import numpy as np
import pandas as pd

 $\textbf{import} \ \texttt{matplotlib.pyplot} \ \textbf{as} \ \texttt{plt}$

import seaborn as sns

from statsmodels.graphics.regressionplots import influence_plot

import statsmodels.formula.api as smf

In [7]:

cars.head()

Out[8]:

	ld	Model	Price	Age_08_04	Mfg_Month	Mfg_Year	KM	Fuel_Type	HP	Met_Color	 Central_Lock	Powered_Windows	Power_Steer
0	1	TOYOTA Corolla 2.0 D4D HATCHB TERRA 2/3- Doors	13500	23	10	2002	46986	Diesel	90	1	 1	1	
1	2	TOYOTA Corolla 2.0 D4D HATCHB TERRA 2/3- Doors	13750	23	10	2002	72937	Diesel	90	1	 1	0	
2	3	TOYOTA Corolla 2.0 D4D HATCHB TERRA 2/3- Doors	13950	24	9	2002	41711	Diesel	90	1	 0	0	
3	4	TOYOTA Corolla 2.0 D4D HATCHB TERRA 2/3- Doors	14950	26	7	2002	48000	Diesel	90	0	 0	0	
4	5	TOYOTA Corolla 2.0 D4D HATCHB SOL 2/3- Doors	13750	30	3	2002	38500	Diesel	90	0	 1	1	

5 rows × 38 columns

<u>▼</u>| In [9]:

cars_cl = cars.drop(cars.iloc[:,:2], axis=1)

In [10]:

cars_cl.head()

Out[10]:

	Price	Age_08_04	Mfg_Month	Mfg_Year	KM	Fuel_Type	HP	Met_Color	Color	Automatic	 Central_Lock	Powered_Windows	Power_
0	13500	23	10	2002	46986	Diesel	90	1	Blue	0	 1	1	
1	13750	23	10	2002	72937	Diesel	90	1	Silver	0	 1	0	
2	13950	24	9	2002	41711	Diesel	90	1	Blue	0	 0	0	
3	14950	26	7	2002	48000	Diesel	90	0	Black	0	 0	0	
4	13750	30	3	2002	38500	Diesel	90	0	Black	0	 1	1	

5 rows × 36 columns

▶

cars_cl.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1436 entries, 0 to 1435
Data columns (total 36 columns):

# 	Column	Non-Null Count	Dtype
0	Price	1436 non-null	int64
1	Age 08 04	1436 non-null	int64
2	Mfg Month	1436 non-null	int64
3	Mfg Year	1436 non-null	int64
4	KM	1436 non-null	int64
5	Fuel Type	1436 non-null	object
6	HP - 11	1436 non-null	int64
7	Met Color	1436 non-null	int64
8	Color	1436 non-null	object
9	Automatic	1436 non-null	int64
10	CC	1436 non-null	int64
11	Doors	1436 non-null	int64
12	Cylinders	1436 non-null	int64
13	Gears	1436 non-null	int64
14	Quarterly_Tax	1436 non-null	int64
15	Weight	1436 non-null	int64
16	Mfr Guarantee	1436 non-null	int64
17	BOVAG_Guarantee	1436 non-null	int64
18	Guarantee_Period	1436 non-null	int64
19	ABS	1436 non-null	int64
20	Airbag_1	1436 non-null	int64
21	Airbag_2	1436 non-null	int64
22	Airco	1436 non-null	int64
23	Automatic_airco	1436 non-null	int64
24	Boardcomputer	1436 non-null	int64
25	CD_Player	1436 non-null	int64
26	Central_Lock	1436 non-null	int64
27	Powered_Windows	1436 non-null	int64
28	Power_Steering	1436 non-null	int64
29	Radio	1436 non-null	int64
30	Mistlamps	1436 non-null	int64
31	Sport_Model	1436 non-null	int64
32	Backseat_Divider	1436 non-null	int64
33	Metallic_Rim	1436 non-null	int64
34	Radio_cassette	1436 non-null	int64
35	Tow_Bar	1436 non-null	int64
dtype	es: int64(34), obje	ect(2)	

dtypes: int64(34), object(2) memory usage: 404.0+ KB

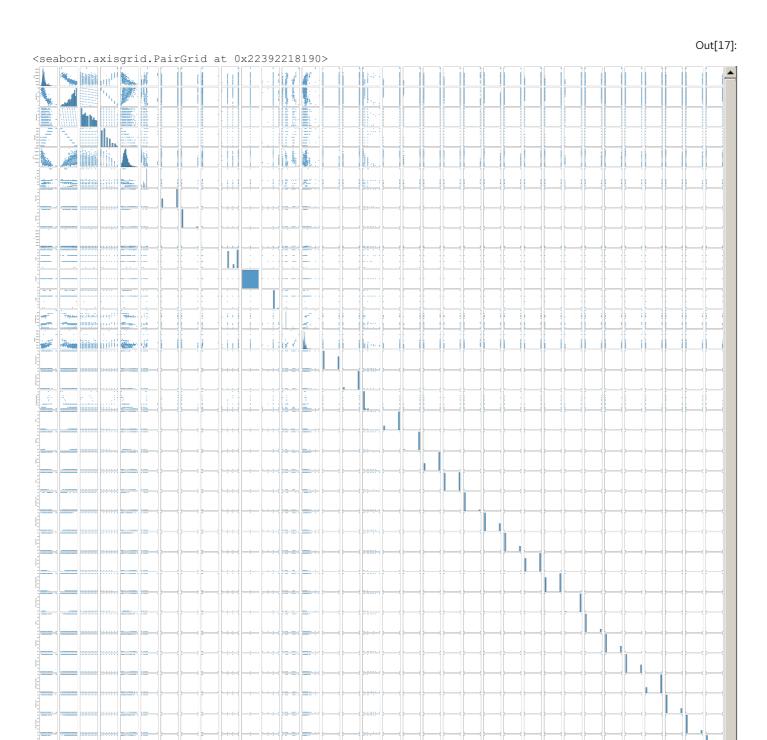
cars_cl.isnull().sum()

In [12]:

Price	0
Age_08_04	0
Mfg_Month	0
Mfg_Year	0
KM	0
Fuel_Type	0
HP - 11	0
Met_Color	0
Color	0
Automatic	0
cc	0
Doors	0
Cylinders	0
Gears	0
Quarterly_Tax	0
Weight	0
Mfr_Guarantee	0
BOVAG_Guarantee	0
Guarantee_Period	0
ABS	0
Airbag_1	0
Airbag 2	0
Airco	0
Automatic_airco	0
Boardcomputer	0
CD_Player	0
Central Lock	0
Powered_Windows	0
Power_Steering	0
Radio	0
Mistlamps	0
Sport_Model	0
Backseat_Divider	0
Metallic_Rim	0
Radio_cassette	0
Tow Bar	0
dtype: int64	Ü
150. 111001	
1 -1	
cars_cl.shape	
(1436, 36)	

cars_cl.dtypes

```
Out[14]:
Price
                         int64
Age_08_04
Mfg_Month
                        int64
                        int64
                         int64
Mfg_Year
KM
                         int64
Fuel_Type
                   object
ΗP
                         int64
                     int64
int64
object
Met_Color
Color
                    int64
int64
int64
Automatic
Doors
                        int64
Cylinders
Gears int64
Quarterly_Tax int64
Weight int64
Mfr_Guarantee int64
BOVAG_Guarantee int64
Guarantee Period int64
ABS
                        int64
                        int64
Airbag_1
Airbag_2
                          int64
                         int64
Airco
Automatic_airco int64
Boardcomputer int64
                         int64
CD_Player
CD_Player int64
Central_Lock int64
Powered_Windows int64
Power_Steering int64
Padio int64
Radio
                         int64
Mistlamps int64
Sport_Model int64
Backseat_Divider int64
Metallic_Rim int64
Radio_cassette int64
Tow_Bar int64
Mistlamps
                        int64
Tow Bar
                        int64
dtype: object
                                                                                                                             In [15]:
cars cl.columns
                                                                                                                            Out[15]:
'Quarterly_Tax', 'Weight', 'Mfr_Guarantee', 'BOVAG_Guarantee', 'Guarantee_Period', 'ABS', 'Airbag_1', 'Airbag_2', 'Airco',
         'Automatic_airco', 'Boardcomputer', 'CD_Player', 'Central_Lock', 'Powered_Windows', 'Power_Steering', 'Radio', 'Mistlamps',
         'Sport_Model', 'Backseat_Divider', 'Metallic_Rim', 'Radio_cassette',
         'Tow Bar'],
        dtype='object')
                                                                                                                             In [16]:
 model = smf.ols('Price~Age 08 04+KM+HP+Doors+Cylinders+Gears+Weight',data=cars cl).fit()
                                                                                                                             In [17]:
 sns.pairplot(cars cl)
```



model.params

Out[18]:

In [18]:

Intercept -410.845504
Age_08_04 -122.242218
KM -0.019994
HP 28.350149
Doors -9.680229
Cylinders -1643.382016
Gears 622.282925
Weight 18.609651

dtype: float64

In [19]:

model.pvalues

	Out[19]
Intercept 1.181900e-07	
Age_08_04 4.387432e-290	
KM 2.238900e-56	
HP 2.231791e-26	
Doors 8.087723e-01	
Cylinders 1.181900e-07	
Gears 1.653931e-03	
Weight 7.856458e-96	
dtype: float64	
	In [20]:
model.tvalues	
	Out[20]:
Intercept -5.323309	
Age_08_04 -46.728942	
KM -16.542560	
HP 10.842418	
Doors -0.242055	
Cylinders -5.323309	
Gears 3.152234	
Weight 22.446903	
dtype: float64	
	In [21]:
model.rsquared	
	0.45211
0.8628024511073656	Out[21]:
0.8628024511073656	1. [22]
	In [22]:
<pre>model.rsquared_adj</pre>	
	Out[22]:
0.8622263942190831	Out[22].
0.0022203742130031	In [23]:
	III [23].

model.summary()

Out[19]:

In [27]:

OLS Regression Results											
Dep. Var	iable:		Pric	ce	R-squa	red:	0.863				
M	lodel:		OL	.S Adj.	Adj. R-squared:			862			
Me	thod:	Le	ast Square	es.	F-statis	tic:	14	498.			
ı	Date:	Wed, 2	23 Jun 202	1	Prob (F- statistic):			0.00			
	Time:		14:07:0	2 Log	-Likeliho	od:	-12381.				
No. Observa	tions:		143	6		AIC:	2.478e	+04			
Df Resid	duals:		142	9	1	BIC:	2.481e	+04			
Df M	lodel:			6							
Covariance	Type:		nonrobus	st							
	/1										
		coef	std err	t	P> t		[0.025	0.975]			
Intercept	-41	0.8455	77.179	-5.323	0.000	-5	62.241	-259.450			
Age_08_04	-12	2.2422	2.616	-46.729	0.000	-1	27.374	-117.111			
KM	-(0.0200	0.001	-16.543	0.000		-0.022	-0.018			
HP	2	8.3501	2.615	10.842	0.000		23.221	33.479			
Doors	-!	9.6802	39.992	-0.242	0.809	-	88.129	68.769			
Cylinders	-164	3.3820	308.714	-5.323	0.000	-22	48.964	-1037.800			
Gears	62	2.2829	197.410	3.152	0.002	2	35.038	1009.528			
Weight	18	8.6097	0.829	22.447	0.000		16.983	20.236			
Omnib	ous: 1	199.596	Durbin-	-Watson:	1.5	64					
Prob(Omnibu	ıs):	0.000	Jarque-E	Bera (JB):	ra (JB): 1569.510						
Ske	ew:	-0.381	1	Prob(JB):	0.	.00					
Kurtosis:		8.065	c	Cond. No.	ond. No. 4.98e+20						

Notes:

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

[2] The smallest eigenvalue is 3.53e-29. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

In [24]:
model_test1 = smf.ols ('Price~Doors', data=cars_cl).fit()
In [25]:
model_test1.pvalues
Out[25]:

Out[25]
Intercept 1.094732e-73
Doors 1.461237e-12

dtype: float64
In [26]:

model_test1.rsquared

Out[26]: 0.03434555943109807

model_test1.rsquared_adj
Out[27]:

0.03367216023962749 In [28]:

cars_cl.columns

```
Out[28]:
Index(['Price', 'Age_08_04', 'Mfg_Month', 'Mfg_Year', 'KM', 'Fuel_Type', 'HP',
               'Met Color', 'Color', 'Automatic', 'cc', 'Doors', 'Cylinders', 'Gears',
               'Quarterly_Tax', 'Weight', 'Mfr_Guarantee', 'BOVAG_Guarantee', 'Guarantee_Period', 'ABS', 'Airbag_1', 'Airbag_2', 'Airco',
              'Automatic_airco', 'Boardcomputer', 'CD_Player', 'Central_Lock',
'Powered_Windows', 'Power_Steering', 'Radio', 'Mistlamps',
'Sport_Model', 'Backseat_Divider', 'Metallic_Rim', 'Radio_cassette',
               'Tow Bar'],
             dtype='object')
                                                                                                                                                                                                                    In [29]:
rsq 1 = smf.ols ('Age 08 04~KM+HP+Doors+Cylinders+Gears+Weight', data=cars cl).fit().rsquared
vif 1 = 1/(1-rsq 1)
rsq_2 = smf.ols ('KM~Age_08_04+HP+Doors+Cylinders+Gears+Weight',data=cars cl).fit().rsquared
vif 2 = 1/(1-rsq 2)
 rsq 3 = smf.ols ('HP~Age 08 04+KM+Doors+Cylinders+Gears+Weight',data=cars cl).fit().rsquared
vif 3 = 1/(1-rsq 3)
rsq 4 = smf.ols ('Doors~Age 08 04+KM+HP+Cylinders+Gears+Weight',data=cars cl).fit().rsquared
vif 4 = 1/(1-rsq 4)
 rsq 5 = smf.ols ('Cylinders~Age 08 04+KM+HP+Doors+Gears+Weight',data=cars cl).fit().rsquared
vif 5 = 1/(1-rsq 5)
 rsq 6 = smf.ols ('Gears~Age 08 04+KM+HP+Doors+Cylinders+Weight',data=cars cl).fit().rsquared
vif_6 = 1/(1-rsq_6)
 rsq_7 = smf.ols ('Weight~Age_08_04+KM+HP+Doors+Cylinders+Gears', data=cars_cl).fit().rsquared ('Meight~Age_08_04+KM+HP+Doors+Cylinders+Gears', data=cars_cl).fit().rsquared ('Meight~Age_08_04+KM+HP+Doors+Cylinders+Gears').fit().rsquared ('Meight~Age_08_04+KM+HP+Doors+Cylinders+Gears').fit().rsquared ('Meight~Age_08_04+KM+HP+Doors+Cylinders+Gears').fit().rsquared ('Meight~Age_08_04+KM+HP+Doors+Cylinders+Gears').fit().rsquared ('Meight~Age_08_04+KM+HP+Doors+Cylinders+Gears').fit().rsquared ('Meight~Age_08_04+KM+HP+Doors+Cylinders+Gears').fit().rsquared ('Meight~Age_08_04+KM+HP+Doors+Cylinders+Gears').fit().rsquared ('Meight~Age_08_04+KM+HP+Doors+Cylinders+Gears').fit().rsquared ('Meight~Age_08_04+KM+HP+Doors+Gears').fit().rsquared ('Meight~Age_08_04+KM+HP+Doors+Gears').fit().fit().rsquared ('Meight~Age_08_04+KM+HP+Doors+Gears').fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().fit().f
vif 7 = 1/(1-rsq 7)
 # Storing vif values in a data frame
df1 = {'Variables': ['Age 08 04','KM','HP','Doors','Cylinders','Gears','Weight'],
                  'VIF': [vif 1, vif 2, vif 3, vif 4, vif 5, vif 6, vif 7]}
Vif frame = pd.DataFrame(df1)
Vif frame
C:\Users\acer\anaconda3\lib\site-packages\statsmodels\regression\linear model.py:1715: RuntimeWarning:
divide by zero encountered in double scalars
    return 1 - self.ssr/self.centered tss
                                                                                                                                                                                                                  Out[29]:
                                VIF
         Variables
0 Age_08_04 1.874542
                 KM 1.627039
                 HP 1.214909
             Doors 1.149301
         Cylinders 0.000000
 5
              Gears 1.096501
            Weight 1.508041
 6
                                                                                                                                                                                                                    In [30]:
cars cl.corr()
                                                                                                                                                                                                                  Out[30]:
                                     Price Age_08_04 Mfg_Month Mfg_Year
                                                                                                                                      Met_Color Automatic
                                                                                                                                                                                               Doors ... Central_Lo
                     Price 1.000000
                                                 -0.876590
                                                                     -0.018138
                                                                                    0.885159
                                                                                                                      0.314990
                                                                                                                                         0.108905
                                                                                                                                                          0.033081 0.126389 0.185326 ...
                                                                                                                                                                                                                      0.3434
                                                                                                       0.569960
                                                                                                      0.505672 0.156622
            Age_08_04 0.876590
                                                  1.000000
                                                                     -0.123255
                                                                                                                                        -0.108150
                                                                                                                                                          0.031717
                                                                                                                                                                                                                     -0.2796
                                                                                                                                                                          0.098084 0.148359 ...
                                                                                       0.983661
            Mfg_Month 0.018138
                                                                                                                                                          0.009146 0.037387 0.012069 ...
                                                 -0.123255
                                                                      1.000000
                                                                                                                                         0.030266
                                                                                                                                                                                                                      0.0100
                                                                                      0.057416  0.020630  0.039312
              Mfg_Year 0.885159
                                                 -0.983661
                                                                     -0.057416
                                                                                      1.000000
                                                                                                                      0.164697
                                                                                                                                         0.103310 \quad \hbox{-0.033567} \quad 0.091892 \quad 0.151442 \quad ...
                                                                                                                                                                                                                      0.2794
                                                                                                       0.504974
                                                                                                                                        -0.080503 -0.081854 0.102683 <sub>0.036197</sub> ...
                                                  0.505672
                                                                                                      1.000000
                                                                     -0.020630
                                                                                                                                                                                                                     -0.1251
                                                                                                                      0.333538
                               0.569960
                                                                                       0.504974
                                                                     -0.039312 0.164697 0.333538
```

1.000000

0.2501

HP 0.314990

-0.156622

Met_Color	Price 0.108905	Age_08_04 -0.108150	Mfg_Month 0.030266	Mfg_Year 0.103310	KM 0.080503	HP 0.058712	Met_Color 1.000000	Automatic -0.019335	cc 0.031812	Doors 0.085243	 Central_Lo 0.1533
Automatic	0.033081	0.031717	0.009146	- 0.033567	0.081854	0.013144	-0.019335	1.000000	0.066740	- 0.027654	 -0.0025
сс	0.126389	-0.098084	0.037387	0.091892	0.102683	0.035856	0.031812	0.066740	1.000000	0.079903	 0.0726
Doors	0.185326	-0.148359	-0.012069	0.151442	- 0.036197	0.092424	0.085243	-0.027654	0.079903	1.000000	 0.1320
Cylinders	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	 N
Gears	0.063104	-0.005364	-0.013063	0.007766	0.015023	0.209477	0.018601	-0.098555	0.014629	0.160141	 0.1269
Quarterly_Tax	0.219197	-0.198431	0.031373	0.193934	0.278165	0.298432	0.011326	-0.055371	0.306996	0.109363	 0.0320
Weight	0.581198	-0.470253	-0.002167	0.473478	0.028598	0.089614	0.057929	0.057249	0.335637	0.302618	 0.2346
Mfr_Guarantee	0.197802	-0.164658	-0.005771	0.166697	0.212851	0.140026	0.154850	0.026194	0.057407	0.037689	 0.0399
BOVAG_Guarantee	0.028133	0.006865	-0.003863	0.006206	0.001438	0.022701	0.010783	0.023393	0.081725	0.014311	 -0.0230
Guarantee_Period	0.146627	-0.152563	0.029010	0.148218	0.138942	0.076163	0.009295	-0.002256	0.017683	0.053654	 0.0589
ABS	0.306138	-0.412887	0.072532	0.402215	0.177203	0.057832	0.022298	-0.016128	0.037806	0.063733	 0.0994
Airbag_1	0.093588	-0.105406	0.003756	0.105359	0.018012	0.025137	0.100055	-0.011895	0.022678	0.053828	 0.1202
Airbag_2	0.248974	-0.329017	0.076749	0.317075	0.139275	0.017644	0.038416	0.001171	0.024738	0.021734	 0.0248
Airco	0.429259	-0.403600	0.057088	0.395674	0.133057	0.241134	0.114190	-0.028353	0.119888	0.170544	 0.5405
Automatic_airco	0.588262	-0.426259	-0.049017	0.437718	0.258221	0.244957	0.027977	0.059057	0.162669	0.054809	 0.1957
Boardcomputer	0.601292	-0.719449	0.017715	0.720567	0.353862	0.129715	0.089886	-0.037069	0.009312	0.089606	 0.2031
CD_Player	0.481374	-0.510895	-0.016736	0.517008	0.266826	0.102300	0.198220	-0.010967	0.057787	0.094653	 0.1940
Central_Lock	0.343458	-0.279631	0.010055	0.279490	0.125177	0.250122	0.153307	-0.002502	0.072634	0.132092	 1.0000
Powered_Windows	0.356518	-0.283856	0.025185	0.280996	0.156242	0.265593	0.145147	-0.005864	0.055299	0.107626	 0.8755
Power_Steering	0.064275	-0.069192	-0.055495	0.079676	0.007397	0.048850	0.086544	-0.004469	0.032933	0.059792	 0.1296
Radio	0.041887	0.013791	0.031601	0.019607	0.013661	0.020998	0.072756	-0.014600	0.000361	0.008318	 -0.0112
Mistlamps	0.222083	-0.126895	-0.033504	0.133737	0.074327	0.210571	0.023821	0.003077	0.017326	0.064705	 0.4874
Sport_Model	0.164121	-0.110988	0.052789	0.102080	0.044784	0.006027	0.003779	0.013175	0.035195	0.129881	 -0.0031
Backseat_Divider	0.102569	-0.116751	0.023245	0.113237	0.045658	0.010908	0.037741	-0.018876	0.055711	0.022542	 0.0584
Metallic_Rim	0.108564	-0.040045	0.023506	0.036022	0.013599	0.206784	0.053829	-0.078095	0.003236	0.039555	 0.2813
Radio_cassette	0.043179	0.012857	0.032576	0.018844	0.015770	0.019919	0.071530	-0.014150	0.000470	0.008265	 -0.0169
Tow_Bar	0.172369	0.188720	-0.042170	0.182206	0.084153	0.068271	0.148536	0.018786	0.002725	0.102292	 -0.0077

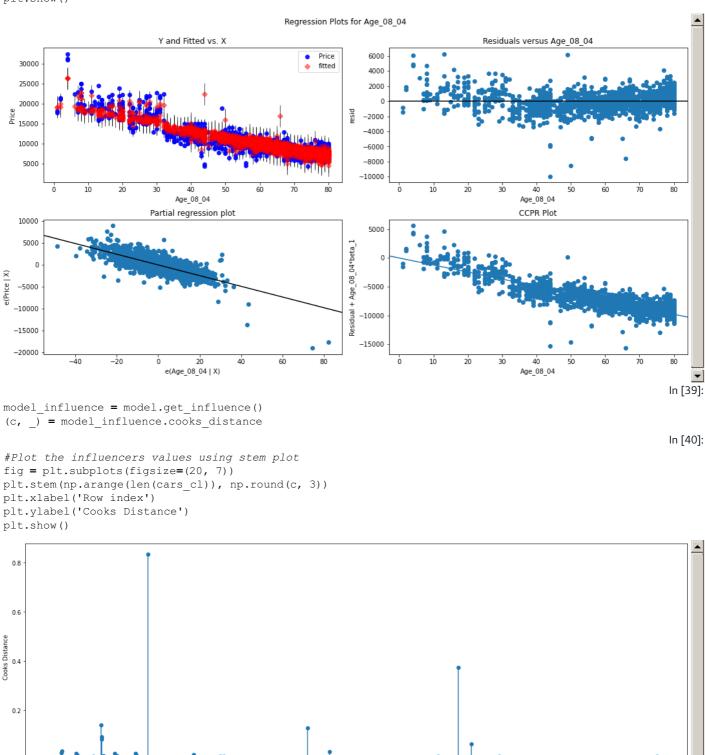
34 rows × 34 columns

In [32]:

```
qqplot=sm.qqplot(model.resid,line='q')
     6000
     4000
     2000
Sample Quantiles
        0
    -2000
    -4000
    -6000
    -8000
   -10000
                    -2
                            -1
                                    Ó
                                            1
                            Theoretical Quantiles
                                                                                                                                  In [33]:
qqplot.get_size_inches()
                                                                                                                                 Out[33]:
array([6., 4.])
                                                                                                                                  In [34]:
qqplot.set_size_inches(15,4)
                                                                                                                                  In [35]:
qqplot
                                                                                                                                 Out[35]:
     6000
     4000
     2000
Sample Quantiles
    -2000
    -4000
    -6000
    -8000
  -10000
                                 -2
                                                                Theoretical Quantiles
                                                                                                                                  In [36]:
def get_standardized_values( vals ):
     return (vals - vals.mean())/vals.std()
                                                                                                                                  In [37]:
plt.scatter(get standardized values(model.fittedvalues),
                {\tt get\_standardized\_values\,(model.resid)\,)}
plt.title('Residual Plot')
plt.xlabel('Standardized Fitted values')
plt.ylabel('Standardized residual values')
plt.show()
                          Residual Plot
Standardized residual values
    2
    0
   -2
   -4
   -6
   -8
       -2
                      Standardized Fitted values
                                                                                                                                  In [38]:
```

fig = plt.figure(figsize=(15,8))

fig = sm.graphics.plot_regress_exog(model, "Age_08_04", fig=fig)



1000

1200

#index and value of influencer where c is more than .5 (np.argmax(c), np.max(c))

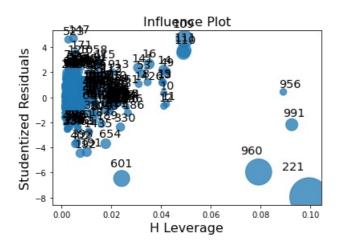
(221, 0.835900750885391)

Out[41]:

In [41]:

In [42]:

from statsmodels.graphics.regressionplots import influence_plot
influence_plot(model)
plt.show()



```
k = cars_cl.shape[1]
n = cars_cl.shape[0]
leverage_cutoff = 3*((k + 1)/n)
```



In []: