In [59]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.formula.api as smf
import statsmodels.api as sm
from statsmodels.graphics.regressionplots import influence_plot
import warnings
warnings.filterwarnings('ignore')
```

In [60]:

```
# import dataset
toyota_1=pd.read_csv("ToyotaCorolla.csv",encoding='latin1')
toyota_1
```

Out[60]:

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

	Id	Model	Price	Age_08_04	Mfg_Month	Mfg_Year	KM	Fuel_Type	HP	Met_Cc
1433	1440	TOYOTA Corolla 1.3 16V HATCHB LINEA TERRA 2/3-...	8500	71	10	1998	17016	Petrol	86	
1434	1441	TOYOTA Corolla 1.3 16V HATCHB LINEA TERRA 2/3-...	7250	70	11	1998	16916	Petrol	86	
1435	1442	TOYOTA Corolla 1.6 LB LINEA TERRA 4/5-Doors	6950	76	5	1998	1	Petrol	110	

1436 rows × 38 columns

EDA

In [61]:

```
toyota_1.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 [62]:

```
toyota_2=pd.concat([toyota_1.iloc[:,2:4],toyota_1.iloc[:,6:7],toyota_1.iloc[:,8:9],toyota_1
toyota_2
```

Out[62]:

	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 [63]:

```
toyota_3=toyota_2.rename({'Age_08_04':'Age','cc':'CC','Quarterly_Tax':'QT'},axis=1)
toyota_3
```

Out[63]:

	Price	Age	KM	HP	CC	Doors	Gears	QT	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 [64]:

```
toyota_3[toyota_3.duplicated()]
```

Out[64]:

	Price	Age	KM	HP	CC	Doors	Gears	QT	Weight
113	24950	8	13253	116	2000	5	5	234	1320

In [65]:

```
toyota_4=toyota_3.drop_duplicates().reset_index(drop=True)
toyota_4
```

Out[65]:

	Price	Age	KM	HP	CC	Doors	Gears	QT	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 [66]:

```
toyota_4[toyota_4.duplicated()]
```

Out[66]:

Price	Age	KM	HP	CC	Doors	Gears	QT	Weight

In [67]:

```
toyota_4.describe()
```

Out[67]:

	Price	Age	KM	HP	CC	Doors	
count	1435.000000	1435.000000	1435.000000	1435.000000	1435.000000	1435.000000	143
mean	10720.915679	55.980488	68571.782578	101.491986	1576.560976	4.032753	5
std	3608.732978	18.563312	37491.094553	14.981408	424.387533	0.952667	0
min	4350.000000	1.000000	1.000000	69.000000	1300.000000	2.000000	3
25%	8450.000000	44.000000	43000.000000	90.000000	1400.000000	3.000000	5
50%	9900.000000	61.000000	63451.000000	110.000000	1600.000000	4.000000	5
75%	11950.000000	70.000000	87041.500000	110.000000	1600.000000	5.000000	5
max	32500.000000	80.000000	243000.000000	192.000000	16000.000000	5.000000	6

Correlation Analysis

In [68]:

```
toyota_4.corr()
```

Out[68]:

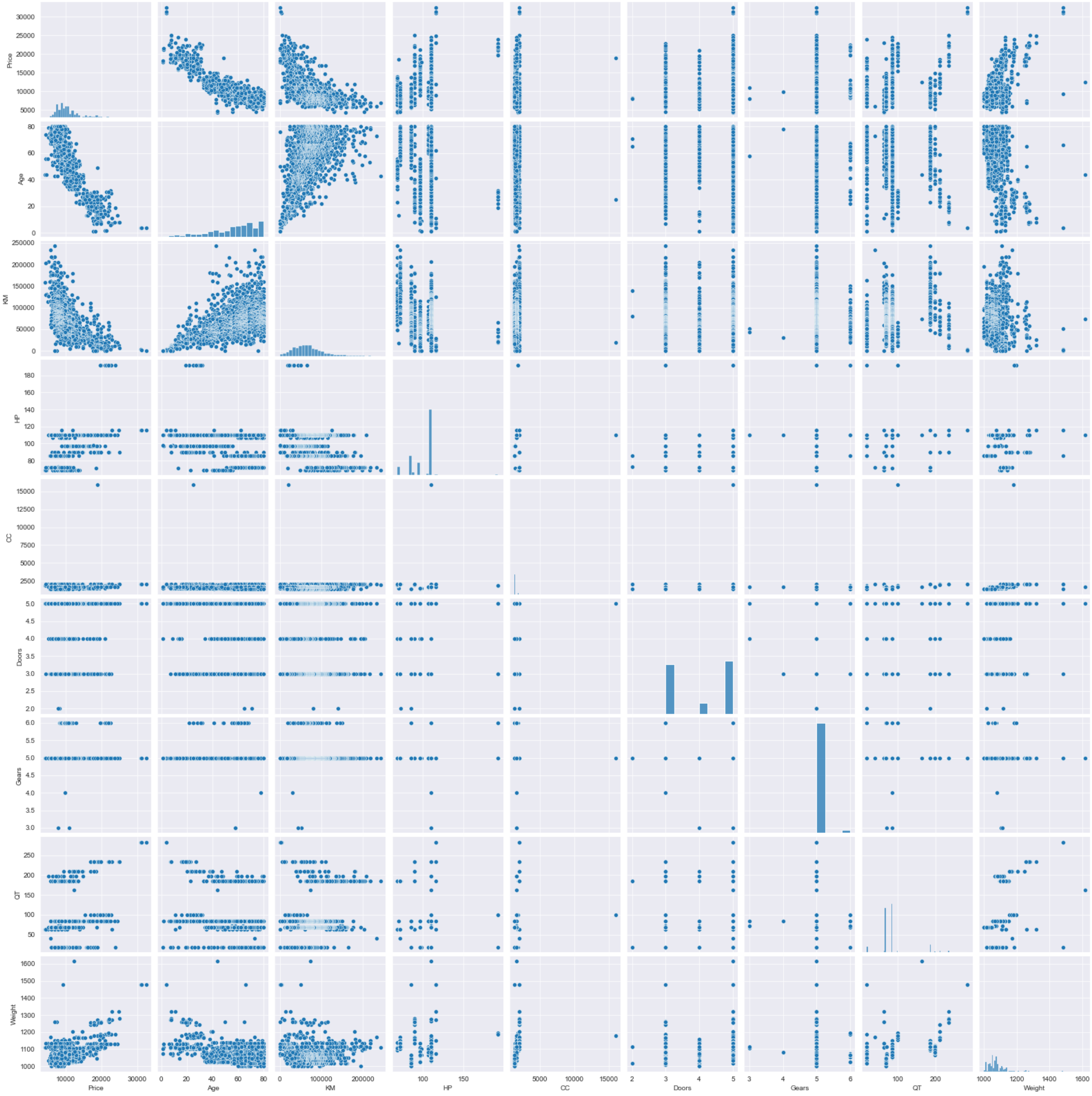
	Price	Age	KM	HP	CC	Doors	Gears	QT	
Price	1.000000	-0.876273	-0.569420	0.314134	0.124375	0.183604	0.063831	0.211508	
Age	-0.876273	1.000000	0.504575	-0.155293	-0.096549	-0.146929	-0.005629	-0.193319	-
KM	-0.569420	0.504575	1.000000	-0.332904	0.103822	-0.035193	0.014890	0.283312	-
HP	0.314134	-0.155293	-0.332904	1.000000	0.035207	0.091803	0.209642	-0.302287	
CC	0.124375	-0.096549	0.103822	0.035207	1.000000	0.079254	0.014732	0.305982	
Doors	0.183604	-0.146929	-0.035193	0.091803	0.079254	1.000000	-0.160101	0.107353	
Gears	0.063831	-0.005629	0.014890	0.209642	0.014732	-0.160101	1.000000	-0.005125	
QT	0.211508	-0.193319	0.283312	-0.302287	0.305982	0.107353	-0.005125	1.000000	
Weight	0.575869	-0.466484	-0.023969	0.087143	0.335077	0.301734	0.021238	0.621988	

In [69]:

```
sns.set_style(style='darkgrid')
sns.pairplot(toyota_4)
```

Out[69]:

```
<seaborn.axisgrid.PairGrid at 0x1b962e65790>
```



Model Building

In [70]:

```
model=smf.ols('Price~Age+KM+HP+CC+Doors+Gears+QT+Weight',data=toyota_4).fit()
model
```

Out[70]:

```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x1b964e81f
70>
```

Model Testing

In [71]:

```
# Finding Coefficient parameters
model.params
```

Out[71]:

```
Intercept   -5472.540368
Age          -121.713891
KM             -0.020737
HP             31.584612
CC             -0.118558
Doors          -0.920189
Gears         597.715894
QT              3.858805
Weight         16.855470
dtype: float64
```

In [72]:

```
#Finding tvalues and pvalues
model.tvalues,np.round(model.pvalues,5)
```

Out[72]:

```
(Intercept    -3.875273
 Age         -46.551876
 KM          -16.552424
 HP           11.209719
 CC           -1.316436
 Doors        -0.023012
 Gears         3.034563
 QT            2.944198
 Weight       15.760663
 dtype: float64,
 Intercept    0.00011
 Age          0.00000
 KM           0.00000
 HP           0.00000
 CC           0.18824
 Doors        0.98164
 Gears        0.00245
 QT           0.00329
 Weight       0.00000
 dtype: float64)
```

In [73]:

```
# Finding rsquared values
model.rsquared , model.rsquared_adj   # Model accuracy is 86.17%
```

Out[73]:

```
(0.8625200256947, 0.8617487495415146)
```

In [74]:

```
# Building SLR and MLR models for insignificant variables 'CC' and 'Doors'
# Also finding their tvalues and pvalues
```

In [75]:

```
slr_cc=smf.ols('Price~CC',data=toyota_4).fit()
slr_cc.tvalues , slr_cc.pvalues # CC has significant pvalue
```

Out[75]:

```
(Intercept    24.879592
 CC            4.745039
 dtype: float64,
 Intercept    7.236022e-114
 CC            2.292856e-06
 dtype: float64)
```

In [76]:

```
slr_Doors=smf.ols('Price~Doors',data=toyota_4).fit()
slr_Doors.tvalues , slr_Doors.pvalues # Doors has significant pvalue
```

Out[76]:

```
(Intercept    19.421546
 Doors         7.070520
 dtype: float64,
 Intercept    8.976407e-75
 Doors        2.404166e-12
 dtype: float64)
```

In [77]:

```
mlr_cc_doors=smf.ols('Price~CC+Doors',data=toyota_4).fit()
mlr_cc_doors.tvalues,mlr_cc_doors.pvalues   # CC & Doors have significant pvalue
```

Out[77]:

```
(Intercept    12.786341
 CC            4.268006
 Doors         6.752236
 dtype: float64,
 Intercept    1.580945e-35
 CC           2.101878e-05
 Doors        2.109558e-11
 dtype: float64)
```

Model Validation Techniques

Two Techniques: 1. Collinearity Check &

```
               2. Residual Analysis
```

In [78]:

```
# 1) Collinearity Problem Check
# Calculate VIF = 1/(1-Rsquare) for all independent variables

rsq_age=smf.ols('Age~KM+HP+CC+Doors+Gears+QT+Weight',data=toyota_4).fit().rsquared
vif_age=1/(1-rsq_age)

rsq_KM=smf.ols('KM~Age+HP+CC+Doors+Gears+QT+Weight',data=toyota_4).fit().rsquared
vif_KM=1/(1-rsq_KM)

rsq_HP=smf.ols('HP~Age+KM+CC+Doors+Gears+QT+Weight',data=toyota_4).fit().rsquared
vif_HP=1/(1-rsq_HP)

rsq_CC=smf.ols('CC~Age+KM+HP+Doors+Gears+QT+Weight',data=toyota_4).fit().rsquared
vif_CC=1/(1-rsq_CC)

rsq_DR=smf.ols('Doors~Age+KM+HP+CC+Gears+QT+Weight',data=toyota_4).fit().rsquared
vif_DR=1/(1-rsq_DR)

rsq_GR=smf.ols('Gears~Age+KM+HP+CC+Doors+QT+Weight',data=toyota_4).fit().rsquared
vif_GR=1/(1-rsq_GR)

rsq_QT=smf.ols('QT~Age+KM+HP+CC+Doors+Gears+Weight',data=toyota_4).fit().rsquared
vif_QT=1/(1-rsq_QT)

rsq_WT=smf.ols('Weight~Age+KM+HP+CC+Doors+Gears+QT',data=toyota_4).fit().rsquared
vif_WT=1/(1-rsq_WT)

# Putting the values in Dataframe format
d1={'Variables':['Age','KM','HP','CC','Doors','Gears','QT','Weight'],
    'Vif':[vif_age,vif_KM,vif_HP,vif_CC,vif_DR,vif_GR,vif_QT,vif_WT]}
Vif_df=pd.DataFrame(d1)
Vif_df
```

Out[78]:

	Variables	Vif
0	Age	1.876236
1	KM	1.757178
2	HP	1.419180
3	CC	1.163470
4	Doors	1.155890
5	Gears	1.098843
6	QT	2.295375
7	Weight	2.487180

In [79]:

```
# None variable has VIF>20, No Collinearity, so consider all varaibles in Regression equati
```

In [80]:

```
# 2) Residual Analysis
# Test for Normality of Residuals (Q-Q Plot) using residual model (model.resid)
sm.qqplot(model.resid,line='q') # 'q' - A line is fit through the quartiles # line = '45'-
plt.title("Normal Q-Q plot of residuals")
plt.show()
```

In [81]:

```
list(np.where(model.resid>6000))  #outliar detection from above QQ plot of residuals
```

Out[81]:

```
[array([109, 146, 522], dtype=int64)]
```

In [82]:

```
list(np.where(model.resid<-6000))
```

Out[82]:

```
[array([220, 600, 959], dtype=int64)]
```

In [83]:

```
# Test for Homoscedasticity or Heteroscedasticity (plotting model's standardized fitted val

def standard_values(vals) : return (vals-vals.mean())/vals.std()  # User defined z = (x - m
```

In [84]:

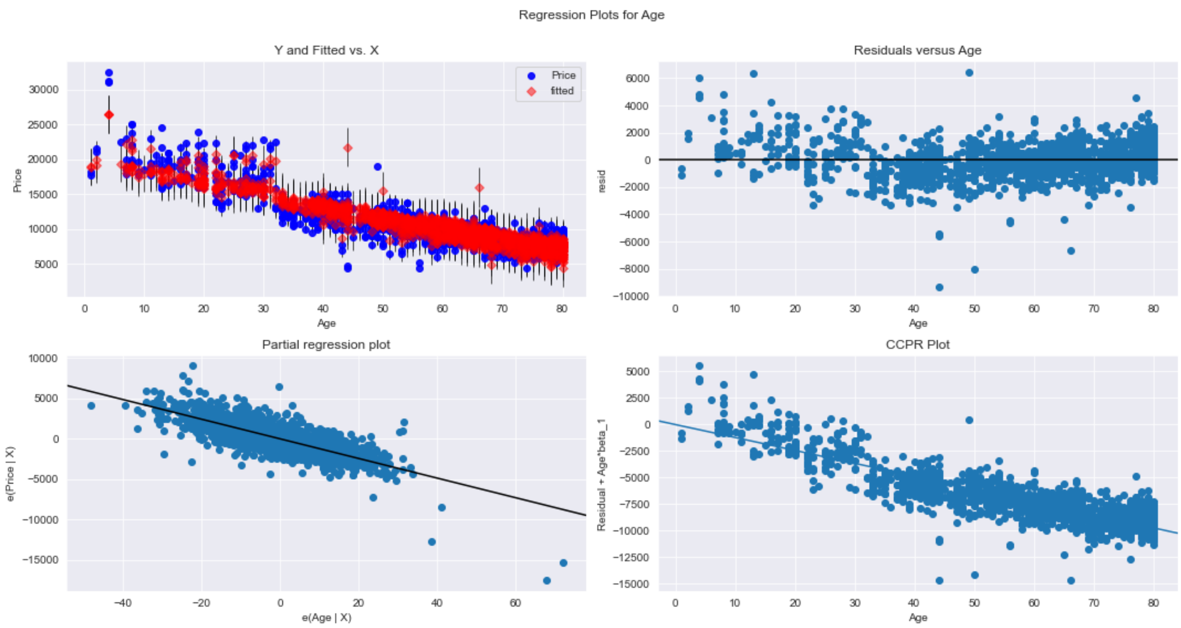
```
plt.scatter(standard_values(model.fittedvalues),standard_values(model.resid))
plt.title('Residual Plot')
plt.xlabel('standardized fitted values')
plt.ylabel('standardized residual values')
plt.show()
```

In [85]:

```
# Test for errors or Residuals Vs Regressors or independent 'x' variables or predictors
# using Residual Regression Plots code graphics.plot_regress_exog(model,'x',fig) # exog = x
```

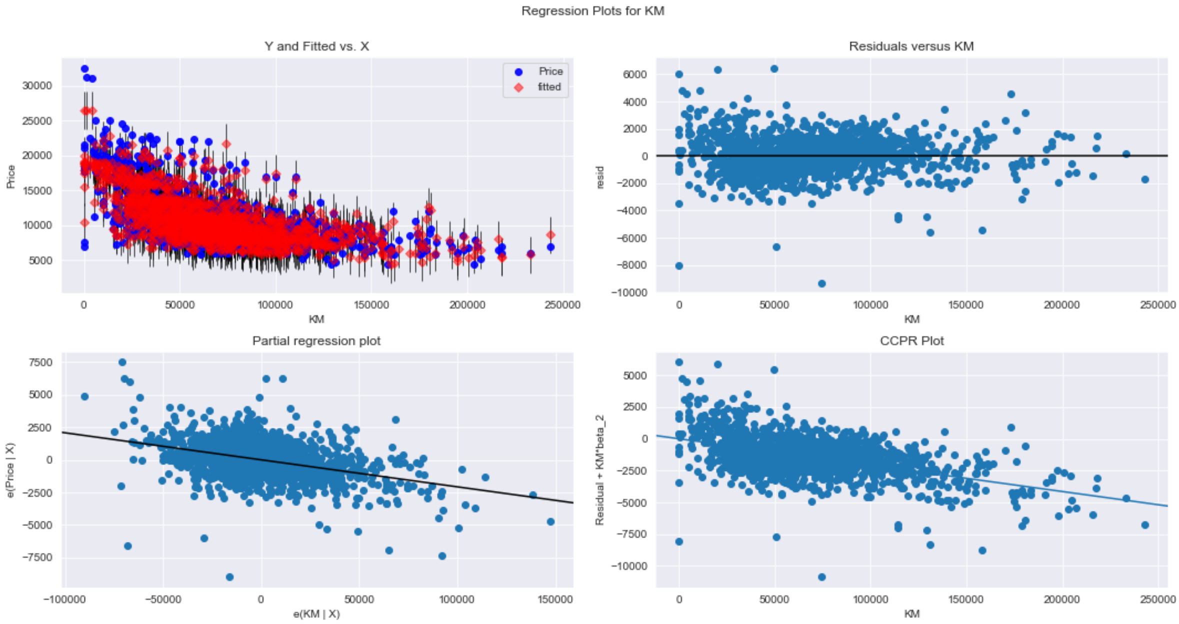
In [86]:

```
fig=plt.figure(figsize=(15,8))
sm.graphics.plot_regress_exog(model,'Age',fig=fig)
plt.show()
```



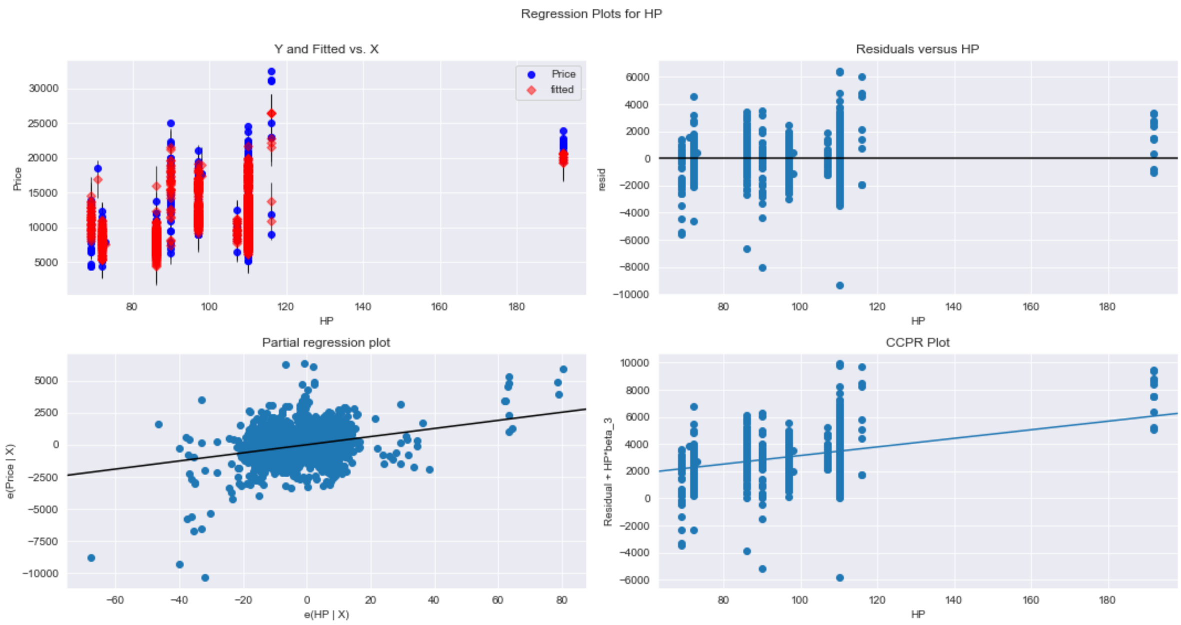
In [87]:

```
fig=plt.figure(figsize=(15,8))
sm.graphics.plot_regress_exog(model,'KM',fig=fig)
plt.show()
```



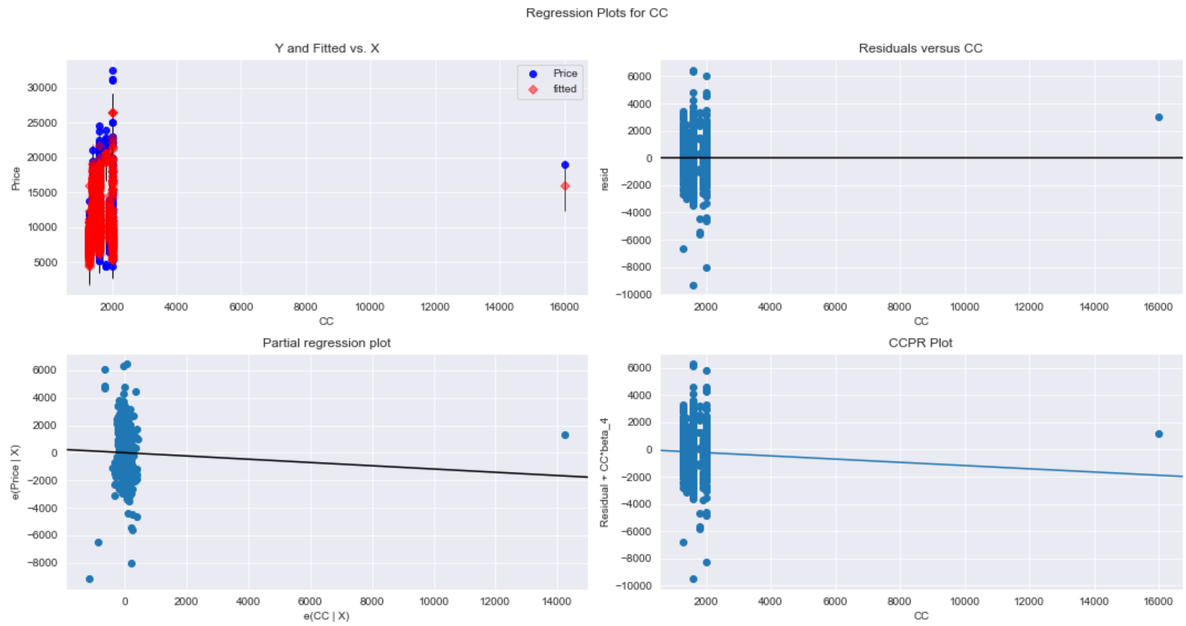
In [88]:

```
fig=plt.figure(figsize=(15,8))
sm.graphics.plot_regress_exog(model,'HP',fig=fig)
plt.show()
```



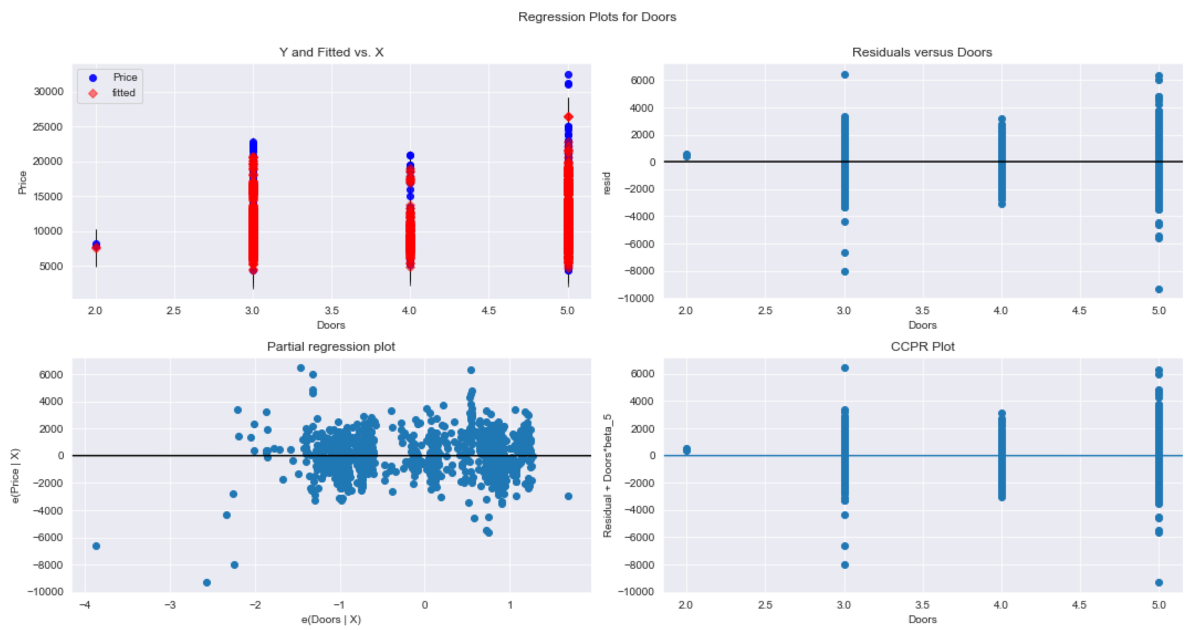
In [89]:

```
fig=plt.figure(figsize=(15,8))
sm.graphics.plot_regress_exog(model,'CC',fig=fig)
plt.show()
```



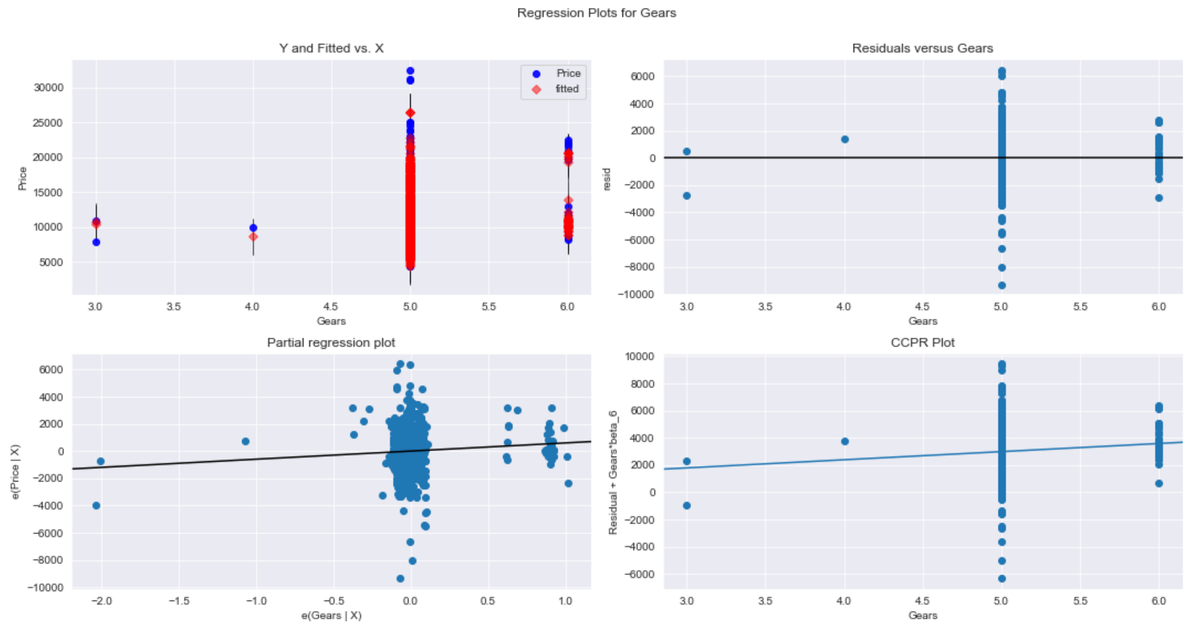
In [90]:

```
fig=plt.figure(figsize=(15,8))
sm.graphics.plot_regress_exog(model,'Doors',fig=fig)
plt.show()
```



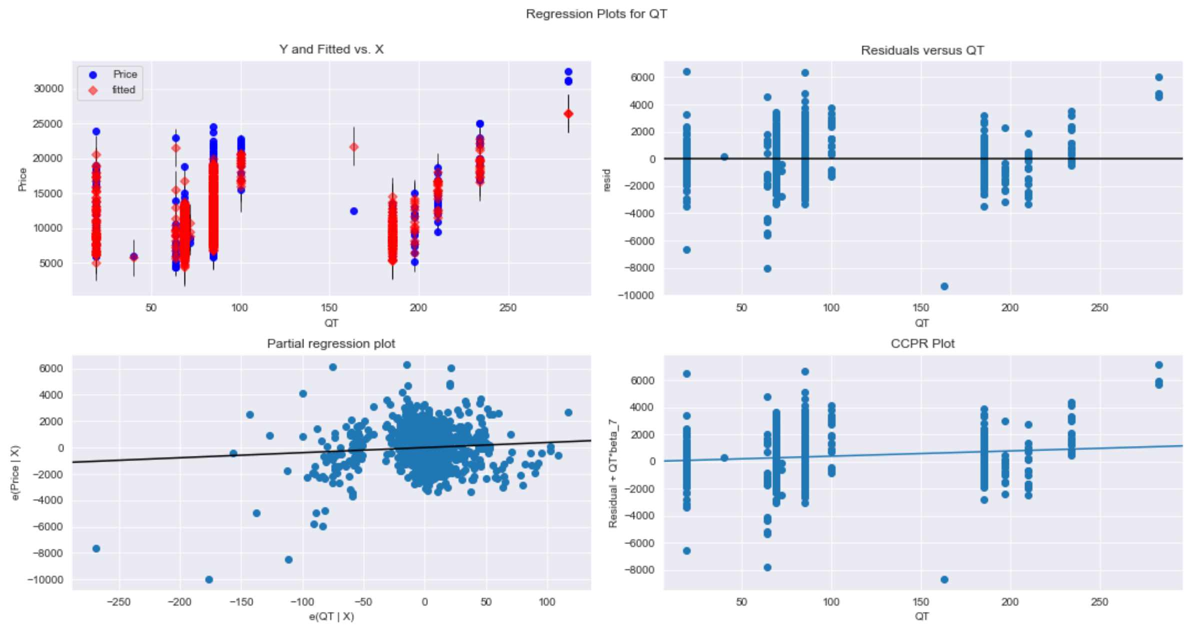
In [91]:

```
fig=plt.figure(figsize=(15,8))
sm.graphics.plot_regress_exog(model,'Gears',fig=fig)
plt.show()
```



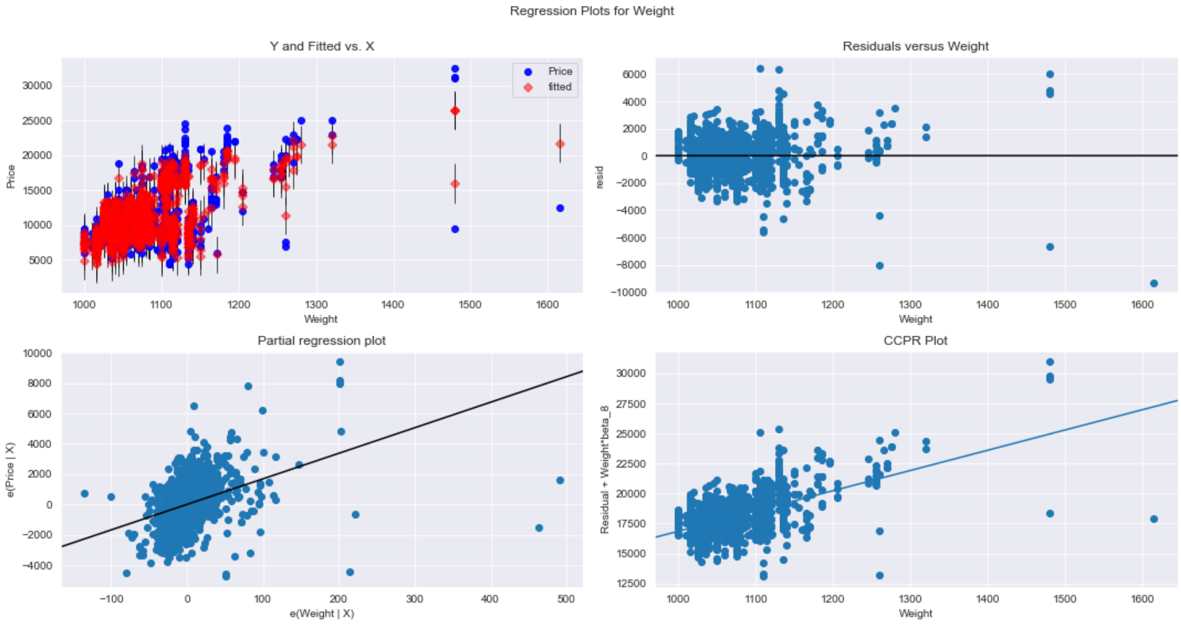
In [92]:

```
fig=plt.figure(figsize=(15,8))
sm.graphics.plot_regress_exog(model,'QT',fig=fig)
plt.show()
```



In [93]:

```
fig=plt.figure(figsize=(15,8))
sm.graphics.plot_regress_exog(model,'Weight',fig=fig)
plt.show()
```



Model Deletion Diagnostics (checking Outliers or Influencers)

Two Techniques : 1. Cook's Distance & 2. Leverage value

In [94]:

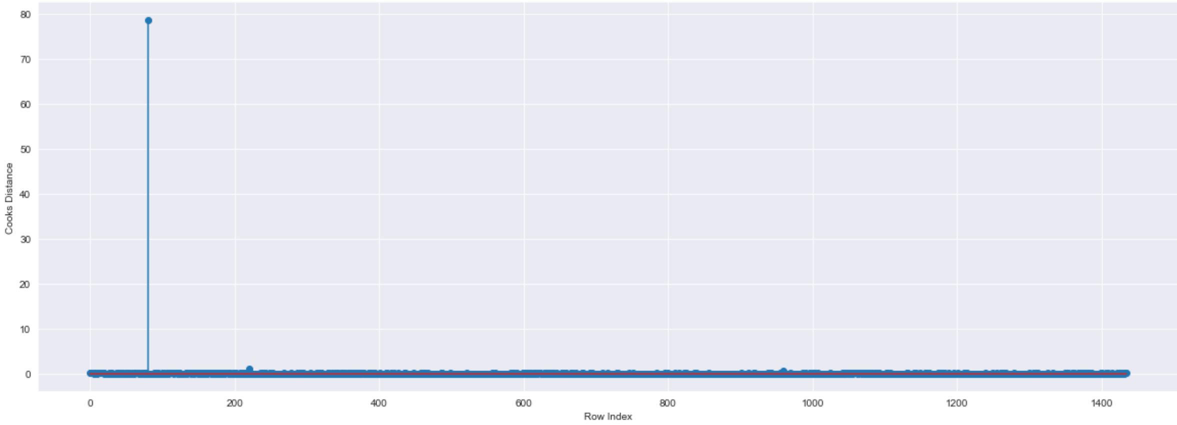
```
# 1. Cook's Distance: If Cook's distance > 1, then it's an outlier
# Get influencers using cook's distance
(c,_)=model.get_influence().cooks_distance
c
```

Out[94]:

```
array([7.22221054e-03, 3.94547973e-03, 5.44224039e-03, ...,
       8.04110550e-07, 6.99854767e-04, 1.08408002e-02])
```

In [95]:

```
# Plot the influencers using the stem plot
fig=plt.figure(figsize=(20,7))
plt.stem(np.arange(len(toyota_4)),np.round(c,3))
plt.xlabel('Row Index')
plt.ylabel('Cooks Distance')
plt.show()
```



In [96]:

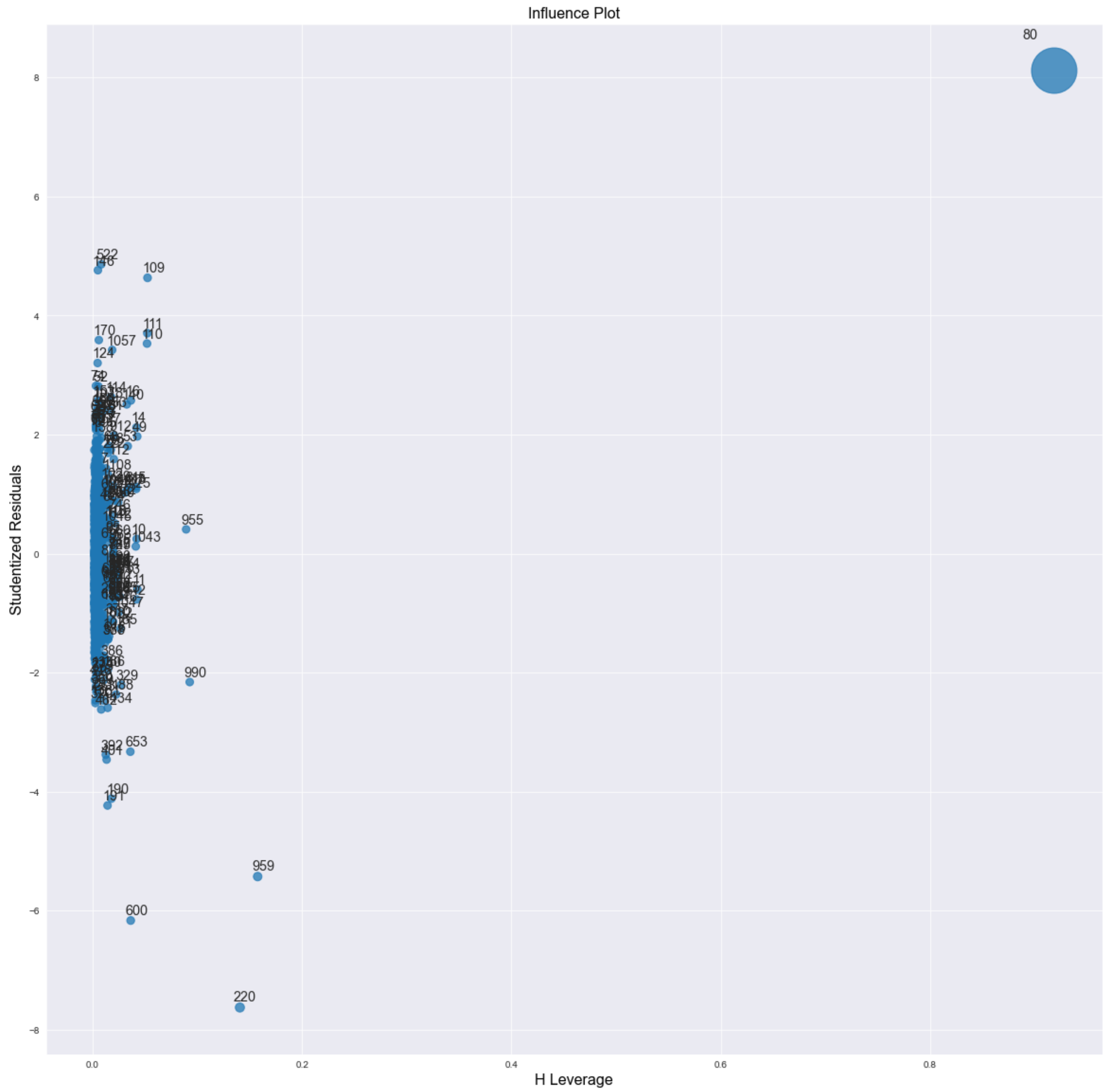
```
# Index and value of influencer where C>0.5
np.argmax(c) , np.max(c)
```

Out[96]:

```
(80, 78.72950582248232)
```

In [97]:

```
# 2. Leverage Value using High Influence Points : Points beyond Leverage_cutoff value are i
fig,ax=plt.subplots(figsize=(20,20))
fig=influence_plot(model,ax = ax)
```



In [98]:

```
# Leverage Cuttoff Value = 3*(k+1)/n ; k = no.of features/columns & n = no. of datapoints
k=toyota_4.shape[1]
n=toyota_4.shape[0]
leverage_cutoff = (3*(k+1))/n
leverage_cutoff
```

Out[98]:

```
0.020905923344947737
```

In [99]:

```
toyota_4[toyota_4.index.isin([80])]
```

Out[99]:

	Price	Age	KM	HP	CC	Doors	Gears	QT	Weight
80	18950	25	20019	110	16000	5	5	100	1180

Improving the Model

In [100]:

```
# Creating a copy of data so that original dataset is not affected
toyo_new=toyota_4.copy()
toyo_new
```

Out[100]:

	Price	Age	KM	HP	CC	Doors	Gears	QT	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 [101]:

```
# Discard the data points which are influencers and reassign the row number (reset_index(dr
toyo5=toyo_new.drop(toyo_new.index[[80]],axis=0).reset_index(drop=True)
toyo5
```

Out[101]:

	Price	Age	KM	HP	CC	Doors	Gears	QT	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

Model Deletion Diagnostics and Final Model

In [102]:

```
while np.max(c)>0.5 :
 model=smf.ols('Price~Age+KM+HP+CC+Doors+Gears+QT+Weight',data=toyo5).fit()
 (c,_)=model.get_influence().cooks_distance
 c
 np.argmax(c) , np.max(c)
 toyo5=toyo5.drop(toyo5.index[[np.argmax(c)]],axis=0).reset_index(drop=True)
 toyo5
else:
 final_model=smf.ols('Price~Age+KM+HP+CC+Doors+Gears+QT+Weight',data=toyo5).fit()
 final_model.rsquared , final_model.aic
 print("Thus model accuracy is improved to",final_model.rsquared)
```

```
Thus model accuracy is improved to 0.8882395145171204
```

In [103]:

```
if np.max(c)>0.5:
 model=smf.ols('Price~Age+KM+HP+CC+Doors+Gears+QT+Weight',data=toyo5).fit()
 (c,_)=model.get_influence().cooks_distance
 c
 np.argmax(c) , np.max(c)
 toyo5=toyo5.drop(toyo5.index[[np.argmax(c)]],axis=0).reset_index(drop=True)
 toyo5
elif np.max(c)<0.5:
 final_model=smf.ols('Price~Age+KM+HP+CC+Doors+Gears+QT+Weight',data=toyo5).fit()
 final_model.rsquared , final_model.aic
 print("Thus model accuracy is improved to",final_model.rsquared)
```

```
Thus model accuracy is improved to 0.8882395145171204
```

In [104]:

```
final_model.rsquared
```

Out[104]:

```
0.8882395145171204
```

In [105]:

```
toyo5
```

Out[105]:

	Price	Age	KM	HP	CC	Doors	Gears	QT	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
...	...	...	...	...	...	...	...	...	...
1426	7500	69	20544	86	1300	3	5	69	1025
1427	10845	72	19000	86	1300	3	5	69	1015
1428	8500	71	17016	86	1300	3	5	69	1015
1429	7250	70	16916	86	1300	3	5	69	1015
1430	6950	76	1	110	1600	5	5	19	1114

1431 rows × 9 columns

Model Predictions

In [109]:

```
# say New data for prediction is
new_data=pd.DataFrame({'Age':12,"KM":40000,"HP":80,"CC":1300,"Doors":4,"Gears":5,"QT":69,"W
new_data
```

Out[109]:

	Age	KM	HP	CC	Doors	Gears	QT	Weight
0	12	40000	80	1300	4	5	69	1012

In [110]:

```
# Manual Prediction of Price
final_model.predict(new_data)
```

Out[110]:

```
0    14341.570181
dtype: float64
```

In [111]:

```
# Automatic Prediction of Price with 90.02% accurcy
pred_y=final_model.predict(toyo5)
pred_y
```

Out[111]:

```
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 [ ]:

In [ ]: