Business Problem

I'm working, with my 17 year old son,
on a domestic business problem.

My son is almost ready to buy his first car.
I'd really like for him to be able to get someting better than my first car.

I want to be able to offer him some fatherly advice about how to get something safer and then also hopefully beter value than this.

but we're still trying to work out what he wants to get.

Lets have a look at the data:...

Load data

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

I found this data on Kaggle.com
It was well reviewed and relevant to my problem.

https://www.kaggle.com/datasets/nelgiriyewithana/australian-vehicle-prices
(https://www.kaggle.com/datasets/nelgiriyewithana/australian-vehicle-prices)

In [2]:
```
avp = pd.read_csv('data/Australian Vehicle Prices.csv')
avp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16734 entries, 0 to 16733
Data columns (total 19 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Brand              16733 non-null  object 
 1   Year               16733 non-null  float64
 2   Model              16733 non-null  object 
 3   Car/Suv            16706 non-null  object 
 4   Title              16733 non-null  object 
 5   UsedOrNew          16733 non-null  object 
 6   Transmission       16733 non-null  object 
 7   Engine             16733 non-null  object 
 8   DriveType          16733 non-null  object 
 9   FuelType           16733 non-null  object 
 10  FuelConsumption    16733 non-null  object 
 11  Kilometres         16733 non-null  object 
 12  ColourExtInt       16733 non-null  object 
 13  Location           16284 non-null  object 
 14  CylindersinEngine  16733 non-null  object 
 15  BodyType           16452 non-null  object 
 16  Doors              15130 non-null  object 
 17  Seats              15029 non-null  object 
 18  Price              16731 non-null  object 
dtypes: float64(1), object(18)
memory usage: 2.4+ MB
```

Target

So far my son's best idea for a car, is that he would like to get a Toyota Supra.

It's a great looking car for sure,
but I'm not sure it is in our price range.

Lets check out the value of a Supra first

In [3]:
```
Supra_options = avp.loc[avp["Model"] == 'Supra']
Supra_options[['Year', 'Model', 'Title', 'Price']]
```

Out[3]:

	Year	Model	Title	Price
7588	2022.0	Supra	2022 Toyota Supra GTS +alcantara Seats	95888
8661	2021.0	Supra	2021 Toyota Supra GTS	97990
12246	2020.0	Supra	2020 Toyota Supra GTS	87990
12261	2021.0	Supra	2021 Toyota Supra GTS +alcantara Seats	94995
15491	2023.0	Supra	2023 Toyota Supra GTS +alcant Seats +matte Paint	102000
15670	1993.0	Supra	1993 Toyota Supra	69880
15971	1994.0	Supra	1994 Toyota Supra TURBO 1994	77888

Yep, even that 1993 Supra at $69,880
Is still way above our price range!

I may need to manage his expectations.

Im going to go ahead and remove anything less than $20,000 as a less unrealistic upper limit of our budget.
but first I'll need to make sure the Price column is numeric.
and generally tidy up the data a bit.

In [4]:
```
avp = avp.drop(avp[avp['Price'] == "POA"].index)
```

In [5]:
```
avp['Price'] = pd.to_numeric(avp['Price'])
```

In [6]:
```
avp = avp[avp['Price'] <= 20000]
avp
```

Out[6]:

	Brand	Year	Model	Car/Suv	Title	UsedOrNew	Transmission	Engine
1	MG	2022.0	MG3	Hatchback	2022 MG MG3 Auto Excite (with Navigation)	USED	Automatic	4 cyl, 1.5 L
5	Toyota	2004.0	Estima	ON FOUR WHEELS	2004 Toyota Estima T EDITION	USED	Automatic	-
7	Nissan	2000.0	Pulsar	Hatchback	2000 Nissan Pulsar LX	USED	Automatic	4 cyl, 1.6 L
9	Honda	2014.0	Jazz	Hatchback	2014 Honda Jazz Hybrid	USED	Automatic	4 cyl, 1.3 L
12	Honda	2015.0	City	USED Dealer ad	2015 Honda City GM VTi-L Sedan 4dr CVT 7sp 1.5...	USED	Automatic	-
...	...	...	...	...	...	...	...	...
16716	Holden	2014.0	Cruze	Hatchback	2014 Holden Cruze Equipe	USED	Automatic	4 cyl, 1.8 L
16717	Mitsubishi	2018.0	Outlander	SUV	2018 Mitsubishi Outlander ES Adas 5 Seat (2WD)	USED	Automatic	4 cyl, 2.4 L
16721	Hyundai	2016.0	Accent	Hatchback	2016 Hyundai Accent Active	USED	Manual	4 cyl, 1.4 L
16722	Hyundai	2016.0	Accent	Sedan	2016 Hyundai Accent Active	USED	Automatic	4 cyl, 1.4 L
16724	Nissan	2009.0	Navara	Ute / Tray	2009 Nissan Navara ST (4X4)	USED	Automatic	4 cyl, 2.5 L

4777 rows × 19 columns

In [7]:
```
avp = avp.dropna()
avp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 4272 entries, 1 to 16724
Data columns (total 19 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Brand              4272 non-null   object 
 1   Year               4272 non-null   float64
 2   Model              4272 non-null   object 
 3   Car/Suv            4272 non-null   object 
 4   Title              4272 non-null   object 
 5   UsedOrNew          4272 non-null   object 
 6   Transmission       4272 non-null   object 
 7   Engine             4272 non-null   object 
 8   DriveType          4272 non-null   object 
 9   FuelType           4272 non-null   object 
 10  FuelConsumption    4272 non-null   object 
 11  Kilometres         4272 non-null   object 
 12  ColourExtInt       4272 non-null   object 
 13  Location           4272 non-null   object 
 14  CylindersinEngine  4272 non-null   object 
 15  BodyType           4272 non-null   object 
 16  Doors              4272 non-null   object 
 17  Seats              4272 non-null   object 
 18  Price              4272 non-null   float64
dtypes: float64(2), object(17)
memory usage: 667.5+ KB
```

Now, because we are looking at other, non superficial factors in determining the value of a vehicle,
I'm going to cut out the following columns as not being relevant to our enquiry:
'Brand', 'Model', 'Title', 'ColourExtInt', and other irrellevant information such as 'Location'.

In [8]:
```
avp = avp.drop(columns=['Brand', 'Model', 'Title', 'ColourExtInt', 'Locatior
avp
```

Out[8]:

	Year	Car/Suv	UsedOrNew	Transmission	Engine	DriveType	FuelType	FuelConsu
1	2022.0	Hatchback	USED	Automatic	4 cyl, 1.5 L	Front	Premium	6.7 L /
7	2000.0	Hatchback	USED	Automatic	4 cyl, 1.6 L	Front	Unleaded	8 L /
9	2014.0	Hatchback	USED	Automatic	4 cyl, 1.3 L	Front	Hybrid	4.5 L /
15	2012.0	Hatchback	USED	Automatic	4 cyl, 1.4 L	Front	Premium	6.2 L /
18	2011.0	Hatchback	USED	Automatic	4 cyl, 2 L	Rear	Diesel	5.4 L /
...	...	...	...	...	...	...	...	
16716	2014.0	Hatchback	USED	Automatic	4 cyl, 1.8 L	Front	Unleaded	7.4 L /
16717	2018.0	SUV	USED	Automatic	4 cyl, 2.4 L	Front	Unleaded	6.8 L /
16721	2016.0	Hatchback	USED	Manual	4 cyl, 1.4 L	Front	Unleaded	5.9 L /
16722	2016.0	Sedan	USED	Automatic	4 cyl, 1.4 L	Front	Unleaded	6.4 L /
16724	2009.0	Ute / Tray	USED	Automatic	4 cyl, 2.5 L	4WD	Diesel	10.5 L /

4272 rows × 14 columns

As we are looking at value for money, Fuel consumption is going to be an important variable here.
But for this to be useful, we need to be sure that we are comparing apples with apples.
And since we are only really looking at Unleaded fuel vehicles,
we may as well get rid of any other fuel types from the dataframe.

In [9]:
```
avp['FuelType'].unique()
```

Out[9]:
```
array(['Premium', 'Unleaded', 'Hybrid', 'Diesel', 'LPG', 'Electric', '-'],
      dtype=object)
```

In [10]:
```
FuelTypes = avp['FuelType'].value_counts()
FuelTypes
```

Out[10]:
```
FuelType
Unleaded    2617
Diesel       904
Premium      721
Hybrid        12
LPG           12
-              5
Electric       1
Name: count, dtype: int64
```

We'll keep Unleaded and Premium,
as Premium is just another type of Unleaded fuel

In [11]:
```
avp = avp.drop(avp[avp['FuelType'] == 'Diesel'].index)
avp = avp.drop(avp[avp['FuelType'] == 'Hybrid'].index)
avp = avp.drop(avp[avp['FuelType'] == 'LPG'].index)
avp = avp.drop(avp[avp['FuelType'] == '-'].index)
# mental note - I'll need to check on how many other '-' values there are ir
avp = avp.drop(avp[avp['FuelType'] == 'Electric'].index)
```

In [12]:
```
avp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3338 entries, 1 to 16722
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Year               3338 non-null   float64
 1   Car/Suv            3338 non-null   object 
 2   UsedOrNew          3338 non-null   object 
 3   Transmission       3338 non-null   object 
 4   Engine             3338 non-null   object 
 5   DriveType          3338 non-null   object 
 6   FuelType           3338 non-null   object 
 7   FuelConsumption    3338 non-null   object 
 8   Kilometres         3338 non-null   object 
 9   CylindersinEngine  3338 non-null   object 
 10  BodyType           3338 non-null   object 
 11  Doors              3338 non-null   object 
 12  Seats              3338 non-null   object 
 13  Price              3338 non-null   float64
dtypes: float64(2), object(12)
memory usage: 391.2+ KB
```

Now we have a dataset with only Unleaded (and Premium) values.
So i can get rid of 'FuelType' as a variable.

In [13]:
```
avp = avp.drop(columns=['FuelType'])
avp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3338 entries, 1 to 16722
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Year               3338 non-null   float64
 1   Car/Suv            3338 non-null   object 
 2   UsedOrNew          3338 non-null   object 
 3   Transmission       3338 non-null   object 
 4   Engine             3338 non-null   object 
 5   DriveType          3338 non-null   object 
 6   FuelConsumption    3338 non-null   object 
 7   Kilometres         3338 non-null   object 
 8   CylindersinEngine  3338 non-null   object 
 9   BodyType           3338 non-null   object 
 10  Doors              3338 non-null   object 
 11  Seats              3338 non-null   object 
 12  Price              3338 non-null   float64
dtypes: float64(2), object(11)
memory usage: 365.1+ KB
```

Now to drop a few other variables that I dont believe will have much bearing on Price or value

In [14]:
```
avp = avp.drop(columns=['Car/Suv', 'BodyType', 'Doors', 'Seats'])
avp
```

Out[14]:

	Year	UsedOrNew	Transmission	Engine	DriveType	FuelConsumption	Kilometres	C
1	2022.0	USED	Automatic	4 cyl, 1.5 L	Front	6.7 L / 100 km	16	
7	2000.0	USED	Automatic	4 cyl, 1.6 L	Front	8 L / 100 km	300539	
15	2012.0	USED	Automatic	4 cyl, 1.4 L	Front	6.2 L / 100 km	55676	
19	2014.0	USED	Automatic	3 cyl, 1 L	Front	5.4 L / 100 km	76289	
20	2012.0	USED	Automatic	4 cyl, 2.4 L	AWD	7.5 L / 100 km	219681	
...	...	...	...	...	...	...	...	
16714	2015.0	USED	Automatic	4 cyl, 1.2 L	Front	5.1 L / 100 km	88000	
16716	2014.0	USED	Automatic	4 cyl, 1.8 L	Front	7.4 L / 100 km	119494	
16717	2018.0	USED	Automatic	4 cyl, 2.4 L	Front	6.8 L / 100 km	142169	
16721	2016.0	USED	Manual	4 cyl, 1.4 L	Front	5.9 L / 100 km	85000	
16722	2016.0	USED	Automatic	4 cyl, 1.4 L	Front	6.4 L / 100 km	97610	

3338 rows × 9 columns

In [15]:
```
avp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3338 entries, 1 to 16722
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Year               3338 non-null   float64
 1   UsedOrNew          3338 non-null   object 
 2   Transmission       3338 non-null   object 
 3   Engine             3338 non-null   object 
 4   DriveType          3338 non-null   object 
 5   FuelConsumption    3338 non-null   object 
 6   Kilometres         3338 non-null   object 
 7   CylindersinEngine  3338 non-null   object 
 8   Price              3338 non-null   float64
dtypes: float64(2), object(7)
memory usage: 260.8+ KB
```

I'll need to do a bit of work to get all these columns into numerical format.

In [16]:
```
columns_to_analyze = ['Year', 'UsedOrNew', 'Transmission', 'Engine', 'DriveT

# Dictionary to store unique value counts for each column
unique_value_counts = {}

# Iterate over each column and calculate the number of unique values
for column in columns_to_analyze:
    unique_value_counts[column] = avp[column].nunique()

# Print the unique value counts for each column
for column, count in unique_value_counts.items():
    print(f"{column}: {count}")
```

```
Year: 33
UsedOrNew: 3
Transmission: 2
Engine: 52
DriveType: 4
FuelConsumption: 113
Kilometres: 3237
CylindersinEngine: 6
Price: 596
```

'UsedOrNew', 'Transmission', 'DriveType', and 'CylindersinEngine'
will be categorical variables.

'Year' as a float is just awkward, let's tidy that up

In [17]:
```
avp['Year'] = avp['Year'].astype('int64')
#avp
```

The 'Engine' column is going to be useful,
for the Engine size,
I'm going to strip that out,
and then i don't need the rest, as we already have 'CylindersinEngine' elsewhere.

In [18]:
```
avp[['Engine1', 'Engine_size']] = avp['Engine'].str.split(',', expand=True)
#avp
```

In [19]:
```
avp = avp.drop(columns=['Engine', 'Engine1'])
#avp
```

In [20]:
```
avp['Engine_size'] = avp['Engine_size'].str.replace(r' L', '')
#avp
```

In [21]:
```
avp['Engine_size'] = pd.to_numeric(avp['Engine_size'])
avp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3338 entries, 1 to 16722
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Year               3338 non-null   int64  
 1   UsedOrNew          3338 non-null   object 
 2   Transmission       3338 non-null   object 
 3   DriveType          3338 non-null   object 
 4   FuelConsumption    3338 non-null   object 
 5   Kilometres         3338 non-null   object 
 6   CylindersinEngine  3338 non-null   object 
 7   Price              3338 non-null   float64
 8   Engine_size        3338 non-null   float64
dtypes: float64(2), int64(1), object(6)
memory usage: 260.8+ KB
```

Next,
'FuelConsumption' is going to be extremely useful.
But not in this format.

In [22]:
```
avp['FuelConsumption'] = avp['FuelConsumption'].str.extract(r'^([\d.]+)').as
avp
```

Out[22]:

	Year	UsedOrNew	Transmission	DriveType	FuelConsumption	Kilometres	Cylindersin
1	2022	USED	Automatic	Front	6.7	16	
7	2000	USED	Automatic	Front	8.0	300539	
15	2012	USED	Automatic	Front	6.2	55676	
19	2014	USED	Automatic	Front	5.4	76289	
20	2012	USED	Automatic	AWD	7.5	219681	
...	...	...	...	...	...	...	
16714	2015	USED	Automatic	Front	5.1	88000	
16716	2014	USED	Automatic	Front	7.4	119494	
16717	2018	USED	Automatic	Front	6.8	142169	
16721	2016	USED	Manual	Front	5.9	85000	
16722	2016	USED	Automatic	Front	6.4	97610	

3338 rows × 9 columns

In [23]:
```
avp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3338 entries, 1 to 16722
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Year               3338 non-null   int64  
 1   UsedOrNew          3338 non-null   object 
 2   Transmission       3338 non-null   object 
 3   DriveType          3338 non-null   object 
 4   FuelConsumption    3338 non-null   float64
 5   Kilometres         3338 non-null   object 
 6   CylindersinEngine  3338 non-null   object 
 7   Price              3338 non-null   float64
 8   Engine_size        3338 non-null   float64
dtypes: float64(3), int64(1), object(5)
memory usage: 260.8+ KB
```

Finally,
'Kilometres' as integer

In [24]:
```
avp = avp.drop(avp[avp['Kilometres'] == '-'].index)
```

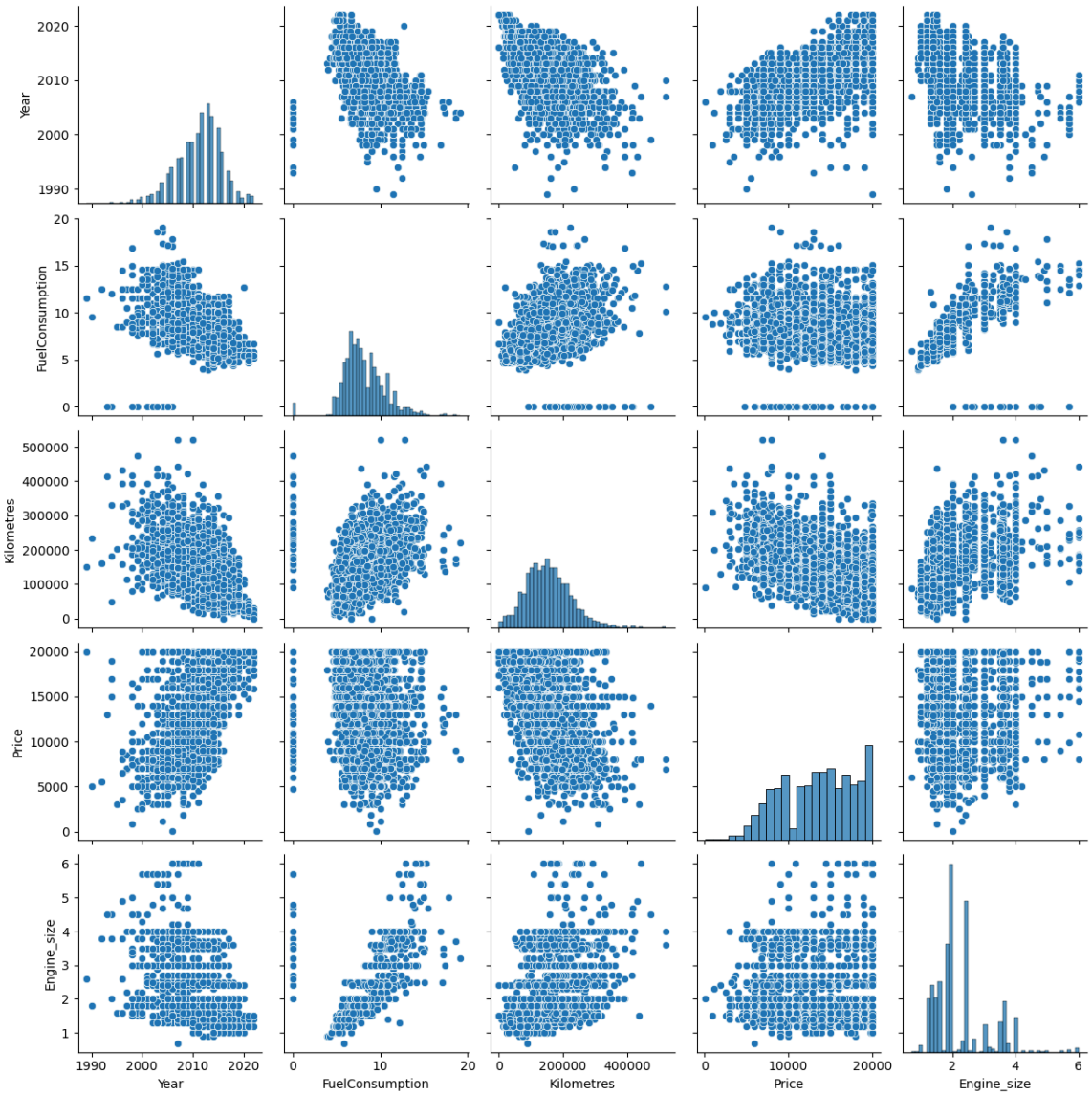
In [25]:
```
avp['Kilometres'] = pd.to_numeric(avp['Kilometres'])
avp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3335 entries, 1 to 16722
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Year               3335 non-null   int64  
 1   UsedOrNew          3335 non-null   object 
 2   Transmission       3335 non-null   object 
 3   DriveType          3335 non-null   object 
 4   FuelConsumption    3335 non-null   float64
 5   Kilometres         3335 non-null   int64  
 6   CylindersinEngine  3335 non-null   object 
 7   Price              3335 non-null   float64
 8   Engine_size        3335 non-null   float64
dtypes: float64(3), int64(2), object(4)
memory usage: 260.5+ KB
```

Let's take a look at some of these relationships

In [26]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [27]:
```
sns.pairplot(avp)
plt.show()
```



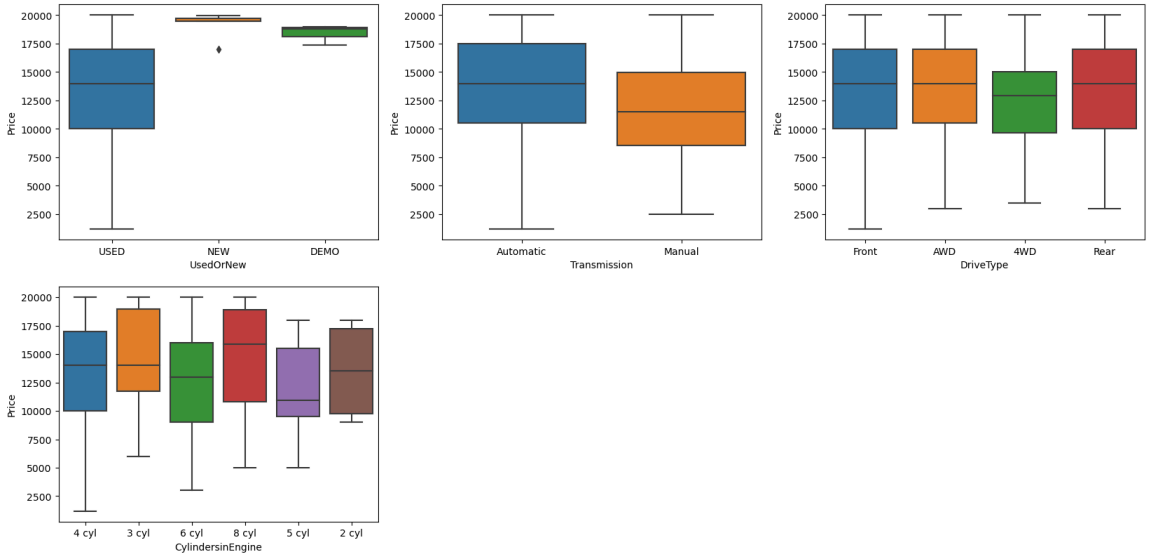
It looks like there are quite a few "0" values in the 'FuelConsumption' column.
I'd better fix that.

In [28]:
```
avp = avp.drop(avp[avp['FuelConsumption'] == 0].index)
```

I'll also take out anything, less than $1000.
As i dont want to waste any time looking at lemons

In [29]:
```
avp = avp.drop(avp[avp['Price'] < 1000].index)
```

In [30]:
```
plt.figure(figsize=(20, 20))

plt.subplot(4,3,1)
sns.boxplot(x = 'UsedOrNew', y = 'Price', data = avp)
plt.subplot(4,3,2)
sns.boxplot(x = 'Transmission', y = 'Price', data = avp)
plt.subplot(4,3,3)
sns.boxplot(x = 'DriveType', y = 'Price', data = avp)
plt.subplot(4,3,4)
sns.boxplot(x = 'CylindersinEngine', y = 'Price', data = avp)

plt.show()
```



I can see from this already, that 'New' and 'Demo' vehicles, are really just outliers within our price range.
$20,000 was a stretch goal anyway, i may as well remove them and make our search a little more realistic.

In [31]:
```
avp = avp.drop(avp[avp['UsedOrNew'] == 'NEW'].index)
avp = avp.drop(avp[avp['UsedOrNew'] == 'DEMO'].index)
```

In [32]:
```
avp = avp.drop(columns=['UsedOrNew'])
```

In [33]:
```
avp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3274 entries, 1 to 16722
Data columns (total 8 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Year               3274 non-null   int64  
 1   Transmission       3274 non-null   object 
 2   DriveType          3274 non-null   object 
 3   FuelConsumption    3274 non-null   float64
 4   Kilometres         3274 non-null   int64  
 5   CylindersinEngine  3274 non-null   object 
 6   Price              3274 non-null   float64
 7   Engine_size        3274 non-null   float64
dtypes: float64(3), int64(2), object(3)
memory usage: 230.2+ KB
```

Now finally,
It is not really 'Price' that i am wanting to show my son , as the target variable.
I am really trying to demonstrate "Value for money".

I can do that by making a new column
which will be a function of 'Price' and 'FuelConsumption',
'Value' = 'Price' / 'FuelConsumption'

In [34]:
```
avp['Value'] = avp['Price'] / avp['FuelConsumption']
avp
```

Out[34]:

	Year	Transmission	DriveType	FuelConsumption	Kilometres	CylindersinEngine	Pr
1	2022	Automatic	Front	6.7	16	4 cyl	1999
7	2000	Automatic	Front	8.0	300539	4 cyl	299
15	2012	Automatic	Front	6.2	55676	4 cyl	1499
19	2014	Automatic	Front	5.4	76289	3 cyl	1240
20	2012	Automatic	AWD	7.5	219681	4 cyl	1399
...	...	...	...	...	...	...	
16714	2015	Automatic	Front	5.1	88000	4 cyl	1190
16716	2014	Automatic	Front	7.4	119494	4 cyl	1199
16717	2018	Automatic	Front	6.8	142169	4 cyl	1998
16721	2016	Manual	Front	5.9	85000	4 cyl	1290
16722	2016	Automatic	Front	6.4	97610	4 cyl	1388

3274 rows × 9 columns

This new 'Value' represents how much money you are spending per unit of fuel consumption.
A higher value for money, indicates that you are getting more value (lower price) for each unit of fuel consumption.
While a lower value for money indicates less value for the money spent on fuel consumption.

'Value' will be our new target variable.

before i go any further, i'd better remove 'Price' and 'FuelConsumption' as variables as they will cause multicollinearity issues later.

In [35]:
```
avp_FC_P = avp[['FuelConsumption', 'Price']].copy()
```

In [36]:
```
avp_final = avp.drop(columns=['FuelConsumption', 'Price'])
```

Step 2: Transform Continuous Variables and Log Transformation of Target Variable

In [37]:
```
import numpy as np
```

In [38]:
```
# Log transformation of the target variable
avp_final['log_Value'] = np.log(avp_final['Value'])

# Specify continuous variables to be transformed (e.g., 'Mileage', 'Engine_S
continuous_vars = ['Year', 'Kilometres', 'Engine_size']

# Apply log transformation to selected continuous variables
for var in continuous_vars:
    avp_final[f'log_{var}'] = np.log(avp_final[var])
```

Train/Test split

In [39]:
```
from sklearn.model_selection import train_test_split
```

In [40]:
```
# Split data into training and testing sets
X = avp_final.drop(['Value', 'log_Value'] + continuous_vars, axis=1)
y = avp_final['log_Value']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, rar
```

In [41]:
```
X_train
```

Out[41]:

	Transmission	DriveType	CylindersinEngine	log_Year	log_Kilometres	log_Engine_size
4419	Automatic	4WD	6 cyl	7.602900	12.609583	1.193922
9385	Manual	Front	4 cyl	7.608374	11.561478	0.182322
5929	Manual	Front	4 cyl	7.609862	11.549074	0.693147
15895	Manual	AWD	4 cyl	7.600402	12.521409	0.693147
10531	Automatic	Front	4 cyl	7.606885	11.564255	0.405465
...	...	...	...	...	...	...
4740	Automatic	Front	4 cyl	7.606885	11.268941	0.916291
4924	Automatic	Front	4 cyl	7.607381	11.639734	0.693147
5844	Automatic	Rear	6 cyl	7.606885	11.701966	1.386294
3381	Automatic	Front	4 cyl	7.608374	11.460168	0.587787
15997	Automatic	4WD	6 cyl	7.604396	12.241401	1.098612

2291 rows × 6 columns

Step 3: Preprocessing (Including Dummy Encoding for Categorical Variables)

In [42]:
```
# Identify categorical variables
categorical_vars = ['Transmission', 'DriveType', 'CylindersinEngine']
# Create dummy variables for categorical variables
X_train_encoded = pd.get_dummies(X_train, columns=categorical_vars, drop_fir
X_test_encoded = pd.get_dummies(X_test, columns=categorical_vars, drop_first
```

1st Iteration

Fit OLS Regression Model

In [43]:
```
import statsmodels.api as sm
```

In [44]:
```
# Add constant term to the independent variables for OLS regression
X_train_model1 = sm.add_constant(X_train_encoded)

# Fit OLS model
ols_model1 = sm.OLS(y_train, X_train_model1)
ols_results1 = ols_model1.fit()

# Print summary of the OLS regression results
print(ols_results1.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_Value   R-squared:                       0.701
Model:                            OLS   Adj. R-squared:                  0.700
Method:                 Least Squares   F-statistic:                     445.4
Date:                Thu, 09 May 2024   Prob (F-statistic):               0.00
Time:                        06:37:50   Log-Likelihood:                -209.15
No. Observations:                2291   AIC:                             444.3
Df Residuals:                    2278   BIC:                             518.9
Df Model:                          12
Covariance Type:            nonrobust
==============================================================================
                                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const                      -1124.2633     24.467    -45.950      0.000   -1172.243   -1076.283
log_Year                     149.0121      3.211     46.412      0.000     142.716     155.308
log_Kilometres                -0.1396      0.012    -12.089      0.000      -0.162      -0.117
log_Engine_size               -0.2931      0.033     -8.878      0.000      -0.358      -0.228
Transmission_Manual           -0.0767      0.015     -5.283      0.000      -0.105      -0.048
DriveType_AWD                 -0.0170      0.028     -0.603      0.547      -0.072       0.038
DriveType_Front               -0.0691      0.024     -2.916      0.004      -0.116      -0.023
DriveType_Rear                 0.0465      0.025      1.852      0.064      -0.003       0.096
CylindersinEngine_3 cyl        0.0440      0.269      0.163      0.870      -0.484       0.572
CylindersinEngine_4 cyl        0.0856      0.267      0.320      0.749      -0.438       0.610
CylindersinEngine_5 cyl       -0.0406      0.284     -0.143      0.886      -0.597       0.516
CylindersinEngine_6 cyl        0.0332      0.268      0.124      0.902      -0.493       0.560
CylindersinEngine_8 cyl        0.2601      0.274      0.948      0.343      -0.278       0.798
==============================================================================
Omnibus:                      270.765   Durbin-Watson:                   2.021
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              776.039
Skew:                          -0.627   Prob(JB):                    3.06e-169
Kurtosis:                       5.561   Cond. No.                     6.29e+04
```

```
==========================================================================
====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is cor
rectly specified.
[2] The condition number is large, 6.29e+04. This might indicate that ther
e are
strong multicollinearity or other numerical problems.
```

In [45]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [46]:
```
vif = pd.DataFrame()
vif['Features'] = X_train_model1.columns
vif['VIF'] = [variance_inflation_factor(X_train_model1.values, i) for i in r
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[46]:

	Features	VIF
0	const	19404227.17
9	CylindersinEngine_4 cyl	399.38
11	CylindersinEngine_6 cyl	350.37
8	CylindersinEngine_3 cyl	50.24
12	CylindersinEngine_8 cyl	29.45
10	CylindersinEngine_5 cyl	9.09
3	log_Engine_size	4.08
6	DriveType_Front	3.88
7	DriveType_Rear	2.49
5	DriveType_AWD	2.05
2	log_Kilometres	1.50
1	log_Year	1.48
4	Transmission_Manual	1.05

There is clearly some significant multicollinearity.
I'll get rid of a few highly correlated pairs.

In [47]:
```
df = X_train_model1.corr().abs().stack().reset_index().sort_values(0, ascend
df['pairs'] = list(zip(df.level_0, df.level_1))
df.set_index(['pairs'], inplace = True)
df.drop(columns=['level_1', 'level_0'], inplace = True)

# cc for correlation coefficient
df.columns = ['cc']
df.drop_duplicates(inplace=True)
df[(df.cc>.5) & (df.cc<1)]
```

Out[47]:

pairs	cc
(CylindersinEngine_4 cyl, CylindersinEngine_6 cyl)	0.888923
(log_Engine_size, CylindersinEngine_6 cyl)	0.715344
(CylindersinEngine_4 cyl, log_Engine_size)	0.658813
(DriveType_Front, log_Engine_size)	0.615525
(DriveType_Front, DriveType_Rear)	0.609671
(log_Kilometres, log_Year)	0.506714

I'll get rid of 'CylindersinEngine_6 cyl', 'CylindersinEngine_4',
and see what that does

Also all those 'Cylinders' categorical variables have very high P values,
number of cylinders must be highly correlated with Engine size, which makes sense.
'DriveType_AWD' also has a high P value.
I'll get rid of them too.

In [48]:
```
X_train_model2 = X_train_model1.drop(columns=['CylindersinEngine_6 cyl'])
```

2nd Iteration

In [49]:
```
# Fit OLS model
ols_model2 = sm.OLS(y_train, X_train_model2)
ols_results2 = ols_model2.fit()

# Print summary of the OLS regression results
print(ols_results2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_Value   R-squared:                       0.701
Model:                            OLS   Adj. R-squared:                  0.700
Method:                 Least Squares   F-statistic:                     486.1
Date:                Thu, 09 May 2024   Prob (F-statistic):               0.00
Time:                        06:37:51   Log-Likelihood:                -209.16
No. Observations:                2291   AIC:                             442.3
Df Residuals:                    2279   BIC:                             511.2
Df Model:                          11
Covariance Type:            nonrobust
==============================================================================
                                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const                      -1124.3325     24.455    -45.975      0.000   -1172.290   -1076.375
log_Year                     149.0255      3.208     46.452      0.000     142.734     155.317
log_Kilometres                -0.1396      0.012    -12.091      0.000      -0.162      -0.117
log_Engine_size               -0.2926      0.033     -8.930      0.000      -0.357      -0.228
Transmission_Manual           -0.0767      0.015     -5.283      0.000      -0.105      -0.048
DriveType_AWD                 -0.0170      0.028     -0.604      0.546      -0.072       0.038
DriveType_Front               -0.0690      0.024     -2.915      0.004      -0.115      -0.023
DriveType_Rear                 0.0464      0.025      1.849      0.065      -0.003       0.096
CylindersinEngine_3 cyl        0.0113      0.051      0.219      0.827      -0.090       0.112
CylindersinEngine_4 cyl        0.0526      0.024      2.174      0.030       0.005       0.100
CylindersinEngine_5 cyl       -0.0736      0.096     -0.767      0.443      -0.262       0.114
CylindersinEngine_8 cyl        0.2269      0.054      4.220      0.000       0.121       0.332
==============================================================================
Omnibus:                      270.716   Durbin-Watson:                   2.020
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              776.173
Skew:                          -0.627   Prob(JB):                     2.86e-169
Kurtosis:                       5.561   Cond. No.                     6.29e+04
==============================================================================
```

```
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is cor
rectly specified.
[2] The condition number is large, 6.29e+04. This might indicate that ther
e are
strong multicollinearity or other numerical problems.
```

In [50]:
```
X_train_model3 = X_train_model2.drop(columns=['CylindersinEngine_3 cyl', 'Dr
```

3rd Iteration

In [51]:
```
# Fit OLS model
ols_model3 = sm.OLS(y_train, X_train_model3)
ols_results3 = ols_model3.fit()

# Print summary of the OLS regression results
print(ols_results3.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_Value   R-squared:                       0.700
Model:                            OLS   Adj. R-squared:                  0.699
Method:                 Least Squares   F-statistic:                     761.4
Date:                Thu, 09 May 2024   Prob (F-statistic):               0.00
Time:                        06:37:51   Log-Likelihood:                -213.18
No. Observations:                2291   AIC:                             442.4
Df Residuals:                    2283   BIC:                             488.2
Df Model:                           7
Covariance Type:            nonrobust
==============================================================================
                                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const                      -1125.9484     24.227    -46.475      0.000   -1173.458   -1078.439
log_Year                     149.2425      3.178     46.965      0.000     143.011     155.474
log_Kilometres                -0.1407      0.012    -12.215      0.000      -0.163      -0.118
log_Engine_size               -0.2922      0.027    -10.840      0.000      -0.345      -0.239
Transmission_Manual           -0.0735      0.014     -5.093      0.000      -0.102      -0.045
DriveType_Front               -0.0806      0.015     -5.212      0.000      -0.111      -0.050
CylindersinEngine_4 cyl        0.0405      0.018      2.244      0.025       0.005       0.076
CylindersinEngine_8 cyl        0.2408      0.053      4.515      0.000       0.136       0.345
==============================================================================
Omnibus:                      267.973   Durbin-Watson:                   2.010
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              781.348
Skew:                          -0.616   Prob(JB):                     2.15e-170
Kurtosis:                       5.583   Cond. No.                     6.22e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 6.22e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [52]:
```
# Calculate MSE and R-squared for the train model
y_pred_train_log = ols_results3.predict(X_train_model3)
#y_pred_train = np.exp(y_pred_train_log)

mse_train = mean_squared_error((y_train), y_pred_train_log)
r_squared_train = r2_score((y_train), y_pred_train_log)

print("Train Model Summary:")
print("Mean Squared Error (MSE) on training data:", mse_train)
print("R-squared on training data:", r_squared_train)
```

```
---------------------------------------------------------------------------
-
NameError                                 Traceback (most recent call las
t)
Cell In[52], line 5
      2 y_pred_train_log = ols_results3.predict(X_train_model3)
      3 #y_pred_train = np.exp(y_pred_train_log)
----> 5 mse_train = mean_squared_error((y_train), y_pred_train_log)
      6 r_squared_train = r2_score((y_train), y_pred_train_log)
      8 print("Train Model Summary:")

NameError: name 'mean_squared_error' is not defined
```

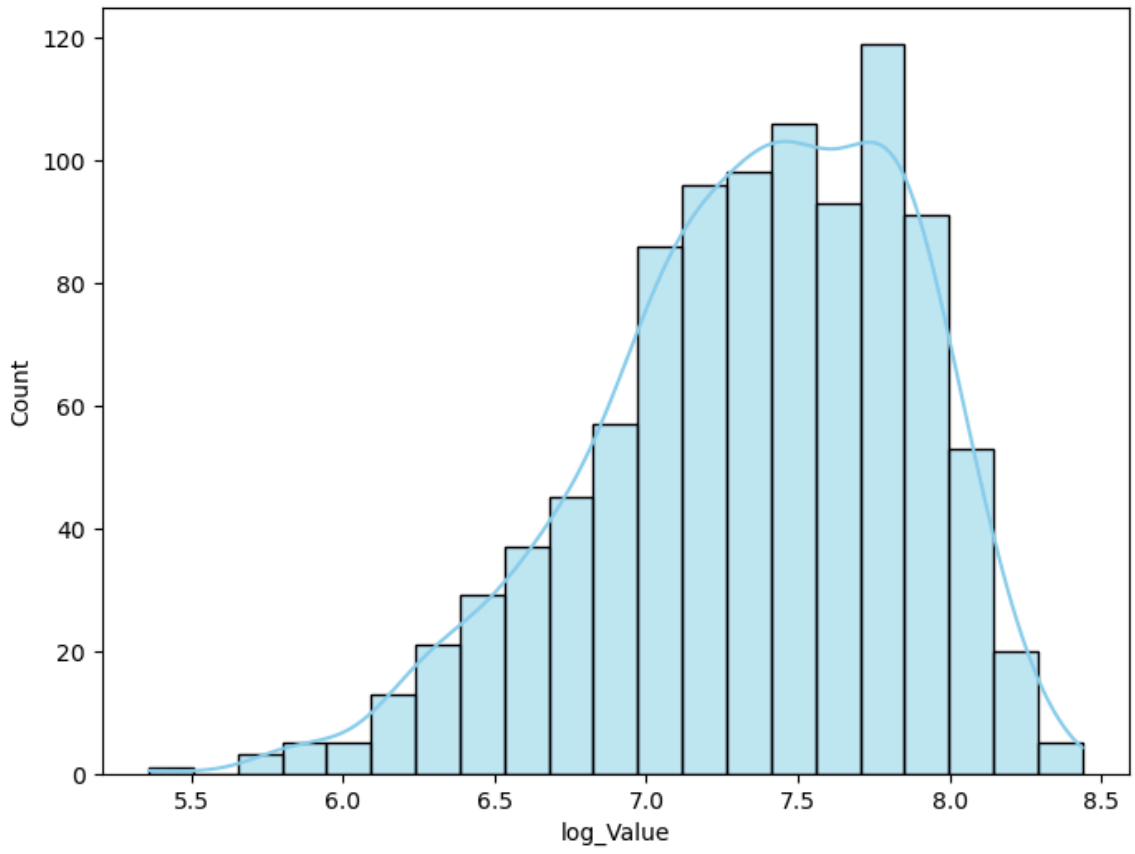
In [ ]:
```
# Use the fitted OLS model to make predictions on the test set
X_test_final = sm.add_constant(X_test_encoded)  # Add constant term to test
y_pred_log = ols_results3.predict(X_test_final[['const', 'log_Year','log_Kil
```

In [ ]:
```
# Evaluate model performance using metrics such as RMSE and R-squared on the
from sklearn.metrics import mean_squared_error, r2_score

mse = mean_squared_error((y_test), y_pred_log)
rmse = np.sqrt(mse)
r_squared = r2_score((y_test), y_pred_log)

print("Test Model Summary:")
print("Mean Squared Error on testing data:", rmse)
print("R-squared:", r_squared)
```

In [ ]:
```
# Visualization of True vs. Predicted Values
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred_log, color='skyblue', alpha=0.5)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], '--', c
plt.title('True vs. Predicted Values')
plt.xlabel('True Values')
plt.ylabel('Predicted Values')
plt.show()
```

In [53]:
```
# Distribution Plot
plt.figure(figsize=(8, 6))
sns.histplot(y_test, color='skyblue', kde=True, label='True Values')
sns.histplot(y_pred_log, color='salmon', kde=True, label='Predicted Values')
plt.title('Distribution of True vs. Predicted Values')
plt.legend()
plt.show()
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[53], line 4
      2 plt.figure(figsize=(8, 6))
      3 sns.histplot(y_test, color='skyblue', kde=True, label='True Values')
----> 4 sns.histplot(y_pred_log, color='salmon', kde=True, label='Predicted Values')
      5 plt.title('Distribution of True vs. Predicted Values')
      6 plt.legend()

NameError: name 'y_pred_log' is not defined
```



I am happy with the ability for my model to predict the Value of a vehicle based on various factors.
Lets have another look at my final model.

In [54]:
```
print(ols_results3.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_Value   R-squared:                       0.700
Model:                            OLS   Adj. R-squared:                  0.699
Method:                 Least Squares   F-statistic:                     761.4
Date:                Thu, 09 May 2024   Prob (F-statistic):               0.00
Time:                        06:37:52   Log-Likelihood:                -213.18
No. Observations:                2291   AIC:                             442.4
Df Residuals:                    2283   BIC:                             488.2
Df Model:                           7
Covariance Type:            nonrobust
==============================================================================
                                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const                      -1125.9484     24.227    -46.475      0.000   -1173.458   -1078.439
log_Year                     149.2425      3.178     46.965      0.000     143.011     155.474
log_Kilometres                -0.1407      0.012    -12.215      0.000      -0.163      -0.118
log_Engine_size               -0.2922      0.027    -10.840      0.000      -0.345      -0.239
Transmission_Manual           -0.0735      0.014     -5.093      0.000      -0.102      -0.045
DriveType_Front               -0.0806      0.015     -5.212      0.000      -0.111      -0.050
CylindersinEngine_4 cyl        0.0405      0.018      2.244      0.025       0.005       0.076
CylindersinEngine_8 cyl        0.2408      0.053      4.515      0.000       0.136       0.345
==============================================================================
Omnibus:                      267.973   Durbin-Watson:                   2.010
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              781.348
Skew:                          -0.616   Prob(JB):                    2.15e-170
Kurtosis:                       5.583   Cond. No.                     6.22e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 6.22e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Findings

1. Year of Manufacture

The year of manufacture has a huge influence on the perceived value of a vehicle. The higher the year of manufacture, the newer the vehicle.
Fuel economy of vehicles is becoming more important for consumers.
this result may also demonstrate improvements in fuel economy engineering over time. so it makes sense that this would be a high influencing factor.

I will certainly be advising my son to buy the newest car he can possibly afford.

2. Engine Size

Engine size is the next most influencial variable on the value of a vehicle.
It is a negative effect,
being that the higher the engine size, the lower the value. This also makes sense.

I will advise my son to try to find a vehicle with a lower engine size
(at least for your first car, Please)

3. ~~CylindersEngine_8 cyl~~

I am choosing to ignore CylindersinEngine_8 cyl's influence on the value of a vehicle, and choose to consider this a statistical outlier.

Further findings.

- It is interesting that manual vehicles are negatively correlated with value.
  It might be interesting to investigate why this is. it may also just be a statistical outlier.
  in any case we will most likely be looking at Automatic transmission vehicles, as this is the majority on the market.
- Perhaps avoid Front wheel drive
- Generally look for 4 cylinder vehicles.