(aggregated_charge_df['Week_start'], format='%m/%d/%Y')
combined_df = pd.merge(
    final_df,
    aggregated_charge_df,
    left_on=['Date', 'Region'],
    right_on=['Week_start', 'Region'],
    how='left'
)
combined_df[['stations_opened_count', 'unique_connector_types']] = combined_df[
    ['stations_opened_count', 'unique_connector_types']
].fillna(0)

combined_df = combined_df.drop(columns=['first_open_date'])
combined_df.drop(columns=['Week_start'], inplace=True)
print(combined_df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 881 entries, 0 to 880
Data columns (total 29 columns):
 #   Column                                                   Non-Null Count  Dtype
---  ------                                                   --------------  -----
 0   Date                                                     881 non-null    datetime64[ns]
 1   New York State Average ($/gal)                           881 non-null    float64
 2   East Coast Production of Gasoline (Thousand Barrels per Day)  881 non-null    float64
 3   East Coast Production of Jet Fuel (Thousand Barrels per Day)  881 non-null    float64
 4   U.S. Production of Gasoline (Thousand Barrels per Day)   881 non-null    float64
 5   U.S. Gasoline Demand (Thousand Barrels per Day)          881 non-null    float64
 6   U.S. Production of Jet Fuel (Thousand Barrels per Day)   881 non-null    float64
 7   NY Conventional Gasoline Spot Price ($/gal)              881 non-null    float64
 8   NY Ultra-Low Sulfur Diesel Spot Price ($/gal)            881 non-null    float64
 9   WTI Crude Oil Spot Price ($/barrel)                      881 non-null    float64
 10  Brent Crude Oil Spot Price ($/barrel)                    881 non-null    float64
 11  Mid-Atlantic ULS Diesel Stocks (Thousand Barrels)        881 non-null    float64
 12  Mid-Atlantic Gasoline Stocks (Thousand Barrels)          881 non-null    float64
 13  East Coast Gasoline Stocks (Thousand Barrels)            881 non-null    float64
 14  East Coast Ethanol Stocks  (Thousand Barrels)            881 non-null    float64
 15  East Coast Jet Fuels Stocks (Thousand Barrels)           881 non-null    float64
 16  U.S. Gasoline Stocks (Thousand Barrels)                  881 non-null    float64
 17  U.S. Crude Oil Stocks (Thousand Barrels)                 881 non-null    float64
 18  New York State Average ($/gal)Diesel                     881 non-null    float64
 19  Region                                                   881 non-null    object
 20  Region Gas Cost ($/gal)                                  881 non-null    float64
 21  Region Diesel Cost ($/gal)                               881 non-null    float64
 22  Registration Count                                       881 non-null    int64
 23  ev_rebate_count                                          881 non-null    int64
 24  avg_ghg_reductions                                       881 non-null    float64
 25  avg_petroleum_reductions                                 881 non-null    float64
 26  avg_rebate_amount                                        881 non-null    float64
 27  stations_opened_count                                    881 non-null    float64
 28  unique_connector_types                                   881 non-null    float64
dtypes: datetime64[ns](1), float64(25), int64(2), object(1)
memory usage: 199.7+ KB
None
```

In [27]:

```
combined_df.head()
```

Out[27]:

	Date	New York State Average ($/gal)	East Coast Production of Gasoline (Thousand Barrels per Day)	East Coast Production of Jet Fuel (Thousand Barrels per Day)	U.S. Production of Gasoline (Thousand Barrels per Day)	U.S. Gasoline Demand (Thousand Barrels per Day)	U.S. Production of Jet Fuel (Thousand Barrels per Day)	NY Conventional Gasoline Spot Price ($/gal)	NY Ultra-Low Sulfur Diesel Spot Price ($/gal)	WTI Crude Oil Spot Price ($/barrel)	...	Region	Reg (C ($/g
0	2017-03-27	2.42	3107.0	76.0	10028.0	9524.0	1731.0	1.49	1.50	47.28	...	Albany	2
1	2017-05-01	2.54	3267.0	108.0	9783.0	9156.0	1738.0	1.53	1.52	49.12	...	Albany	2
2	2017-05-29	2.51	3376.0	87.0	10430.0	9822.0	1701.0	1.61	1.58	50.21	...	Albany	2
3	2017-06-26	2.45	3342.0	106.0	10334.0	9538.0	1775.0	1.39	1.37	43.09	...	Albany	2
4	2017-07-31	2.44	3371.0	103.0	10295.0	9842.0	1781.0	1.61	1.59	48.27	...	Albany	2

5 rows × 29 columns

In [35]:
```
combined_df.to_csv('output_file.csv', index=False)
```

Predictive Modeling

In [30]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

X = combined_df.drop(columns=['Registration Count', 'Date'])
y = combined_df['Registration Count']

categorical_cols = X.select_dtypes(include=['object']).columns
numerical_cols = X.select_dtypes(include=['float64', 'int64']).columns
# Create a column transformer for one-hot encoding categorical data and scaling numerical data
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numerical_cols),
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_cols)
    ]
)


X_train, X_test, y_train, y_test = train_test_split(X_processed, y, test_size=0.2, random_state=42)

# Linear Regression
lr = LinearRegression()
lr.fit(X_train, y_train)

# Decision Tree Regressor
dtr = DecisionTreeRegressor(max_depth=5, random_state=42)
dtr.fit(X_train, y_train)

# Random Forest Regressor
rfr = RandomForestRegressor(n_estimators=100, random_state=42)
rfr.fit(X_train, y_train)
```

```python
models = {'Linear Regression': lr, 'Decision Tree': dtr, 'Random Forest': rfr}
for name, model in models.items():
    y_pred = model.predict(X_test)
    print(f"\n{name} Performance:")
    print(f"Mean Absolute Error (MAE): {mean_absolute_error(y_test, y_pred):.2f}")
    print(f"Mean Squared Error (MSE): {mean_squared_error(y_test, y_pred):.2f}")
    print(f"R² Score: {r2_score(y_test, y_pred):.2f}")
```

```
Linear Regression Performance:
Mean Absolute Error (MAE): 1159.13
Mean Squared Error (MSE): 4462935.35
R² Score: 0.85

Decision Tree Performance:
Mean Absolute Error (MAE): 1357.89
Mean Squared Error (MSE): 4891575.51
R² Score: 0.84

Random Forest Performance:
Mean Absolute Error (MAE): 806.96
Mean Squared Error (MSE): 3052400.56
R² Score: 0.90
```

Linear Regression

In [37]:

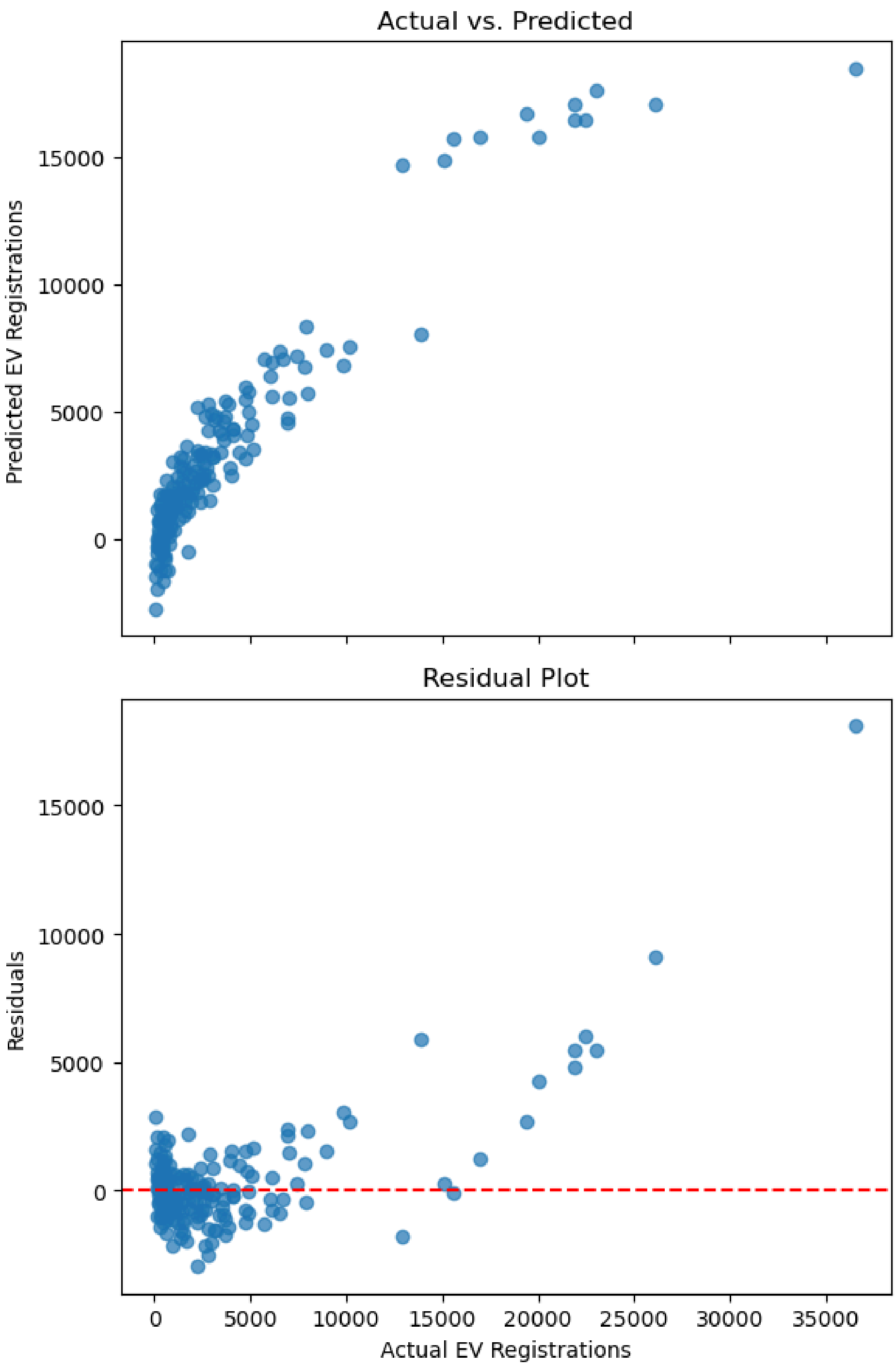
```python
import pandas as pd

# Extract feature names from your preprocessor (if used)
feature_names = preprocessor.get_feature_names_out()

# Combine feature names with coefficients
coefficients = pd.DataFrame({
    'Feature': feature_names,
    'Coefficient': lr.coef_
})

# Sort coefficients by absolute value
coefficients['Absolute Coefficient'] = coefficients['Coefficient'].abs()
coefficients = coefficients.sort_values(by='Absolute Coefficient', ascending=False)

# Display top 10 features
display(coefficients.head(10))
```

	Feature	Coefficient	Absolute Coefficient
36	cat__Region_New York City	11842.152792	11842.152792
41	cat__Region_White Plains	3275.727212	3275.727212
27	cat__Region_Batavia	-3140.416088	3140.416088
35	cat__Region_Nassau	2867.593897	2867.593897
9	num__Brent Crude Oil Spot Price ($/barrel)	2851.203576	2851.203576
28	cat__Region_Binghamton	-2604.301282	2604.301282
33	cat__Region_Ithaca	-2570.762784	2570.762784
7	num__NY Ultra-Low Sulfur Diesel Spot Price ($/...	-2553.625022	2553.625022
19	num__Region Diesel Cost ($/gal)	2376.959430	2376.959430
18	num__Region Gas Cost ($/gal)	-2351.550562	2351.550562

In [58]:

```python
import matplotlib.pyplot as plt

# Predicted values
y_pred = lr.predict(X_test)
residuals = y_test - y_pred

# Create a single figure with two subplots (stacked vertically)
fig, axes = plt.subplots(nrows=2, ncols=1, figsize=(6, 9), sharex=True)

# Actual vs. Predicted Plot
```

```
axes[0].scatter(y_test, y_pred, alpha=0.7)
axes[0].set_ylabel('Predicted EV Registrations')
axes[0].set_title('Actual vs. Predicted')

# Residual Plot
axes[1].scatter(y_test, residuals, alpha=0.7)
axes[1].axhline(0, color='red', linestyle='--')
axes[1].set_xlabel('Actual EV Registrations')
axes[1].set_ylabel('Residuals')
axes[1].set_title('Residual Plot')

# Adjust layout for better spacing
plt.tight_layout()
plt.show()
```



- As we can see, the model systematically under estimates for larger values

In [41]:
```
results = pd.DataFrame({
    'Actual': y_test,
```

```
    'Predicted': y_pred,
    'Residual': residuals
}).reset_index(drop=True)

results['Absolute Residual'] = results['Residual'].abs()
results = results.sort_values(by='Absolute Residual', ascending=False)
print(results.head(10))
```

```
     Actual     Predicted      Residual  Absolute Residual
115   36574  18468.020298  18105.979702       18105.979702
56    26128  17040.051312   9087.948688        9087.948688
104   22498  16471.348244   6026.651756        6026.651756
63    13922   8007.438502   5914.561498        5914.561498
124   21919  16441.543059   5477.456941        5477.456941
164   23030  17572.089090   5457.910910        5457.910910
144   21888  17077.995044   4810.004956        4810.004956
62    20017  15741.389905   4275.610095        4275.610095
57     9832   6809.762174   3022.237826        3022.237826
2      2229   5184.600163  -2955.600163        2955.600163
```

- Does penalization help? Somewhat, but probably not enough to warrant adding this to the presentation

In [43]:

```
from sklearn.linear_model import Ridge, Lasso
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import numpy as np

# Ridge Regression
ridge = Ridge(alpha=1.0, max_iter=5000)  # Alpha controls the strength of regularization
ridge.fit(X_train, y_train)
y_pred_ridge = ridge.predict(X_test)

# Evaluate Ridge Regression
ridge_mae = mean_absolute_error(y_test, y_pred_ridge)
ridge_mse = mean_squared_error(y_test, y_pred_ridge)
ridge_r2 = r2_score(y_test, y_pred_ridge)

# Lasso Regression
lasso = Lasso(alpha=0.1, max_iter=5000)  # Alpha controls the strength of regularization
lasso.fit(X_train, y_train)
y_pred_lasso = lasso.predict(X_test)

# Evaluate Lasso Regression
lasso_mae = mean_absolute_error(y_test, y_pred_lasso)
lasso_mse = mean_squared_error(y_test, y_pred_lasso)
lasso_r2 = r2_score(y_test, y_pred_lasso)

{
    "Ridge Regression": {
        "MAE": ridge_mae,
        "MSE": ridge_mse,
        "R2": ridge_r2
    },
    "Lasso Regression": {
        "MAE": lasso_mae,
        "MSE": lasso_mse,
        "R2": lasso_r2
    }
}
```

Out[43]:

```
{'Ridge Regression': {'MAE': 1180.0939915469633,
  'MSE': 4701917.439467263,
  'R2': 0.8417170881761846},
 'Lasso Regression': {'MAE': 1158.52238861471,
  'MSE': 4465570.270308316,
  'R2': 0.8496733567873223}}
```

In [59]:

```
# Get feature names and coefficients
lasso_coefficients = pd.DataFrame({
    'Feature': preprocessor.get_feature_names_out(),
    'Coefficient': lasso.coef_
})

# Filter non-zero coefficients
```

```
important_features = lasso_coefficients[lasso_coefficients['Coefficient'] != 0]

# Sort by absolute value of coefficients
important_features['Absolute Coefficient'] = important_features['Coefficient'].abs()
important_features = important_features.sort_values(by='Absolute Coefficient', ascending=False)

print(important_features.head(10))
```

```
                                         Feature   Coefficient  \
36                        cat__Region_New York City  13000.445377   
41                         cat__Region_White Plains   4430.080038   
35                               cat__Region_Nassau   4035.104195   
9          num__Brent Crude Oil Spot Price ($/barrel)   2831.370334   
37                            cat__Region_Rochester   2648.496193   
7   num__NY Ultra-Low Sulfur Diesel Spot Price ($/...  -2542.145941   
19                   num__Region Diesel Cost ($/gal)   2364.331019   
18                      num__Region Gas Cost ($/gal)  -2308.841796   
27                              cat__Region_Batavia  -1963.658478   
26                               cat__Region_Albany   1647.386451   

    Absolute Coefficient  
36          13000.445377  
41           4430.080038  
35           4035.104195  
9            2831.370334  
37           2648.496193  
7            2542.145941  
19           2364.331019  
18           2308.841796  
27           1963.658478  
26           1647.386451  
/var/folders/rj/9p72k2_n4n5dp_xbmdt7ygdc0000gn/T/ipykernel_3944/1488081104.py:11: SettingWithCopyWarning: 
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returni
ng-a-view-versus-a-copy
  important_features['Absolute Coefficient'] = important_features['Coefficient'].abs()
```

Decision Tree

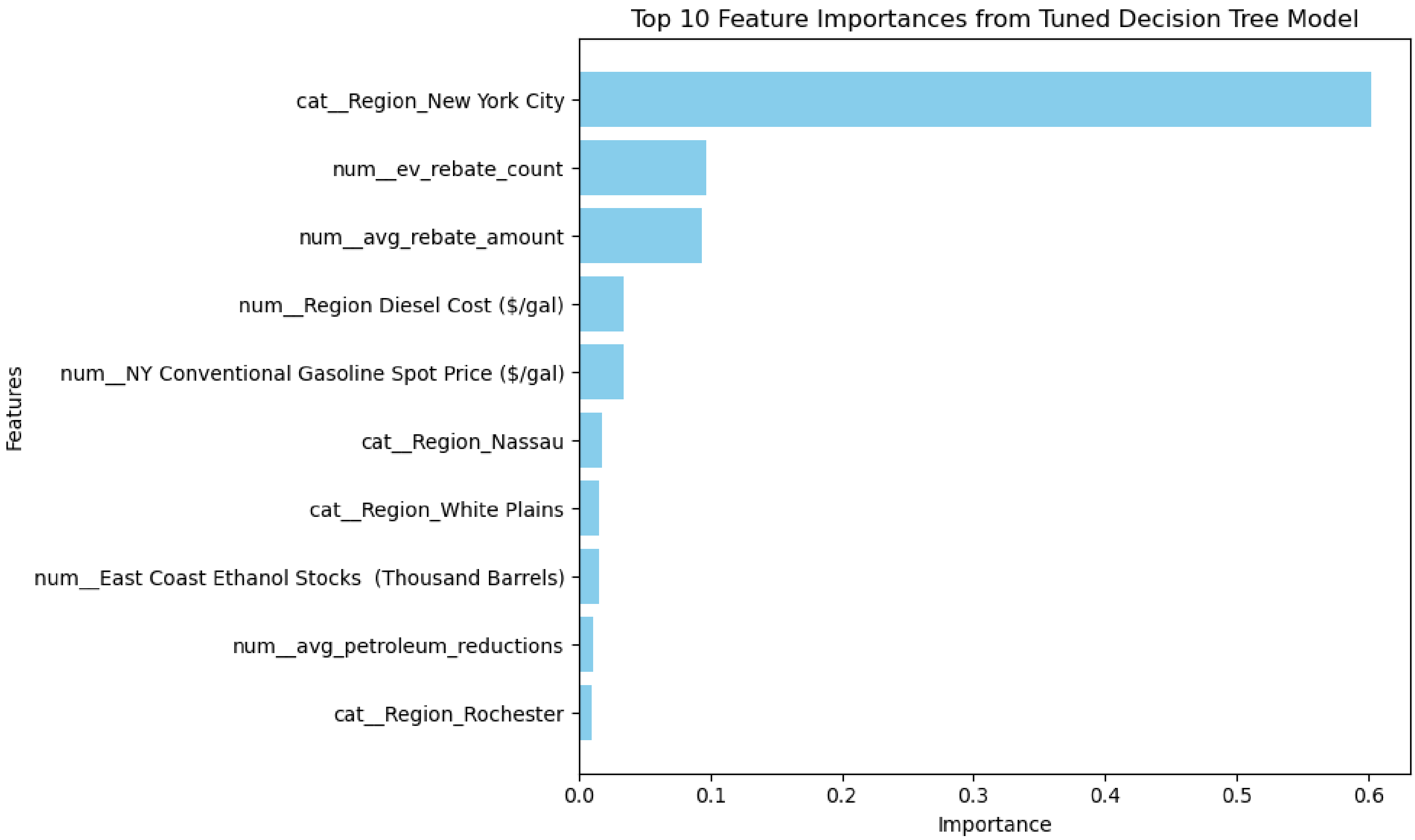
In [65]:

```
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

# Train a Decision Tree Regressor
dt = DecisionTreeRegressor(random_state=42)
dt.fit(X_train, y_train)
y_pred_dt = dt.predict(X_test)

# Evaluate the Decision Tree model
dt_mae = mean_absolute_error(y_test, y_pred_dt)
dt_mse = mean_squared_error(y_test, y_pred_dt)
dt_r2 = r2_score(y_test, y_pred_dt)

# Display the results of the initial Decision Tree model
initial_results = {
    "Decision Tree Initial Performance": {
        "MAE": dt_mae,
        "MSE": dt_mse,
        "R²": dt_r2
    }
}

# Perform Grid Search for Hyperparameter Tuning
param_grid = {
    'max_depth': [3, 10, 13, 15, 17, None],
    'min_samples_split': [2, 3, 5, 6, 7, 8, 12],
    'min_samples_leaf': [1, 2, 3, 4]
}

grid_search = GridSearchCV(estimator=DecisionTreeRegressor(random_state=42),
                           param_grid=param_grid,
```

```python
                           scoring='r2',
                           cv=5,
                           n_jobs=-1)
grid_search.fit(X_train, y_train)

# Best hyperparameters from Grid Search
best_params = grid_search.best_params_

# Evaluate the best model
best_dt = grid_search.best_estimator_
y_pred_best_dt = best_dt.predict(X_test)

best_dt_mae = mean_absolute_error(y_test, y_pred_best_dt)
best_dt_mse = mean_squared_error(y_test, y_pred_best_dt)
best_dt_r2 = r2_score(y_test, y_pred_best_dt)

# Display the results of the tuned Decision Tree model
tuned_results = {
    "Decision Tree Tuned Performance": {
        "MAE": best_dt_mae,
        "MSE": best_dt_mse,
        "R²": best_dt_r2
    },
    "Best Hyperparameters": best_params
}

{**initial_results, **tuned_results}
```

Out[65]:
```
{'Decision Tree Initial Performance': {'MAE': 998.8418079096045,
  'MSE': 4387061.192090396,
  'R²': 0.8523162457076228},
 'Decision Tree Tuned Performance': {'MAE': 992.9324703965871,
  'MSE': 4209996.703635765,
  'R²': 0.8582768528799105},
 'Best Hyperparameters': {'max_depth': 15,
  'min_samples_leaf': 1,
  'min_samples_split': 7}}
```

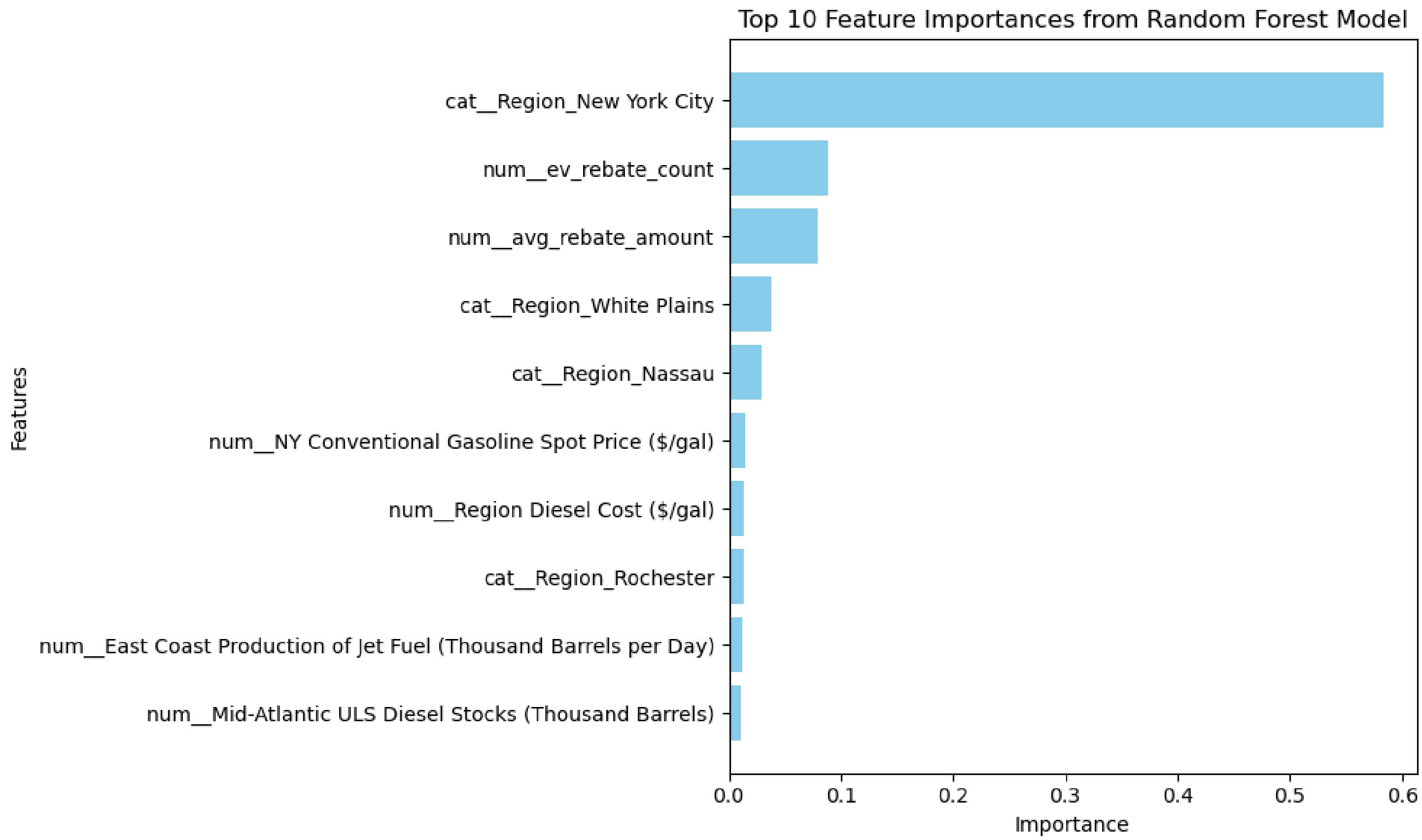
In [74]:
```python
import pandas as pd
import matplotlib.pyplot as plt

features = feature_names

# Train a Decision Tree Regressor (re-initialize if necessary)
from sklearn.tree import DecisionTreeRegressor
best_dt = DecisionTreeRegressor(max_depth=10, min_samples_split=5, min_samples_leaf=2, random_state=42)
best_dt.fit(X_train, y_train)

# Extract feature importances
feature_importances = best_dt.feature_importances_

# Create a DataFrame for feature importances
importance_df = pd.DataFrame({'Feature': features, 'Importance': feature_importances})
importance_df = importance_df.sort_values(by='Importance', ascending=False)

plt.figure(figsize=(10, 6))
plt.barh(importance_df['Feature'].head(10), importance_df['Importance'].head(10), color='skyblue')
plt.xlabel('Importance')
plt.ylabel('Features')
plt.title('Top 10 Feature Importances from Tuned Decision Tree Model')
plt.gca().invert_yaxis()  # Invert y-axis to have the most important feature at the top
plt.tight_layout()
plt.show()
```



Random Forest

In [79]:

```
feature_importances = rfr.feature_importances_
importance_df = pd.DataFrame({'Feature': features, 'Importance': feature_importances})
importance_df = importance_df.sort_values(by='Importance', ascending=False)
plt.figure(figsize=(10, 6))
plt.barh(importance_df['Feature'].head(10), importance_df['Importance'].head(10), color='skyblue')
plt.xlabel('Importance')
plt.ylabel('Features')
plt.title('Top 10 Feature Importances from Random Forest Model')
plt.gca().invert_yaxis()  # Invert y-axis for better readability
plt.tight_layout()
plt.show()
```



Neural Network

In [80]:
```
from sklearn.neural_network import MLPRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

mlp = MLPRegressor(
    hidden_layer_sizes=(100, 50),
    activation='relu',
    solver='adam',
    max_iter=10000,
    random_state=42
)

mlp.fit(X_train, y_train)
y_pred_mlp = mlp.predict(X_test)
print("\nNeural Network Regressor Performance:")
print(f"Mean Absolute Error (MAE): {mean_absolute_error(y_test, y_pred_mlp):.2f}")
print(f"Mean Squared Error (MSE): {mean_squared_error(y_test, y_pred_mlp):.2f}")
print(f"R² Score: {r2_score(y_test, y_pred_mlp):.2f}")
```

```
Neural Network Regressor Performance:
Mean Absolute Error (MAE): 703.14
Mean Squared Error (MSE): 1605178.77
R² Score: 0.95
```