In [1]:
```python
import pandas as pd

# Use double backslashes or forward slashes in the file path
file_path = r'C:\Users\Sharon\Desktop\Docs\EV\Electric_Vehicle_Population_Data.c

# Read the CSV file
ev_data = pd.read_csv(file_path)

# Display the first few rows of the data
print(ev_data.head())
```

```
   VIN (1-10)     County       City State  Postal Code  Model Year   Make  \
0  5YJYGDEE1L       King    Seattle    WA      98122.0        2020  TESLA
1  7SAYGDEE9P  Snohomish    Bothell    WA      98021.0        2023  TESLA
2  5YJSA1E4XK       King    Seattle    WA      98109.0        2019  TESLA
3  5YJSA1E27G       King   Issaquah    WA      98027.0        2016  TESLA
4  5YJYGDEE5M     Kitsap  Suquamish    WA      98392.0        2021  TESLA

     Model           Electric Vehicle Type  \
0  MODEL Y  Battery Electric Vehicle (BEV)
1  MODEL Y  Battery Electric Vehicle (BEV)
2  MODEL S  Battery Electric Vehicle (BEV)
3  MODEL S  Battery Electric Vehicle (BEV)
4  MODEL Y  Battery Electric Vehicle (BEV)

   Clean Alternative Fuel Vehicle (CAFV) Eligibility  Electric Range  \
0            Clean Alternative Fuel Vehicle Eligible             291
1  Eligibility unknown as battery range has not b...               0
2            Clean Alternative Fuel Vehicle Eligible             270
3            Clean Alternative Fuel Vehicle Eligible             210
4  Eligibility unknown as battery range has not b...               0

   Base MSRP  Legislative District  DOL Vehicle ID  \
0          0                  37.0       125701579
1          0                   1.0       244285107
2          0                  36.0       156773144
3          0                   5.0       165103011
4          0                  23.0       205138552

                Vehicle Location  \
0   POINT (-122.30839 47.610365)
1  POINT (-122.179458 47.802589)
2   POINT (-122.34848 47.632405)
3   POINT (-122.03646 47.534065)
4   POINT (-122.55717 47.733415)

                                Electric Utility  2020 Census Tract
0   CITY OF SEATTLE - (WA)|CITY OF TACOMA - (WA)       5.303301e+10
1                         PUGET SOUND ENERGY INC       5.306105e+10
2   CITY OF SEATTLE - (WA)|CITY OF TACOMA - (WA)       5.303301e+10
3  PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)       5.303303e+10
4                         PUGET SOUND ENERGY INC       5.303594e+10
```

In [2]:
```python
ev_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 177866 entries, 0 to 177865
Data columns (total 17 columns):
 #   Column                                             Non-Null Count   Dtype  
---  ------                                             --------------   -----  
 0   VIN (1-10)                                         177866 non-null  object 
 1   County                                             177861 non-null  object 
 2   City                                               177861 non-null  object 
 3   State                                              177866 non-null  object 
 4   Postal Code                                        177861 non-null  float64
 5   Model Year                                         177866 non-null  int64  
 6   Make                                               177866 non-null  object 
 7   Model                                              177866 non-null  object 
 8   Electric Vehicle Type                              177866 non-null  object 
 9   Clean Alternative Fuel Vehicle (CAFV) Eligibility  177866 non-null  object 
 10  Electric Range                                     177866 non-null  int64  
 11  Base MSRP                                          177866 non-null  int64  
 12  Legislative District                               177477 non-null  float64
 13  DOL Vehicle ID                                     177866 non-null  int64  
 14  Vehicle Location                                   177857 non-null  object 
 15  Electric Utility                                   177861 non-null  object 
 16  2020 Census Tract                                  177861 non-null  float64
dtypes: float64(3), int64(4), object(10)
memory usage: 23.1+ MB
```

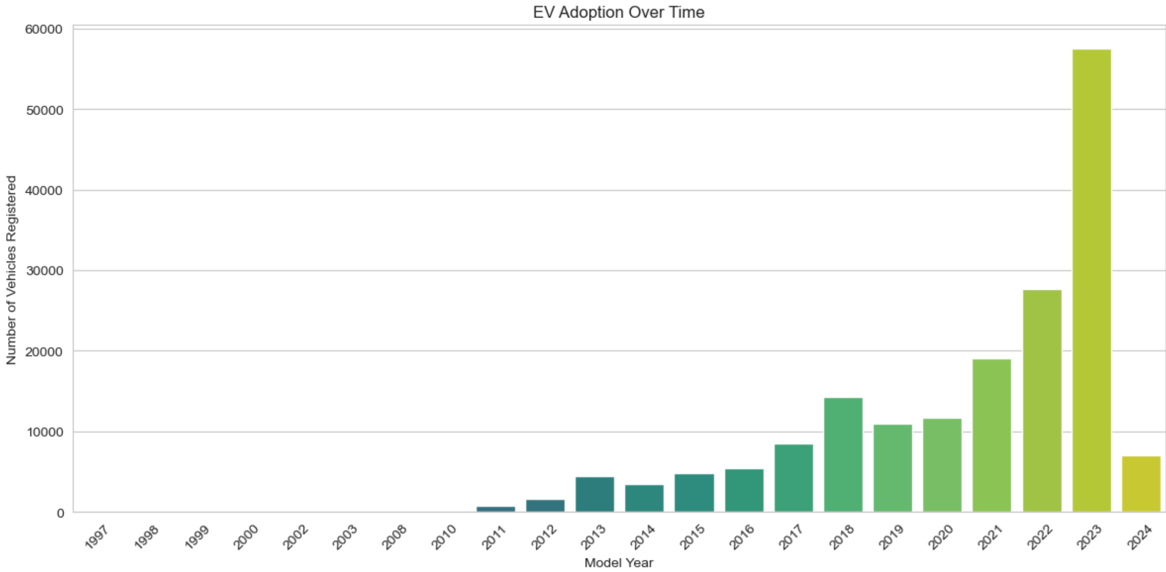
In [3]:
```
ev_data.isnull().sum()
```

Out[3]:
```
VIN (1-10)                                             0
County                                                 5
City                                                   5
State                                                  0
Postal Code                                            5
Model Year                                             0
Make                                                   0
Model                                                  0
Electric Vehicle Type                                  0
Clean Alternative Fuel Vehicle (CAFV) Eligibility      0
Electric Range                                         0
Base MSRP                                              0
Legislative District                                 389
DOL Vehicle ID                                         0
Vehicle Location                                       9
Electric Utility                                       5
2020 Census Tract                                      5
dtype: int64
```

In [4]:
```
ev_data = ev_data.dropna()
```

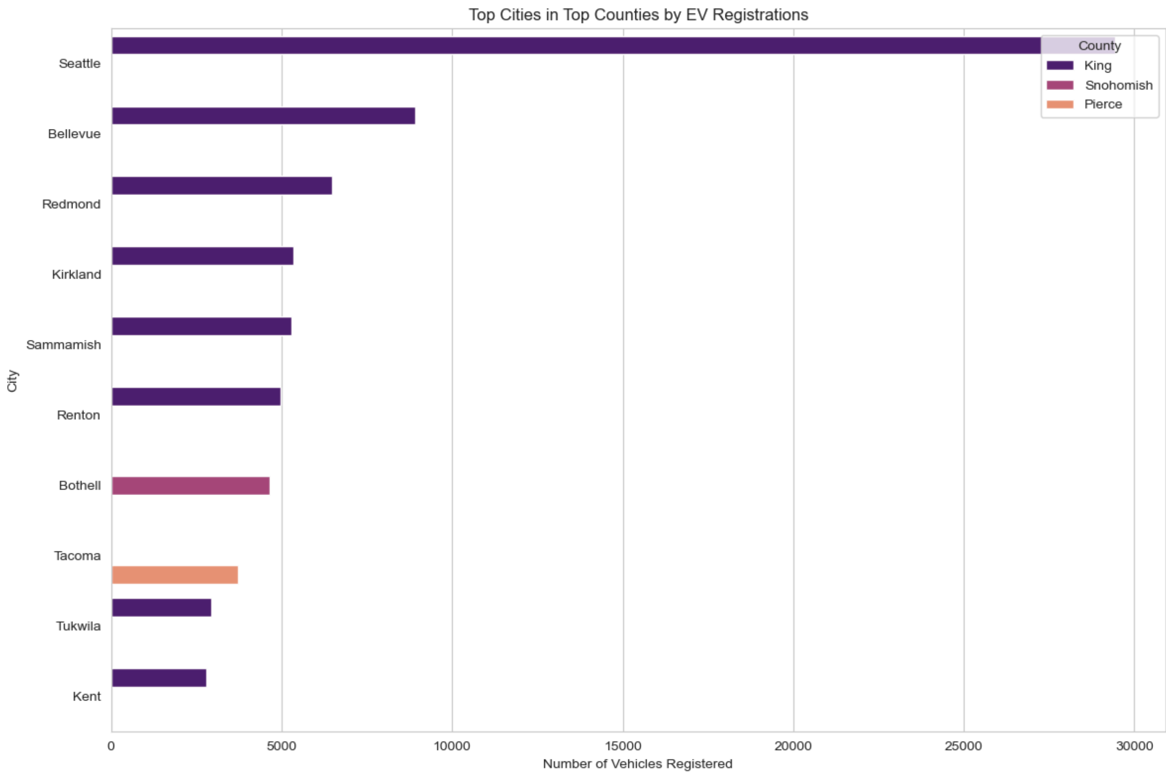
In [5]:
```
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style("whitegrid")

# EV Adoption Over Time
plt.figure(figsize=(12, 6))
ev_adoption_by_year = ev_data['Model Year'].value_counts().sort_index()
sns.barplot(x=ev_adoption_by_year.index, y=ev_adoption_by_year.values, palette="
plt.title('EV Adoption Over Time')
plt.xlabel('Model Year')
plt.ylabel('Number of Vehicles Registered')
plt.xticks(rotation=45)
```

```
plt.tight_layout()
plt.show()
```

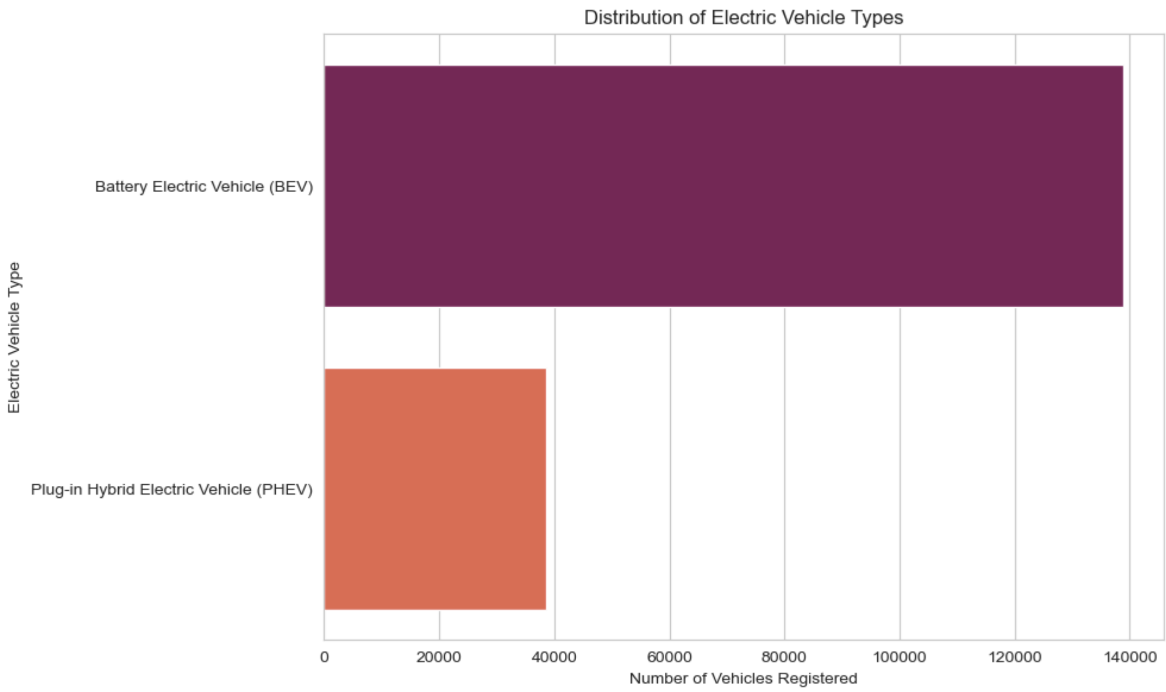


In [6]:

```
# geographical distribution at county level
ev_county_distribution = ev_data['County'].value_counts()
top_counties = ev_county_distribution.head(3).index

# filtering the dataset for these top counties
top_counties_data = ev_data[ev_data['County'].isin(top_counties)]

# analyzing the distribution of EVs within the cities of these top counties
ev_city_distribution_top_counties = top_counties_data.groupby(['County', 'City']

# visualize the top 10 cities across these counties
top_cities = ev_city_distribution_top_counties.head(10)

plt.figure(figsize=(12, 8))
sns.barplot(x='Number of Vehicles', y='City', hue='County', data=top_cities, pal
plt.title('Top Cities in Top Counties by EV Registrations')
plt.xlabel('Number of Vehicles Registered')
plt.ylabel('City')
plt.legend(title='County')
plt.tight_layout()
plt.show()
```

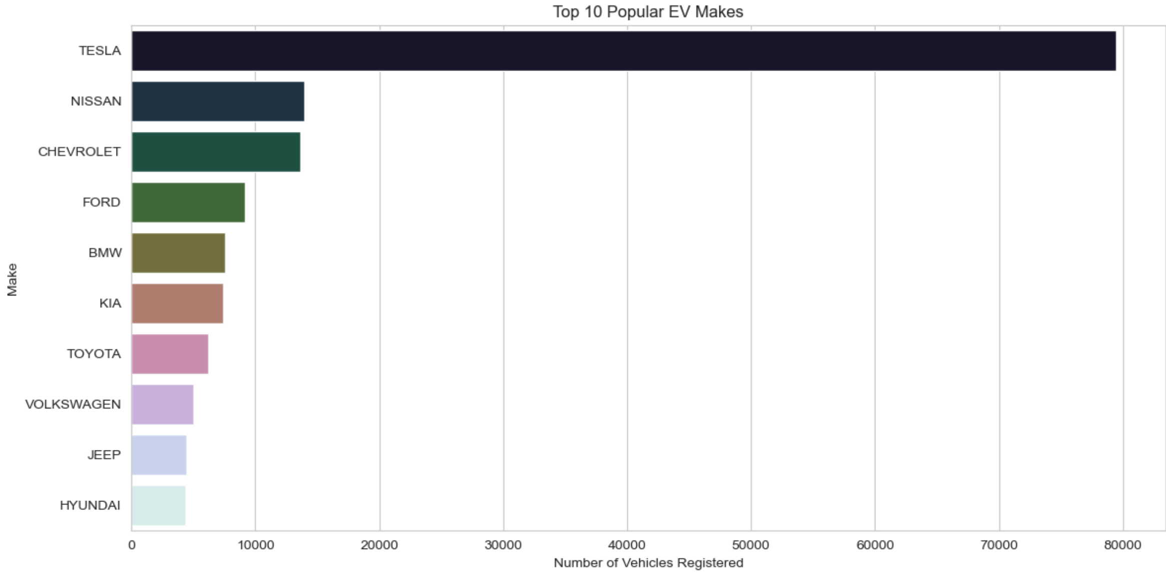


In [7]:
```
# analyzing the distribution of electric vehicle Types
ev_type_distribution = ev_data['Electric Vehicle Type'].value_counts()

plt.figure(figsize=(10, 6))
sns.barplot(x=ev_type_distribution.values, y=ev_type_distribution.index, palette
plt.title('Distribution of Electric Vehicle Types')
plt.xlabel('Number of Vehicles Registered')
plt.ylabel('Electric Vehicle Type')
plt.tight_layout()
plt.show()
```



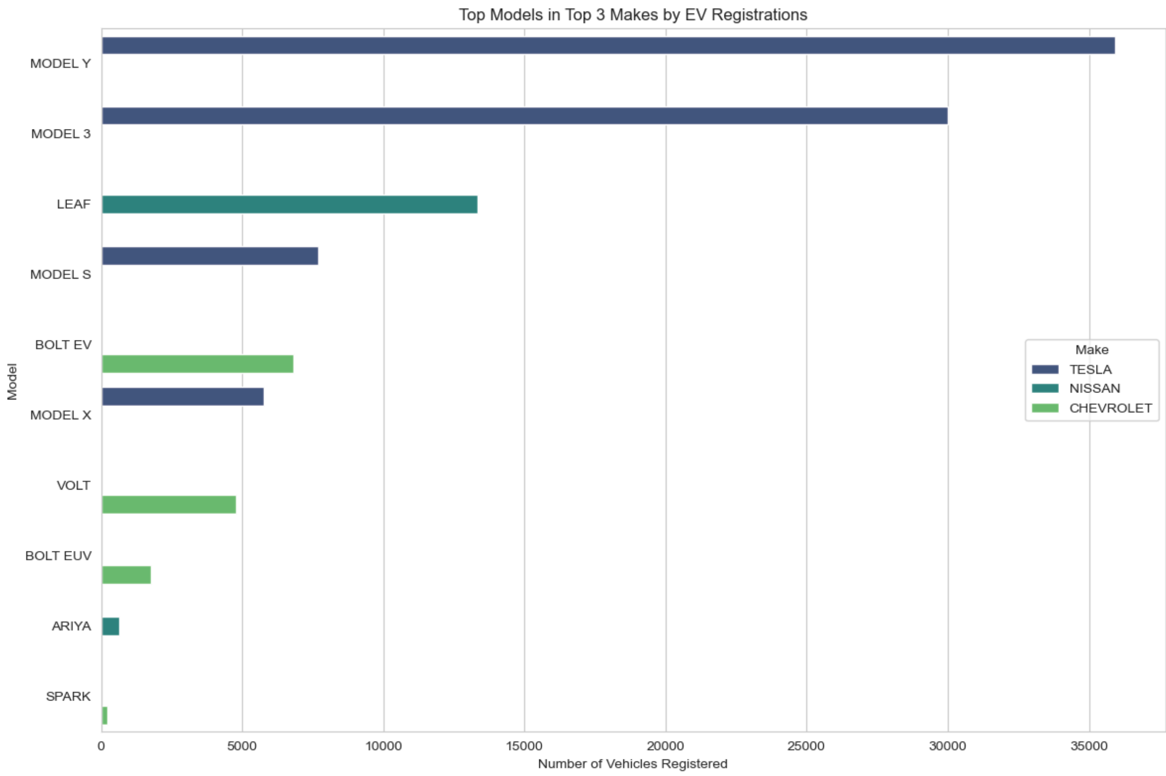
In [8]:
```
# analyzing the popularity of EV manufacturers
ev_make_distribution = ev_data['Make'].value_counts().head(10)  # Limiting to to
```

```
plt.figure(figsize=(12, 6))
sns.barplot(x=ev_make_distribution.values, y=ev_make_distribution.index, palette
plt.title('Top 10 Popular EV Makes')
plt.xlabel('Number of Vehicles Registered')
plt.ylabel('Make')
plt.tight_layout()
plt.show()
```



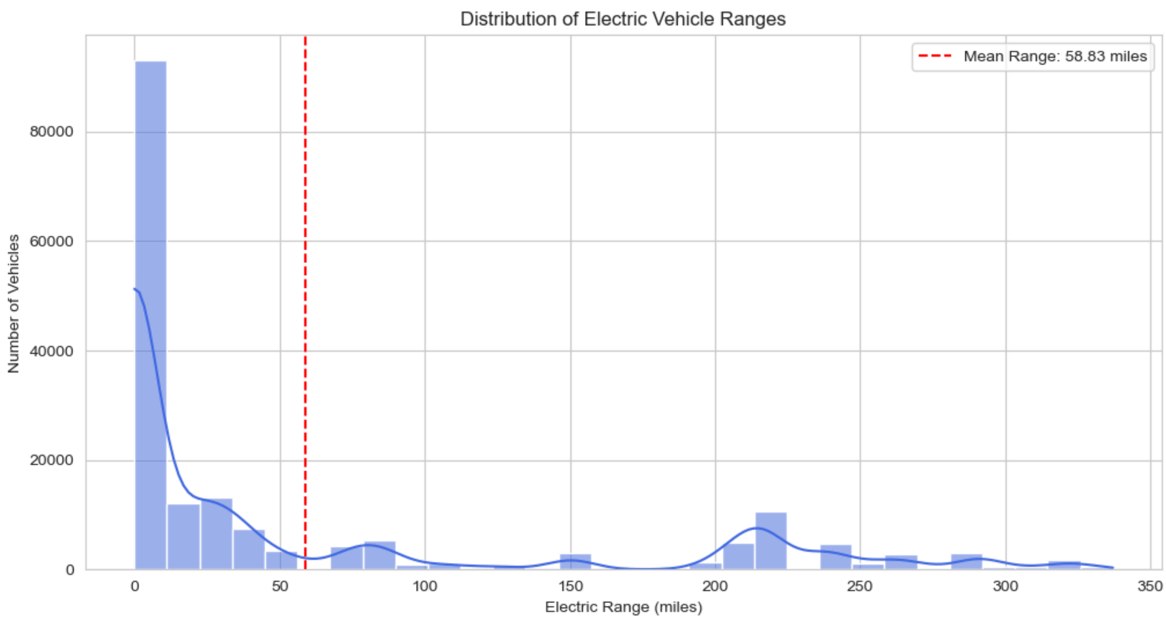
In [9]:

```
# selecting the top 3 manufacturers based on the number of vehicles registered
top_3_makes = ev_make_distribution.head(3).index

# filtering the dataset for these top manufacturers
top_makes_data = ev_data[ev_data['Make'].isin(top_3_makes)]

# analyzing the popularity of EV models within these top manufacturers
ev_model_distribution_top_makes = top_makes_data.groupby(['Make', 'Model']).size

# visualizing the top 10 models across these manufacturers for clarity
top_models = ev_model_distribution_top_makes.head(10)

plt.figure(figsize=(12, 8))
sns.barplot(x='Number of Vehicles', y='Model', hue='Make', data=top_models, pale
plt.title('Top Models in Top 3 Makes by EV Registrations')
plt.xlabel('Number of Vehicles Registered')
plt.ylabel('Model')
plt.legend(title='Make', loc='center right')
plt.tight_layout()
plt.show()
```



In [10]:
```
# analyzing the distribution of electric range
plt.figure(figsize=(12, 6))
sns.histplot(ev_data['Electric Range'], bins=30, kde=True, color='royalblue')
plt.title('Distribution of Electric Vehicle Ranges')
plt.xlabel('Electric Range (miles)')
plt.ylabel('Number of Vehicles')
plt.axvline(ev_data['Electric Range'].mean(), color='red', linestyle='--', label
plt.legend()
plt.show()
```

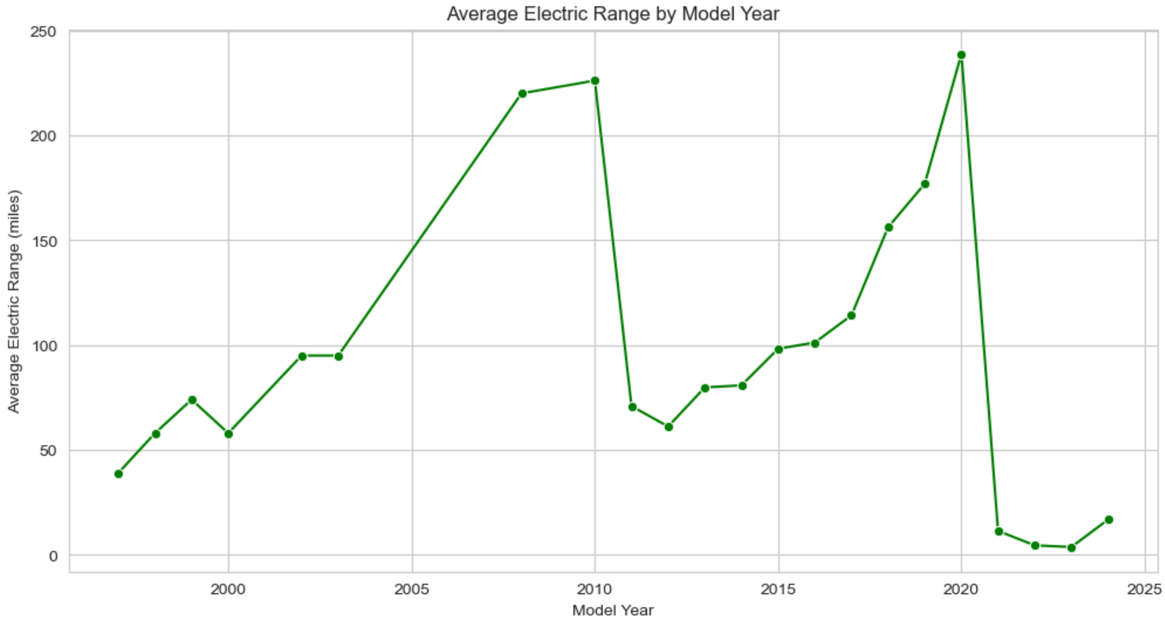
```
C:\Users\Sharon\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarni
ng: use_inf_as_na option is deprecated and will be removed in a future version. C
onvert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



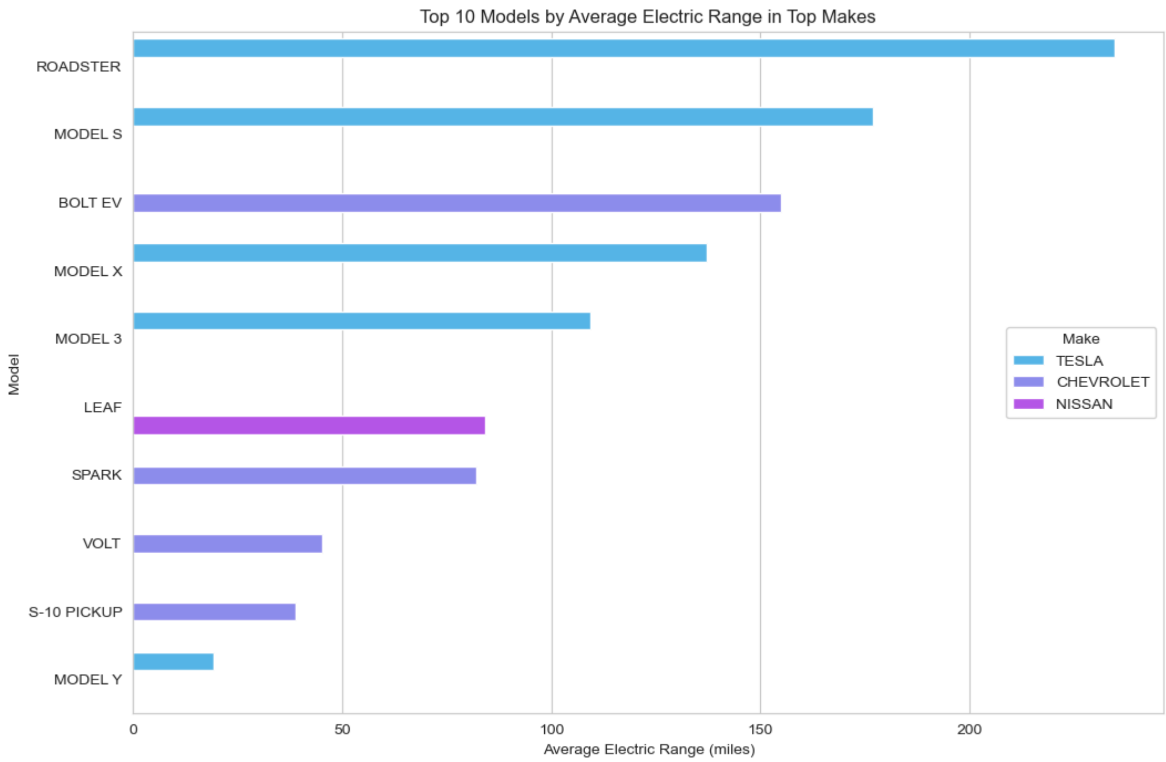
In [11]:
```
# calculating the average electric range by model year
average_range_by_year = ev_data.groupby('Model Year')['Electric Range'].mean().r
```

```python
plt.figure(figsize=(12, 6))
sns.lineplot(x='Model Year', y='Electric Range', data=average_range_by_year, mar
plt.title('Average Electric Range by Model Year')
plt.xlabel('Model Year')
plt.ylabel('Average Electric Range (miles)')
plt.grid(True)
plt.show()
```

```
C:\Users\Sharon\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarni
ng: use_inf_as_na option is deprecated and will be removed in a future version. C
onvert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\Sharon\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarni
ng: use_inf_as_na option is deprecated and will be removed in a future version. C
onvert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



In [12]:
```python
average_range_by_model = top_makes_data.groupby(['Make', 'Model'])['Electric Ran

# the top 10 models with the highest average electric range
top_range_models = average_range_by_model.head(10)

plt.figure(figsize=(12, 8))
barplot = sns.barplot(x='Electric Range', y='Model', hue='Make', data=top_range_
plt.title('Top 10 Models by Average Electric Range in Top Makes')
plt.xlabel('Average Electric Range (miles)')
plt.ylabel('Model')
plt.legend(title='Make', loc='center right')
plt.show()
```



In [13]:

```
# calculate the number of EVs registered each year
ev_registration_counts = ev_data['Model Year'].value_counts().sort_index()
ev_registration_counts
```

Out[13]:

```
Model Year
1997        1
1998        1
1999        5
2000        7
2002        2
2003        1
2008       19
2010       23
2011      775
2012     1614
2013     4399
2014     3496
2015     4826
2016     5469
2017     8534
2018    14286
2019    10913
2020    11740
2021    19063
2022    27708
2023    57519
2024     7072
Name: count, dtype: int64
```

In [14]:

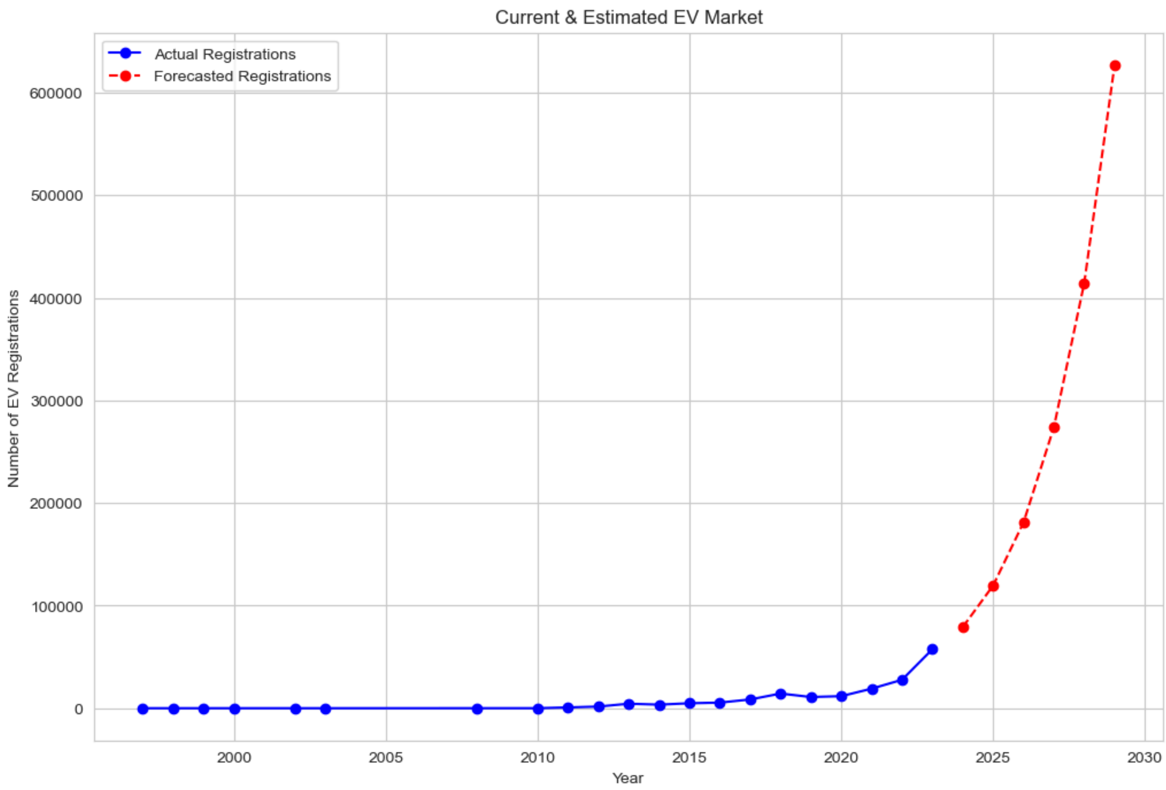
```
from scipy.optimize import curve_fit
import numpy as np

# filter the dataset to include years with complete data, assuming 2023 is the l
filtered_years = ev_registration_counts[ev_registration_counts.index <= 2023]

# define a function for exponential growth to fit the data
```

```python
def exp_growth(x, a, b):
    return a * np.exp(b * x)

# prepare the data for curve fitting
x_data = filtered_years.index - filtered_years.index.min()
y_data = filtered_years.values

# fit the data to the exponential growth function
params, covariance = curve_fit(exp_growth, x_data, y_data)

# use the fitted function to forecast the number of EVs for 2024 and the next fi
forecast_years = np.arange(2024, 2024 + 6) - filtered_years.index.min()
forecasted_values = exp_growth(forecast_years, *params)

# create a dictionary to display the forecasted values for easier interpretation
forecasted_evs = dict(zip(forecast_years + filtered_years.index.min(), forecaste

print(forecasted_evs)
```

```
{2024: 79079.20808938889, 2025: 119653.96274428742, 2026: 181047.22020265696, 202
7: 273940.74706208805, 2028: 414497.01805382164, 2029: 627171.3128407666}
```

In [15]:

```python
# prepare data for plotting
years = np.arange(filtered_years.index.min(), 2029 + 1)
actual_years = filtered_years.index
forecast_years_full = np.arange(2024, 2029 + 1)

# actual and forecasted values
actual_values = filtered_years.values
forecasted_values_full = [forecasted_evs[year] for year in forecast_years_full]

plt.figure(figsize=(12, 8))
plt.plot(actual_years, actual_values, 'bo-', label='Actual Registrations')
plt.plot(forecast_years_full, forecasted_values_full, 'ro--', label='Forecasted

plt.title('Current & Estimated EV Market')
plt.xlabel('Year')
plt.ylabel('Number of EV Registrations')
plt.legend()
plt.grid(True)

plt.show()
```


Current & Estimated EV Market
Actual Registrations
Forecasted Registrations
Number of EV Registrations
Year
0
100000
200000
300000
400000
500000
600000
2000
2005
2010
2015
2020
2025
2030

In [ ]: