In [1]:
```
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
```

In [2]:
```
data = pd.read_csv('ToyotaCorolla.csv', encoding = 'latin1')
data.head()
```

Out[2]:

	Id	Model	Price	Age_08_04	Mfg_Month	Mfg_Year	KM	Fuel_Type	HP	Met_Colo
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	(

5 rows × 38 columns

In [3]:
```
data.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 [4]:
```
data.describe()
```

Out[4]:

	Id	Price	Age_08_04	Mfg_Month	Mfg_Year	KM
count	1436.000000	1436.000000	1436.000000	1436.000000	1436.000000	1436.000000
mean	721.555014	10730.824513	55.947075	5.548747	1999.625348	68533.259749
std	416.476890	3626.964585	18.599988	3.354085	1.540722	37506.448872
min	1.000000	4350.000000	1.000000	1.000000	1998.000000	1.000000
25%	361.750000	8450.000000	44.000000	3.000000	1998.000000	43000.000000
50%	721.500000	9900.000000	61.000000	5.000000	1999.000000	63389.500000
75%	1081.250000	11950.000000	70.000000	8.000000	2001.000000	87020.750000
max	1442.000000	32500.000000	80.000000	12.000000	2004.000000	243000.000000

8 rows × 35 columns

In [5]:
```
data1=data.iloc[:,[2,3,6,8,12,13,15,16,17]]
data1.dtypes
```

Out[5]:
```
Price            int64
Age_08_04        int64
KM               int64
HP               int64
cc               int64
Doors            int64
Gears            int64
Quarterly_Tax    int64
Weight           int64
dtype: object
```

In [6]:
```
data2=data1.rename({"Age_08_04":"age","Quarterly_Tax":"tax","Weight
data2.head()
```

Out[6]:

	Price	age	KM	HP	cc	door	Gears	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

In [7]:
```
data2.isnull().sum()
```

Out[7]:
```
Price     0
age       0
KM        0
HP        0
cc        0
door      0
Gears     0
tax       0
weight    0
dtype: int64
```

In [8]:
```
data2.duplicated().value_counts()
data2[data2.duplicated()]
```

Out[8]:

	Price	age	KM	HP	cc	door	Gears	tax	weight
113	24950	8	13253	116	2000	5	5	234	1320

In [9]:
```
data2.drop_duplicates(inplace=True)
```

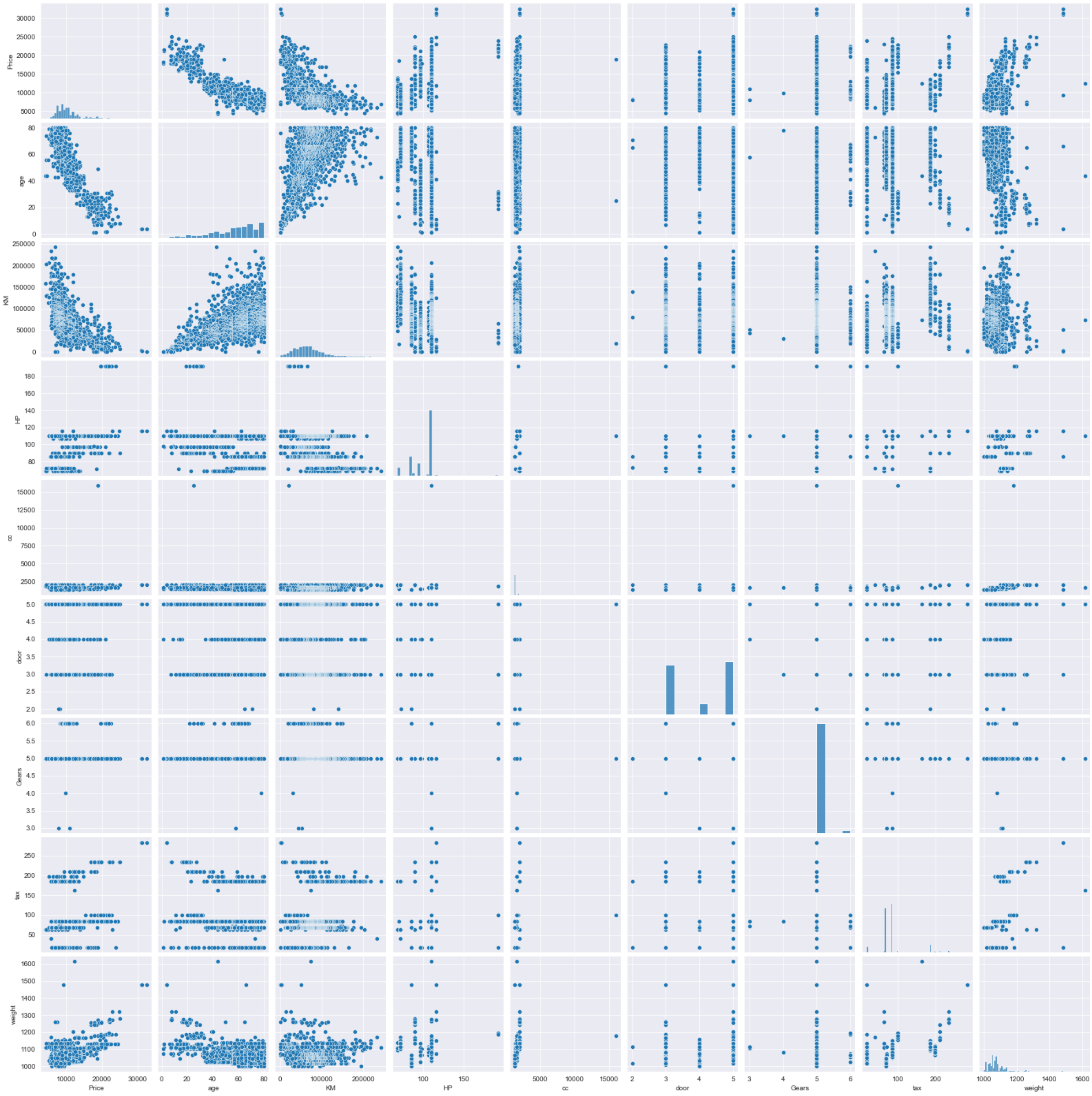
In [10]:
```
data2.corr()
```

Out[10]:

	Price	age	KM	HP	cc	door	Gears	t
Price	1.000000	-0.876273	-0.569420	0.314134	0.124375	0.183604	0.063831	0.2115
age	-0.876273	1.000000	0.504575	-0.155293	-0.096549	-0.146929	-0.005629	-0.1933
KM	-0.569420	0.504575	1.000000	-0.332904	0.103822	-0.035193	0.014890	0.2833
HP	0.314134	-0.155293	-0.332904	1.000000	0.035207	0.091803	0.209642	-0.3022
cc	0.124375	-0.096549	0.103822	0.035207	1.000000	0.079254	0.014732	0.3059
door	0.183604	-0.146929	-0.035193	0.091803	0.079254	1.000000	-0.160101	0.1073
Gears	0.063831	-0.005629	0.014890	0.209642	0.014732	-0.160101	1.000000	-0.0051
tax	0.211508	-0.193319	0.283312	-0.302287	0.305982	0.107353	-0.005125	1.0000
weight	0.575869	-0.466484	-0.023969	0.087143	0.335077	0.301734	0.021238	0.6219

In [11]:
```
sns.set_style(style="darkgrid")
sns.pairplot(data= data2)
```

Out[11]: <seaborn.axisgrid.PairGrid at 0x7ffd7683ed00>



removing gears column as it has very less correlation with Price

In [12]:
```
data3 = data2.drop("Gears", axis=1)
data3.head()
```

Out[12]:

	Price	age	KM	HP	cc	door	tax	weight
0	13500	23	46986	90	2000	3	210	1165
1	13750	23	72937	90	2000	3	210	1165
2	13950	24	41711	90	2000	3	210	1165
3	14950	26	48000	90	2000	3	210	1165
4	13750	30	38500	90	2000	3	210	1170

In [13]:
```
data3.corr()
```

Out[13]:

	Price	age	KM	HP	cc	door	tax	weig
Price	1.000000	-0.876273	-0.569420	0.314134	0.124375	0.183604	0.211508	0.5758
age	-0.876273	1.000000	0.504575	-0.155293	-0.096549	-0.146929	-0.193319	-0.4664
KM	-0.569420	0.504575	1.000000	-0.332904	0.103822	-0.035193	0.283312	-0.0239
HP	0.314134	-0.155293	-0.332904	1.000000	0.035207	0.091803	-0.302287	0.0871
cc	0.124375	-0.096549	0.103822	0.035207	1.000000	0.079254	0.305982	0.3350
door	0.183604	-0.146929	-0.035193	0.091803	0.079254	1.000000	0.107353	0.3017
tax	0.211508	-0.193319	0.283312	-0.302287	0.305982	0.107353	1.000000	0.6219
weight	0.575869	-0.466484	-0.023969	0.087143	0.335077	0.301734	0.621988	1.0000

In [14]:
```
model=smf.ols("Price~age+KM+HP+cc+door+tax+weight",data = data3).fi
model.summary()
```

Out[14]:

OLS Regression Results

Dep. Variable:	Price	**R-squared:**	0.862
Model:	OLS	**Adj. R-squared:**	0.861
Method:	Least Squares	**F-statistic:**	1269.
Date:	Wed, 07 Dec 2022	**Prob (F-statistic):**	0.00
Time:	01:16:36	**Log-Likelihood:**	-12371.
No. Observations:	1435	**AIC:**	2.476e+04
Df Residuals:	1427	**BIC:**	2.480e+04
Df Model:	7		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-2636.3843	1061.677	-2.483	0.013	-4718.999	-553.770
age	-121.8478	2.622	-46.476	0.000	-126.991	-116.705
KM	-0.0205	0.001	-16.325	0.000	-0.023	-0.018
HP	33.6479	2.742	12.270	0.000	28.269	39.027
cc	-0.1227	0.090	-1.358	0.175	-0.300	0.054
door	-23.9806	39.372	-0.609	0.543	-101.214	53.253
tax	4.0353	1.313	3.073	0.002	1.459	6.611
weight	16.8844	1.072	15.743	0.000	14.781	18.988

Omnibus:	149.646	**Durbin-Watson:**	1.551
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	980.896
Skew:	-0.217	**Prob(JB):**	1.00e-213
Kurtosis:	7.027	**Cond. No.**	2.34e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.34e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

In [15]:
```
m1 = smf.ols('Price~cc', data= data3).fit()
m1.summary()
```

Out[15]:

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:	Wed, 07 Dec 2022	**Prob (F-statistic):**	2.29e-06
Time:	01:16:36	**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 [16]:
```
m1 = smf.ols('Price~door', data= data3).fit()
m1.summary()
```

Out[16]:

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:	Wed, 07 Dec 2022	**Prob (F-statistic):**	2.40e-12
Time:	01:16:36	**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
door	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 [17]:
```
data4 = data3.drop("cc", axis = 1)
data4.head()
```

Out[17]:

	Price	age	KM	HP	door	tax	weight
0	13500	23	46986	90	3	210	1165
1	13750	23	72937	90	3	210	1165
2	13950	24	41711	90	3	210	1165
3	14950	26	48000	90	3	210	1165
4	13750	30	38500	90	3	210	1170

In [18]:
```
data4.corr()
```

Out[18]:

	Price	age	KM	HP	door	tax	weight
Price	1.000000	-0.876273	-0.569420	0.314134	0.183604	0.211508	0.575869
age	-0.876273	1.000000	0.504575	-0.155293	-0.146929	-0.193319	-0.466484
KM	-0.569420	0.504575	1.000000	-0.332904	-0.035193	0.283312	-0.023969
HP	0.314134	-0.155293	-0.332904	1.000000	0.091803	-0.302287	0.087143
door	0.183604	-0.146929	-0.035193	0.091803	1.000000	0.107353	0.301734
tax	0.211508	-0.193319	0.283312	-0.302287	0.107353	1.000000	0.621988
weight	0.575869	-0.466484	-0.023969	0.087143	0.301734	0.621988	1.000000

In [19]:
```
m3= smf.ols('Price~age+KM+HP+door+tax+weight',data=data4).fit()
m3.summary()
```

Out[19]:

OLS Regression Results

Dep. Variable:	Price	**R-squared:**	0.861
Model:	OLS	**Adj. R-squared:**	0.861
Method:	Least Squares	**F-statistic:**	1480.
Date:	Wed, 07 Dec 2022	**Prob (F-statistic):**	0.00
Time:	01:16:37	**Log-Likelihood:**	-12372.
No. Observations:	1435	**AIC:**	2.476e+04
Df Residuals:	1428	**BIC:**	2.479e+04
Df Model:	6		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-2518.7574	1058.453	-2.380	0.017	-4595.046	-442.468
age	-121.8917	2.622	-46.483	0.000	-127.036	-116.748
KM	-0.0206	0.001	-16.455	0.000	-0.023	-0.018
HP	33.3055	2.731	12.194	0.000	27.947	38.663
door	-23.2523	39.380	-0.590	0.555	-100.502	53.997
tax	3.8184	1.304	2.929	0.003	1.261	6.376
weight	16.6515	1.059	15.724	0.000	14.574	18.729

Omnibus:	145.933	**Durbin-Watson:**	1.548
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	937.411
Skew:	-0.206	**Prob(JB):**	2.78e-204
Kurtosis:	6.938	**Cond. No.**	2.33e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.33e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

vif calculation

In [20]:
```
rsq_age=smf.ols('age~KM+HP+door+tax+weight',data=data4).fit().rsqua
vif_age=1/(1-rsq_age)
```

In [21]:
```
rsq_KM=smf.ols('KM~age+HP+door+tax+weight',data=data4).fit().rsquar
vif_KM=1/(1-rsq_KM)
```

In [22]:
```
rsq_HP=smf.ols('HP~age+KM+door+tax+weight',data=data4).fit().rsquar
vif_HP=1/(1-rsq_HP)
```

In [23]:
```
rsq_door=smf.ols('door~age+KM+HP+tax+weight',data=data4).fit().rsqu
vif_door=1/(1-rsq_door)
```

In [24]:
```
rsq_tax=smf.ols('tax~age+KM+HP+door+weight',data=data4).fit().rsqua
vif_tax=1/(1-rsq_tax)
```

In [25]:
```
rsq_Weight=smf.ols('weight~age+KM+HP+door+tax',data=data4).fit().rs
vif_Weight=1/(1-rsq_Weight)
```

In [26]:
```
d1 = {'variables':['age','KM','HP','door','tax','weight'],
     'vif':[vif_age,vif_KM,vif_HP,vif_door,vif_tax,vif_Weight]}
```

In [27]:
```
vif_frame = pd.DataFrame(d1)
vif_frame
```

Out[27]:

	variables	vif
0	age	1.875416
1	KM	1.738917
2	HP	1.325246
3	door	1.113939
4	tax	2.256997
5	weight	2.423423

residual analysis for normality

In [28]:
```
res=m3.resid
res.head(10)
```

Out[28]:
```
0   -3339.719690
1   -2555.830091
2   -2876.350450
3   -1503.183434
4   -2494.317424
5   -2587.641707
6     195.534750
7    1876.021951
8    1276.335218
9   -1598.873899
dtype: float64
```

In [29]:
```
res.mean()
```

Out[29]:
```
1.042505291384687e-09
```

In [30]:
```
import statsmodels.api as sm
qqplot=sm.qqplot(res,line='q')
plt.title('test for normality of residuals(q-qplot)')
plt.show
```

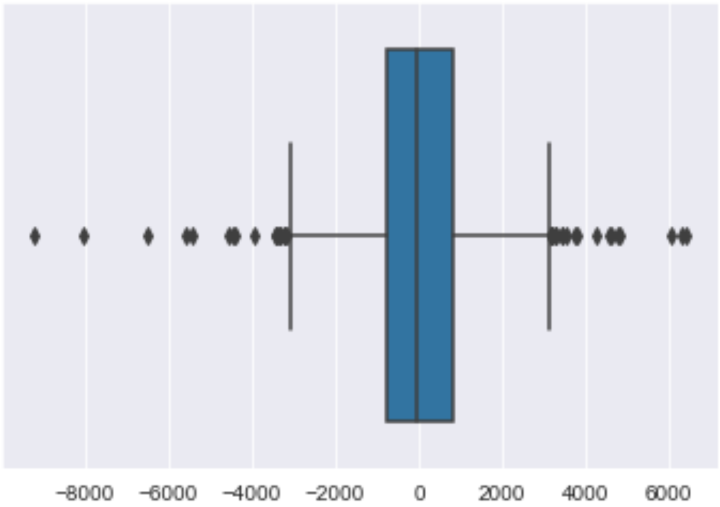
```
/opt/anaconda3/lib/python3.9/site-packages/statsmodels/graphics/gofplots.py:993: UserWarning: marker is redundantly defined by the 'marker' keyword argument and the fmt string "bo" (-> marker='o'). The keyword argument will take precedence.
  ax.plot(x, y, fmt, **plot_style)
```

Out[30]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```

In [31]:
```
sns.boxplot(m3.resid)
```

```
/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:
36: FutureWarning: Pass the following variable as a keyword arg: x
. From version 0.12, the only valid positional argument will be `d
ata`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  warnings.warn(
```

Out[31]: <AxesSubplot:>



In [32]:
```
list(np.where(m3.resid<-6000))
```

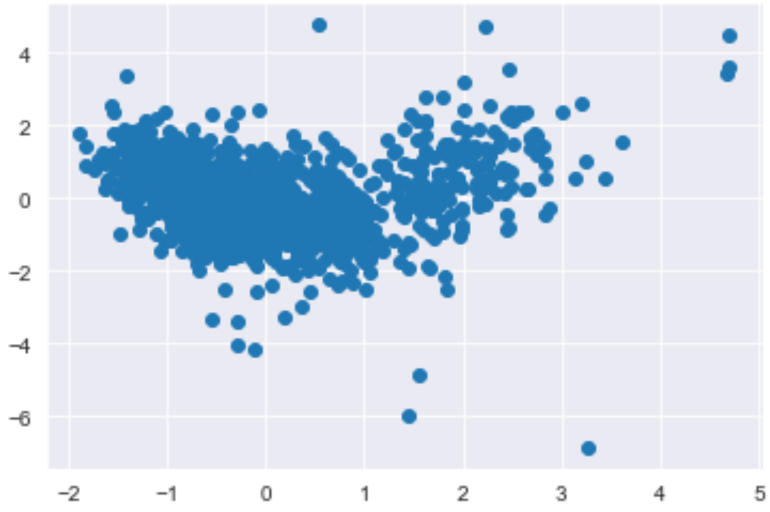
Out[32]: [array([220, 600, 959])]

residual plot for homoscedasticity

In [33]:
```
def get_standardized_values(vals):
    return(vals - vals.mean())/vals.std()
```

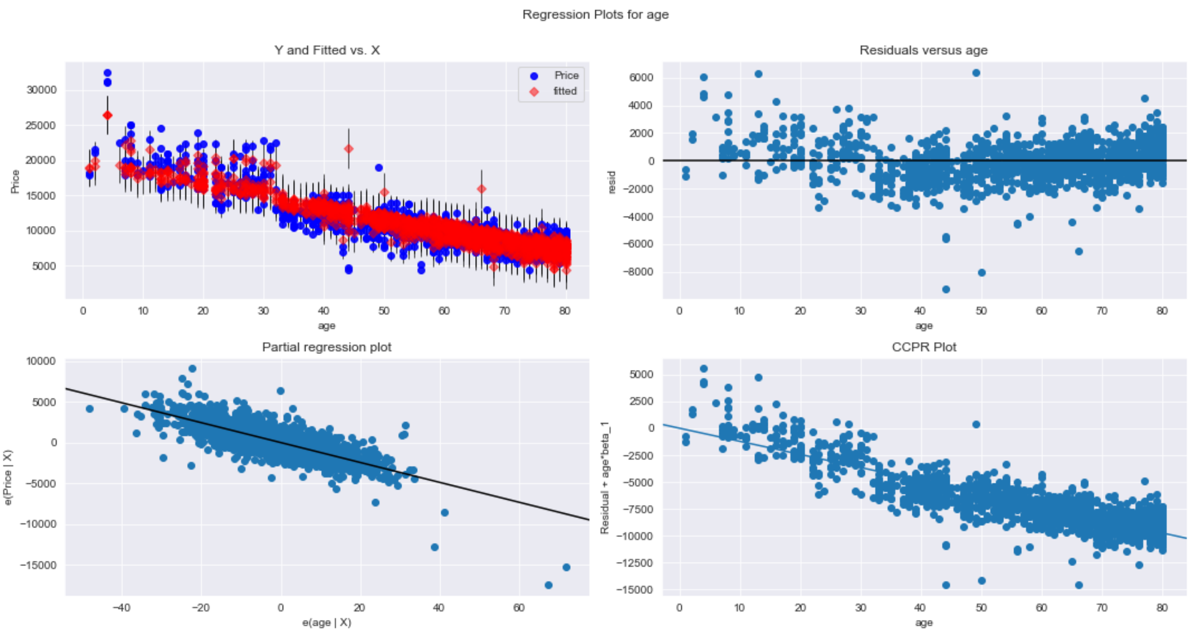
In [34]:
```
plt.scatter(get_standardized_values(m3.fittedvalues),
            get_standardized_values(m3.resid))
```

Out[34]: <matplotlib.collections.PathCollection at 0x7ffd79bd3490>



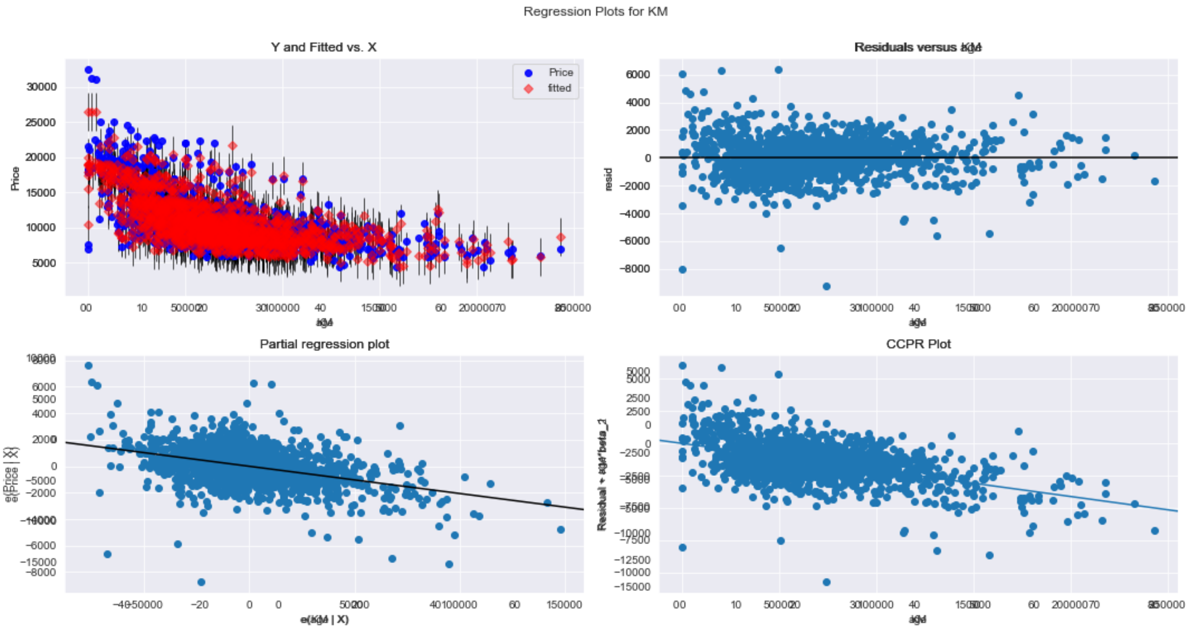
residual vs regressor

In [35]:
```
fig = plt.figure(figsize=(15,8))
fig = sm.graphics.plot_regress_exog(m3,'age',fig=fig)
plt.show()
```

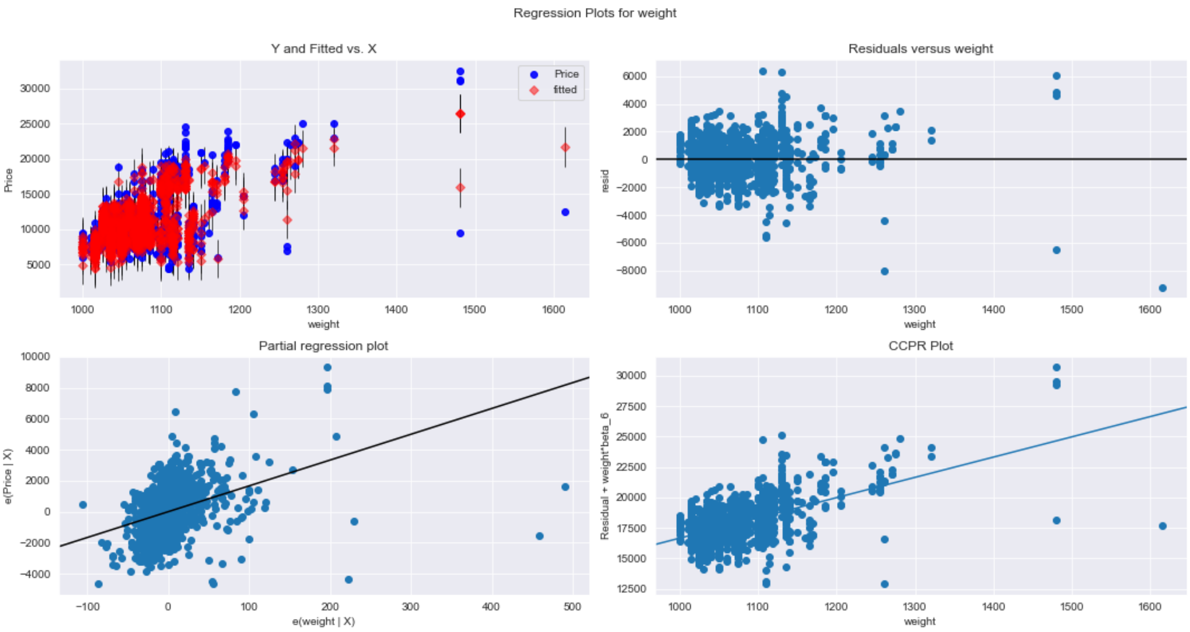


In [36]:
```
fig = sm.graphics.plot_regress_exog(m3,'KM',fig=fig)
fig
```

Out[36]:

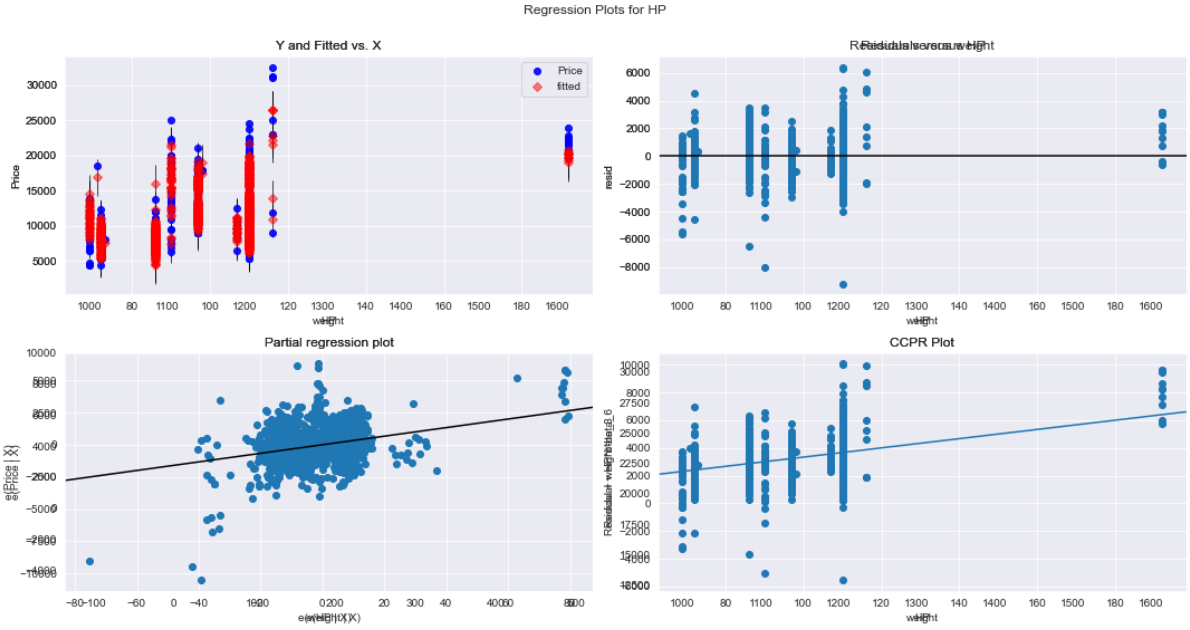


In [37]:
```
fig = plt.figure(figsize=(15,8))
fig = sm.graphics.plot_regress_exog(m3,'weight',fig=fig)
plt.show()
```



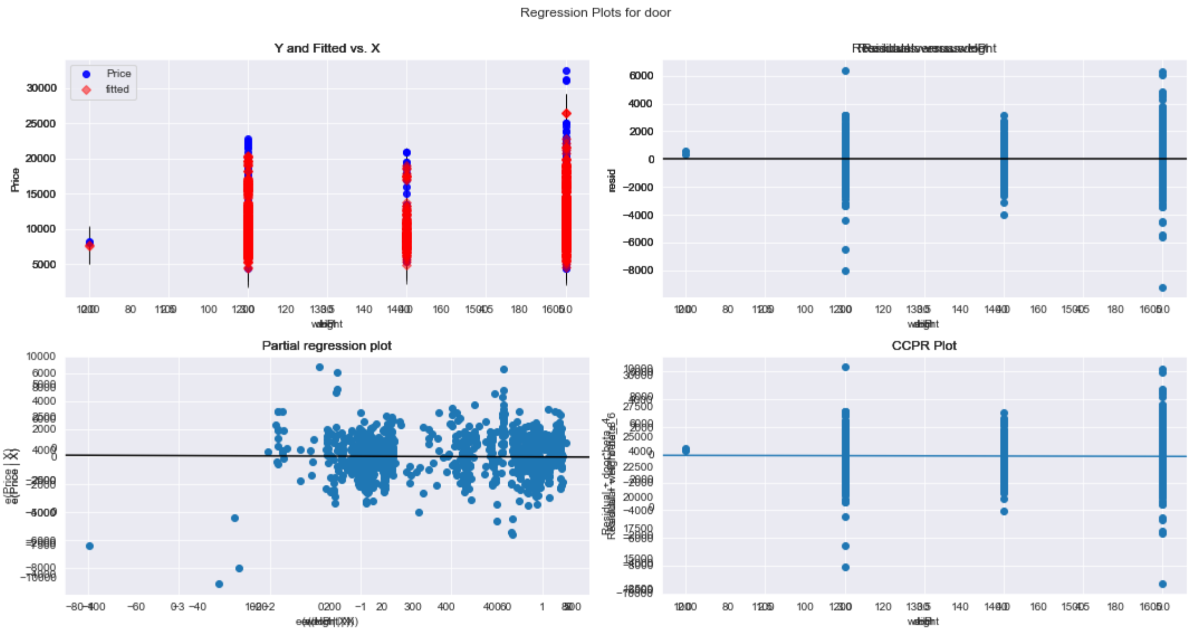
In [38]:
```
sm.graphics.plot_regress_exog(m3,'HP',fig=fig)
```

Out[38]:



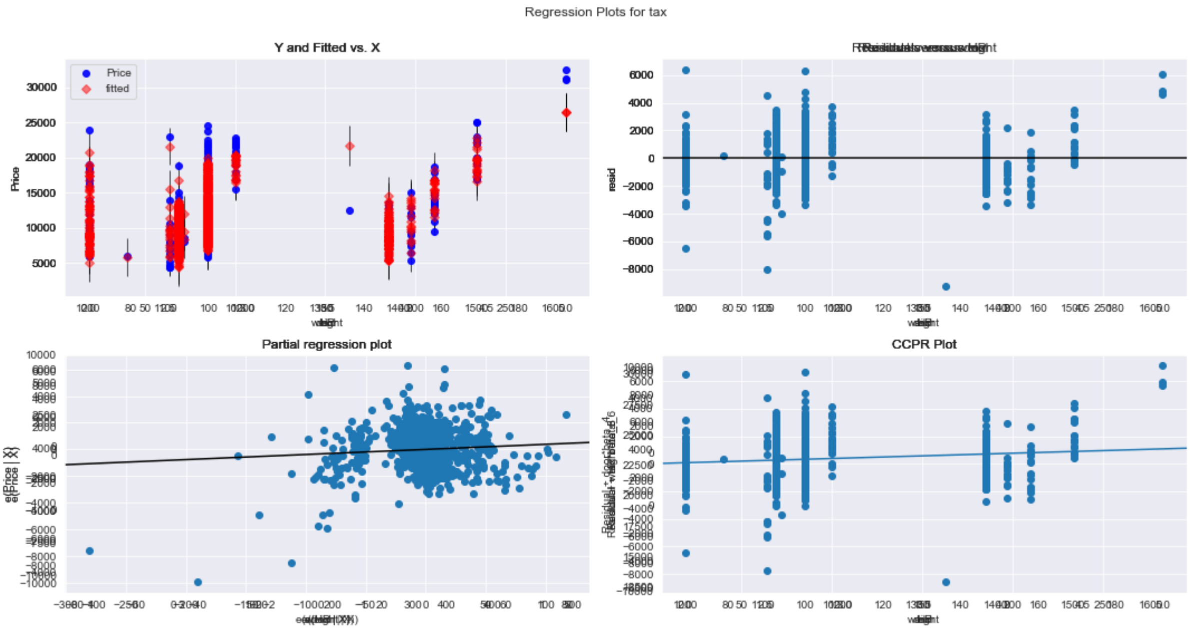
In [39]:
```
sm.graphics.plot_regress_exog(m3,'door',fig=fig)
```

Out[39]:



In [40]:
```
sm.graphics.plot_regress_exog(m3,'tax',fig=fig)
```

Out[40]:



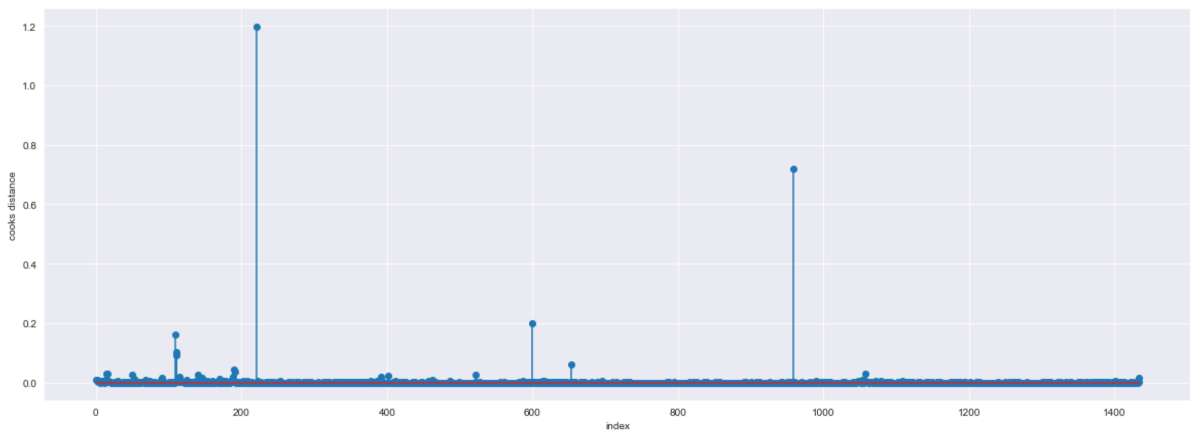
In [41]:
```
model_influence=m3.get_influence()
(c, _) = model_influence.cooks_distance
```

In [42]:
```
c
```

Out[42]:
```
array([9.38906054e-03, 5.17943805e-03, 7.10668449e-03, ...,
       2.10208718e-06, 8.65451174e-04, 1.37001373e-02])
```

In [43]:
```
fig=plt.subplots(figsize=(20,7))
plt.stem(np.arange(len(data4)),np.round(c,3))
plt.xlabel("index")
plt.ylabel("cooks distance")
```

Out[43]:
```
Text(0, 0.5, 'cooks distance')
```



In [44]:
```
np.argmax(c),np.max(c)
```

Out[44]:
```
(220, 1.1987544668622254)
```

In [45]:
```
data_new=data4.drop(data4.index[220],axis=0)
data_new.head()
```

Out[45]:

	Price	age	KM	HP	door	tax	weight
0	13500	23	46986	90	3	210	1165
1	13750	23	72937	90	3	210	1165
2	13950	24	41711	90	3	210	1165
3	14950	26	48000	90	3	210	1165
4	13750	30	38500	90	3	210	1170

In [46]:
```
m4 = smf.ols("Price~age+KM+HP+door+tax+weight",data=data_new).fit()
m4.summary()
```

Out[46]:

OLS Regression Results

Dep. Variable:	Price	**R-squared:**	0.867
Model:	OLS	**Adj. R-squared:**	0.866
Method:	Least Squares	**F-statistic:**	1546.
Date:	Wed, 07 Dec 2022	**Prob (F-statistic):**	0.00
Time:	01:16:50	**Log-Likelihood:**	-12336.
No. Observations:	1434	**AIC:**	2.469e+04
Df Residuals:	1427	**BIC:**	2.472e+04
Df Model:	6		
Covariance Type:	nonrobust		

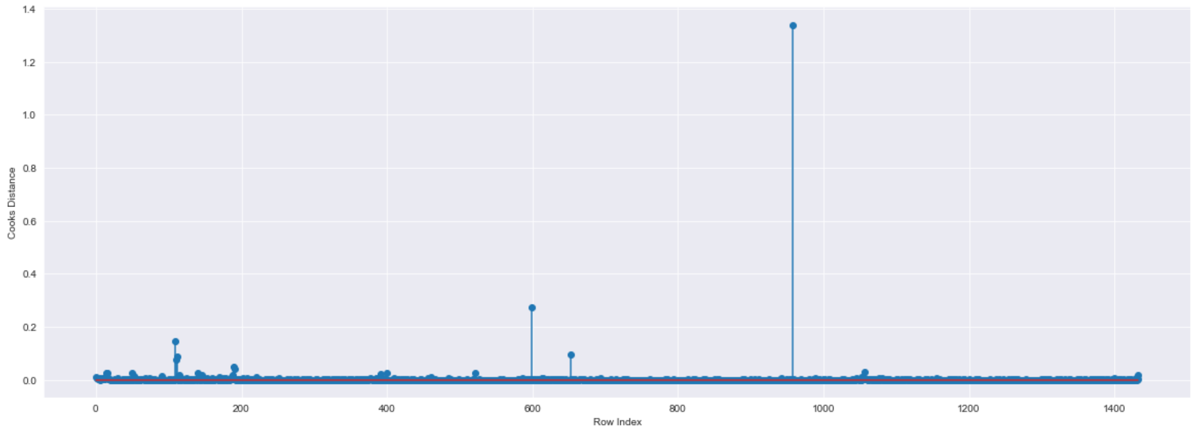
	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-5450.5835	1109.915	-4.911	0.000	-7627.823	-3273.344
age	-119.1731	2.599	-45.861	0.000	-124.271	-114.076
KM	-0.0208	0.001	-16.937	0.000	-0.023	-0.018
HP	31.5845	2.690	11.741	0.000	26.308	36.861
door	-46.5493	38.767	-1.201	0.230	-122.595	29.497
tax	1.9212	1.304	1.473	0.141	-0.637	4.479
weight	19.6687	1.114	17.648	0.000	17.482	21.855

Omnibus:	131.540	**Durbin-Watson:**	1.580
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	729.534
Skew:	-0.206	**Prob(JB):**	3.83e-159
Kurtosis:	6.470	**Cond. No.**	2.49e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.49e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

In [51]:
```
model_influence_1 = m4.get_influence()
(c1, _) = model_influence_1.cooks_distance
```

In [52]:
```
fig = plt.subplots(figsize = (20,7))
plt.stem(np.arange(len(data_new)), np.round(c1,3))
plt.xlabel("Row Index")
plt.ylabel("Cooks Distance")
plt.show()
```



In [54]:
```
np.argmax(c1), np.max(c1)
```

Out[54]: (958, 1.3402996914231093)

In [55]:
```
dataa = data_new.drop(data_new.index[958],axis=0).reset_index()
```

In [56]:
```
dataa
```

Out[56]:

	index	Price	age	KM	HP	door	tax	weight
0	0	13500	23	46986	90	3	210	1165
1	1	13750	23	72937	90	3	210	1165
2	2	13950	24	41711	90	3	210	1165
3	3	14950	26	48000	90	3	210	1165
4	4	13750	30	38500	90	3	210	1170
...	...	...	...	...	...	...	...	...
1428	1431	7500	69	20544	86	3	69	1025
1429	1432	10845	72	19000	86	3	69	1015
1430	1433	8500	71	17016	86	3	69	1015
1431	1434	7250	70	16916	86	3	69	1015
1432	1435	6950	76	1	110	5	19	1114

1433 rows × 8 columns

In [57]:
```
dataa1 = data_new.drop(data_new.index[958],axis=0).reset_index()
```

In [59]:
```
dataa1.drop(['index'],axis = 1)
```

Out[59]:

	Price	age	KM	HP	door	tax	weight
0	13500	23	46986	90	3	210	1165
1	13750	23	72937	90	3	210	1165
2	13950	24	41711	90	3	210	1165
3	14950	26	48000	90	3	210	1165
4	13750	30	38500	90	3	210	1170
...	...	...	...	...	...	...	...
1428	7500	69	20544	86	3	69	1025
1429	10845	72	19000	86	3	69	1015
1430	8500	71	17016	86	3	69	1015
1431	7250	70	16916	86	3	69	1015
1432	6950	76	1	110	5	19	1114

1433 rows × 7 columns

In [60]:
```
m5 = smf.ols("Price~age+KM+HP+door+tax+weight",data=dataa1).fit()
m5.summary()
```

Out[60]:

OLS Regression Results

Dep. Variable:	Price	**R-squared:**	0.871
Model:	OLS	**Adj. R-squared:**	0.870
Method:	Least Squares	**F-statistic:**	1602.
Date:	Wed, 07 Dec 2022	**Prob (F-statistic):**	0.00
Time:	01:36:40	**Log-Likelihood:**	-12305.
No. Observations:	1433	**AIC:**	2.462e+04
Df Residuals:	1426	**BIC:**	2.466e+04
Df Model:	6		
Covariance Type:	nonrobust		

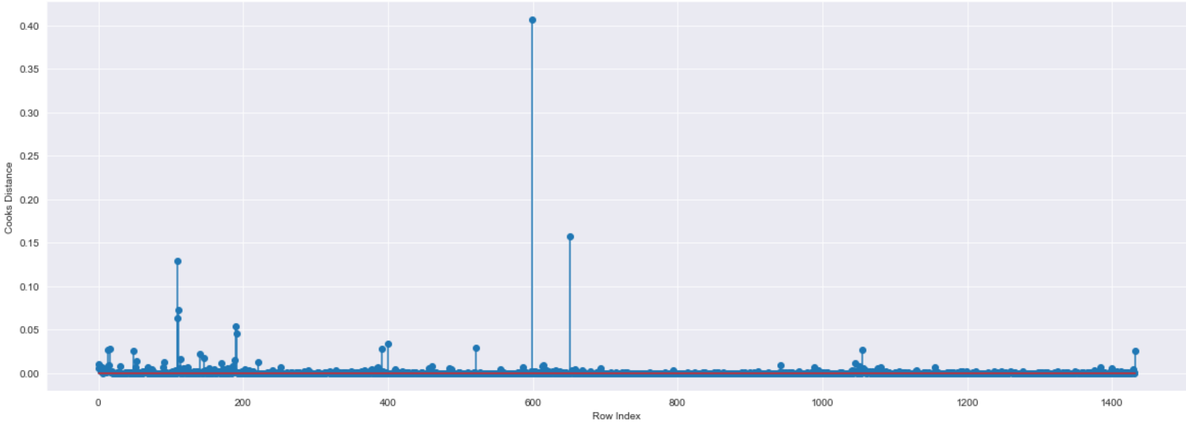
	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-8477.4104	1181.676	-7.174	0.000	-1.08e+04	-6159.400
age	-116.1584	2.598	-44.713	0.000	-121.254	-111.062
KM	-0.0211	0.001	-17.446	0.000	-0.023	-0.019
HP	28.3392	2.692	10.525	0.000	23.058	33.621
door	-82.8874	38.556	-2.150	0.032	-158.519	-7.255
tax	-0.8966	1.351	-0.664	0.507	-3.546	1.753
weight	23.0339	1.206	19.103	0.000	20.669	25.399

Omnibus:	135.138	**Durbin-Watson:**	1.631
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	741.678
Skew:	-0.235	**Prob(JB):**	8.84e-162
Kurtosis:	6.493	**Cond. No.**	2.69e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.69e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

In [61]:
```
model_influence_2 = m5.get_influence()
(c2, _) = model_influence_2.cooks_distance
```

In [63]:
```
fig = plt.subplots(figsize = (20,7))
plt.stem(np.arange(len(dataa1)), np.round(c2,3))
plt.xlabel("Row Index")
plt.ylabel("Cooks Distance")
plt.show()
```



In [64]:
```
np.argmax(c2), np.max(c2)
```

Out[64]: (599, 0.40743303734736 79)

In [65]:
```
data.shape
```

Out[65]: (1436, 38)

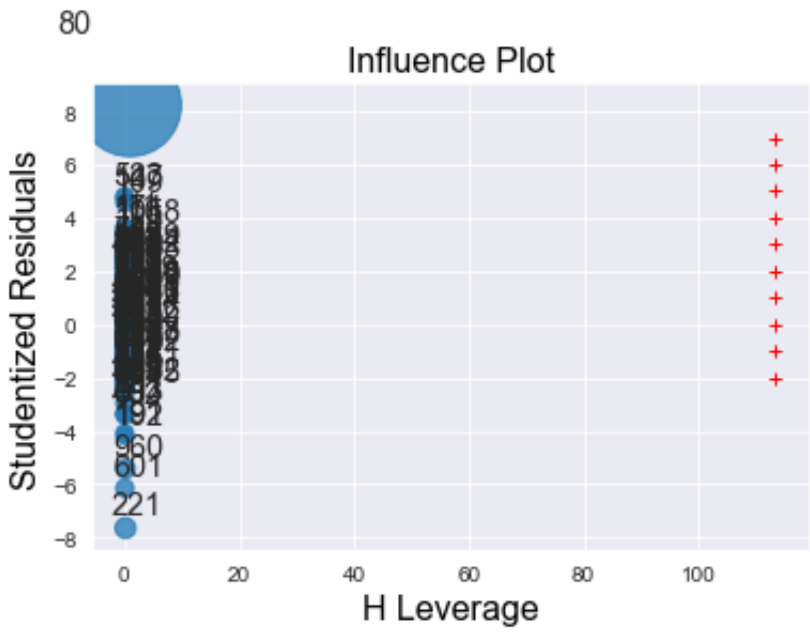
In [66]:
```
k= data.shape[0]
n = data.shape[1]
lev_cutoff = 3*((k+1)/n)
lev_cutoff
```

Out[66]: 113.44736842105263

In [67]:
```
from statsmodels.graphics.regressionplots import influence_plot
```

In [73]:
```
influence_plot(model, aplha = 0.5)

y= [i for i in range (-2,8)]
x= [lev_cutoff for i in range(10)]
plt.plot(x,y,'r+')
plt.show()
```



In [74]:
```
final_model = smf.ols("Price~age+KM+HP+door+tax+weight",data=dataa1
```

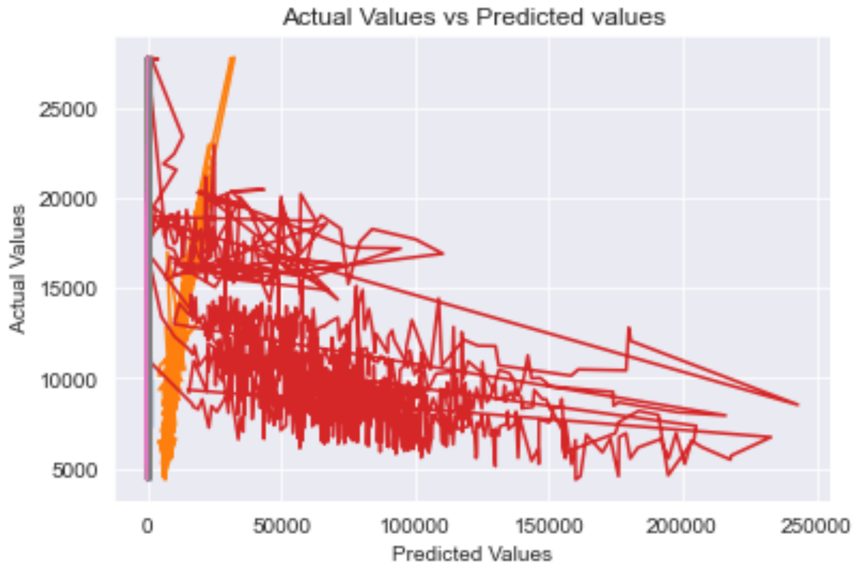
In [75]:
```
final_model.rsquared , final_model.aic
```

Out[75]:
```
(0.8707773883293434, 24624.807746446797)
```

In [76]:
```
pred_y = final_model.predict(dataa1)
pred_y
```

Out[76]:
```
0       16807.692483
1       16260.176738
2       16802.826307
3       16437.823729
4       16288.791032
            ...
1428     8810.603810
1429     8264.364896
1430     8422.381886
1431     8540.650133
1432    11040.126985
Length: 1433, dtype: float64
```

In [77]:
```
x1 = dataa1
y1 = pred_y
plt.title('Actual Values vs Predicted values')
plt.xlabel("Predicted Values")
plt.ylabel(" Actual Values")
plt.plot(x1,y1)
plt.show()
```



In [ ]: