Q.1) Prepare a prediction model for predicting Price.

Consider only the below columns

("Price","Age_08_04","KM","HP","cc","Doors","Gears","Qu

Model -- model of the car

Price -- Offer Price in EUROs

Age_08_04 -- Age in months as in August 2004

KM -- Accumulated Kilometers on odometer

HP -- Horse Power

cc -- Cylinder Volume in cubic centimeters

Doors -- Number of doors

Gears -- Number of gear positions

Quarterly_Tax -- Quarterly road tax in EUROs

Weight -- Weight in Kilograms

In [87]:
```
import pandas as pd
import numpy as np
```

In [88]:
```
corolla=pd.read_csv('ToyotaCorolla.csv', encoding='cp1252')
corolla
```

Out[88]:

	Id	Model	Price	Age_08_04	Mfg_Month	Mfg_Year	KM	Fuel_Type	HP	Met_Color
0	1	TOYOTA Corolla 2.0 D4D HATCHB TERRA 2/3-Doors	13500	23	10	2002	46986	Diesel	90	1
1	2	TOYOTA Corolla 2.0 D4D HATCHB TERRA 2/3-Doors	13750	23	10	2002	72937	Diesel	90	1
2	3	TOYOTA Corolla 2.0 D4D HATCHB TERRA 2/3-Doors	13950	24	9	2002	41711	Diesel	90	1
3	4	TOYOTA Corolla 2.0 D4D HATCHB TERRA 2/3-Doors	14950	26	7	2002	48000	Diesel	90	0
4	5	TOYOTA Corolla 2.0 D4D HATCHB SOL 2/3-Doors	13750	30	3	2002	38500	Diesel	90	0
...	...	...	...	...	...	...	...	...	...	...
1431	1438	TOYOTA Corolla 1.3 16V HATCHB G6 2/3-Doors	7500	69	12	1998	20544	Petrol	86	1
1432	1439	TOYOTA Corolla 1.3 16V HATCHB LINEA TERRA 2/3-...	10845	72	9	1998	19000	Petrol	86	0
1433	1440	TOYOTA Corolla 1.3 16V HATCHB LINEA TERRA 2/3-...	8500	71	10	1998	17016	Petrol	86	0

	Id	Model	Price	Age_08_04	Mfg_Month	Mfg_Year	KM	Fuel_Type	HP	Met_Color
1434	1441	TOYOTA Corolla 1.3 16V HATCHB LINEA TERRA 2/3-...	7250	70	11	1998	16916	Petrol	86	1
1435	1442	TOYOTA Corolla 1.6 LB LINEA TERRA 4/5-Doors	6950	76	5	1998	1	Petrol	110	0

1436 rows × 38 columns

EDA

In [89]:
```
#shape of the data
corolla.shape
```

Out[89]:
```
(1436, 38)
```

In [90]:
```
corolla.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1436 entries, 0 to 1435
Data columns (total 38 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Id                1436 non-null   int64
 1   Model             1436 non-null   object
 2   Price             1436 non-null   int64
 3   Age_08_04         1436 non-null   int64
 4   Mfg_Month         1436 non-null   int64
 5   Mfg_Year          1436 non-null   int64
 6   KM                1436 non-null   int64
 7   Fuel_Type         1436 non-null   object
 8   HP                1436 non-null   int64
 9   Met_Color         1436 non-null   int64
 10  Color             1436 non-null   object
 11  Automatic         1436 non-null   int64
 12  cc                1436 non-null   int64
 13  Doors             1436 non-null   int64
 14  Cylinders         1436 non-null   int64
 15  Gears             1436 non-null   int64
 16  Quarterly_Tax     1436 non-null   int64
 17  Weight            1436 non-null   int64
 18  Mfr_Guarantee     1436 non-null   int64
 19  BOVAG_Guarantee   1436 non-null   int64
 20  Guarantee_Period  1436 non-null   int64
 21  ABS               1436 non-null   int64
 22  Airbag_1          1436 non-null   int64
 23  Airbag_2          1436 non-null   int64
 24  Airco             1436 non-null   int64
 25  Automatic_airco   1436 non-null   int64
 26  Boardcomputer     1436 non-null   int64
 27  CD_Player         1436 non-null   int64
 28  Central_Lock      1436 non-null   int64
 29  Powered_Windows   1436 non-null   int64
 30  Power_Steering    1436 non-null   int64
 31  Radio             1436 non-null   int64
 32  Mistlamps         1436 non-null   int64
 33  Sport_Model       1436 non-null   int64
 34  Backseat_Divider  1436 non-null   int64
 35  Metallic_Rim      1436 non-null   int64
 36  Radio_cassette    1436 non-null   int64
 37  Tow_Bar           1436 non-null   int64
dtypes: int64(35), object(3)
memory usage: 426.4+ KB
```

In [91]:
```
#consider only these

data=corolla[["Price","Age_08_04","KM","HP","cc","Doors","Gears","Quarterly_Tax",
data
```

Out[91]:

	Price	Age_08_04	KM	HP	cc	Doors	Gears	Quarterly_Tax	Weight
0	13500	23	46986	90	2000	3	5	210	1165
1	13750	23	72937	90	2000	3	5	210	1165
2	13950	24	41711	90	2000	3	5	210	1165
3	14950	26	48000	90	2000	3	5	210	1165
4	13750	30	38500	90	2000	3	5	210	1170
...	...	...	...	...	...	...	...	...	...
1431	7500	69	20544	86	1300	3	5	69	1025
1432	10845	72	19000	86	1300	3	5	69	1015
1433	8500	71	17016	86	1300	3	5	69	1015
1434	7250	70	16916	86	1300	3	5	69	1015
1435	6950	76	1	110	1600	5	5	19	1114

1436 rows × 9 columns

In [92]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1436 entries, 0 to 1435
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Price          1436 non-null   int64
 1   Age_08_04      1436 non-null   int64
 2   KM             1436 non-null   int64
 3   HP             1436 non-null   int64
 4   cc             1436 non-null   int64
 5   Doors          1436 non-null   int64
 6   Gears          1436 non-null   int64
 7   Quarterly_Tax  1436 non-null   int64
 8   Weight         1436 non-null   int64
dtypes: int64(9)
memory usage: 101.1 KB
```

All data are in numeric type.

In [93]:
```
data.shape
```

Out[93]: (1436, 9)

In [94]:
```
#null values
data.isna().sum()
```

Out[94]:
```
Price           0
Age_08_04       0
KM              0
HP              0
cc              0
Doors           0
Gears           0
Quarterly_Tax   0
Weight          0
dtype: int64
```

there is no null value present in data.

In [95]:
```
data.duplicated().sum()
```

Out[95]:
```
1
```

In [96]:
```
#show the duplicates
data[data.duplicated()]
```

Out[96]:

	Price	Age_08_04	KM	HP	cc	Doors	Gears	Quarterly_Tax	Weight
113	24950	8	13253	116	2000	5	5	234	1320

In [97]:
```
#remove duplicates
data.drop_duplicates(inplace=True)
```

```
C:\Users\Lenovo\AppData\Local\Temp\ipykernel_3620\1511750288.py:2: SettingWithC
opyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/sta
ble/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pyd
ata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-c
opy)
  data.drop_duplicates(inplace=True)
```

In [98]:
```
#reseeting the index
data.reset_index(drop=True,inplace=True)
```

In [99]:
```
data.duplicated().sum()
```

Out[99]:
```
0
```

In [100]:
```
data.describe()
```

Out[100]:

	Price	Age_08_04	KM	HP	cc	Doors	G
count	1435.000000	1435.000000	1435.000000	1435.000000	1435.000000	1435.000000	1435.00
mean	10720.915679	55.980488	68571.782578	101.491986	1576.560976	4.032753	5.02
std	3608.732978	18.563312	37491.094553	14.981408	424.387533	0.952667	0.18
min	4350.000000	1.000000	1.000000	69.000000	1300.000000	2.000000	3.00
25%	8450.000000	44.000000	43000.000000	90.000000	1400.000000	3.000000	5.00
50%	9900.000000	61.000000	63451.000000	110.000000	1600.000000	4.000000	5.00
75%	11950.000000	70.000000	87041.500000	110.000000	1600.000000	5.000000	5.00
max	32500.000000	80.000000	243000.000000	192.000000	16000.000000	5.000000	6.00

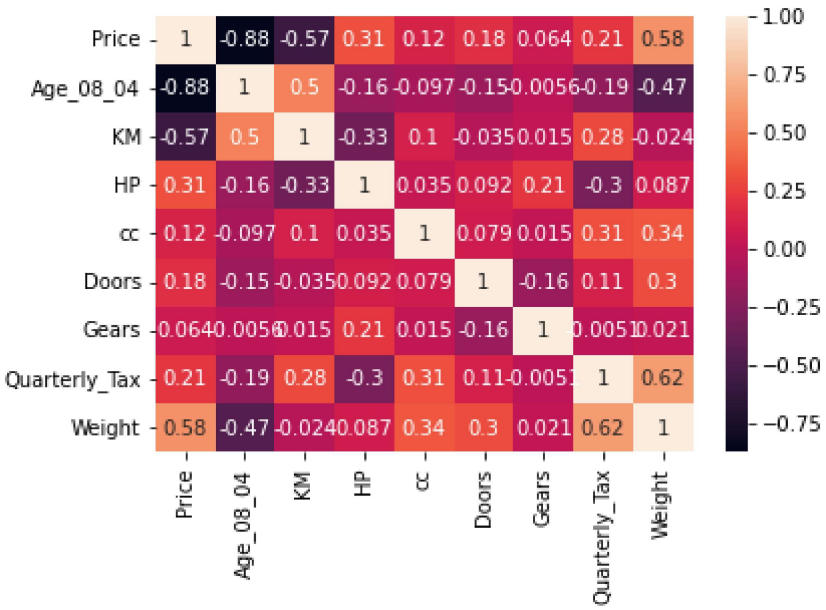
In [101]:
```
#correlation coefficient
corrl=data.corr()
corrl
```

Out[101]:

	Price	Age_08_04	KM	HP	cc	Doors	Gears	Quarterl
Price	1.000000	-0.876273	-0.569420	0.314134	0.124375	0.183604	0.063831	0.2
Age_08_04	-0.876273	1.000000	0.504575	-0.155293	-0.096549	-0.146929	-0.005629	-0.1
KM	-0.569420	0.504575	1.000000	-0.332904	0.103822	-0.035193	0.014890	0.2
HP	0.314134	-0.155293	-0.332904	1.000000	0.035207	0.091803	0.209642	-0.3
cc	0.124375	-0.096549	0.103822	0.035207	1.000000	0.079254	0.014732	0.3
Doors	0.183604	-0.146929	-0.035193	0.091803	0.079254	1.000000	-0.160101	0.1
Gears	0.063831	-0.005629	0.014890	0.209642	0.014732	-0.160101	1.000000	-0.0
Quarterly_Tax	0.211508	-0.193319	0.283312	-0.302287	0.305982	0.107353	-0.005125	1.0
Weight	0.575869	-0.466484	-0.023969	0.087143	0.335077	0.301734	0.021238	0.6

In [102]:
```
#Heatmap
import seaborn as sns
sns.heatmap(corrl, annot=True)
```

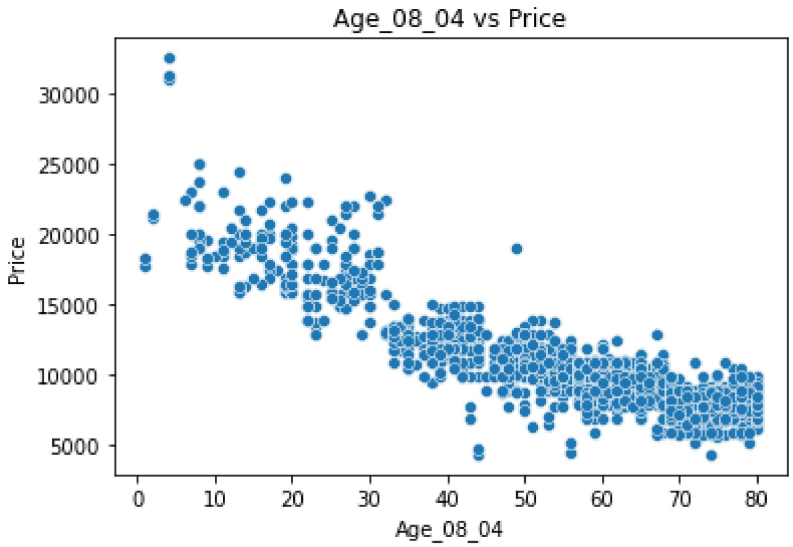
Out[102]: <AxesSubplot:>

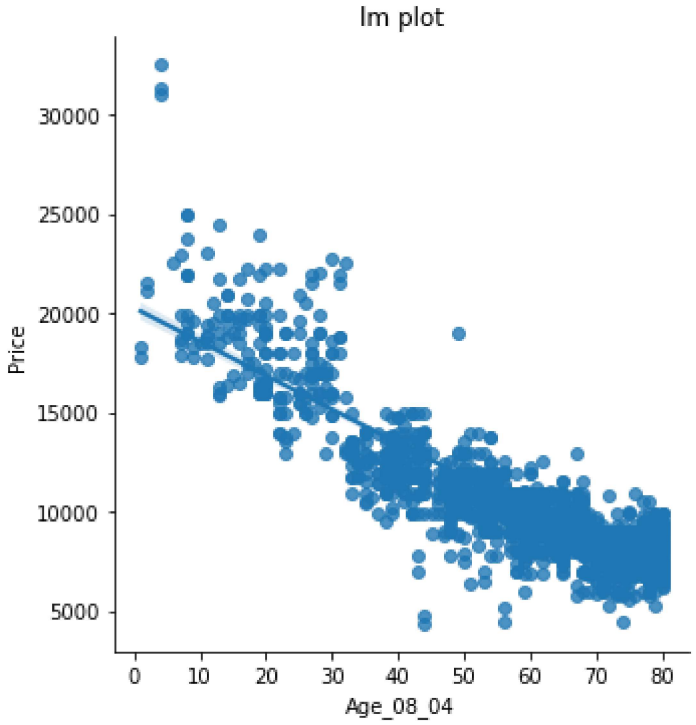


By observing the heatmap,we can say that there is no multicollinearity between input variables. Hence,assumption of no multicollinearity satisfied.

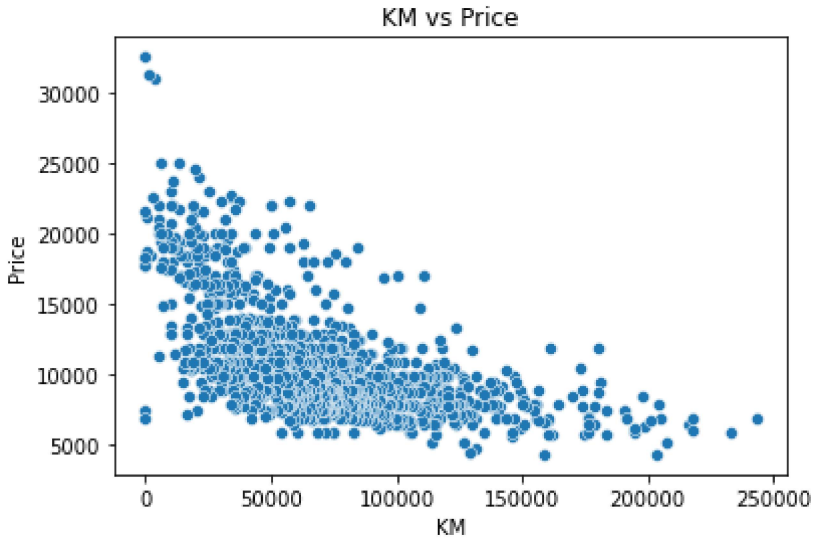
Data Visualization

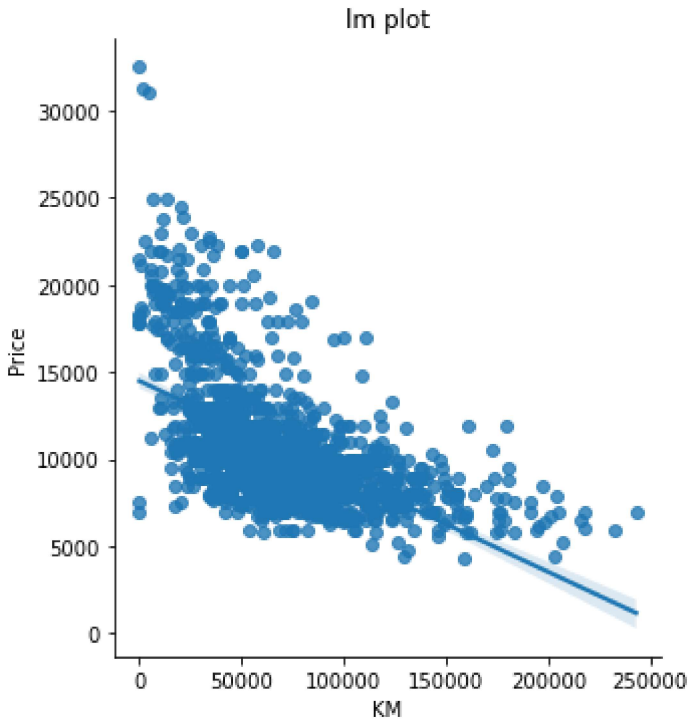
In [103]:
```
#Scatter plot
import matplotlib.pyplot as plt
sns.scatterplot(x='Age_08_04',y='Price',data=data)
plt.title('Age_08_04 vs Price')

#lm plot for linearity
sns.lmplot(x='Age_08_04',y='Price',data=data)
plt.title('lm plot')
plt.show()
```



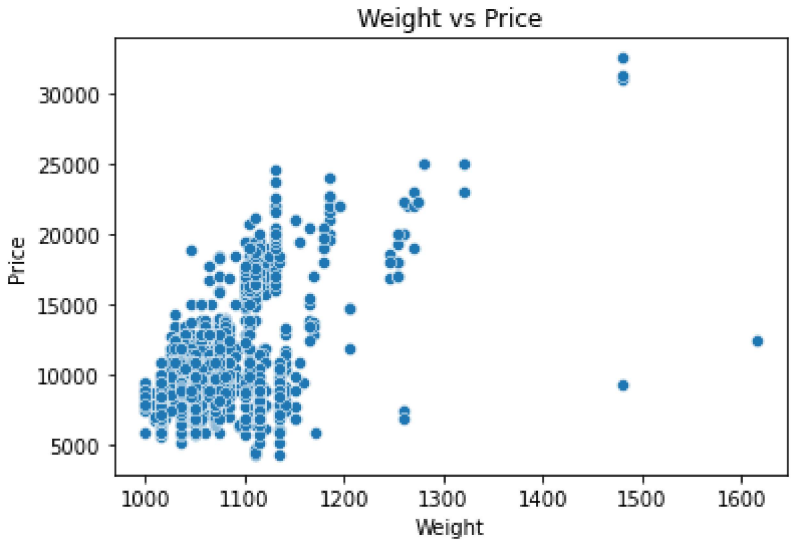


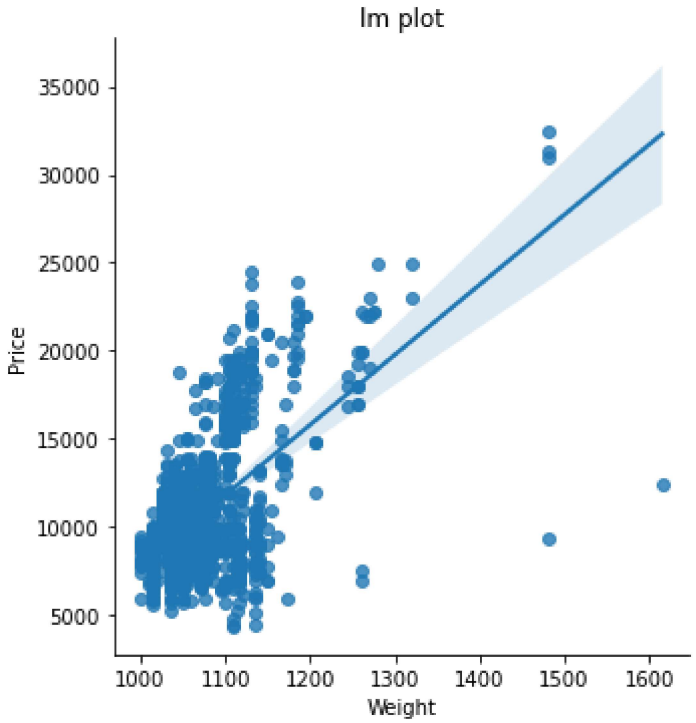
In [104]:
```
#Scatter plot
import matplotlib.pyplot as plt
sns.scatterplot(x='KM',y='Price',data=data)
plt.title('KM vs Price')

#lm plot for linearity
sns.lmplot(x='KM',y='Price',data=data)
plt.title('lm plot')
plt.show()
```





In [105]:
```
#Scatter plot
import matplotlib.pyplot as plt
sns.scatterplot(x='Weight',y='Price',data=data)
plt.title('Weight vs Price')

#lm plot for linearity
sns.lmplot(x='Weight',y='Price',data=data)
plt.title('lm plot')
plt.show()
```





Data Prepration

In [106]:
```
#split data predictors(y) and regressors(x)
x=data.drop('Price',axis=1)
y=data[['Price']]
```

In [107]:
```
x, y
```

Out[107]:
```
(      Age_08_04     KM   HP    cc  Doors  Gears  Quarterly_Tax  Weight
 0            23  46986   90  2000      3      5            210    1165
 1            23  72937   90  2000      3      5            210    1165
 2            24  41711   90  2000      3      5            210    1165
 3            26  48000   90  2000      3      5            210    1165
 4            30  38500   90  2000      3      5            210    1170
 ...         ...    ...  ...   ...    ...    ...            ...     ...
 1430         69  20544   86  1300      3      5             69    1025
 1431         72  19000   86  1300      3      5             69    1015
 1432         71  17016   86  1300      3      5             69    1015
 1433         70  16916   86  1300      3      5             69    1015
 1434         76      1  110  1600      5      5             19    1114

 [1435 rows x 8 columns],
       Price
 0     13500
 1     13750
 2     13950
 3     14950
 4     13750
 ...     ...
 1430   7500
 1431  10845
 1432   8500
 1433   7250
 1434   6950

 [1435 rows x 1 columns])
```

MOdel Building

StandardScaler Transformation

we scale features that bring every feature in the same range, and the model uses every feature wisely.

In [108]:
```
from sklearn.preprocessing import StandardScaler
std_scaler = StandardScaler()
X_scaled = std_scaler.fit_transform(x)
X_scaled = pd.DataFrame(data=X_scaled,columns = x.columns)
X_scaled
```

Out[108]:

	Age_08_04	KM	HP	cc	Doors	Gears	Quarterly_Tax	Weight
0	-1.777268	-0.575958	-0.767351	0.998113	-1.084443	-0.140475	3.003513	1.774964
1	-1.777268	0.116474	-0.767351	0.998113	-1.084443	-0.140475	3.003513	1.774964
2	-1.723380	-0.716707	-0.767351	0.998113	-1.084443	-0.140475	3.003513	1.774964
3	-1.615603	-0.548902	-0.767351	0.998113	-1.084443	-0.140475	3.003513	1.774964
4	-1.400049	-0.802384	-0.767351	0.998113	-1.084443	-0.140475	3.003513	1.870688
...	...	...	...	...	...	...	...	...
1430	0.701602	-1.281492	-1.034441	-0.651898	-1.084443	-0.140475	-0.440104	-0.905299
1431	0.863267	-1.322689	-1.034441	-0.651898	-1.084443	-0.140475	-0.440104	-1.096747
1432	0.809379	-1.375627	-1.034441	-0.651898	-1.084443	-0.140475	-0.440104	-1.096747
1433	0.755490	-1.378295	-1.034441	-0.651898	-1.084443	-0.140475	-0.440104	-1.096747
1434	1.078821	-1.829626	0.568103	0.055249	1.015659	-0.140475	-1.661245	0.798582

1435 rows × 8 columns

Model Training using linear regression

In [109]:
```
from sklearn.linear_model import LinearRegression
linear_model = LinearRegression()
linear_model.fit(X_scaled,y)
```

Out[109]:
```
LinearRegression()
```
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [110]:
```
#coefficients
linear_model.coef_
```

Out[110]:
```
array([[-2.25862554e+03, -7.77200045e+02,  4.73017054e+02,
        -5.02968400e+01, -8.76327907e-01,  1.12674914e+02,
         1.57999990e+02,  8.80423097e+02]])
```

In [111]:
```
#intercept
linear_model.intercept_
```

Out[111]:
```
array([10720.91567944])
```

In [112]:
```
#predicted values
y_pred = linear_model.predict(X_scaled)
y_pred
```

Out[112]:
```
array([[16791.95887083],
       [16253.80041357],
       [16779.63521013],
       ...,
       [ 8455.43440191],
       [ 8579.22204117],
       [10396.0875261 ]])
```

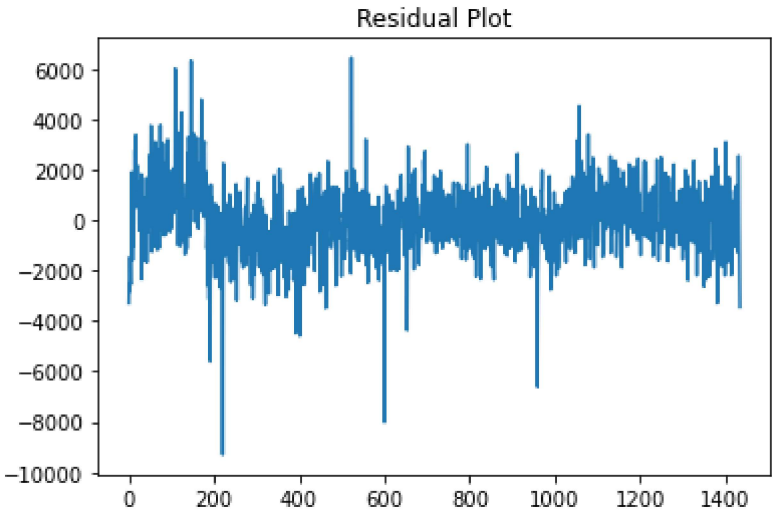
In [113]:
```
#residuals  error=actual value - predicted value
error = y - y_pred
error
```

Out[113]:

	Price
0	-3291.958871
1	-2503.800414
2	-2829.635210
3	-1455.789389
4	-2450.217277
...	...
1430	-1294.255037
1431	2552.422658
1432	44.565598
1433	-1329.222041
1434	-3446.087526

1435 rows × 1 columns

In [114]:
```
plt.plot(error)
plt.title('Residual Plot')
plt.show()
```



Model Building || Model Training Using OLS method

In [115]:
```
#model fitting by using raw data
import statsmodels.formula.api as smf
model = smf.ols('Price~Age_08_04+KM+HP+cc+Doors+Gears+Quarterly_Tax+Weight',data=
model
```

Out[115]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x1e2efe29580>
```

In [116]:
```
model.params
```

Out[116]:
```
Intercept       -5472.540368
Age_08_04        -121.713891
KM                 -0.020737
HP                 31.584612
cc                 -0.118558
Doors              -0.920189
Gears             597.715894
Quarterly_Tax       3.858805
Weight             16.855470
dtype: float64
```

In [117]:
```
model.summary()
```

Out[117]:

OLS Regression Results

Dep. Variable:	Price	**R-squared:**	0.863
Model:	OLS	**Adj. R-squared:**	0.862
Method:	Least Squares	**F-statistic:**	1118.
Date:	Mon, 17 Oct 2022	**Prob (F-statistic):**	0.00
Time:	11:46:54	**Log-Likelihood:**	-12366.
No. Observations:	1435	**AIC:**	2.475e+04
Df Residuals:	1426	**BIC:**	2.480e+04
Df Model:	8		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-5472.5404	1412.169	-3.875	0.000	-8242.692	-2702.389
Age_08_04	-121.7139	2.615	-46.552	0.000	-126.843	-116.585
KM	-0.0207	0.001	-16.552	0.000	-0.023	-0.018
HP	31.5846	2.818	11.210	0.000	26.058	37.112
cc	-0.1186	0.090	-1.316	0.188	-0.295	0.058
Doors	-0.9202	39.988	-0.023	0.982	-79.362	77.522
Gears	597.7159	196.969	3.035	0.002	211.335	984.097
Quarterly_Tax	3.8588	1.311	2.944	0.003	1.288	6.430
Weight	16.8555	1.069	15.761	0.000	14.758	18.953

Omnibus:	149.666	**Durbin-Watson:**	1.544
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1000.538
Skew:	-0.204	**Prob(JB):**	5.44e-218
Kurtosis:	7.070	**Cond. No.**	3.13e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.13e+06. This might indicate that there are strong multicollinearity or other numerical problems.

After observing model's summary we find that 'CC' and "Doors' are insignificant to predict the 'Price' of a car. bcoz there p-value is greater than significance level (0.05),

so we have to accept the null hypothesis i.e. there is no linear relationship between 'Price' and 'CC' and 'Price' and 'Doors'

Build model individually using SLR

In [118]:
```
model_cc = smf.ols('Price~cc',data=data).fit()
model_cc
```

Out[118]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x1e2f227df10>
```

In [119]:
```
model_cc.summary()
```

Out[119]:

OLS Regression Results

Dep. Variable:	Price	**R-squared:**	0.015
Model:	OLS	**Adj. R-squared:**	0.015
Method:	Least Squares	**F-statistic:**	22.52
Date:	Mon, 17 Oct 2022	**Prob (F-statistic):**	2.29e-06
Time:	11:46:54	**Log-Likelihood:**	-13779.
No. Observations:	1435	**AIC:**	2.756e+04
Df Residuals:	1433	**BIC:**	2.757e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	9053.5368	363.894	24.880	0.000	8339.715	9767.359
cc	1.0576	0.223	4.745	0.000	0.620	1.495

Omnibus:	463.846	**Durbin-Watson:**	0.269
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1386.822
Skew:	1.645	**Prob(JB):**	7.17e-302
Kurtosis:	6.518	**Cond. No.**	6.28e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 6.28e+03. This might indicate that there are strong multicollinearity or other numerical problems.

In [120]:
```
model_Doors = smf.ols('Price~Doors',data=data).fit()
model_Doors
```

Out[120]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x1e2f1d047f0>
```

In [121]:
```
model_Doors.summary()
```

Out[121]:

OLS Regression Results

Dep. Variable:	Price	**R-squared:**	0.034
Model:	OLS	**Adj. R-squared:**	0.033
Method:	Least Squares	**F-statistic:**	49.99
Date:	Mon, 17 Oct 2022	**Prob (F-statistic):**	2.40e-12
Time:	11:46:54	**Log-Likelihood:**	-13765.
No. Observations:	1435	**AIC:**	2.753e+04
Df Residuals:	1433	**BIC:**	2.755e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	7916.1452	407.596	19.422	0.000	7116.596	8715.694
Doors	695.4978	98.366	7.071	0.000	502.541	888.454

Omnibus:	465.543	**Durbin-Watson:**	0.289
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1403.980
Skew:	1.647	**Prob(JB):**	1.35e-305
Kurtosis:	6.554	**Cond. No.**	19.0

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [122]:
```
# taking both 'cc' and 'Doors' together
model_1 = smf.ols('Price~cc+Doors',data=data).fit()
model_1
```

Out[122]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x1e2f1d1b220>
```

In [123]:
```
model_1.summary()
```

Out[123]:

OLS Regression Results

Dep. Variable:	Price	**R-squared:**	0.046
Model:	OLS	**Adj. R-squared:**	0.045
Method:	Least Squares	**F-statistic:**	34.40
Date:	Mon, 17 Oct 2022	**Prob (F-statistic):**	2.55e-15
Time:	11:46:55	**Log-Likelihood:**	-13756.
No. Observations:	1435	**AIC:**	2.752e+04
Df Residuals:	1432	**BIC:**	2.753e+04
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	6568.3395	513.700	12.786	0.000	5560.655	7576.024
cc	0.9398	0.220	4.268	0.000	0.508	1.372
Doors	662.3187	98.089	6.752	0.000	469.906	854.732

Omnibus:	448.494	**Durbin-Watson:**	0.291
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1297.612
Skew:	1.602	**Prob(JB):**	1.69e-282
Kurtosis:	6.382	**Cond. No.**	9.09e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 9.09e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Calculating VIF for the test of Multicollinearity

In [124]:
```
rsq_age=smf.ols('Age_08_04~KM+HP+cc+Doors+Gears+Quarterly_Tax+Weight',data=data).
vif_age=1/(1-rsq_age)

rsq_km=smf.ols('KM ~ Age_08_04+HP+cc+Doors+Gears+Quarterly_Tax+Weight',data=data)
vif_km=1/(1-rsq_km)

rsq_hp=smf.ols('HP ~ Age_08_04+KM+cc+Doors+Gears+Quarterly_Tax+Weight',data=data)
vif_hp=1/(1-rsq_hp)

rsq_cc=smf.ols('cc ~ Age_08_04+KM+HP+Doors+Gears+Quarterly_Tax+Weight',data=data)
vif_cc=1/(1-rsq_cc)

rsq_Doors=smf.ols('Doors ~ Age_08_04+KM+HP+cc+Gears+Quarterly_Tax+Weight',data=da
vif_Doors=1/(1-rsq_Doors)

rsq_Gears=smf.ols('Gears ~ Age_08_04+KM+HP+cc+Doors+Quarterly_Tax+Weight',data=da
vif_Gears=1/(1-rsq_Gears)

rsq_Quarterly_Tax=smf.ols('Quarterly_Tax ~ Age_08_04+KM+HP+cc+Doors+Gears+Weight'
vif_Quarterly_Tax=1/(1-rsq_Quarterly_Tax)

rsq_Weight=smf.ols('Weight ~ Age_08_04+KM+HP+cc+Doors+Gears+Quarterly_Tax',data=d
vif_Weight=1/(1-rsq_Weight)
```

In [125]:
```
#create dataframe from VIF factor of all columns
VIF=pd.DataFrame(data={'vif_age':[vif_age],'vif_km':[vif_km],'vif_hp':[vif_hp],
                       'vif_cc':[vif_cc],'vif_Doors':[vif_Doors],'vif_Gears':[vi
                       'vif_Quarterly_Tax':[vif_Quarterly_Tax],'vif_Weight':[vif
                  }).T #transpose of data frame using .T
VIF
```

Out[125]:

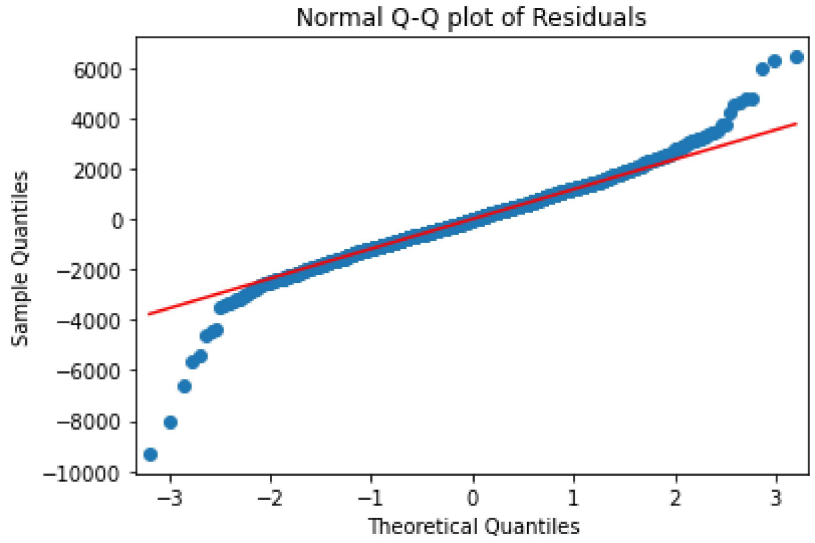
	0
vif_age	1.876236
vif_km	1.757178
vif_hp	1.419180
vif_cc	1.163470
vif_Doors	1.155890
vif_Gears	1.098843
vif_Quarterly_Tax	2.295375
vif_Weight	2.487180

By observing VIF of each input variable,the values are less that 5,hence we can say that there is no Multicollinearity.

Residual Analysis

Test for normality of residuals(errors = actual - predicted)

In [126]:
```
import statsmodels.api as sm
sm.qqplot(model.resid,line='q')
plt.title("Normal Q-Q plot of Residuals")
plt.show()
```

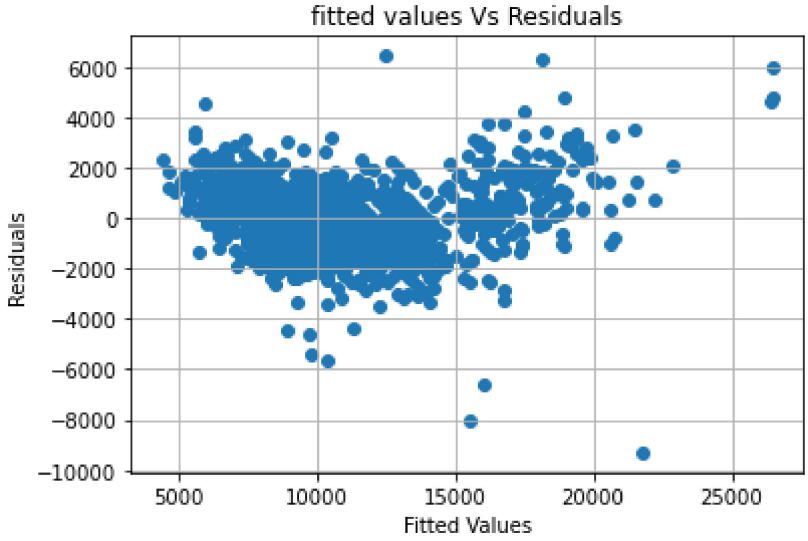


Maximum points are close to straight line, hence Normality Condition satisfied

Residual Plot For Homoscedasticity

A scatterplot of residuals versus predicted values is good way to check for homoscedasticity. There should be no clear pattern in the distribution; if there is a cone-shaped pattern (as shown below), the data is heteroscedastic.

In [127]:
```
plt.scatter(x=model.fittedvalues,y=model.resid)
plt.xlabel('Fitted Values')
plt.ylabel('Residuals')
plt.title('fitted values Vs Residuals')
plt.grid(True)
plt.show()
```

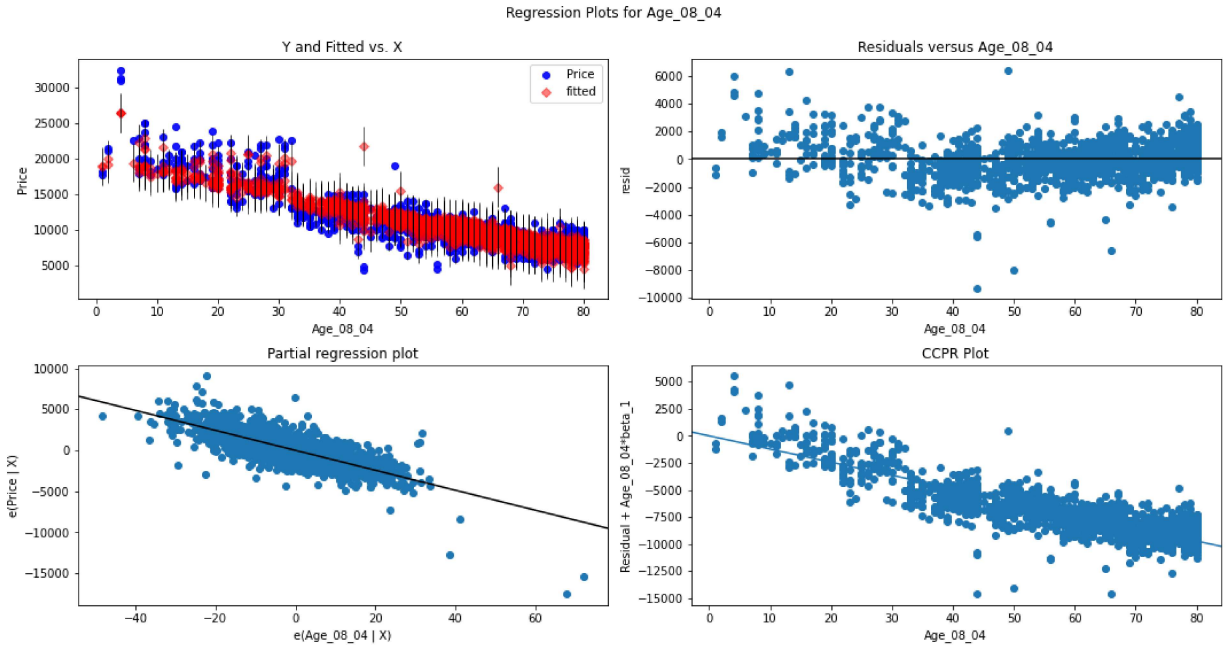


here by above plot we can say that the datapoints are close towards zero,hence the assumption for Homoscedasticity satisfied.

Residual Vs Regressors

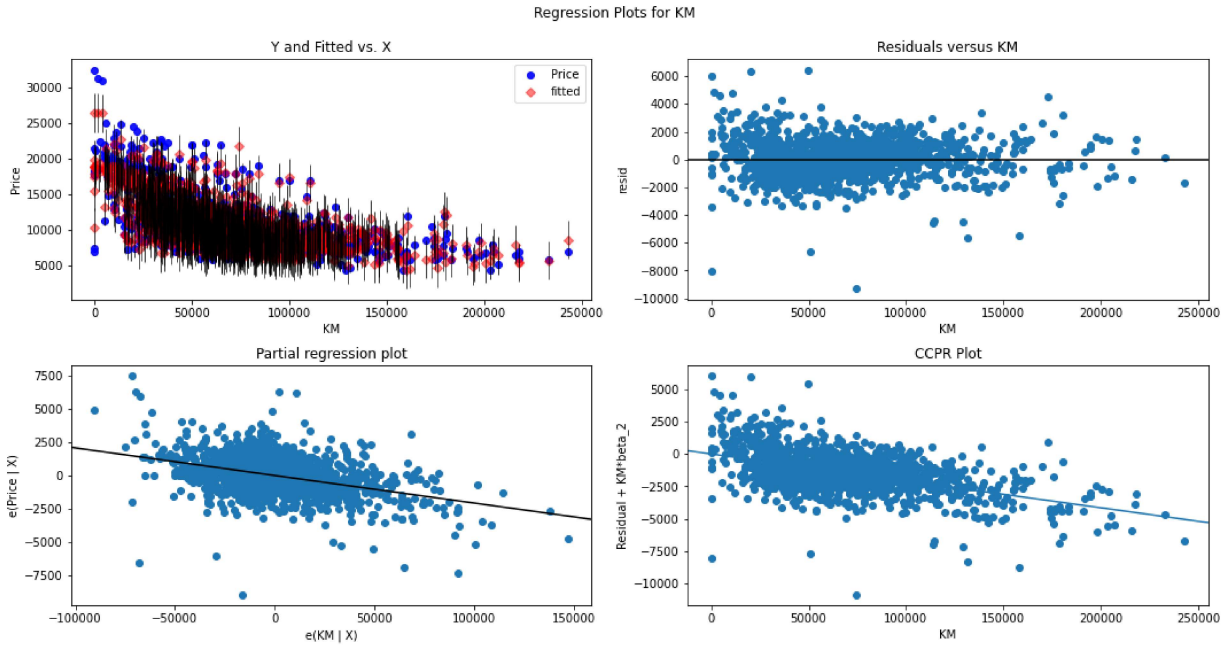
In [128]:
```
fig = plt.figure(figsize=(15,8))
fig = sm.graphics.plot_regress_exog(model, "Age_08_04", fig=fig)
plt.show()
```

```
eval_env: 1
```



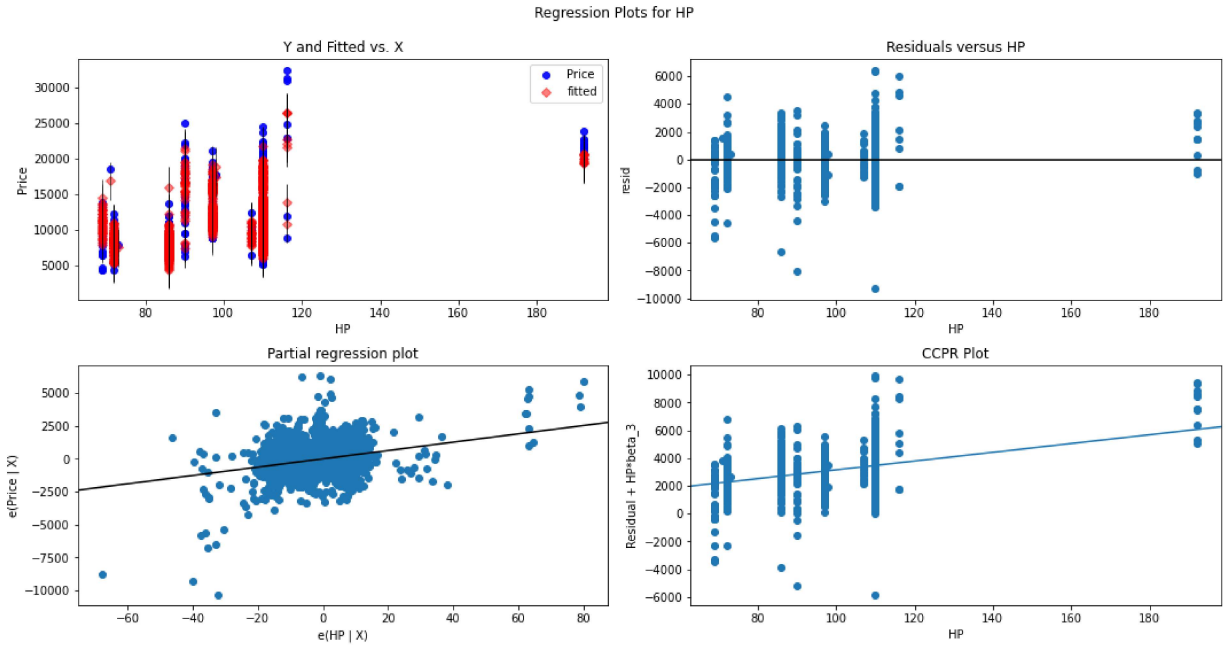
In [129]:
```
fig = plt.figure(figsize=(15,8))
fig = sm.graphics.plot_regress_exog(model, "KM", fig=fig)
plt.show()
```

```
eval_env: 1
```



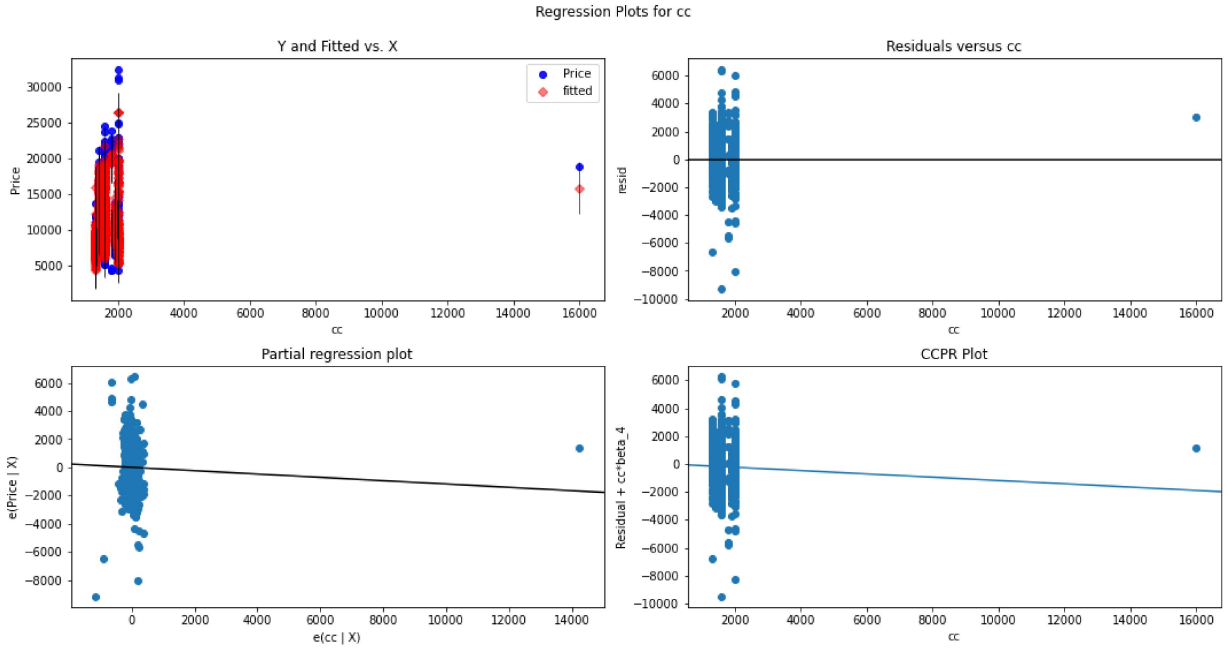
In [130]:
```
fig = plt.figure(figsize=(15,8))
fig = sm.graphics.plot_regress_exog(model, "HP", fig=fig)
plt.show()
```

```
eval_env: 1
```



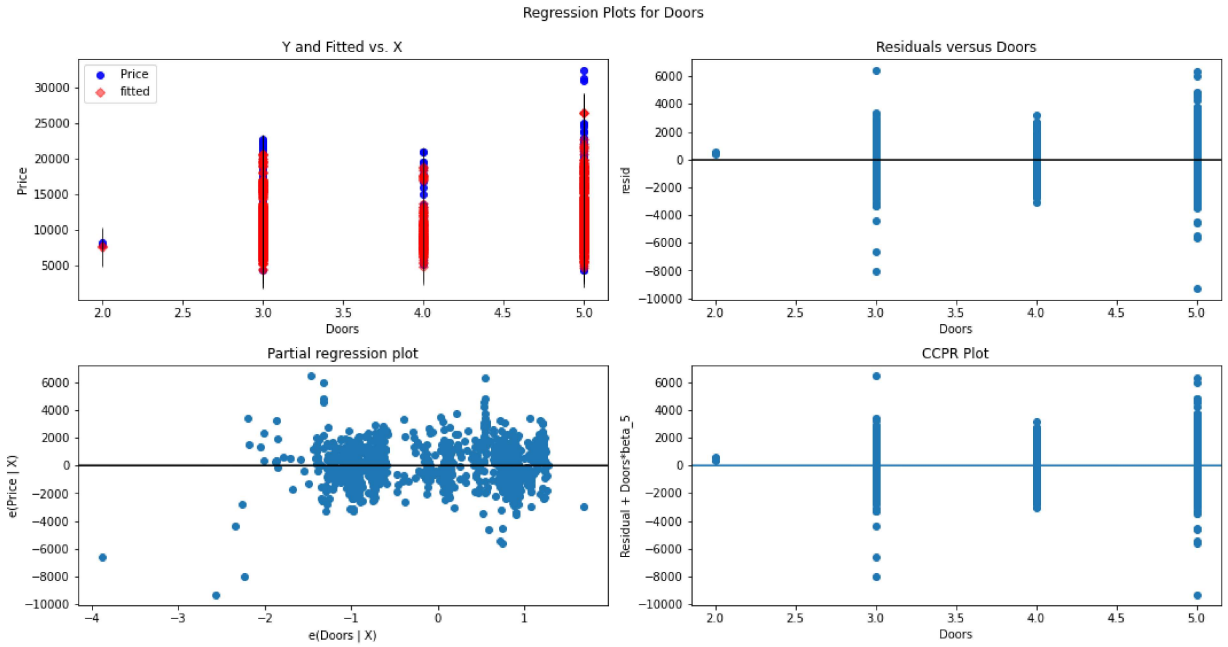
In [131]:
```
fig = plt.figure(figsize=(15,8))
fig = sm.graphics.plot_regress_exog(model, "cc", fig=fig)
plt.show()
```

```
eval_env: 1
```



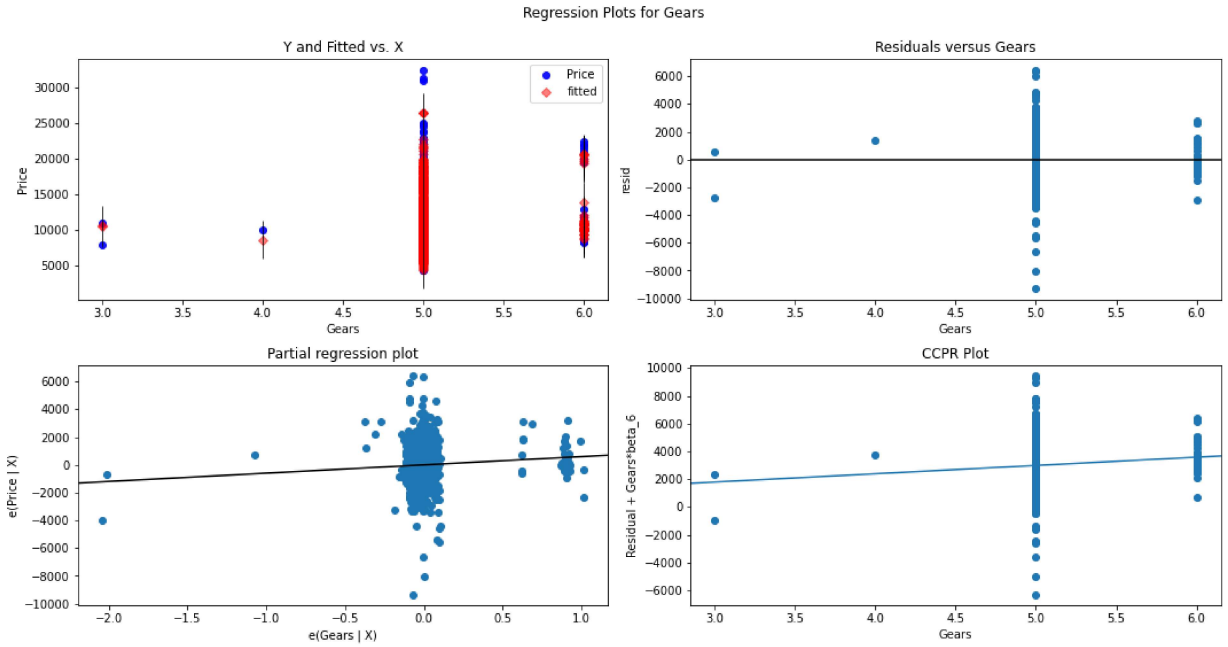
In [132]:
```
fig = plt.figure(figsize=(15,8))
fig = sm.graphics.plot_regress_exog(model, "Doors", fig=fig)
plt.show()
```

```
eval_env: 1
```



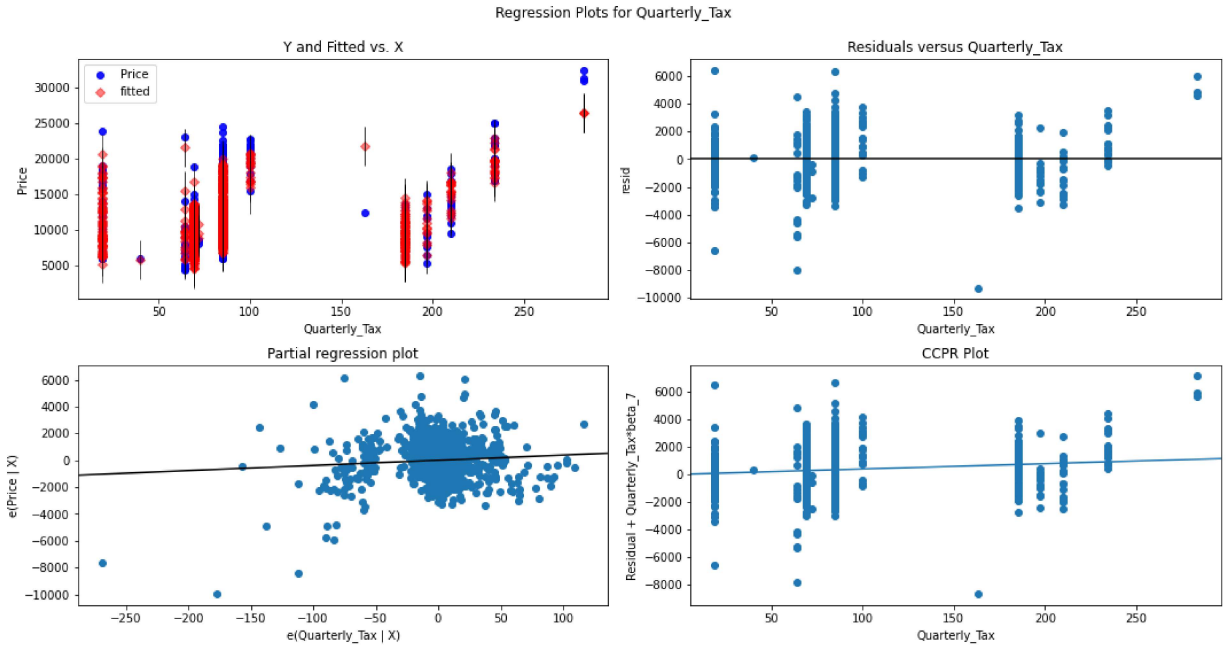
In [133]:
```
fig = plt.figure(figsize=(15,8))
fig = sm.graphics.plot_regress_exog(model, "Gears", fig=fig)
plt.show()
```

```
eval_env: 1
```



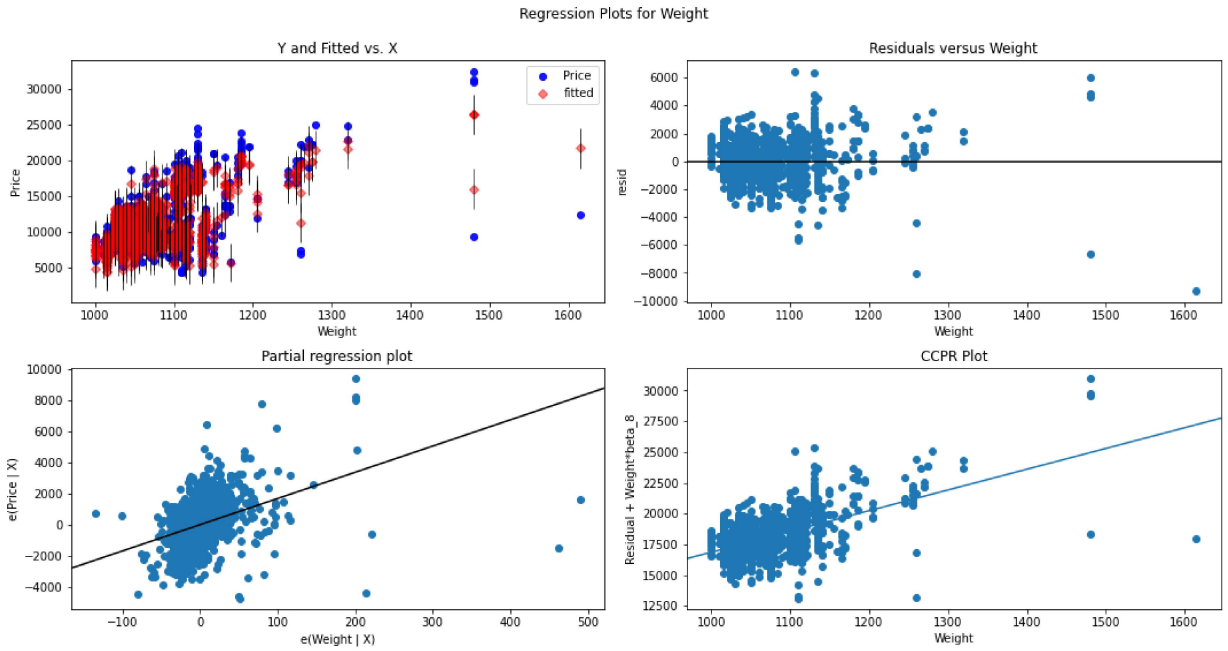
In [134]:
```
fig = plt.figure(figsize=(15,8))
fig = sm.graphics.plot_regress_exog(model, "Quarterly_Tax", fig=fig)
plt.show()
```

```
eval_env: 1
```



In [135]:
```
fig = plt.figure(figsize=(15,8))
fig = sm.graphics.plot_regress_exog(model, "Weight", fig=fig)
plt.show()
```

```
eval_env: 1
```

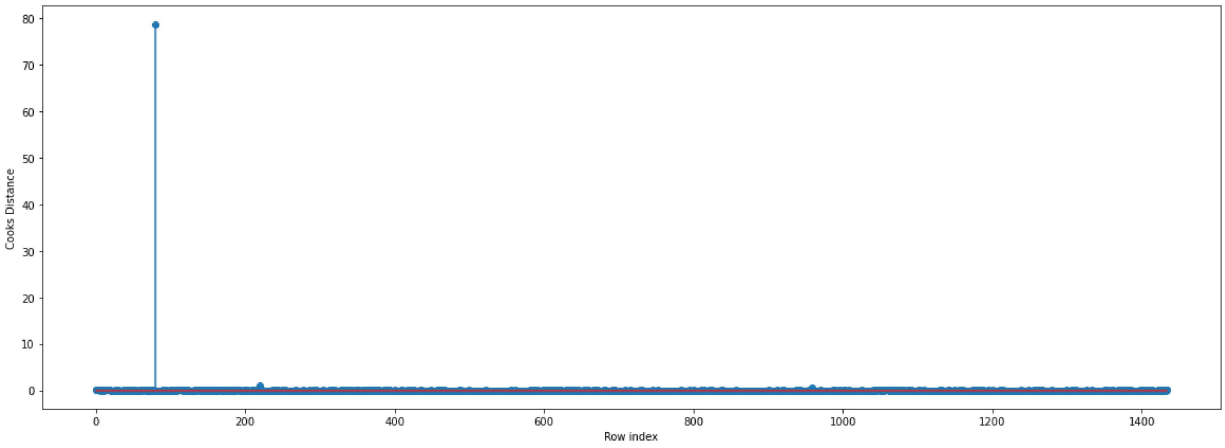


Detecting Influencers/Outliers

Cook's distance

In [136]:
```
model_influence = model.get_influence()
(c,_)=model_influence.cooks_distance
```

In [137]:
```
#Plot the influencers values using stem plot
fig = plt.subplots(figsize=(20, 7))
plt.stem(np.arange(len(data)), np.round(c, 3))
plt.xlabel('Row index')
plt.ylabel('Cooks Distance')
plt.show()
```

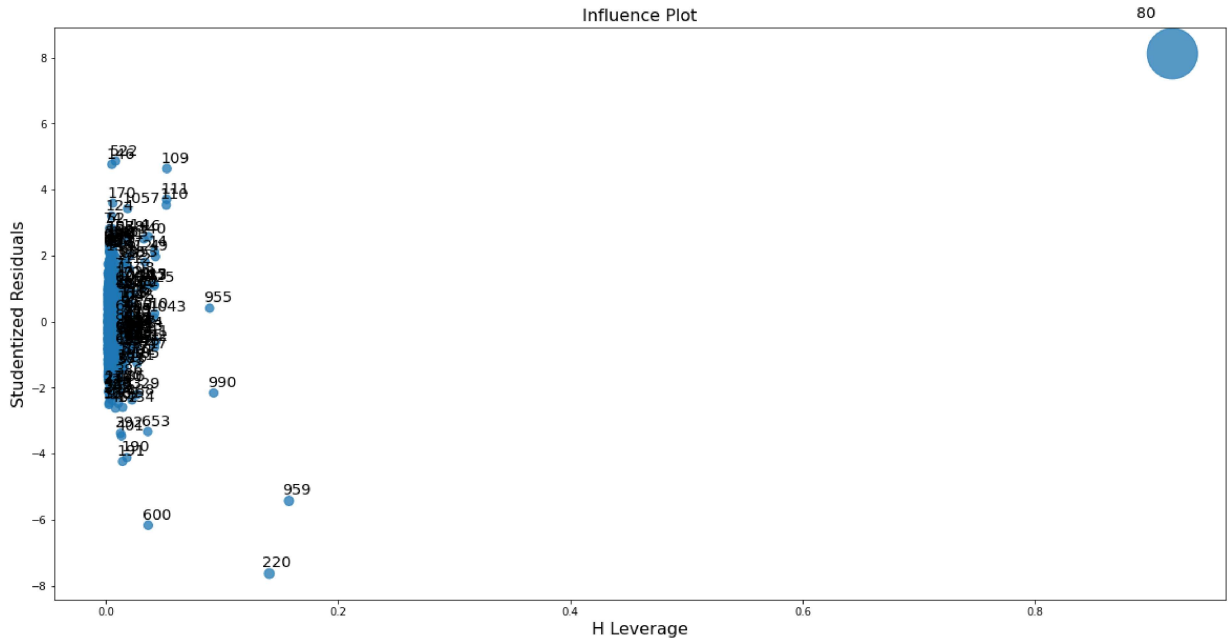


In [138]:
```
(np.argmax(c), np.max(c)) #np.argmax(c) gives the index no. and np.max() gives th
```

Out[138]:
```
(80, 78.72950582271353)
```

Leverage value

In [139]:
```
from statsmodels.graphics.regressionplots import influence_plot
fig,ax=plt.subplots(figsize=(20,10))
fig=influence_plot(model,ax=ax)
plt.show()
```



In [140]:
```
k = data.shape[1]
n = data.shape[0]
leverage_cutoff = 3*((k + 1)/n)
leverage_cutoff
```

Out[140]: 0.020905923344947737

In [141]:
```
#idex of influencer
data[data.index.isin([80])]
```

Out[141]:

	Price	Age_08_04	KM	HP	cc	Doors	Gears	Quarterly_Tax	Weight
80	18950	25	20019	110	16000	5	5	100	1180

Improving Model

In [142]:
```
imp_data=data.copy()
imp_data
```

Out[142]:

	Price	Age_08_04	KM	HP	cc	Doors	Gears	Quarterly_Tax	Weight
0	13500	23	46986	90	2000	3	5	210	1165
1	13750	23	72937	90	2000	3	5	210	1165
2	13950	24	41711	90	2000	3	5	210	1165
3	14950	26	48000	90	2000	3	5	210	1165
4	13750	30	38500	90	2000	3	5	210	1170
...	...	...	...	...	...	...	...	...	...
1430	7500	69	20544	86	1300	3	5	69	1025
1431	10845	72	19000	86	1300	3	5	69	1015
1432	8500	71	17016	86	1300	3	5	69	1015
1433	7250	70	16916	86	1300	3	5	69	1015
1434	6950	76	1	110	1600	5	5	19	1114

1435 rows × 9 columns

In [143]:
```
#Discard the data points which are influencers and reasign the row number (reset_
new_data=imp_data.drop(imp_data.index[80],axis=0).reset_index(drop=True)
new_data
```

Out[143]:

	Price	Age_08_04	KM	HP	cc	Doors	Gears	Quarterly_Tax	Weight
0	13500	23	46986	90	2000	3	5	210	1165
1	13750	23	72937	90	2000	3	5	210	1165
2	13950	24	41711	90	2000	3	5	210	1165
3	14950	26	48000	90	2000	3	5	210	1165
4	13750	30	38500	90	2000	3	5	210	1170
...	...	...	...	...	...	...	...	...	...
1429	7500	69	20544	86	1300	3	5	69	1025
1430	10845	72	19000	86	1300	3	5	69	1015
1431	8500	71	17016	86	1300	3	5	69	1015
1432	7250	70	16916	86	1300	3	5	69	1015
1433	6950	76	1	110	1600	5	5	19	1114

1434 rows × 9 columns

In [144]:
```
#dropping all influencers which are present in our new data
while np.max(c)>0.5 :
    model=smf.ols('Price~Age_08_04+KM+HP+cc+Doors+Gears+Quarterly_Tax+Weight', da
    (c,_)=model.get_influence().cooks_distance
    c
    np.argmax(c) , np.max(c)
    new_data=new_data.drop(new_data.index[[np.argmax(c)]],axis=0).reset_index(dro
    new_data
else:
    final_model=smf.ols('Price~Age_08_04+KM+HP+cc+Doors+Gears+Quarterly_Tax+Weigh
    print('r-square :', final_model.rsquared ,'\n' , 'AIC     :',final_model.aic)
    print('Model Accuracy is improved to :',final_model.rsquared)
```

```
r-square : 0.8882395145171204
 AIC     : 24382.707627340686
Model Accuracy is improved to : 0.8882395145171204
```

Model R Squared value is : 88.82%

In [145]:
```
#our final imporoved data
new_data.head()
```

Out[145]:

	Price	Age_08_04	KM	HP	cc	Doors	Gears	Quarterly_Tax	Weight
0	13500	23	46986	90	2000	3	5	210	1165
1	13750	23	72937	90	2000	3	5	210	1165
2	13950	24	41711	90	2000	3	5	210	1165
3	14950	26	48000	90	2000	3	5	210	1165
4	13750	30	38500	90	2000	3	5	210	1170

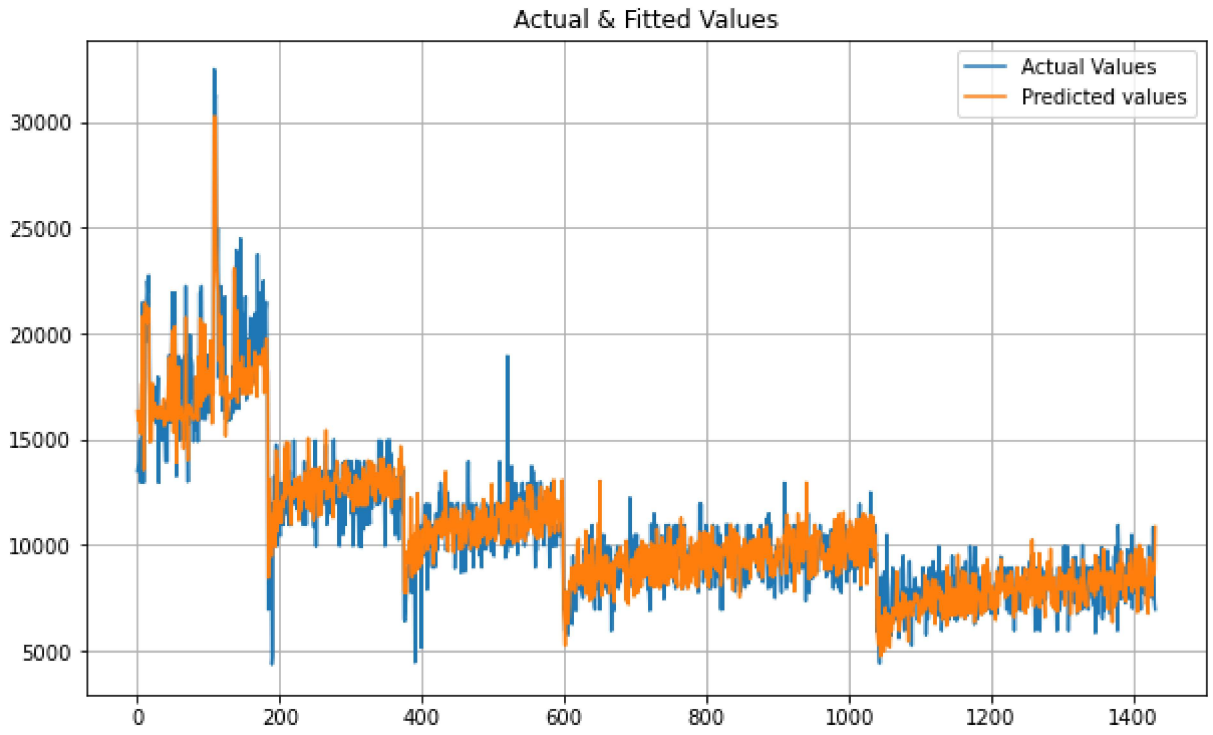
Model Prediction

In [146]:
```
actual=new_data['Price']
```

In [147]:
```
pred_values= final_model.fittedvalues
pred_values
```

Out[147]:
```
0       16345.352610
1       15886.635544
2       16328.224968
3       15996.318854
4       15883.424182
            ...
1426     9161.230587
1427     8536.091326
1428     8681.531063
1429     8793.668694
1430    10860.695492
Length: 1431, dtype: float64
```

In [148]:
```
#plot for actual and fitted  values
plt.figure(figsize=(10,6))
plt.plot(actual,label='Actual Values')
plt.plot(pred_values,label='Predicted values')
plt.title('Actual & Fitted Values')
legend=plt.legend()
plt.grid(True)
plt.show()
```



In [152]:
```
#prediction for new data
new_input=pd.DataFrame({'Age_08_04': 60, 'KM':60256, 'HP':115.23, 'cc':1566, 'Doo
                        'Weight':1100}, index=[1])
```

In [155]:
```
#now, predict car price based on new inputs
print("Car price is: ", final_model.predict(new_input))
```

```
Car price is:  1    11883.663501
dtype: float64
```