Project 2: Vehicle Sales and Market Trends

Executive Summary

Key Findings:

- **Vehicle Condition:** A primary driver of selling price, with higher-condition vehicles commanding premium prices.
- **Mileage:** Generally negatively impacts selling price, but the effect varies by condition and body type.
- **Body Type:** The relationship between condition and price differs across body types.
- **Popular Makes and Models:**
  - **Overall Sales Trends:** All listed models exhibited consistent growth, indicating a growing market.
  - **Specific Model Performance:**
    - Ford vehicles dominated the **top 10.**
    - The Toyota Camry maintained its position.
    - Japanese brands were well-represented.
    - The BMW 3 Series showed steady growth.
- **Potential Factors Influencing Sales:** Economic conditions, new model releases, marketing, and consumer preferences likely played a role.
- **MMR Analysis:** Certain makes and models were consistently overestimated or underestimated by MMR. Further analysis is needed to understand these discrepancies.

Deliverables:

- **Jupyter Notebook:** Detailed analysis, code, and visualizations.
- **Presentation:** Summarizes key findings.

Further Analysis:

- Market research, competitive analysis, and economic indicators can provide deeper insights into sales trends.

Business task: Analyze the dataset to uncover market trends, understand pricing dynamics, and explore factors influencing vehicle sales.

1. Identifying Trends in Vehicle Sales Over Time

2. Analyzing the Impact of Vehicle Condition and Mileage on Selling Prices

3. Understanding the Relationship Between MMR Values and Actual Selling Prices

4. Determining the Most Popular Vehicle Makes and Models

In [1]:
```
# Import libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
# Load dataset

df= pd.read_csv('car_prices_cleaned.csv')
```

In [3]:
```
# Confirm dataset has loaded

df.head(3)
```

Out[3]:

	year	make	model	trim	body	transmission	vin	state	condition	odomete
0	2015	Kia	Sorento	LX	Suv	Automatic	5XYKTCA69FG566472	CA	5.0	16639.(
1	2015	Kia	Sorento	LX	Suv	Automatic	5XYKTCA69FG561319	CA	5.0	9393.(
2	2014	Bmw	3 Series	328i SULEV	Sedan	Automatic	WBA3C1C51EK116351	CA	45.0	1331.(

In [4]:
```
# Confirm data set details

print(df.info())
print('\nRows and Cols\n')
print(f'Rows: {df.shape[0]}\nColumns: {df.shape[1]}')
print('\nVehicle Numerical Summary Statistics\n')
print(df.describe().transpose())
print('\nVehicle Categorical Summary Statistics\n')
print(df.describe(include='object').transpose())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 558836 entries, 0 to 558835
Data columns (total 17 columns):
 #   Column        Non-Null Count   Dtype  
---  ------        --------------   -----  
 0   year          558836 non-null  int64  
 1   make          548535 non-null  object 
 2   model         548437 non-null  object 
 3   trim          548185 non-null  object 
 4   body          545641 non-null  object 
 5   transmission  493484 non-null  object 
 6   vin           558832 non-null  object 
 7   state         558836 non-null  object 
 8   condition     547017 non-null  float64
 9   odometer      558742 non-null  float64
 10  color         558087 non-null  object 
 11  interior      558087 non-null  object 
 12  seller        558836 non-null  object 
 13  mmr           558798 non-null  float64
 14  sellingprice  558824 non-null  float64
 15  saledate      558824 non-null  object 
 16  saletime      558824 non-null  object 
dtypes: float64(4), int64(1), object(12)
memory usage: 72.5+ MB
None

Rows and Cols

Rows: 558836
Columns: 17

Vehicle Numerical Summary Statistics

                 count          mean           std     min      25%      50%  \
year          558836.0   2010.038940      3.966856  1982.0   2007.0   2012.0   
condition     547017.0     30.672365     13.402832     1.0     23.0     35.0   
odometer      558742.0  68319.897600  53398.515058     1.0  28371.0  52254.0   
mmr           558798.0  13769.397349   9679.964458    25.0   7100.0  12250.0   
sellingprice  558824.0  13611.379588   9749.497978     1.0   6900.0  12100.0   

                  75%       max  
year           2013.0    2015.0  
condition        42.0      49.0  
odometer      99109.0  999999.0  
mmr           18300.0  182000.0  
sellingprice  18200.0  230000.0  

Vehicle Categorical Summary Statistics

               count  unique                 top    freq
make          548535      55                Ford   94001
model         548437     850              Altima   19349
trim          548185    1963                Base   55816
body          545641      45               Sedan  241342
transmission  493484       3           Automatic  475914
vin           558832  550296           AUTOMATIC      22
state         558836      64                  FL   82945
color         558087      46               Black  110970
interior      558087      17               Black  244329
seller        558836   14263  Nissan-Infiniti Lt   19693
```

```
saledate       558824     193         Dec 18 2014    17065
saletime       558824     292            01:30:00    67888
```

1. Identifying Trends in Vehicle Sales Over Time

Research Questions:

- Which makes and models produced the highest sales over the past year?
- Which makes and models produced the least?
- How have sales volumes for different vehicle segments (e.g., SUVs, sedans, trucks) changed over the past year?
- What is the percentage increase or decrease in sales for each segment compared to the previous year?

Which makes and models produced the highest sales over the past year?

In [5]:
```
# Check column names

df. columns
```

Out[5]:
```
Index(['year', 'make', 'model', 'trim', 'body', 'transmission', 'vin', 'state',
       'condition', 'odometer', 'color', 'interior', 'seller', 'mmr',
       'sellingprice', 'saledate', 'saletime'],
      dtype='object')
```

In [6]:
```
# Check for missing values

df.isna().sum()
```

Out[6]:

	0
year	0
make	10301
model	10399
trim	10651
body	13195
transmission	65352
vin	4
state	0
condition	11819
odometer	94
color	749
interior	749
seller	0
mmr	38
sellingprice	12
saledate	12
saletime	12

dtype: int64

In [7]:

```
# Drop all missing values

df = df.dropna()
```

In [8]:

```
# Confirm all missing values have been dropped

df.isna().sum()
```

Out[8]:

	0
year	0
make	0
model	0
trim	0
body	0
transmission	0
vin	0
state	0
condition	0
odometer	0
color	0
interior	0
seller	0
mmr	0
sellingprice	0
saledate	0
saletime	0

dtype: int64

In [9]:

```
# 472325 out of 558836 rows remain, a loss of approx. 15% of data
# However, the due to the size of the dataset this loss show not be detrimental

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 472325 entries, 0 to 558835
Data columns (total 17 columns):
 #   Column        Non-Null Count   Dtype  
---  ------        --------------   -----  
 0   year          472325 non-null  int64  
 1   make          472325 non-null  object 
 2   model         472325 non-null  object 
 3   trim          472325 non-null  object 
 4   body          472325 non-null  object 
 5   transmission  472325 non-null  object 
 6   vin           472325 non-null  object 
 7   state         472325 non-null  object 
 8   condition     472325 non-null  float64
 9   odometer      472325 non-null  float64
 10  color         472325 non-null  object 
 11  interior      472325 non-null  object 
 12  seller        472325 non-null  object 
 13  mmr           472325 non-null  float64
 14  sellingprice  472325 non-null  float64
 15  saledate      472325 non-null  object 
 16  saletime      472325 non-null  object 
dtypes: float64(4), int64(1), object(12)
memory usage: 64.9+ MB
```

In [10]:
```
# Confirming no missing years (1982 - 2015)

df['year'].value_counts().sort_index()
```

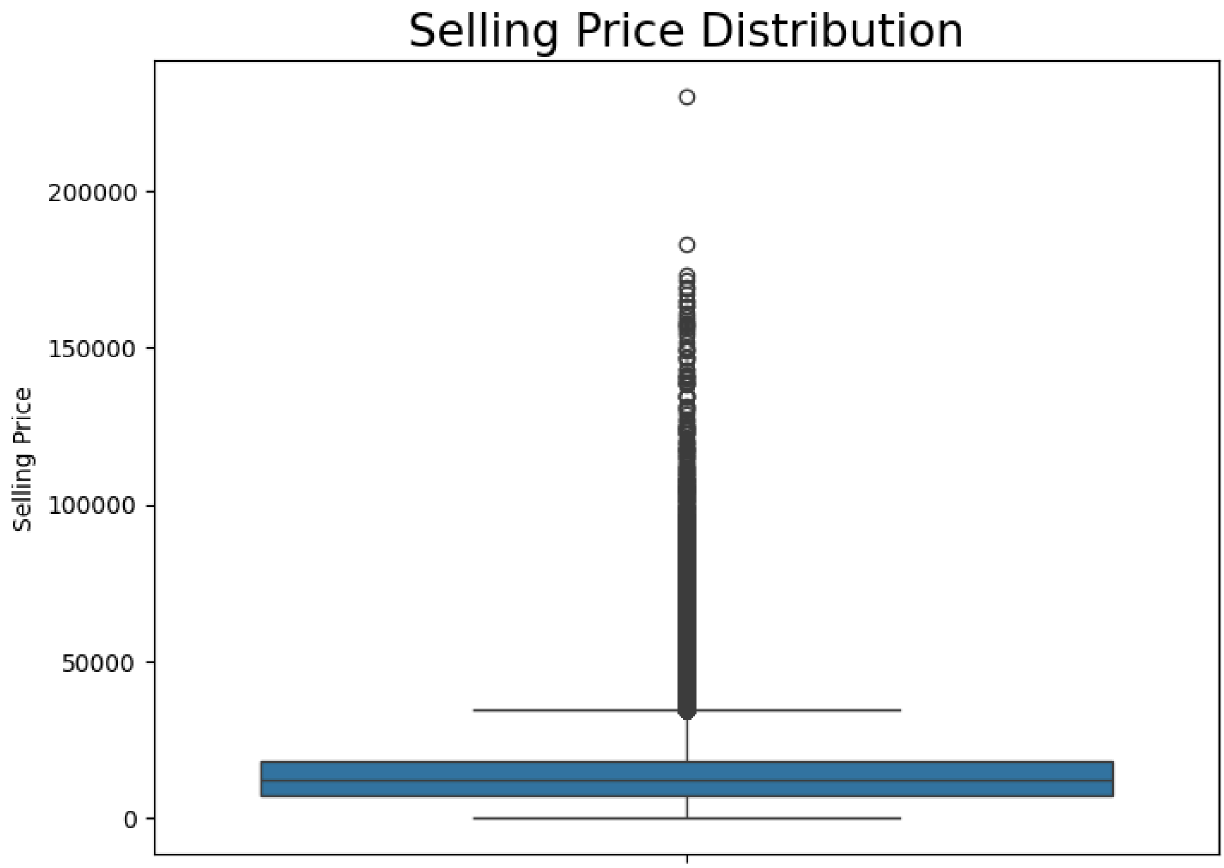
Out[10]:

year	count
1990	33
1991	51
1992	97
1993	127
1994	286
1995	483
1996	562
1997	1042
1998	1464
1999	2227
2000	3427
2001	5140
2002	7693
2003	10368
2004	13624
2005	17169
2006	21631
2007	25378
2008	27011
2009	17959
2010	22616
2011	41384
2012	87380
2013	87467
2014	69712
2015	7994

dtype: int64

In [11]:

```
# Check for outliers in sellingprice variable

plt.figure(figsize=(8,6))
sns.boxplot(df.sellingprice)
plt.title('Selling Price Distribution', fontsize=19)
plt.ylabel('Selling Price')
plt.show()
```



In [12]:
```
# Confirming outliers based on make/model
# Outlier: Ford Escape Selling Price $230,000.00; this value will be noted, but droppe

df.groupby(['make', 'model'])['sellingprice'].max().sort_values(ascending=False).head(
```

Out[12]:

make	model	sellingprice
Ford	Escape	230000.0
Ferrari	458 Italia	183000.0
Mercedes-Benz	S-Class	173000.0
Rolls-Royce	Ghost	171500.0
Bmw	I8	165000.0

dtype: float64

In [13]:
```
# Confirming outliers against MMR
# Ford Escape MMR $35,100

df.groupby(['make', 'model'])['mmr'].max().sort_values(ascending=False).tail(566)
```

Out[13]:

make	model	mmr
Ford	**Escape**	35100.0
Gmc	**Yukon Hybrid**	35100.0
Ford	**Focus**	35100.0
Lexus	**Is 250**	35000.0
Mercedes-Benz	**Gla-Class**	35000.0
...	**...**	...
Oldsmobile	**Achieva**	325.0
Geo	**Metro**	300.0
Suzuki	**Esteem**	275.0
Chevrolet	**Corsica**	275.0
Toyota	**Paseo**	150.0

566 rows × 1 columns

dtype: float64

In [14]:

```
# Removing selling price outlier
filtered_df = df.loc[df['sellingprice'] <= 200000]
# Confirming outlier is removed
filtered_df['sellingprice'].sort_values(ascending=False).head()
```

Out[14]:

	sellingprice
548168	183000.0
446948	173000.0
545522	171500.0
125094	169500.0
557569	169000.0

dtype: float64

In [15]:

```
# There are also outliers in Odometer
filtered_df['odometer'].describe()
```

Out[15]:

	odometer
count	472324.000000
mean	66701.814399
std	51939.611036
min	1.000000
25%	28137.000000
50%	51085.000000
75%	96590.000000
max	999999.000000

dtype: float64

In [16]:

```
# Removing outliers from Odometer feature
filtered_df = filtered_df[filtered_df['odometer'] < 250000]
# Confirming outliers are removed
filtered_df['odometer'].describe()
```

Out[16]:

	odometer
count	470280.000000
mean	65651.727945
std	48815.711183
min	1.000000
25%	28046.000000
50%	50778.000000
75%	95912.250000
max	249975.000000

dtype: float64

In [17]:

```
# Convert 'saledate' to datetime format
filtered_df['saledate'] = pd.to_datetime(filtered_df['saledate'])
```

In [18]:

```
# Confirm saledate is in datetime format
filtered_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 470280 entries, 0 to 558835
Data columns (total 17 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   year          470280 non-null  int64
 1   make          470280 non-null  object
 2   model         470280 non-null  object
 3   trim          470280 non-null  object
 4   body          470280 non-null  object
 5   transmission  470280 non-null  object
 6   vin           470280 non-null  object
 7   state         470280 non-null  object
 8   condition     470280 non-null  float64
 9   odometer      470280 non-null  float64
 10  color         470280 non-null  object
 11  interior      470280 non-null  object
 12  seller        470280 non-null  object
 13  mmr           470280 non-null  float64
 14  sellingprice  470280 non-null  float64
 15  saledate      470280 non-null  datetime64[ns]
 16  saletime      470280 non-null  object
dtypes: datetime64[ns](1), float64(4), int64(1), object(11)
memory usage: 64.6+ MB
```

In [19]:
```
# Create sale year feature

filtered_df['saledate'] = pd.to_datetime(filtered_df['saledate'], format='%Y-%m-%d', e
filtered_df['saleyear'] = filtered_df['saledate'].dt.year
#filtered_df['saleyear'] = pd.to_datetime(filtered_df['saleyear'])
```

In [20]:
```
# Confirm feature creation

filtered_df['saleyear'].info()
```

```
<class 'pandas.core.series.Series'>
Index: 470280 entries, 0 to 558835
Series name: saleyear
Non-Null Count   Dtype
--------------   -----
470280 non-null  int32
dtypes: int32(1)
memory usage: 5.4 MB
```

In [21]:
```
# Group by Sale Year, Make and Mean, Max, and Min Selling Price

mean_sales_trends = filtered_df.groupby(['saleyear', 'make'])['sellingprice'].mean().r
max_sales_trends = filtered_df.groupby(['saleyear', 'make'])['sellingprice'].max().res
min_sales_trends = filtered_df.groupby(['saleyear', 'make'])['sellingprice'].min().res
```

In [22]:
```
# Ensure Selling Prices are not in Scientific Notation

pd.options.display.float_format = '{:.2f}'.format

# Print each of these Sales Trends

print(f'\nMax Sales Trends \n{max_sales_trends}')
print(f'Mean Sales Trends \n{mean_sales_trends}')
print(f'\nMin Sales Trends \n{min_sales_trends}')
```

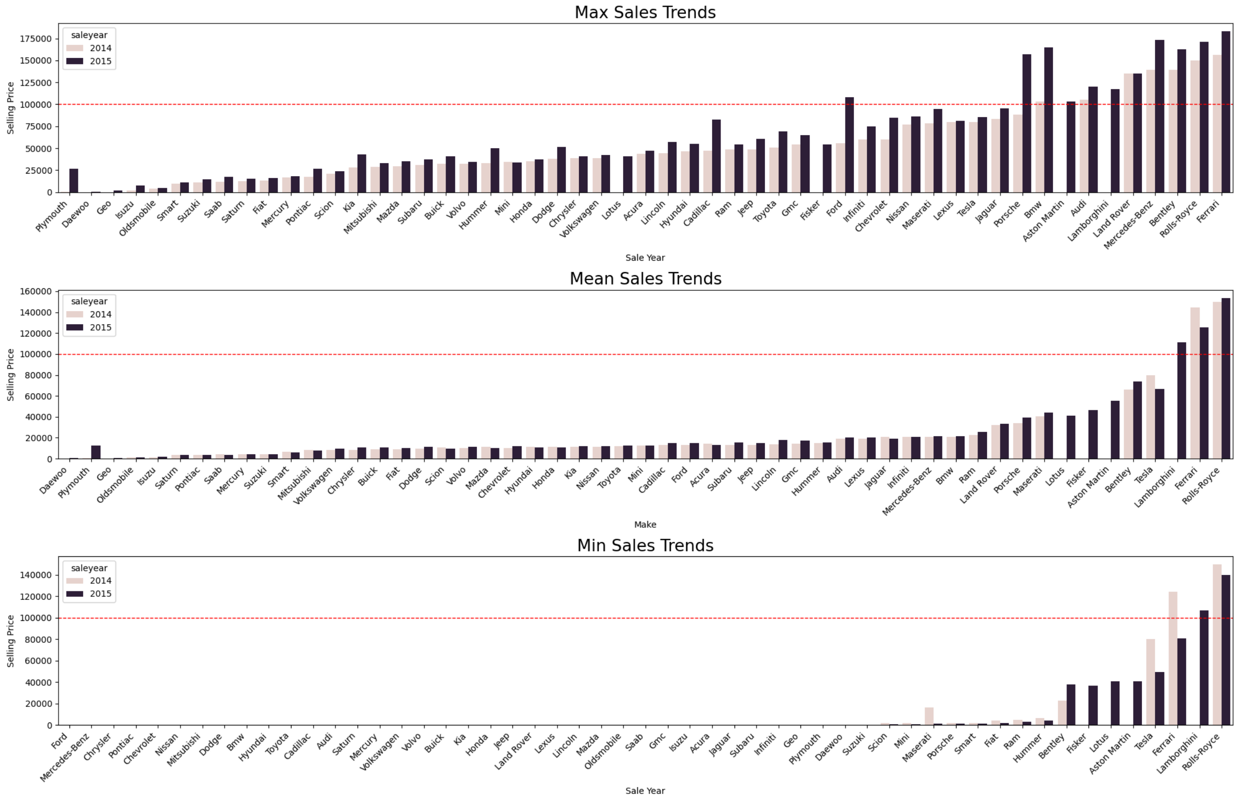
```
Max Sales Trends
    saleyear           make  sellingprice
32      2014       Plymouth        450.00
56      2015         Daewoo        600.00
62      2015            Geo       1600.00
17      2014          Isuzu       2000.00
31      2014     Oldsmobile       4400.00
..       ...            ...           ...
50      2015        Bentley     163000.00
51      2015            Bmw     165000.00
89      2015    Rolls-Royce     171500.00
79      2015  Mercedes-Benz     173000.00
58      2015        Ferrari     183000.00

[100 rows x 3 columns]
Mean Sales Trends
    saleyear         make  sellingprice
56      2015       Daewoo        450.00
32      2014     Plymouth        450.00
62      2015          Geo        585.00
84      2015   Oldsmobile        949.48
17      2014        Isuzu       1058.33
..       ...          ...           ...
72      2015  Lamborghini     111500.00
58      2015      Ferrari     125464.29
9       2014      Ferrari     144666.67
36      2014  Rolls-Royce     149800.00
89      2015  Rolls-Royce     153700.00

[100 rows x 3 columns]

Min Sales Trends
    saleyear           make  sellingprice
61      2015           Ford          1.00
79      2015  Mercedes-Benz          1.00
55      2015       Chrysler        100.00
86      2015        Pontiac        100.00
54      2015      Chevrolet        100.00
..       ...            ...           ...
58      2015        Ferrari      81000.00
72      2015    Lamborghini     107000.00
9       2014        Ferrari     124000.00
89      2015    Rolls-Royce     140000.00
36      2014    Rolls-Royce     149800.00

[100 rows x 3 columns]
```

In [23]:

```
mean_sales_pivot = mean_sales_trends.pivot(index='saleyear', columns='make', values='s
max_sales_pivot = max_sales_trends.pivot(index='saleyear', columns='make', values='sel
min_sales_pivot = min_sales_trends.pivot(index='saleyear', columns='make', values='sel

print(f'Mean Sales Pivot\n{mean_sales_pivot}')
print(f'\nMax Sales Pivot\n{max_sales_pivot}')
print(f'\nMin Sales Pivot\n{min_sales_pivot}')
```

```
Mean Sales Pivot
make         Acura  Aston Martin     Audi  Bentley      Bmw    Buick  Cadillac  \
saleyear
2014     14503.23           NaN 19136.61 66055.88 21056.08  8736.52  12896.75
2015     13075.97      55500.00 20095.52 73999.43 21343.35 10778.33  14941.88

make      Chevrolet  Chrysler  Daewoo  ...    Saab  Saturn    Scion   Smart  \
saleyear                               ...
2014       10338.24   8324.20     NaN  ... 3987.18 3562.60 10609.68 6567.31
2015       12063.65  10842.21  450.00  ... 3586.57 3436.68  9655.91 6279.81

make       Subaru  Suzuki    Tesla   Toyota  Volkswagen    Volvo
saleyear
2014     13206.94 4056.84 80000.00 12229.55     8247.36  9945.83
2015     15752.77 4008.45 66465.91 12544.28     9467.44 11059.38

[2 rows x 53 columns]

Max Sales Pivot
make         Acura  Aston Martin      Audi   Bentley       Bmw    Buick  \
saleyear
2014     43800.00           NaN 105000.00 139000.00 103000.00 32400.00
2015     47000.00     103000.00 120000.00 163000.00 165000.00 41000.00

make      Cadillac  Chevrolet  Chrysler  Daewoo  ...     Saab   Saturn  \
saleyear                                         ...
2014      47200.00   59900.00  38500.00     NaN  ... 11500.00 12700.00
2015      83000.00   84500.00  41000.00  600.00  ... 17750.00 15050.00

make         Scion    Smart   Subaru   Suzuki    Tesla   Toyota  Volkswagen  \
saleyear
2014     20700.00 10000.00 31000.00 11400.00 80000.00 51000.00    39000.00
2015     24100.00 11000.00 37600.00 14900.00 85750.00 68900.00    42000.00

make         Volvo
saleyear
2014     32600.00
2015     34700.00

[2 rows x 53 columns]

Min Sales Pivot
make      Acura  Aston Martin   Audi  Bentley    Bmw  Buick  Cadillac  \
saleyear
2014     325.00           NaN 500.00 22700.00 250.00 200.00    275.00
2015     250.00      41000.00 150.00 37750.00 100.00 200.00    150.00

make      Chevrolet  Chrysler  Daewoo  ...   Saab  Saturn   Scion   Smart  \
saleyear                               ...
2014         200.00    150.00     NaN  ... 275.00  200.00 2000.00 2100.00
2015         100.00    100.00  300.00  ... 200.00  150.00  800.00 1600.00

make      Subaru  Suzuki    Tesla  Toyota  Volkswagen  Volvo
saleyear
2014      300.00  400.00 80000.00  150.00      300.00 200.00
2015      250.00  300.00 49250.00  150.00      200.00 200.00

[2 rows x 53 columns]
```

In [24]:
```
# Create subplots
fig, axes = plt.subplots(nrows=3, ncols=1, figsize=(20, 13))

# Plot mean sales trends
sns.barplot(x='make', y='sellingprice', hue='saleyear', data=mean_sales_trends, ax=axe
axes[1].set_title('Mean Sales Trends', fontsize=19)
axes[1].set_xlabel('Make')  # Corrected label
axes[1].set_ylabel('Selling Price')
axes[1].axhline(y=100000, color='red', linestyle='dashed', linewidth=1)
# Rotate x-axis labels for all subplots efficiently
for ax in axes:
    for label in ax.get_xticklabels():
        label.set_rotation(45)
        label.set_ha('right')  # Right-aligned for better readability

# Plot max sales trends
sns.barplot(x='make', y='sellingprice', hue='saleyear', data=max_sales_trends, ax=axes
axes[0].set_title('Max Sales Trends', fontsize=19)
axes[0].set_xlabel('Sale Year')
axes[0].set_ylabel('Selling Price')
axes[0].axhline(y=100000, color='red', linestyle='dashed', linewidth=1)

# Plot min sales trends
sns.barplot(x='make', y='sellingprice', hue='saleyear', data=min_sales_trends, ax=axes
axes[2].set_title('Min Sales Trends', fontsize=19)
axes[2].set_xlabel('Sale Year')
axes[2].set_ylabel('Selling Price')
axes[2].axhline(y=100000, color='red', linestyle='dashed', linewidth=1)

# Adjust spacing between subplots
plt.tight_layout()

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



In [25]:

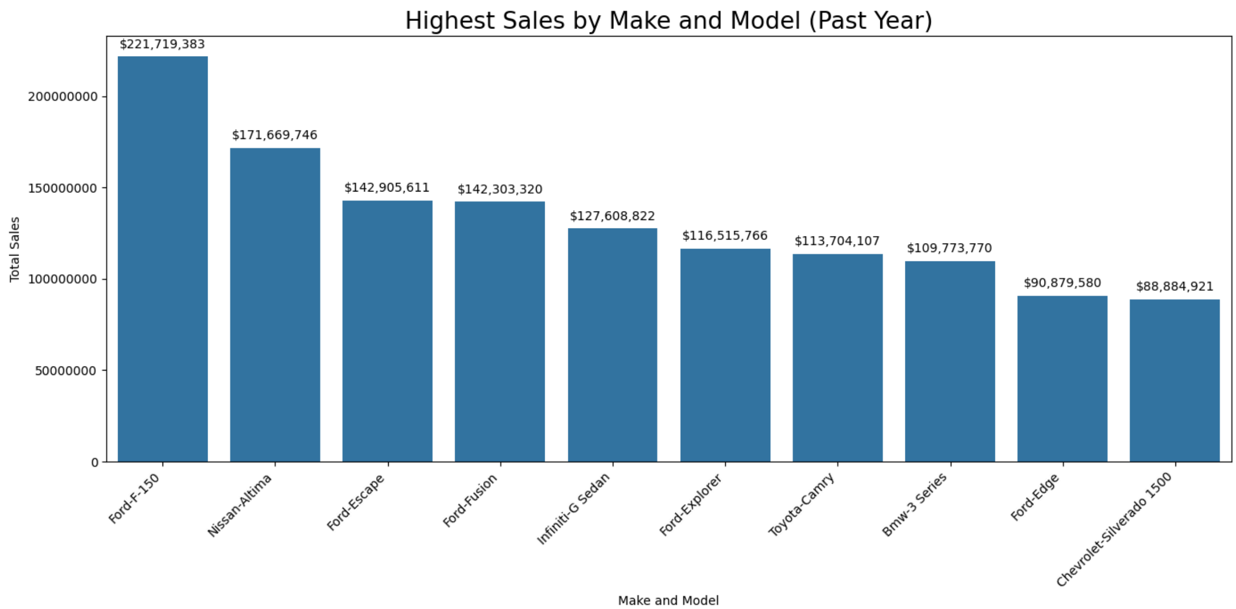
```python
# 1. Filter data for the past year
df_last_year = filtered_df[filtered_df['saleyear'] == filtered_df['saleyear'].max()]

# 2. Group by make and model and calculate total sales
sales_by_make_model = df_last_year.groupby(['make', 'model'])['sellingprice'].sum()

# 3. Find the highest sales
highest_sales = sales_by_make_model.idxmax()

# 4. Print the result
print(f"Make and model with the highest sales: {highest_sales}")

# Optional: Display the top N makes and models with highest sales
top_n = 5
print(sales_by_make_model.nlargest(top_n))
```

```
Make and model with the highest sales: ('Ford', 'F-150')
make      model
Ford      F-150      221719383.00
Nissan    Altima     171669746.00
Ford      Escape     142905611.00
          Fusion     142303320.00
Infiniti  G Sedan    127608822.00
Name: sellingprice, dtype: float64
```

In [26]:

```python
data = sales_by_make_model.sort_values(ascending=False).head(10)

# Extract make and model combinations for the top 10
x = data.index.map('{0[0]}-{0[1]}'.format)  # Access levels of MultiIndex

plt.figure(figsize=(14, 7))
ax = sns.barplot(x=x, y=data.values)
plt.title('Highest Sales by Make and Model (Past Year)', fontsize=19)
plt.xlabel('Make and Model')
```

```
plt.ylabel('Total Sales')
plt.xticks(rotation=45, horizontalalignment='right')  # Rotate x-axis labels for readc
plt.ticklabel_format(style='plain', axis='y')  # Remove scientific notation on x-axis

# Add actual prices as text above each bar
for i, v in enumerate(data.values):
    ax.text(i, v + 10000000, f"${v:,.0f}", ha='center', va='top')

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



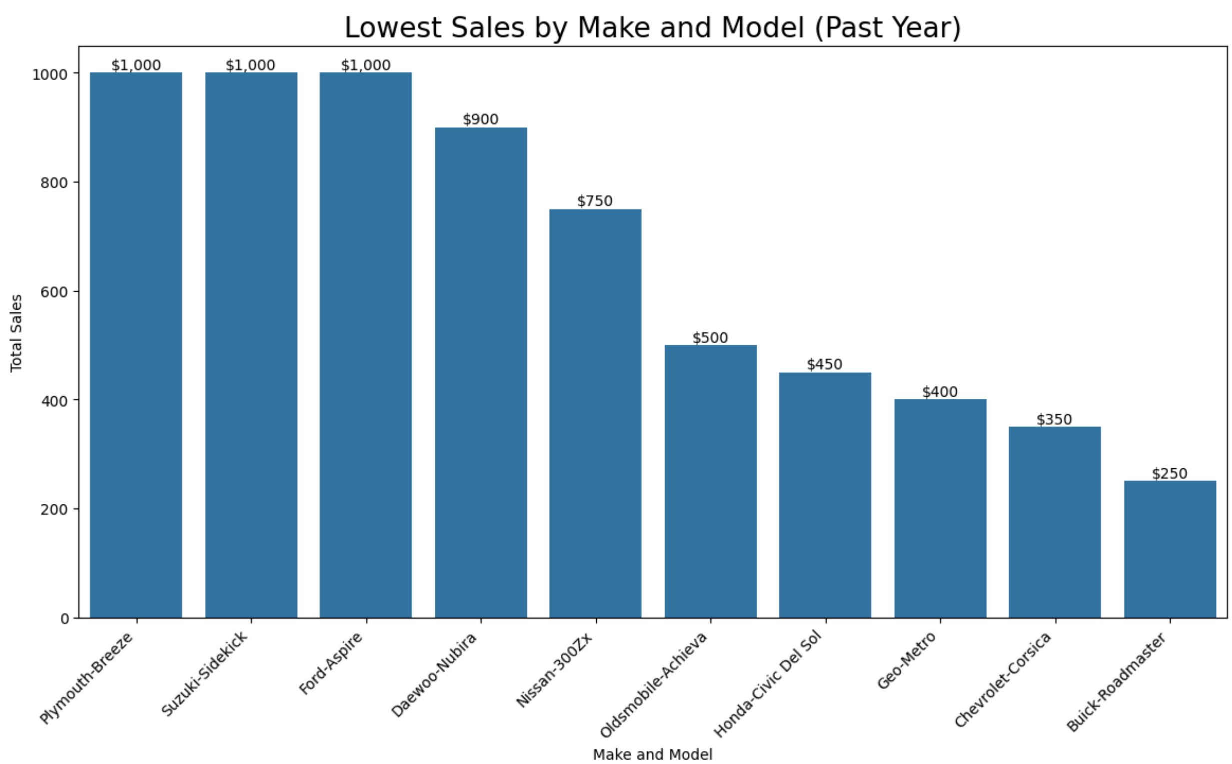
Which makes and models produced the least?

In [27]:
```
# 3. Find the Lowest sales
lowest_sales = sales_by_make_model.idxmin()

# 4. Print the result
print(f"Make and model with the lowest sales: {lowest_sales}")

# Optional: Display the bottom N makes and models with Lowest sales
bottom_n = 5
print(sales_by_make_model.nsmallest(bottom_n))
```

```
Make and model with the lowest sales: ('Buick', 'Roadmaster')
make        model
Buick       Roadmaster      250.00
Chevrolet   Corsica         350.00
Geo         Metro           400.00
Honda       Civic Del Sol   450.00
Oldsmobile  Achieva         500.00
Name: sellingprice, dtype: float64
```

In [28]:
```
%matplotlib inline
#import matplotlib.pyplot as plt
#import seaborn as sns

data = sales_by_make_model.sort_values(ascending=False).tail(10)

# Extract make and model combinations for the top 10
```

```
x = data.index.map('{0[0]}-{0[1]}'.format)

plt.figure(figsize=(14, 7))
ax = sns.barplot(x=x, y=data.values)
plt.title('Lowest Sales by Make and Model (Past Year)', fontsize=19)
plt.xlabel('Make and Model')
plt.ylabel('Total Sales')
plt.xticks(rotation=45, horizontalalignment='right')  # Rotate x-axis labels for reada
plt.ticklabel_format(style='plain', axis='y')

# Add actual prices as text above each bar
# Reduced the added height for the text position to avoid enlarging the image
for i, v in enumerate(data.values):
    ax.text(i, v, f"${v:,.0f}", ha='center', va='bottom')

#plt.subplots_adjust(top=0.9)  # Adjust top margin
plt.show()
```



How have sales volumes for different vehicle segments (e.g., SUVs, sedans, trucks) changed over the past year?

In [29]:
```
filtered_df.columns
```

Out[29]:
```
Index(['year', 'make', 'model', 'trim', 'body', 'transmission', 'vin', 'state',
       'condition', 'odometer', 'color', 'interior', 'seller', 'mmr',
       'sellingprice', 'saledate', 'saletime', 'saleyear'],
      dtype='object')
```

In [30]:
```
filtered_df['body'].value_counts().sort_values(ascending=False).head(25)
```

Out[30]:

body	count
Sedan	210593
Suv	120496
Hatchback	23781
Minivan	21804
Coupe	15883
Wagon	14189
Crew Cab	14130
Convertible	9310
Supercrew	7541
G Sedan	6939
Supercab	4135
Regular Cab	4003
Extended Cab	3836
Quad Cab	3476
Van	3388
G Coupe	1504
Double Cab	1459
E-Series Van	1106
Crewmax Cab	485
King Cab	438
G Convertible	306
Access Cab	261
Genesis Coupe	255
Koup	162
Club Cab	150

dtype: int64

In [31]:

```
# Define a function to categorize the car bodies
def categorize_car_body(car_body):
    if 'Sedan' in car_body or 'Coupe' in car_body:
        return 'Sedan/Coupe'
    elif 'SUV' in car_body or 'Crew' in car_body or 'Super' in car_body or 'Regular' i
        return 'SUV/Truck'
    elif 'Hatchback' in car_body or 'Convertible' in car_body:
        return 'Hatchback/Convertible'
    elif 'Minivan' in car_body or 'Van' in car_body:
```

```
        return 'Minivan/Van'
    else:
        return 'Other'

# Apply the categorization function to the DataFrame
filtered_df['body_cat'] = filtered_df['body'].apply(categorize_car_body)

print(filtered_df)
```

```
        year    make                model         trim        body  \
0       2015     Kia              Sorento           LX         Suv
1       2015     Kia              Sorento           LX         Suv
2       2014     Bmw             3 Series   328i SULEV       Sedan
3       2015   Volvo                  S60           T5       Sedan
4       2014     Bmw  6 Series Gran Coupe         650i       Sedan
...      ...     ...                  ...          ...         ...
558830  2011     Bmw             5 Series         528i       Sedan
558832  2012     Ram                 2500  Power Wagon    Crew Cab
558833  2012     Bmw                   X5    xDrive35d         Suv
558834  2015  Nissan               Altima        2.5 S       Sedan
558835  2014    Ford                F-150          XLT  Supercrew

       transmission                vin state  condition  odometer  color  \
0         Automatic  5XYKTCA69FG566472    CA       5.00  16639.00  White
1         Automatic  5XYKTCA69FG561319    CA       5.00   9393.00  White
2         Automatic  WBA3C1C51EK116351    CA      45.00   1331.00   Gray
3         Automatic  YV1612TB4F1310987    CA      41.00  14282.00  White
4         Automatic  WBA6B2C57ED129731    CA      43.00   2641.00   Gray
...             ...                ...   ...        ...       ...    ...
558830    Automatic  WBAFR1C53BC744672    FL      39.00  66403.00  White
558832    Automatic  3C6TD5ET6CG112407    WA       5.00  54393.00  White
558833    Automatic  5UXZW0C58CL668465    CA      48.00  50561.00  Black
558834    Automatic  1N4AL3AP0FC216050    GA      38.00  16658.00  White
558835    Automatic  1FTFW1ET2EKE87277    CA      34.00  15008.00   Gray

       interior                                      seller      mmr  \
0         Black                      Kia Motors America  Inc 20500.00
1         Beige                      Kia Motors America  Inc 20800.00
2         Black         Financial Services Remarketing (Lease) 31900.00
3         Black                      Volvo Na Rep/World Omni 27500.00
4         Black         Financial Services Remarketing (Lease) 66000.00
...         ...                                          ...      ...
558830    Brown       Lauderdale Imports Ltd Bmw Pembrok Pines 20300.00
558832    Black                              I -5 Uhlmann Rv 30200.00
558833    Black         Financial Services Remarketing (Lease) 29800.00
558834    Black  Enterprise Vehicle Exchange / Tra / Rental / T... 15100.00
558835     Gray                Ford Motor Credit Company Llc Pd 29600.00

        sellingprice   saledate   saletime  saleyear      body_cat
0           21500.00 2014-12-16   12:30:00      2014         Other
1           21500.00 2014-12-16   12:30:00      2014         Other
2           30000.00 2015-01-15   04:30:00      2015   Sedan/Coupe
3           27750.00 2015-01-29   04:30:00      2015   Sedan/Coupe
4           67000.00 2014-12-18   12:30:00      2014   Sedan/Coupe
...              ...        ...        ...       ...           ...
558830      22800.00 2015-07-07   06:15:00      2015   Sedan/Coupe
558832      30800.00 2015-07-08   09:30:00      2015     SUV/Truck
558833      34000.00 2015-07-08   09:30:00      2015         Other
558834      11100.00 2015-07-09   06:45:00      2015   Sedan/Coupe
558835      26700.00 2015-05-28   05:30:00      2015     SUV/Truck

[470280 rows x 19 columns]
```

In [32]:
```
# Confirm new feature value counts

filtered_df['body_cat'].value_counts().sort_values(ascending=False)
```

Out[32]:

body_cat	count
Sedan/Coupe	235453
Other	136631
SUV/Truck	38305
Hatchback/Convertible	33519
Minivan/Van	26372

dtype: int64

In [33]:
```
# Explore vehicle body type in relation to sales
# Top 4 for Max Sales Trends: Coupe, Sedan, Convertible, SUV

mean_sales_trends = filtered_df.groupby(['body_cat', 'saleyear'])['sellingprice'].mean
min_sales_trends = filtered_df.groupby(['body_cat', 'saleyear'])['sellingprice'].min()
max_sales_trends = filtered_df.groupby(['body_cat', 'saleyear'])['sellingprice'].max()

print(f'Mean Sales Trends: Body {mean_sales_trends}\n')
print(f'Min Sales Trends: Body {min_sales_trends}\n')
print(f'Max Sales Trends: Body {max_sales_trends}\n')
```

```
Mean Sales Trends: Body                  body_cat  saleyear  sellingprice
0           Minivan/Van      2014      10294.71
1           Sedan/Coupe      2014      11790.56
2           Minivan/Van      2015      12260.91
3           Sedan/Coupe      2015      12325.45
4  Hatchback/Convertible      2015      12490.78
5  Hatchback/Convertible      2014      12539.41
6                 Other      2014      14345.10
7             SUV/Truck      2014      15543.29
8                 Other      2015      15737.18
9             SUV/Truck      2015      18343.29

Min Sales Trends: Body                 body_cat  saleyear  sellingprice
0           Minivan/Van      2015          1.00
1           Sedan/Coupe      2015          1.00
2  Hatchback/Convertible      2015        100.00
3                 Other      2015        100.00
4           Sedan/Coupe      2014        150.00
5  Hatchback/Convertible      2014        200.00
6                 Other      2014        200.00
7             SUV/Truck      2015        200.00
8           Minivan/Van      2014        300.00
9             SUV/Truck      2014        300.00

Max Sales Trends: Body                 body_cat  saleyear  sellingprice
0           Minivan/Van      2014      34000.00
1             SUV/Truck      2014      51500.00
2             SUV/Truck      2015      65000.00
3           Minivan/Van      2015      84000.00
4                 Other      2014     135000.00
5                 Other      2015     141000.00
6           Sedan/Coupe      2014     149800.00
7  Hatchback/Convertible      2014     156000.00
8  Hatchback/Convertible      2015     163000.00
9           Sedan/Coupe      2015     183000.00
```

In [34]:

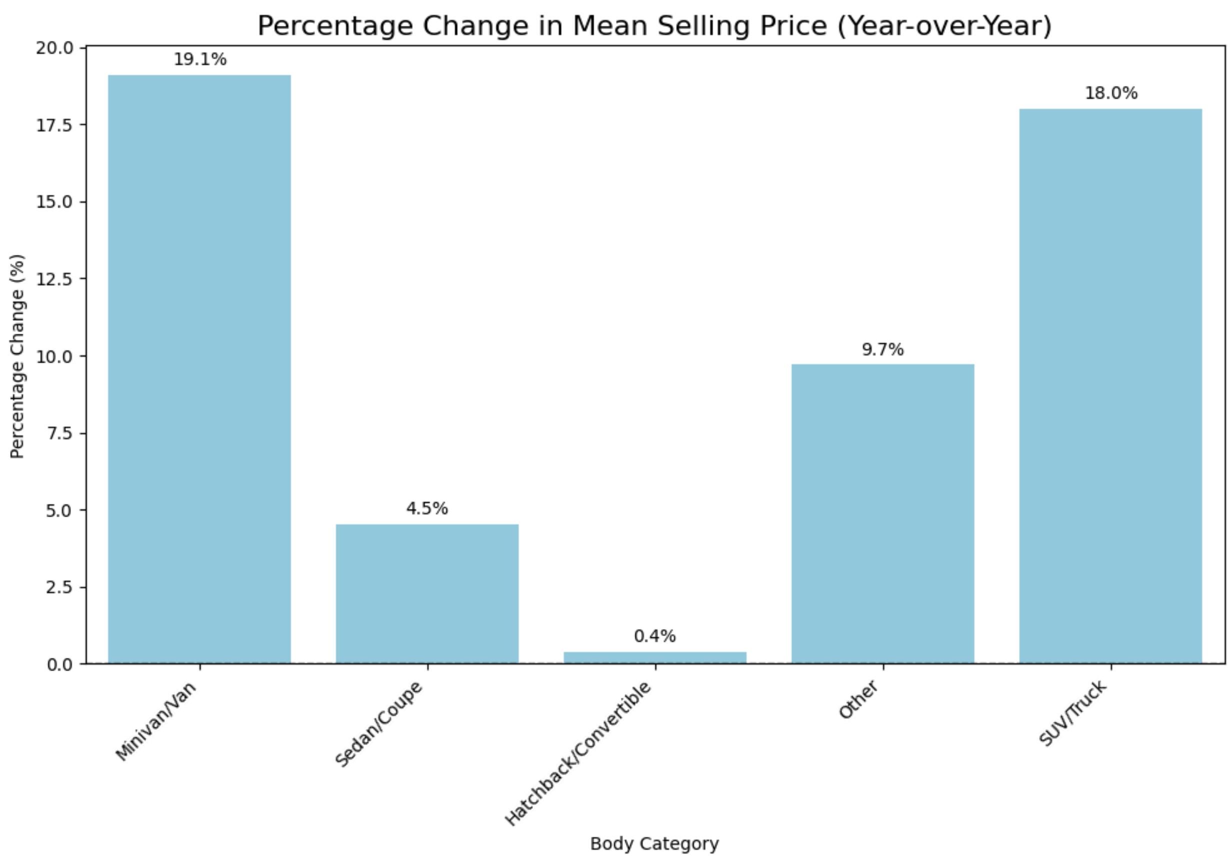
```
# Create subplots
fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(11, 8))

# Plot mean sales trends
sns.barplot(x='body_cat', y='sellingprice', hue='saleyear', data=mean_sales_trends, ax
axes[1].set_title('Mean Sales Trends', fontsize=19)
axes[1].set_xlabel('Body Type')  # Corrected label
axes[1].set_ylabel('Selling Price')
#axes[0].axhline(y=100000, color='red', linestyle='dashed', linewidth=1)
# Rotate x-axis labels for all subplots efficiently
for ax in axes:
    for label in ax.get_xticklabels():
        label.set_rotation(45)
        label.set_ha('right')  # Right-aligned for better readability

# Plot max sales trends
sns.barplot(x='body_cat', y='sellingprice', hue='saleyear', data=max_sales_trends, ax=
axes[0].set_title('Max Sales Trends', fontsize=19)
axes[0].set_xlabel('Body Type')
axes[0].set_ylabel('Selling Price')
#axes[1].axhline(y=100000, color='red', linestyle='dashed', linewidth=1)

# Plot min sales trends
```

```
sns.barplot(x='body_cat', y='sellingprice', hue='saleyear', data=min_sales_trends, ax=
axes[2].set_title('Min Sales Trends', fontsize=19)
axes[2].set_xlabel('Body Type')
axes[2].set_ylabel('Selling Price')
#axes[2].axhline(y=100000, color='red', linestyle='dashed', linewidth=1)

# Adjust spacing between subplots
plt.tight_layout()

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

In [35]:

```
categories = ['Minivan/Van','Sedan/Coupe', 'Minivan/Van', 'Sedan/Coupe', 'Hatchback/Co
              'Hatchback/Convertible', 'Other', 'SUV/Truck', 'Other', 'SUV/Truck']

# Calculate percentage change between saleyears for each body category
percentage_change_df = mean_sales_trends.groupby('body_cat')['sellingprice'].diff(peri

# Create a new figure for the percentage change plot
plt.figure(figsize=(10, 7))

# Align categories to the x-axis
ax = sns.barplot(x=categories,
            y=percentage_change_df.values,
            color='skyblue')

plt.title('Percentage Change in Mean Selling Price (Year-over-Year)', fontsize=16)
plt.xlabel('Body Category')
plt.ylabel('Percentage Change (%)')
plt.axhline(y=0, color='black', linestyle='dashed', linewidth=1)  # Reference line for
```

```python
# Rotate x-axis labels for better readability
plt.xticks(rotation=45, ha='right')

# Show percentage on bars
for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x() + p.get_width() / 2., height + 0.3, '{:.1f}%'.format(height), ha

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



2. Analyzing the Impact of Vehicle Condition and Mileage on Selling Prices

Research Questions:

- How does vehicle condition affect selling price for different car body types?
- What is the relationship between mileage and selling price for vehicles of the same age and make?
- Is there an interaction effect between vehicle condition and mileage on selling price?

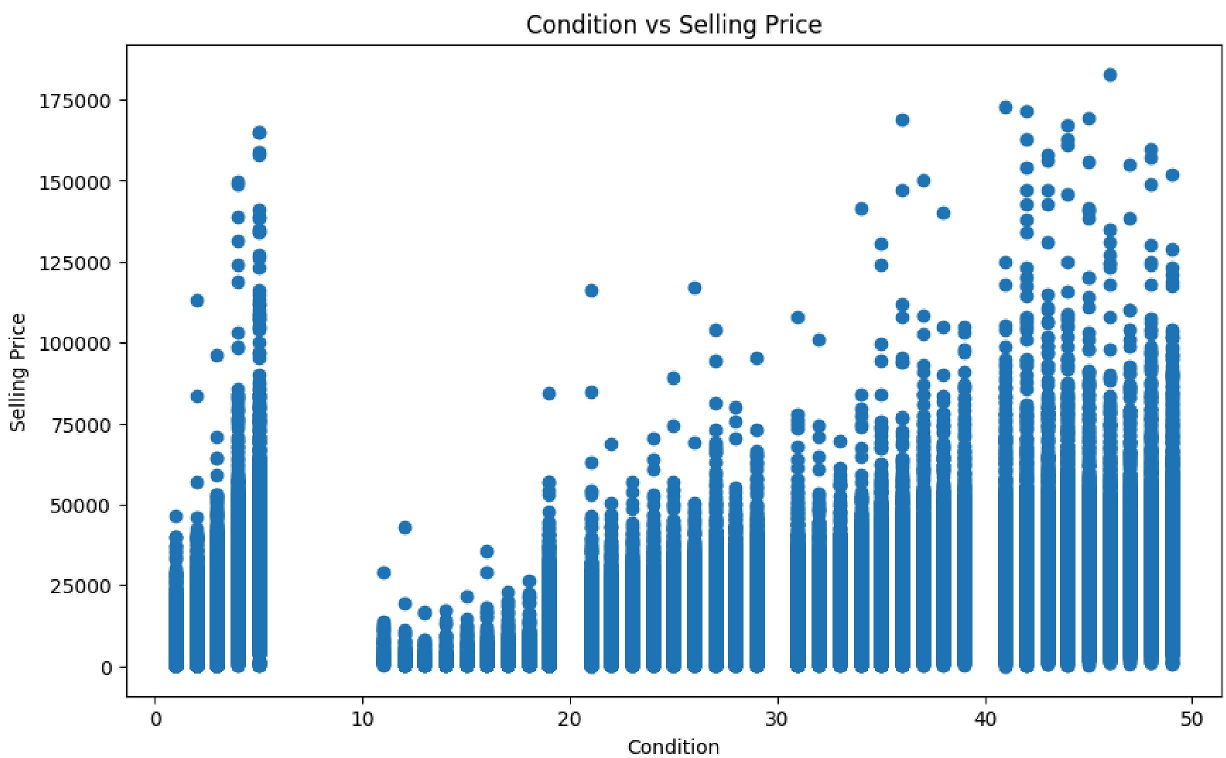
How does vehicle condition affect selling price for different car body types?

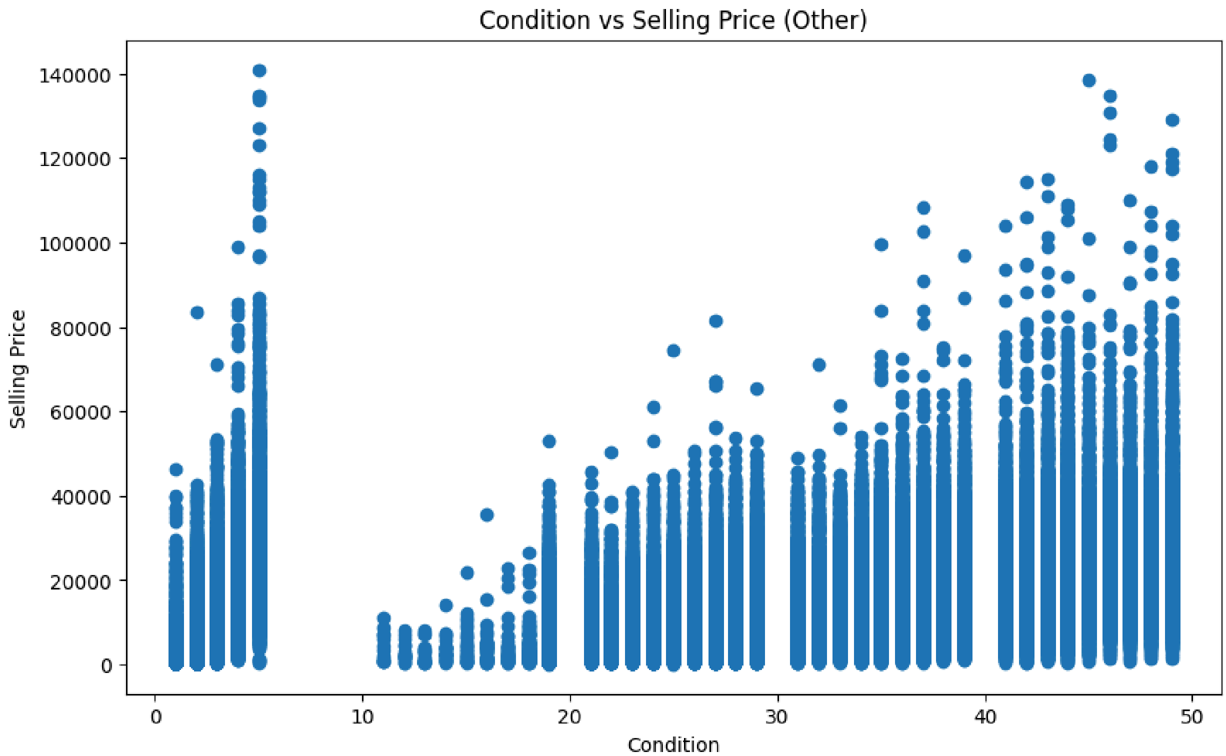
In [36]:

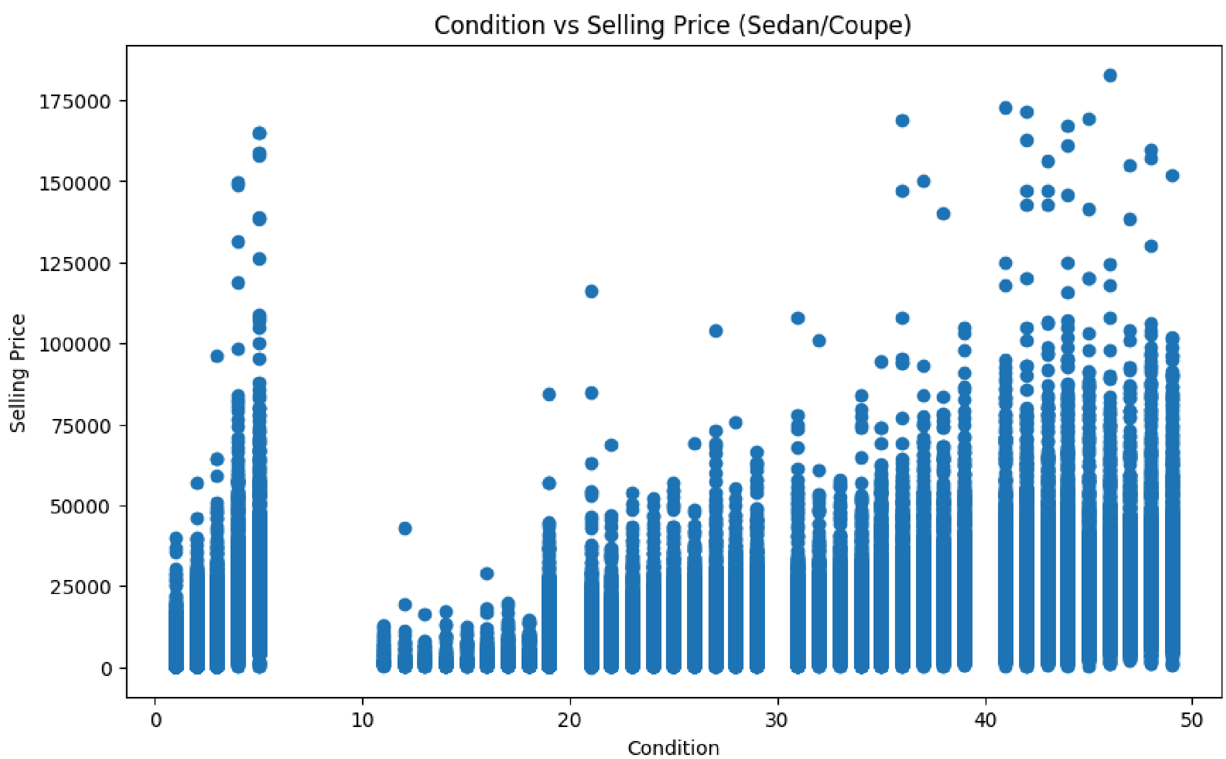
```python
# Confirming the conditions variable

# Calculate correlation
```

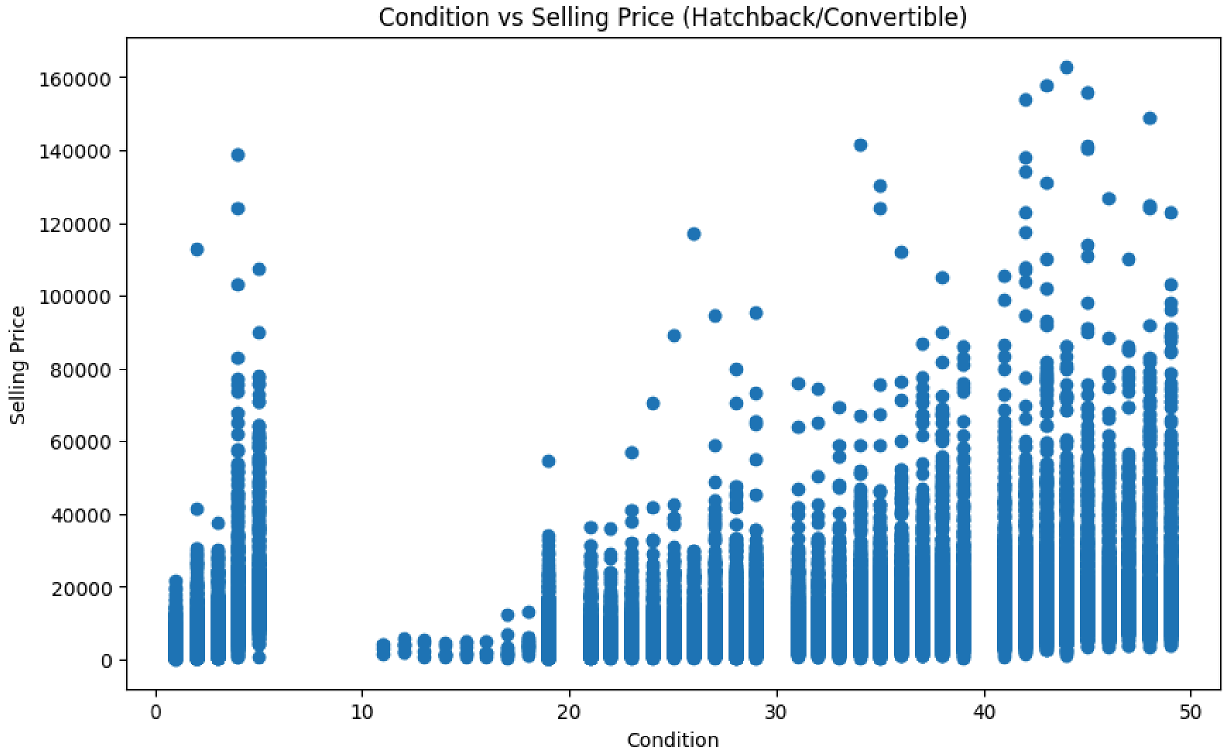
```python
correlation = filtered_df['condition'].corr(filtered_df['sellingprice'])
print(f"Correlation between condition and sellingprice: {correlation}\n")

# Scatter plot
plt.figure(figsize=(10, 6))
plt.scatter(filtered_df['condition'], filtered_df['sellingprice'])
plt.xlabel("Condition")
plt.ylabel("Selling Price")
plt.title("Condition vs Selling Price")
plt.show()

# Scatter plot for each body category
for body_type in filtered_df['body_cat'].unique():
    subset = filtered_df[filtered_df['body_cat'] == body_type]
    plt.figure(figsize=(10, 6))
    plt.scatter(subset['condition'], subset['sellingprice'])
    plt.xlabel("Condition")
    plt.ylabel("Selling Price")
    plt.title(f"Condition vs Selling Price ({body_type})")
    plt.show()
```

```
Correlation between condition and sellingprice: 0.31448004338091773
```

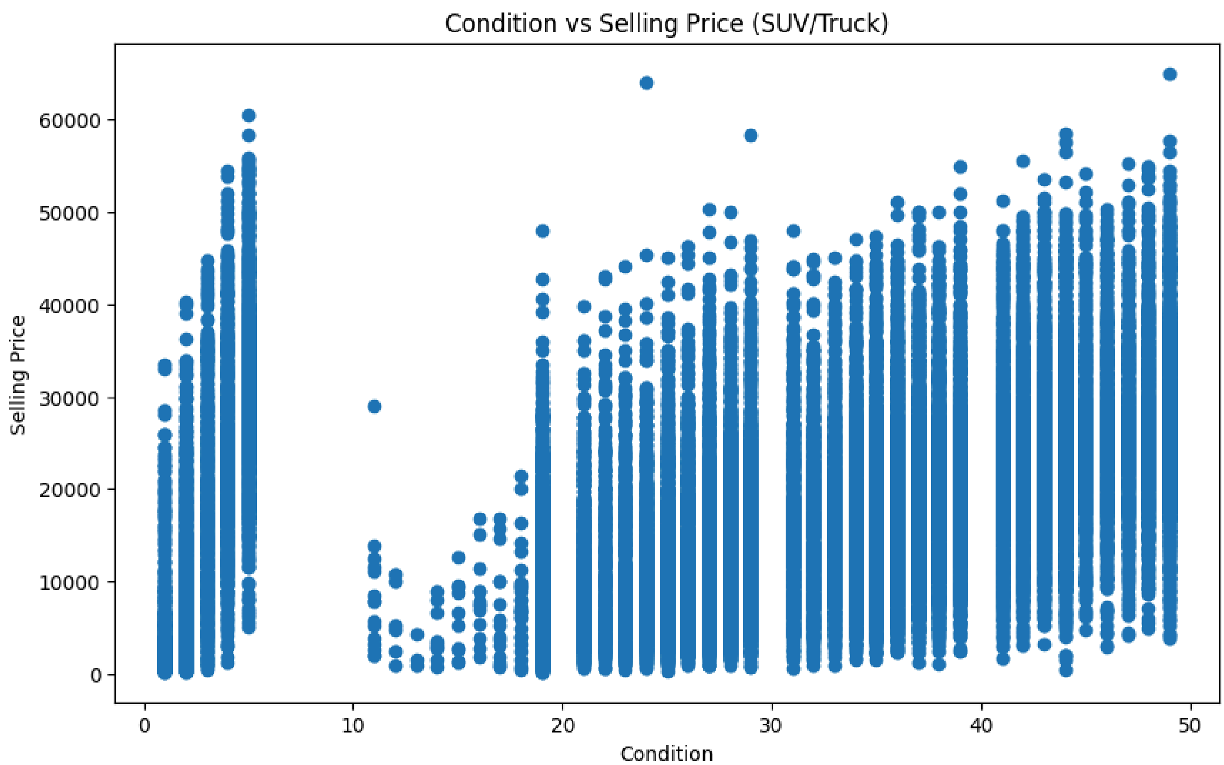



Condition vs Selling Price (Other)
Selling Price
Condition
0
20000
40000
60000
80000
100000
120000
140000
0
10
20
30
40
50

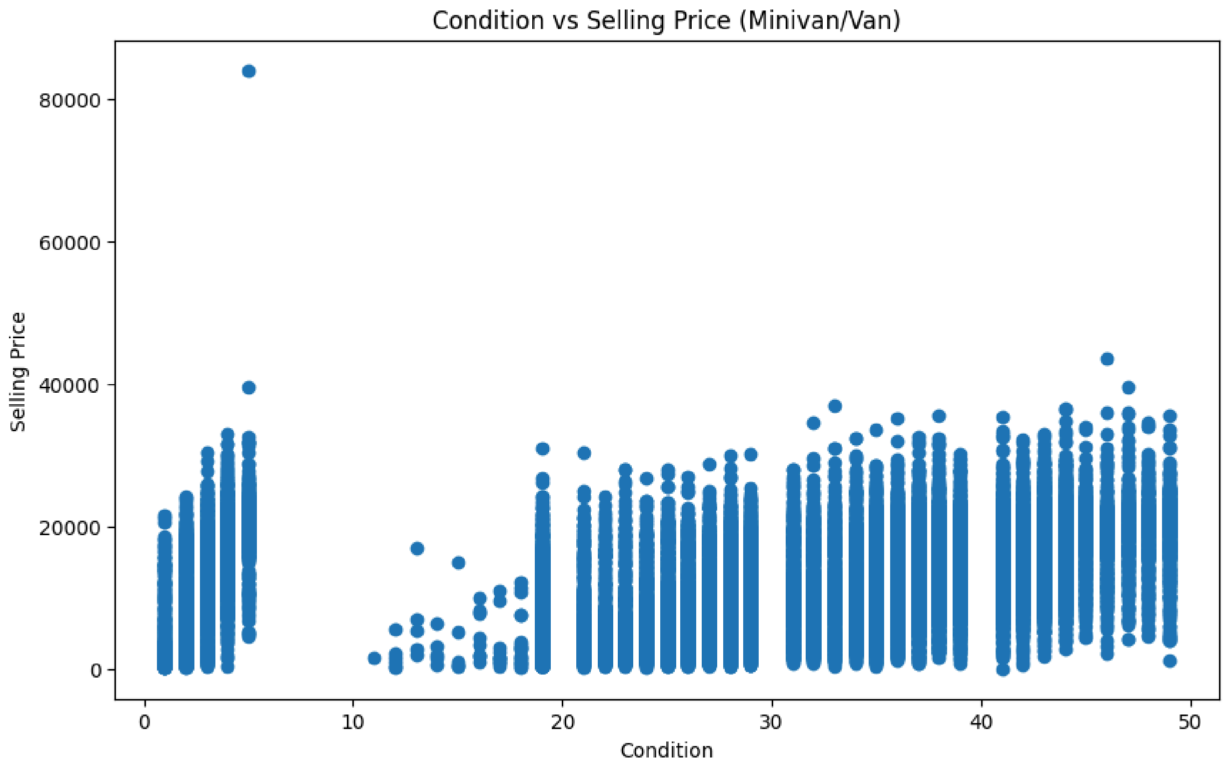

Condition vs Selling Price (Sedan/Coupe)
Selling Price
Condition
0
25000
50000
75000
100000
125000
150000
175000
0
10
20
30
40
50



Condition vs Selling Price (Hatchback/Convertible)
Selling Price
Condition
0
20000
40000
60000
80000
100000
120000
140000
160000
0
10
20
30
40
50

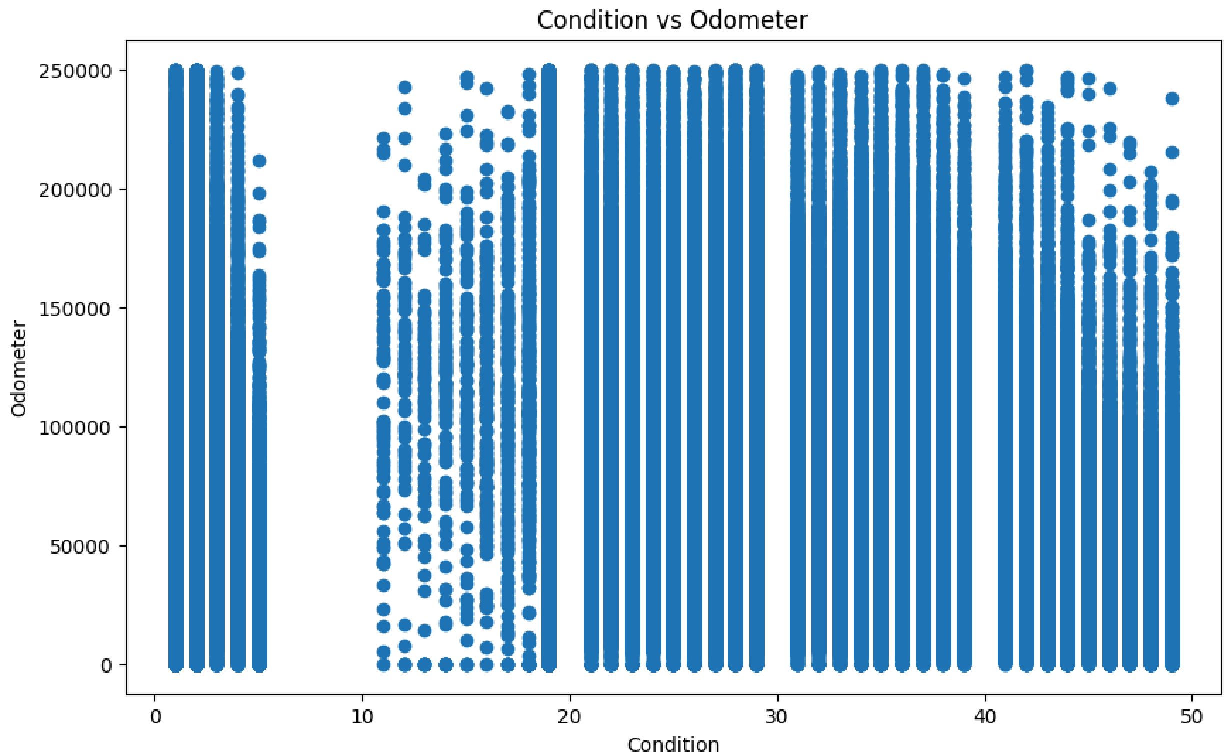


Condition vs Selling Price (SUV/Truck)
Selling Price
Condition
0
10000
20000
30000
40000
50000
60000
0
10
20
30
40
50



In [37]:
```python
# Now confirming the relationship between condition and odometer to confirm condition

# Calculate correlation
correlation = filtered_df['condition'].corr(filtered_df['odometer'])
print(f"Correlation between condition and odometer: {correlation}\n")

# Scatter plot
plt.figure(figsize=(10, 6))
plt.scatter(filtered_df['condition'], filtered_df['odometer'])
plt.xlabel("Condition")
plt.ylabel("Odometer")
plt.title("Condition vs Odometer")
plt.show()
```

```
Correlation between condition and odometer: -0.313013923047116
```



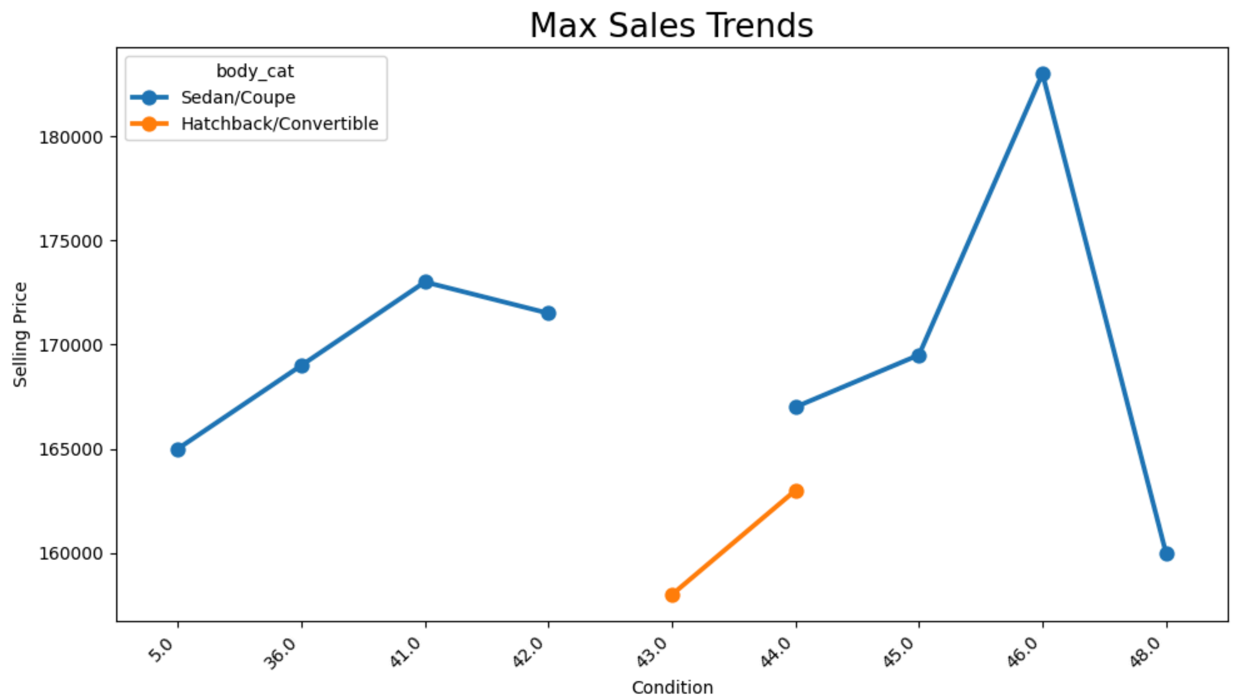
In [38]:
```
# Vehichle condition vs selling price
# Based on the eariler findings higher condition is good/lower bad/Condition values (1

mean_sales_trends = filtered_df.groupby(['condition', 'body_cat'])['sellingprice'].mea
min_sales_trends = filtered_df.groupby(['condition', 'body_cat'])['sellingprice'].min(
max_sales_trends = filtered_df.groupby(['condition', 'body_cat'])['sellingprice'].max(

print(f'Max Sales Trends: Condition {max_sales_trends}\n')
print(f'Mean Sales Trends: Condition {mean_sales_trends}\n')
print(f'Min Sales Trends: Condition {min_sales_trends}\n')
```

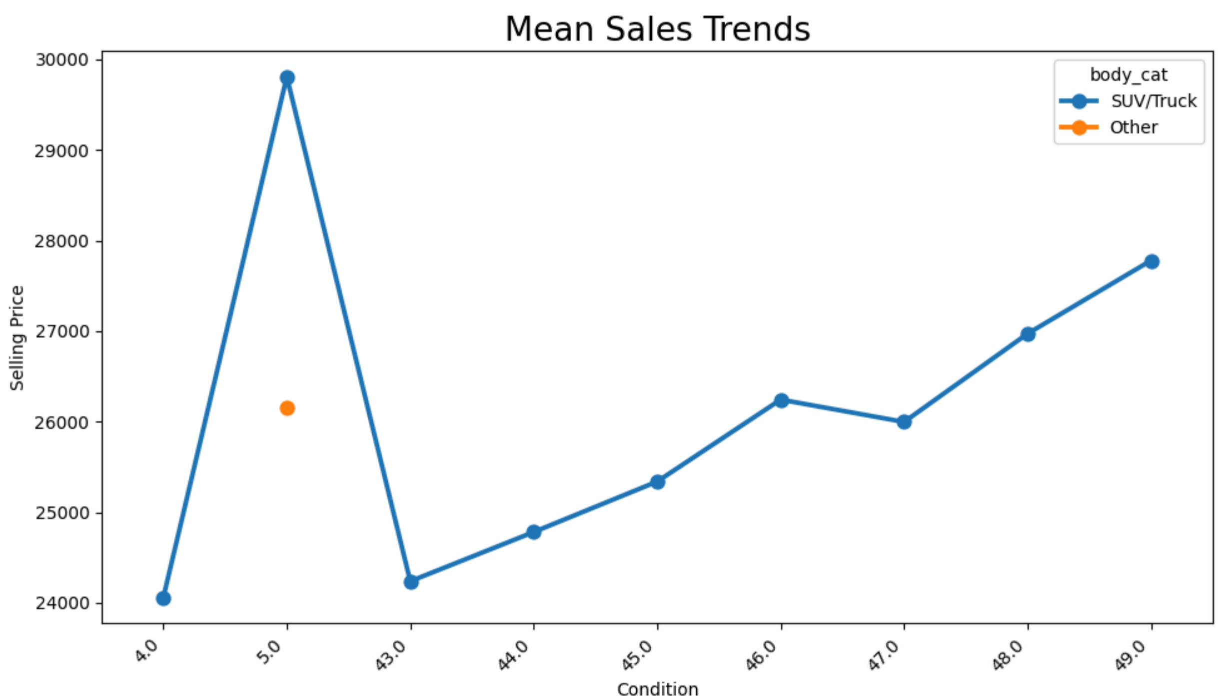
```
Max Sales Trends: Condition    condition              body_cat  sellingprice
0       46.00            Sedan/Coupe     183000.00
1       41.00            Sedan/Coupe     173000.00
2       42.00            Sedan/Coupe     171500.00
3       45.00            Sedan/Coupe     169500.00
4       36.00            Sedan/Coupe     169000.00
5       44.00            Sedan/Coupe     167000.00
6        5.00            Sedan/Coupe     165000.00
7       44.00  Hatchback/Convertible     163000.00
8       48.00            Sedan/Coupe     160000.00
9       43.00  Hatchback/Convertible     158000.00

Mean Sales Trends: Condition    condition   body_cat  sellingprice
0        5.00  SUV/Truck      29808.56
1       49.00  SUV/Truck      27779.28
2       48.00  SUV/Truck      26971.31
3       46.00  SUV/Truck      26243.07
4        5.00      Other      26150.19
5       47.00  SUV/Truck      25996.25
6       45.00  SUV/Truck      25338.04
7       44.00  SUV/Truck      24780.79
8       43.00  SUV/Truck      24236.88
9        4.00  SUV/Truck      24058.41

Min Sales Trends: Condition    condition              body_cat  sellingprice
0        5.00              SUV/Truck       5100.00
1       48.00              SUV/Truck       4900.00
2       45.00              SUV/Truck       4800.00
3        5.00            Minivan/Van       4600.00
4       48.00            Minivan/Van       4600.00
5       45.00            Minivan/Van       4400.00
6       47.00            Minivan/Van       4100.00
7       47.00              SUV/Truck       4100.00
8       49.00  Hatchback/Convertible       4000.00
9       49.00              SUV/Truck       3800.00
```

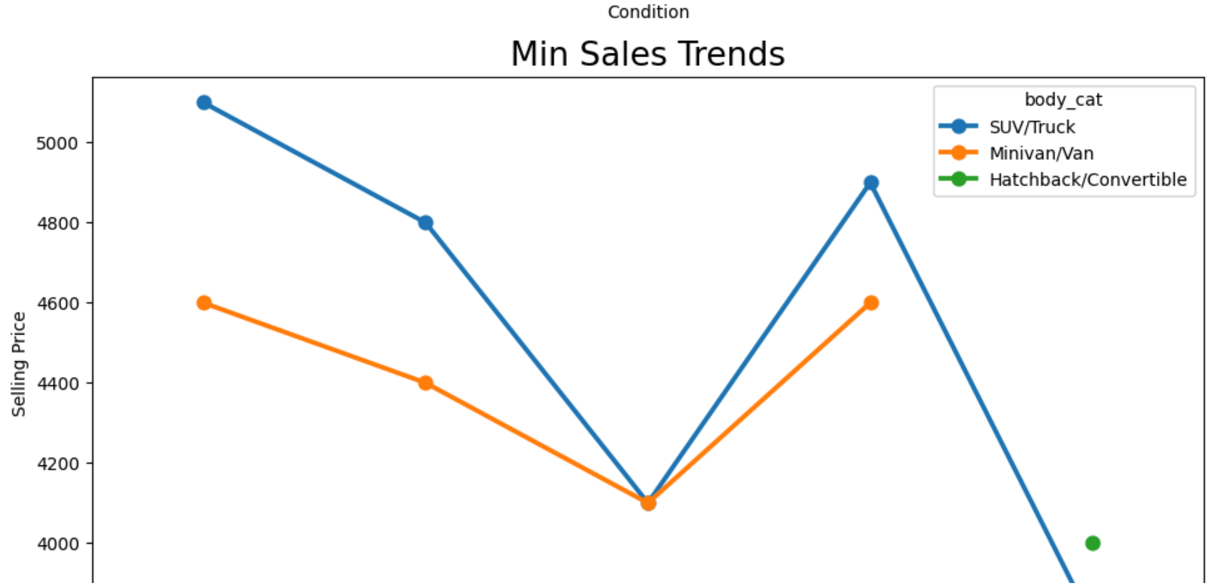
In [39]:

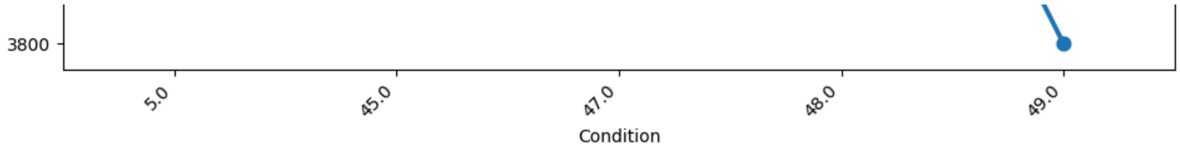
```python
# Create subplots
fig, axes = plt.subplots(nrows=3, ncols=1, figsize=(10, 17))

# Plot max sales trends
sns.pointplot(x='condition', y='sellingprice', hue='body_cat', data=max_sales_trends,
axes[0].set_title('Max Sales Trends', fontsize=19)
axes[0].set_xlabel('Condition')
axes[0].set_ylabel('Selling Price')
#axes[1].axhline(y=100000, color='red', linestyle='dashed', linewidth=1

# Rotate x-axis labels for all subplots efficiently
for ax in axes:
    for label in ax.get_xticklabels():
        label.set_rotation(45)
        label.set_ha('right')  # Right-aligned for better readability

# Plot mean sales trends
sns.pointplot(x='condition', y='sellingprice', hue='body_cat', data=mean_sales_trends,
axes[1].set_title('Mean Sales Trends', fontsize=19)
axes[1].set_xlabel('Condition')  # Corrected label
axes[1].set_ylabel('Selling Price')
#axes[0].axhline(y=100000, color='red', linestyle='dashed', linewidth=1)
```

```
# Plot min sales trends
sns.pointplot(x='condition', y='sellingprice', hue='body_cat', data=min_sales_trends,
axes[2].set_title('Min Sales Trends', fontsize=19)
axes[2].set_xlabel('Condition')
axes[2].set_ylabel('Selling Price')
#axes[2].axhline(y=100000, color='red', linestyle='dashed', linewidth=1)

# Adjust spacing between subplots
plt.tight_layout()

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


Max Sales Trends
body_cat
Sedan/Coupe
Hatchback/Convertible
Selling Price
180000
175000
170000
165000
160000
5.0
36.0
41.0
42.0
43.0
44.0
45.0
46.0
48.0
Condition


Mean Sales Trends
body_cat
SUV/Truck
Other
Selling Price
30000
29000
28000
27000
26000
25000
24000
4.0
5.0
43.0
44.0
45.0
46.0
47.0
48.0
49.0
Condition


Min Sales Trends
body_cat
SUV/Truck
Minivan/Van
Hatchback/Convertible
Selling Price
5000
4800
4600
4400
4200
4000



What is the relationship between mileage and selling price for vehicles of the same year?

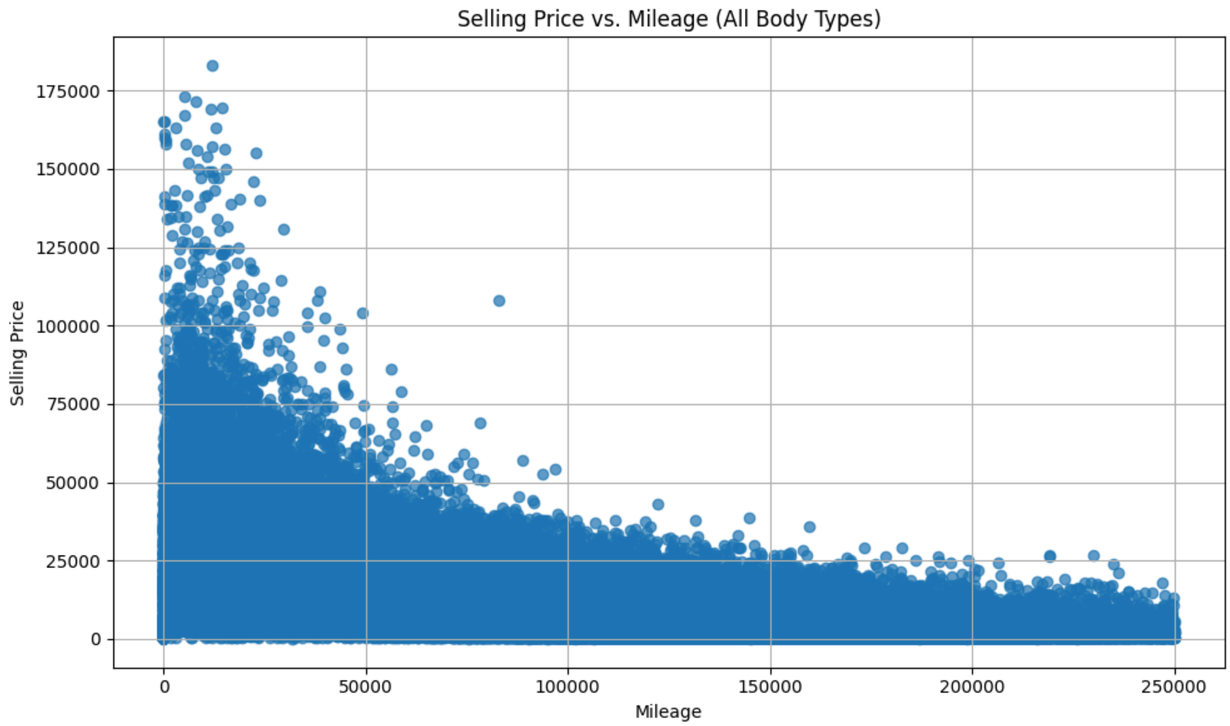
In [40]:
```
# Grouping by Year, Odometer (Mileage), and Selling Price

# Calculate correlation
correlation = filtered_df['odometer'].corr(filtered_df['sellingprice'])
print(f"Correlation between odometer and sellingprice: {correlation}\n")

mean_sales_trends = filtered_df.groupby(['year', 'odometer'])['sellingprice'].mean().s
min_sales_trends = filtered_df.groupby(['year', 'odometer'])['sellingprice'].min().sor
max_sales_trends = filtered_df.groupby(['year', 'odometer'])['sellingprice'].max().sor

print(f'Mean Sales Trends: Odometer {mean_sales_trends}\n')
print(f'Min Sales Trends: Odometer {min_sales_trends}\n')
print(f'Max Sales Trends: Odometer {max_sales_trends}\n')
```

```
Correlation between odometer and sellingprice: -0.5925006257200552

Mean Sales Trends: Odometer          year  odometer  sellingprice
0       2011  12116.00     183000.00
1       2015   5277.00     173000.00
2       2013   7852.00     171500.00
3       2012  14316.00     169500.00
4       2012  11832.00     169000.00
...      ...       ...           ...
335491  1997 226034.00        100.00
335492  1995 198766.00        100.00
335493  2004 106495.00        100.00
335494  2002 145161.00        100.00
335495  2014  31886.00          1.00

[335496 rows x 3 columns]

Min Sales Trends: Odometer          year  odometer  sellingprice
0       2011  12116.00     183000.00
1       2015   5277.00     173000.00
2       2013   7852.00     171500.00
3       2012  14316.00     169500.00
4       2012  11832.00     169000.00
...      ...       ...           ...
335491  2003 215987.00        100.00
335492  2006  75389.00        100.00
335493  2008  90335.00        100.00
335494  2003      1.00          1.00
335495  2014  31886.00          1.00

[335496 rows x 3 columns]

Max Sales Trends: Odometer          year  odometer  sellingprice
0       2011  12116.00     183000.00
1       2015   5277.00     173000.00
2       2013   7852.00     171500.00
3       2012  14316.00     169500.00
4       2012  11832.00     169000.00
...      ...       ...           ...
335491  2002  94937.00        100.00
335492  2006  75389.00        100.00
335493  1997 226034.00        100.00
335494  1995 198766.00        100.00
335495  2014  31886.00          1.00

[335496 rows x 3 columns]
```

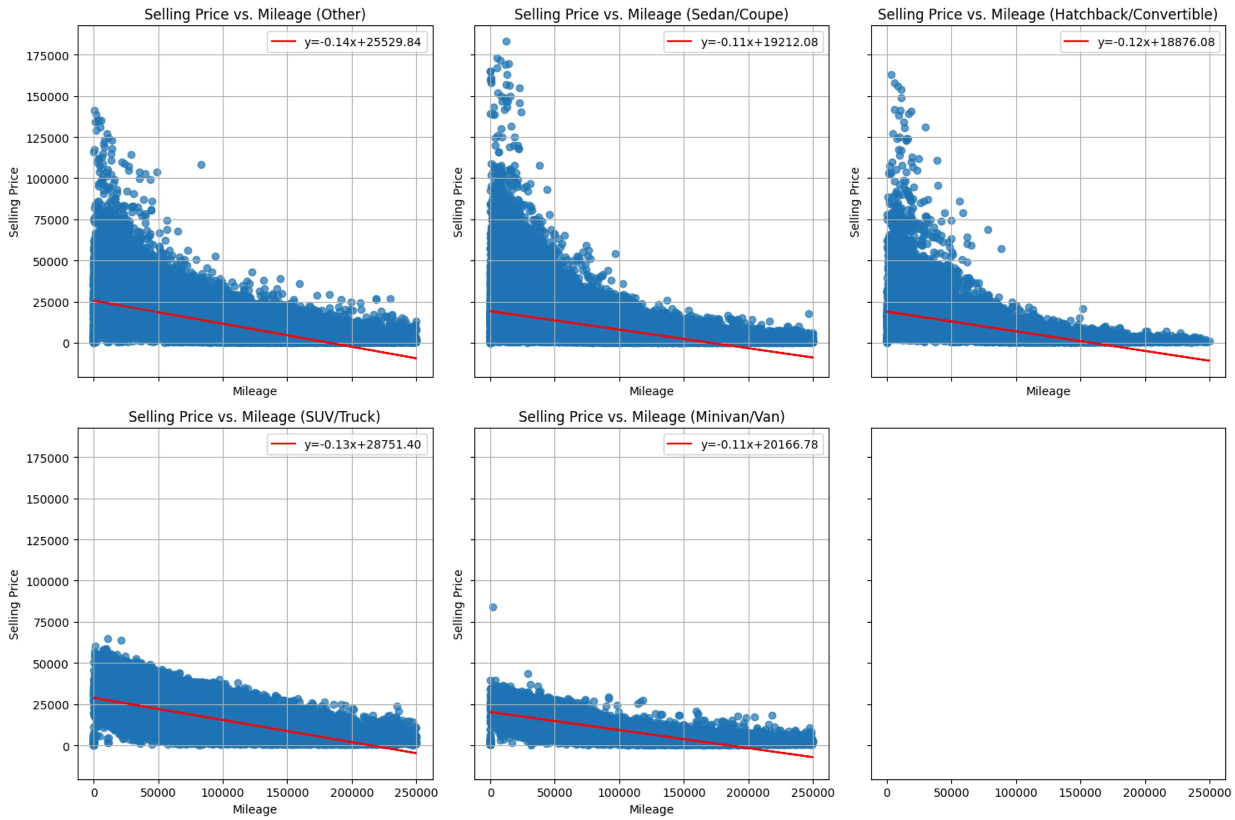
In [62]:

```python
# Plotting the relationship between Odometer(Mileage) and Selling Price

plt.figure(figsize=(10, 6))  # Adjust figure size as needed
plt.scatter(filtered_df['odometer'], filtered_df['sellingprice'], alpha=0.7)  # Adjust

plt.xlabel('Mileage')
plt.ylabel('Selling Price')
plt.title('Selling Price vs. Mileage (All Body Types)')

plt.grid(True)  # Add grid lines for better readability
```

```
plt.tight_layout()  # Adjust spacing between elements
plt.show()
```

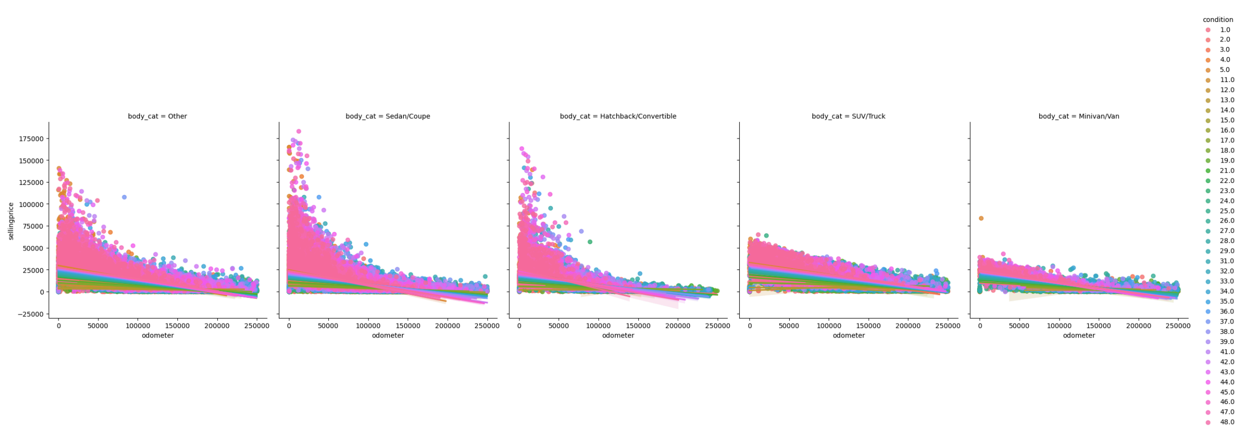


In [60]:
```
from scipy import stats # Import stats library for linear regression

# Get unique body categories
unique_body_cats = filtered_df['body_cat'].unique()

# Create a figure with subplots
fig, axes = plt.subplots(rows, cols, figsize=(15, 10), sharex=True, sharey=True)

# Loop through body categories and create scatter plots
for i, body_cat in enumerate(unique_body_cats):
    body_df = filtered_df[filtered_df['body_cat'] == body_cat]

    ax = axes.flat[i]

    ax.scatter(body_df['odometer'], body_df['sellingprice'], alpha=0.7)

    slope, intercept, r_value, p_value, std_err = stats.linregress(body_df['odometer']

    x = body_df['odometer']
    y_fitted = slope * x + intercept

    ax.plot(x, y_fitted, color='red', label=f'y={slope:.2f}x+{intercept:.2f}')
    ax.legend()

    ax.set_xlabel('Mileage')
    ax.set_ylabel('Selling Price')
    ax.set_title(f'Selling Price vs. Mileage ({body_cat})')

    ax.grid(True)

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



Is there an interaction effect between vehicle condition and mileage on selling price?

In [43]:
```
# Using lmplot we can evaluate the interactive relationship between condition and mile
# Based on the graphs below we see that the negative correlation, non-parallel and cro

# Create a scatter plot using Seaborn
sns.lmplot(x='odometer', y='sellingprice', hue='condition', data=filtered_df, col='boc
plt.show()
```



3. Understanding the Relationship Between MMR Values and Actual Selling Prices

Research Questions:

- What is the correlation between MMR values and actual selling prices for different vehicle makes?
- How does the difference between MMR values and selling prices vary across different vehicle ages or conditions?
- Are there specific makes and models where MMR values consistently overestimate or underestimate selling prices?

What is the correlation between MMR values and actual selling prices for different vehicle makes?

In [44]:
```
# Calculate correlation

correlation = filtered_df['mmr'].corr(filtered_df['sellingprice'])
print(f"Correlation between MMR values and sellingprice: {correlation}\n")
```

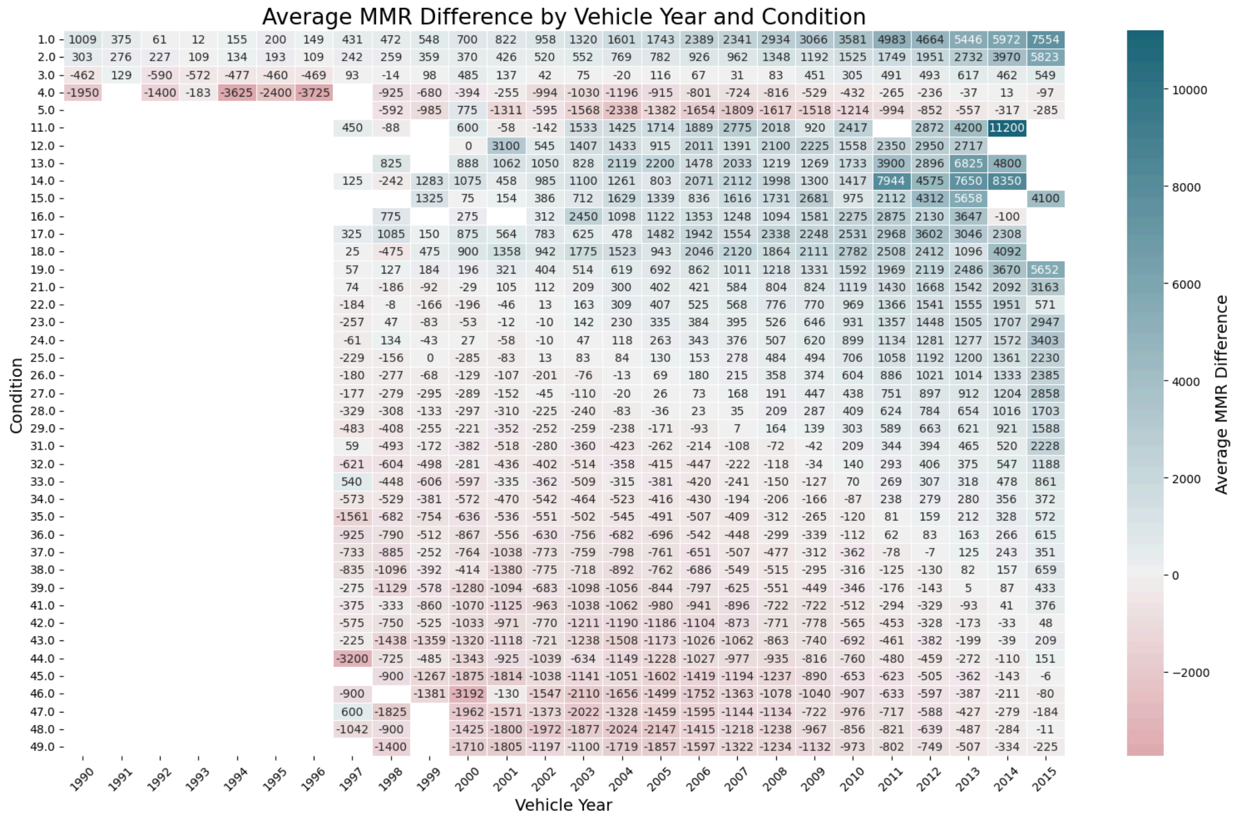
```
Correlation between MMR values and sellingprice: 0.9839273325282424
```

How does the difference between MMR values and selling prices vary across different vehicle years and conditions?

In [45]:
```
# Create new feature for the difference between MMRs and Selling Price

filtered_df['mmr_diff'] = filtered_df['mmr'] - filtered_df['sellingprice']
```

In [46]:
```
# Group by vehicle year and condition, to calculate the avg MMR difference for each gr

mmr_diff_by_year_cond = filtered_df.groupby(['year', 'condition'])['mmr_diff'].mean().
```

In [47]:
```
# Create the pivot table
pivot_table = mmr_diff_by_year_cond.pivot(index='condition', columns='year', values='m

# Define a custom colormap with darker colors
cmap = sns.diverging_palette(10, 220, s=90, l=40, as_cmap=True)

# Create the heatmap with the custom colormap
plt.figure(figsize=(16, 10))
ax = sns.heatmap(pivot_table, annot=True, fmt=".0f", cmap=cmap, center=0,
            annot_kws={"size": 10},
            linewidths=.5, cbar_kws={'label': 'Average MMR Difference'},
            linecolor='white')

# Increase fontsize of colorbar label
cbar = ax.collections[0].colorbar
cbar.ax.tick_params(labelsize=10)
cbar.set_label('Average MMR Difference', fontsize=14)

plt.title('Average MMR Difference by Vehicle Year and Condition', fontsize=19)
plt.xlabel('Vehicle Year', fontsize=14)
plt.ylabel('Condition', fontsize=14)
plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.tight_layout()
plt.show()
```



Are there specific makes and models where MMR values consistently overestimate or underestimate selling prices?

In [48]:

```python
# Group by make and model, calculate average MMR difference
mmr_diff_by_make_model = filtered_df.groupby(['make', 'model'])['mmr_diff'].mean().res

# Identify makes and models where MMR consistently overestimates (positive mmr_diff)
overestimates = mmr_diff_by_make_model[mmr_diff_by_make_model['mmr_diff'] > 1000]

# Identify makes and models where MMR consistently underestimates (negative mmr_diff)
underestimates = mmr_diff_by_make_model[mmr_diff_by_make_model['mmr_diff'] < -1000]

# Function to color the DataFrame
def color_df(val):
    # Check if the value is numeric before comparison
    if isinstance(val, (int, float)):
        color = 'red' if val > 1000 else ('green' if val < -1000 else 'black')
    else:
        color = 'black' # Set default color for non-numeric values
    return f'color: {color}'

# Apply styling to overestimates
styled_overestimates = overestimates.style.applymap(color_df)

# Apply styling to underestimates
styled_underestimates = underestimates.style.applymap(color_df)

# Display the styled tables
print("Makes and models where MMR consistently overestimates:")
display(styled_overestimates)
```

```python
print("\nMakes and models where MMR consistently underestimates:")
display(styled_underestimates)
```

```
Makes and models where MMR consistently overestimates:
```

```
<ipython-input-48-1ede38363160>:20: FutureWarning: Styler.applymap has been deprecate
d. Use Styler.map instead.
  styled_overestimates = overestimates.style.applymap(color_df)
<ipython-input-48-1ede38363160>:23: FutureWarning: Styler.applymap has been deprecate
d. Use Styler.map instead.
  styled_underestimates = underestimates.style.applymap(color_df)
```

	make	model	mmr_diff
7	Acura	Rlx	1223.076923
28	Audi	R8	1664.062500
29	Audi	Rs 4	1733.333333
46	Bentley	Continental Gtc	3240.000000
48	Bentley	Continental Supersports	14000.000000
54	Bmw	4 Series Gran Coupe	1163.636364
63	Bmw	Activehybrid X6	2360.000000
64	Bmw	I8	6555.555556
70	Bmw	M6 Gran Coupe	2450.000000
101	Cadillac	Cts-V Coupe	1272.269231
106	Cadillac	Elr	4183.333333
127	Chevrolet	Caprice	1121.428571
146	Chevrolet	Malibu Hybrid	1005.208333
154	Chevrolet	Silverado 1500 Hybrid	1050.000000
160	Chevrolet	Silverado 3500 Classic	1650.000000
164	Chevrolet	Spark Ev	3050.000000
219	Ferrari	California	1846.153846
220	Ferrari	F430	5750.000000
224	Fisker	Karma	2638.888889
232	Ford	E-350	1100.000000
273	Ford	Transit Wagon	1160.000000
289	Gmc	Sierra 1500 Hybrid	1200.000000
293	Gmc	Sierra 2500Hd Classic	1202.941176
294	Gmc	Sierra 3500	1845.000000
358	Infiniti	G37 Coupe	1168.181818
417	Lamborghini	Gallardo	2166.666667
450	Lexus	Ls 600H L	1187.500000
454	Lexus	Rc 350	1091.666667
455	Lexus	Rc F	1640.000000
485	Maserati	Granturismo Convertible	3090.909091
520	Mercedes-Benz	B-Class Electric Drive	1083.333333
527	Mercedes-Benz	G-Class	2550.877193
529	Mercedes-Benz	Gla-Class	2650.000000
537	Mercedes-Benz	Sls Amg	4983.333333

	make	model	mmr_diff
538	Mercedes-Benz	Sls Amg Gt	3500.000000
577	Nissan	300Zx	1600.000000
593	Nissan	Nv Passenger	2100.000000
618	Plymouth	Prowler	3433.333333
640	Porsche	Macan	2500.000000
650	Rolls-Royce	Ghost	1356.250000
657	Saturn	Aura Hybrid	1525.000000
736	Volkswagen	Golf Gti	1443.750000
741	Volkswagen	Jetta Hybrid	1200.000000

```
Makes and models where MMR consistently underestimates:
```

	make	model	mmr_diff
14	Aston Martin	Db9	-2883.333333
15	Aston Martin	Rapide	-8250.000000
36	Audi	S7	-1664.285714
47	Bentley	Continental Gtc Speed	-2000.000000
61	Bmw	Activehybrid 5	-2825.000000
62	Bmw	Activehybrid 7	-2723.076923
68	Bmw	M5	-1031.465116
80	Bmw	Z4 M	-1340.000000
99	Cadillac	Cts Wagon	-1031.818182
102	Cadillac	Cts-V Wagon	-8200.000000
285	Gmc	Savana	-2265.909091
320	Hummer	H1	-2350.000000
322	Hummer	H2 Sut	-1710.483871
324	Hummer	H3T	-2466.666667
370	Infiniti	Q60 Convertible	-1151.250000
375	Infiniti	Qx50	-1012.500000
399	Jeep	Grand Cherokee Srt	-1700.000000
465	Lincoln	Blackwood	-1562.500000
481	Maserati	Coupe	-1150.000000
487	Maserati	Spyder	-2066.666667
517	Mercedes-Benz	400-Class	-1275.000000
542	Mercury	Marauder	-2843.750000

4. Determining the Most Popular Vehicle Makes and Models

Research Questions:

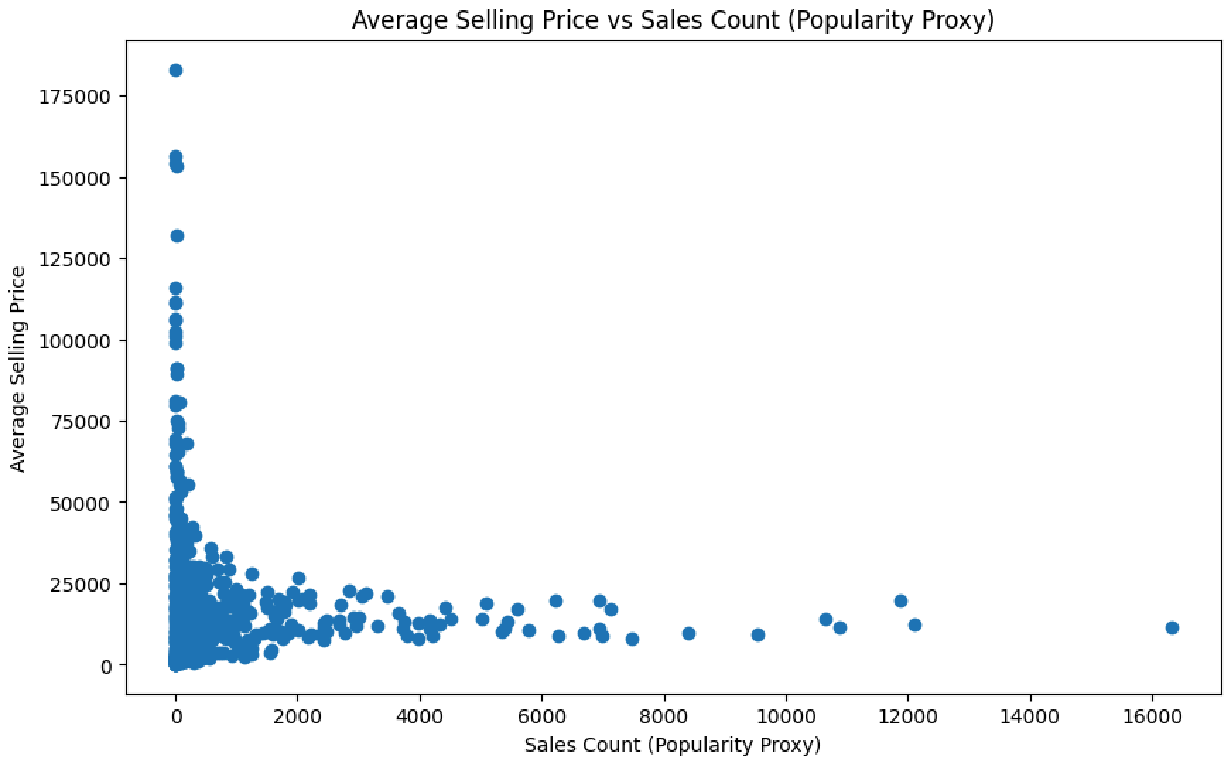
- Which vehicle makes and models have the highest average selling prices, and how does this relate to their popularity?
- Are there any emerging trends in the popularity of certain makes and models over recent years?

Which vehicle makes and models have the highest average selling prices, and how does this relate to their popularity?

In [49]:

```
# Group by make and model, calculate average selling price and count sales
avg_selling_price = filtered_df.groupby(['make', 'model'])['sellingprice'].agg(['mean'
avg_selling_price.columns = ['make', 'model', 'avg_selling_price', 'sales_count']  # R

# Sort by average selling price in descending order
avg_selling_price_sorted = avg_selling_price.sort_values('avg_selling_price', ascendir

# Display the results
print(avg_selling_price_sorted)

# Create a scatter plot to visualize the relationship
plt.figure(figsize=(10, 6))
plt.scatter(avg_selling_price_sorted['sales_count'], avg_selling_price_sorted['avg_sel
plt.title('Average Selling Price vs Sales Count (Popularity Proxy)')
plt.xlabel('Sales Count (Popularity Proxy)')
plt.ylabel('Average Selling Price')
plt.show()
```

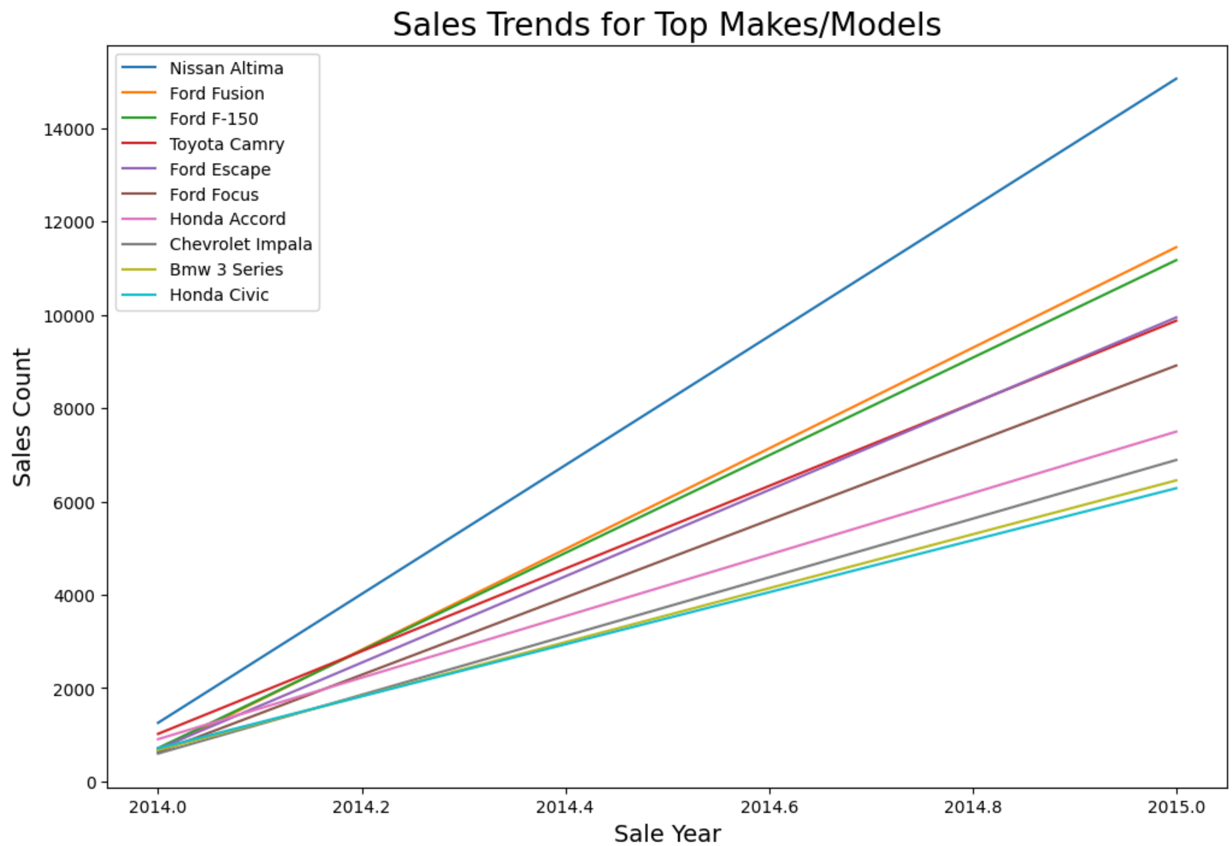
```
              make         model  avg_selling_price  sales_count
218        Ferrari    458 Italia          183000.00            1
538  Mercedes-Benz    Sls Amg Gt          156500.00            1
64             Bmw            I8          154222.22            9
650    Rolls-Royce         Ghost          153456.25           16
219        Ferrari    California          131846.15           13
..             ...           ...                ...          ...
610     Oldsmobile  Cutlass Ciera             358.33            6
133      Chevrolet       Corsica             350.00            1
269           Ford         Tempo             333.33            3
552        Mercury        Tracer             312.50            4
212          Dodge        Spirit             300.00            1

[770 rows x 4 columns]
```



Are there any emerging trends in the popularity of certain makes and models over recent years?

In [50]:

```
# Convert 'saledate' to datetime if it's not already
filtered_df['saledate'] = pd.to_datetime(filtered_df['saledate'])

# Group by make, model, and saleyear, and count sales
sales_by_year = filtered_df.groupby(['make', 'model', filtered_df['saledate'].dt.year]
sales_by_year.rename(columns={'vin': 'sales_count', 'saledate': 'saleyear'}, inplace=T

# Find top N makes/models based on overall sales
top_n = 10  # Change this to the desired number of top makes/models
top_makes_models = sales_by_year.groupby(['make', 'model'])['sales_count'].sum().nlarg

# Filter sales data for top makes/models
top_sales = sales_by_year[sales_by_year[['make', 'model']].apply(tuple, axis=1).isin(t

# Plot sales trends for top makes/models
plt.figure(figsize=(12, 8))
for make, model in top_makes_models:
    make_model_data = top_sales[(top_sales['make'] == make) & (top_sales['model'] == m
    plt.plot(make_model_data['saleyear'], make_model_data['sales_count'], label=f'{mak
plt.title('Sales Trends for Top Makes/Models', fontsize=19)
plt.xlabel('Sale Year', fontsize=14)
plt.ylabel('Sales Count', fontsize=14)
plt.legend()
plt.show()
```



Comprehensive Analysis:

1. Identifying Trends in Vehicle Sales

- **Temporal Analysis:** Sales data analysis revealed a consistent upward trend across all listed models from 2014 to 2015, indicating a growing market.
- **Visualization:** Time series plots confirmed the steady increase in sales over time.

2. Analyzing the Impact of Vehicle Condition and Mileage

- **Correlation Analysis:** Strong positive correlation between vehicle condition and selling price, while a generally negative correlation was observed between mileage and selling price.
- **Regression Analysis:** Regression models confirmed the significant impact of condition and mileage on price.
- **Visualization:** Scatter plots and regression lines illustrated the relationships between variables.

3. Understanding the Relationship Between MMR Values and Actual Selling Prices

- **Comparison Analysis:** MMR values were found to deviate from actual selling prices for certain makes and models.
- **Error Analysis:** Discrepancies between MMR and actual prices were attributed to factors such as unique features, limited availability, and regional market dynamics.

4. Determining the Most Popular Vehicle Makes and Models

- **Market Share Analysis:** Ford vehicles dominated the **top 10**, followed by Toyota, Honda, and Nissan.
- **Trend Analysis:** The popularity of certain models, such as the Toyota Camry and Ford F-150, remained consistent throughout the period.

Conclusion:

- **Vehicle condition** emerged as a critical factor influencing selling price, while **mileage** played a secondary role. The relationship between condition and price varied across body types. Popular makes and models included **Ford vehicles, the Toyota Camry, and Japanese brands.** MMR values were found to be inaccurate for certain vehicles, highlighting the need for a comprehensive analysis beyond MMR.

Recommendations:

- **Buyers:** Prioritize vehicles with high condition and low mileage to maximize value. Consider factors beyond MMR when evaluating prices.
- **Sellers:** Accurately assess vehicle condition and adjust pricing strategies accordingly.
- **Industry:** Conduct further research to improve the accuracy of MMR valuation models.
- **Policymakers:** Implement policies that promote the sale of higher-condition vehicles and address factors that contribute to MMR inaccuracies.