In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
df = pd.read_csv('50_startups.csv')
df.head()
```

Out[2]:

	R&D Spend	Administration	Marketing Spend	State	Profit
0	165349.20	136897.80	471784.10	New York	192261.83
1	162597.70	151377.59	443898.53	California	191792.06
2	153441.51	101145.55	407934.54	Florida	191050.39
3	144372.41	118671.85	383199.62	New York	182901.99
4	142107.34	91391.77	366168.42	Florida	166187.94

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 5 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   R&D Spend        50 non-null     float64
 1   Administration   50 non-null     float64
 2   Marketing Spend  50 non-null     float64
 3   State            50 non-null     object
 4   Profit           50 non-null     float64
dtypes: float64(4), object(1)
memory usage: 2.1+ KB
```

In [4]:
```
df.describe()
```

Out[4]:

	R&D Spend	Administration	Marketing Spend	Profit
count	50.000000	50.000000	50.000000	50.000000
mean	73721.615600	121344.639600	211025.097800	112012.639200
std	45902.256482	28017.802755	122290.310726	40306.180338
min	0.000000	51283.140000	0.000000	14681.400000
25%	39936.370000	103730.875000	129300.132500	90138.902500
50%	73051.080000	122699.795000	212716.240000	107978.190000
75%	101602.800000	144842.180000	299469.085000	139765.977500
max	165349.200000	182645.560000	471784.100000	192261.830000

In [5]:
```
df.corr()
```

Out[5]:

	R&D Spend	Administration	Marketing Spend	Profit
R&D Spend	1.000000	0.241955	0.724248	0.972900
Administration	0.241955	1.000000	-0.032154	0.200717
Marketing Spend	0.724248	-0.032154	1.000000	0.747766
Profit	0.972900	0.200717	0.747766	1.000000

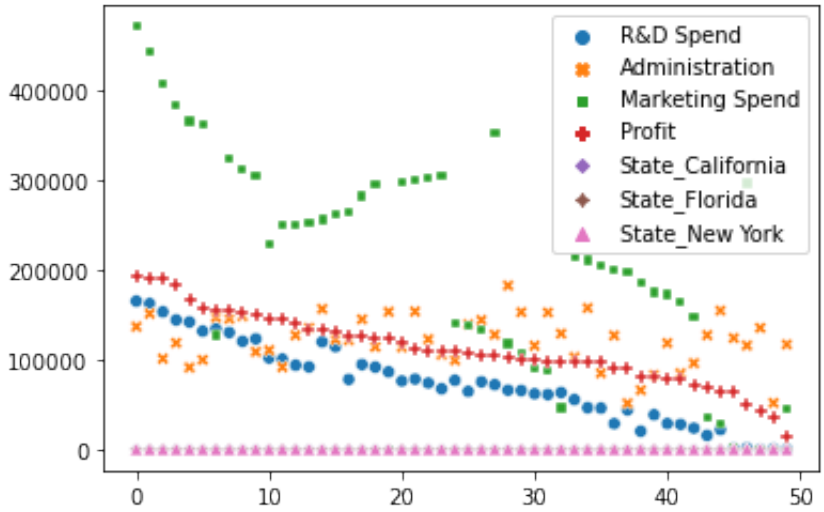
In [6]:
```
df = pd.get_dummies(df,["State"])
df.head()
```

Out[6]:

	R&D Spend	Administration	Marketing Spend	Profit	State_California	State_Florida	State_New Yo
0	165349.20	136897.80	471784.10	192261.83	0	0	
1	162597.70	151377.59	443898.53	191792.06	1	0	
2	153441.51	101145.55	407934.54	191050.39	0	1	
3	144372.41	118671.85	383199.62	182901.99	0	0	
4	142107.34	91391.77	366168.42	166187.94	0	1	

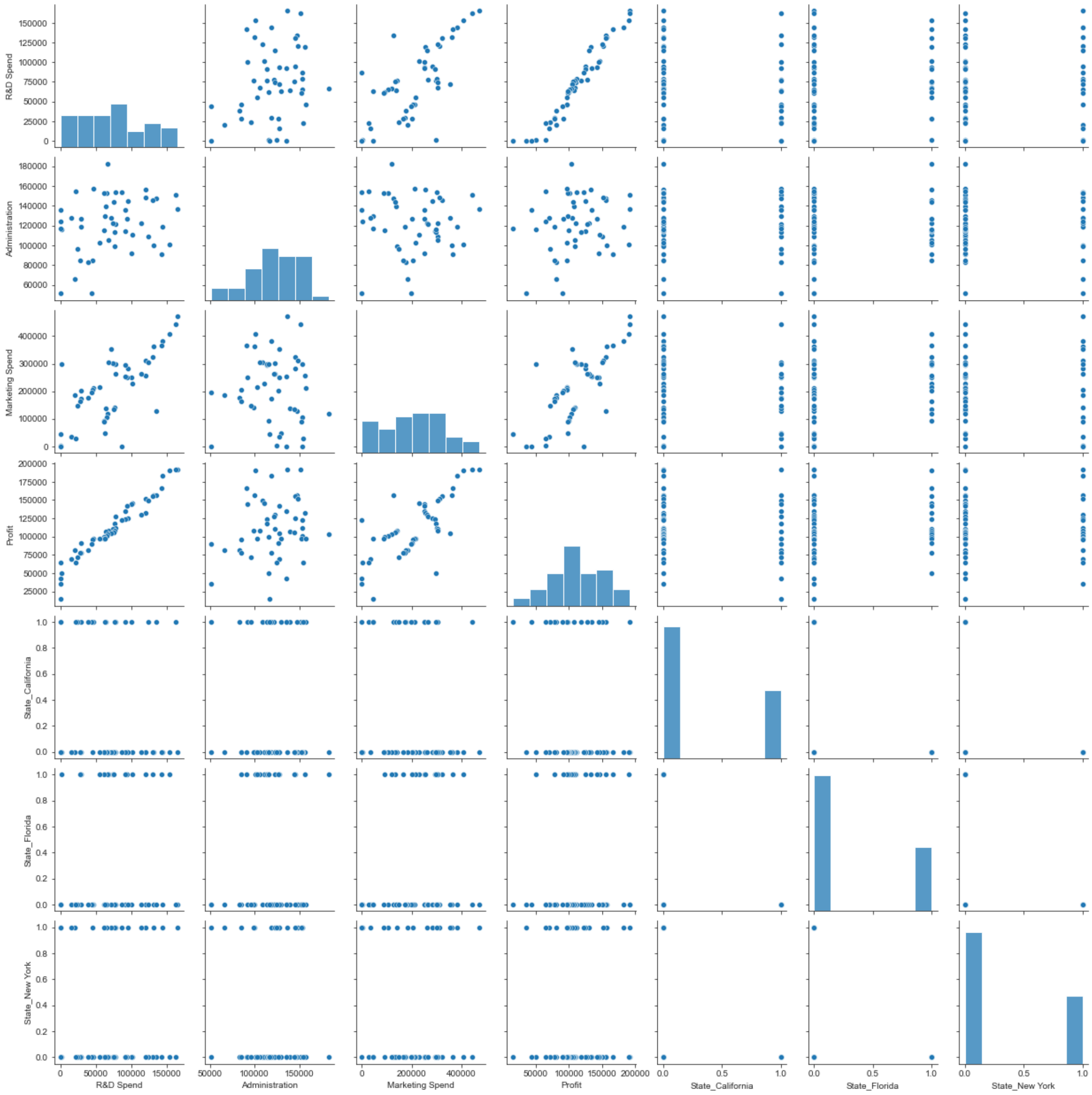
In [7]:
```
sns.scatterplot(data=df)
```

Out[7]: <AxesSubplot:>



In [8]:
```
sns.set_style(style='ticks')
sns.pairplot(df)
```

Out[8]: <seaborn.axisgrid.PairGrid at 0x7fa2d8803d30>



In [9]:
```
df.corr()
```

Out[9]:

	R&D Spend	Administration	Marketing Spend	Profit	State_California	State_Flo
R&D Spend	1.000000	0.241955	0.724248	0.972900	-0.143165	0.105
Administration	0.241955	1.000000	-0.032154	0.200717	-0.015478	0.010
Marketing Spend	0.724248	-0.032154	1.000000	0.747766	-0.168875	0.205
Profit	0.972900	0.200717	0.747766	1.000000	-0.145837	0.116
State_California	-0.143165	-0.015478	-0.168875	-0.145837	1.000000	-0.492
State_Florida	0.105711	0.010493	0.205685	0.116244	-0.492366	1.000
State_New York	0.039068	0.005145	-0.033670	0.031368	-0.515152	-0.492

In [ ]:

we noticed the state_new_York they have very low correletion value so we drop this column

In [10]:
```
df = df.drop("State_New York",axis=1)
df.head()
```

Out[10]:

	R&D Spend	Administration	Marketing Spend	Profit	State_California	State_Florida
0	165349.20	136897.80	471784.10	192261.83	0	0
1	162597.70	151377.59	443898.53	191792.06	1	0
2	153441.51	101145.55	407934.54	191050.39	0	1
3	144372.41	118671.85	383199.62	182901.99	0	0
4	142107.34	91391.77	366168.42	166187.94	0	1

In [11]:
```
df1=df.rename({"R&D Spend":"rd",
               "Administration":"admin",
               "Marketing Spend":"ms","State_California":"sc","
df1.head()
```

Out[11]:

	rd	admin	ms	Profit	sc	sf
0	165349.20	136897.80	471784.10	192261.83	0	0
1	162597.70	151377.59	443898.53	191792.06	1	0
2	153441.51	101145.55	407934.54	191050.39	0	1
3	144372.41	118671.85	383199.62	182901.99	0	0
4	142107.34	91391.77	366168.42	166187.94	0	1

In [12]:
```
df1.corr()
```

Out[12]:

	rd	admin	ms	Profit	sc	sf
rd	1.000000	0.241955	0.724248	0.972900	-0.143165	0.105711
admin	0.241955	1.000000	-0.032154	0.200717	-0.015478	0.010493
ms	0.724248	-0.032154	1.000000	0.747766	-0.168875	0.205685
Profit	0.972900	0.200717	0.747766	1.000000	-0.145837	0.116244
sc	-0.143165	-0.015478	-0.168875	-0.145837	1.000000	-0.492366
sf	0.105711	0.010493	0.205685	0.116244	-0.492366	1.000000

In [13]:
```
import statsmodels.formula.api as smf
model=smf.ols("Profit~rd+admin+ms+sc+sf",data=df1).fit()
model.summary()
```

Out[13]:

OLS Regression Results

Dep. Variable:	Profit	**R-squared:**	0.951
Model:	OLS	**Adj. R-squared:**	0.945
Method:	Least Squares	**F-statistic:**	169.9
Date:	Mon, 05 Dec 2022	**Prob (F-statistic):**	1.34e-27
Time:	16:25:35	**Log-Likelihood:**	-525.38
No. Observations:	50	**AIC:**	1063.
Df Residuals:	44	**BIC:**	1074.
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	5.008e+04	6952.587	7.204	0.000	3.61e+04	6.41e+04
rd	0.8060	0.046	17.369	0.000	0.712	0.900
admin	-0.0270	0.052	-0.517	0.608	-0.132	0.078
ms	0.0270	0.017	1.574	0.123	-0.008	0.062
sc	41.8870	3256.039	0.013	0.990	-6520.229	6604.003
sf	240.6758	3338.857	0.072	0.943	-6488.349	6969.701

Omnibus:	14.782	**Durbin-Watson:**	1.283
Prob(Omnibus):	0.001	**Jarque-Bera (JB):**	21.266
Skew:	-0.948	**Prob(JB):**	2.41e-05
Kurtosis:	5.572	**Cond. No.**	1.47e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.47e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

Calculating VIF

In [14]:
```
rsq_rd = smf.ols('rd~admin+ms+sc+sf',data=df1).fit().rsquared
vif_rd = 1/(1-rsq_rd)

rsq_admin = smf.ols('admin~rd+ms+sc+sf',data=df1).fit().rsquared
vif_admin = 1/(1-rsq_admin)

rsq_ms = smf.ols('ms~admin+rd+sc+sf',data=df1).fit().rsquared
vif_ms = 1/(1-rsq_ms)

rsq_sc = smf.ols("sc~admin+rd+ms+sf",data=df1).fit().rsquared
vif_sc = 1/(1-rsq_sc)

rsq_sf = smf.ols("sf~admin+rd+ms+sc",data=df1).fit().rsquared
vif_sf = 1/(1-rsq_sf)
```

In [15]:
```
d1={'variables':['rd','admin','ms',"sc","sf"],
    'vif':[vif_rd,vif_admin,vif_ms,vif_sc,vif_sf]}

vif=pd.DataFrame(d1)
vif
```

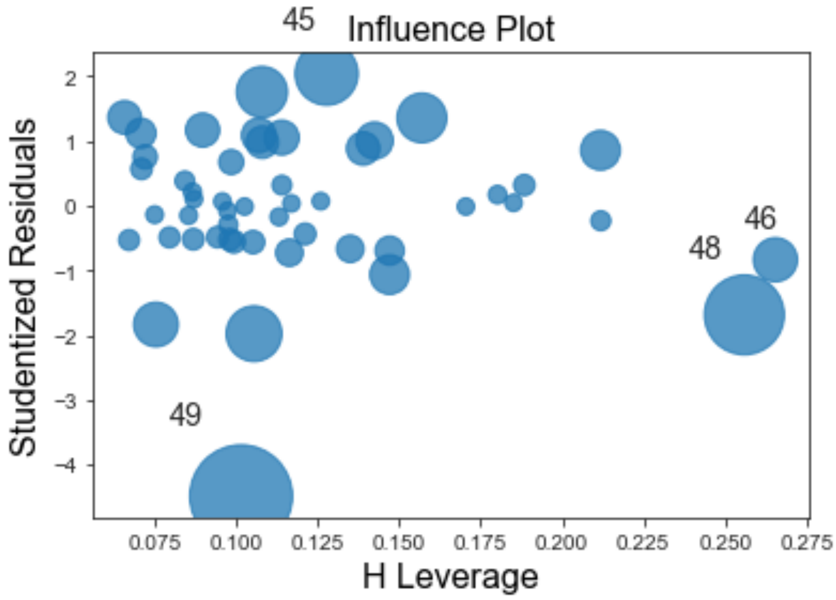
Out[15]:

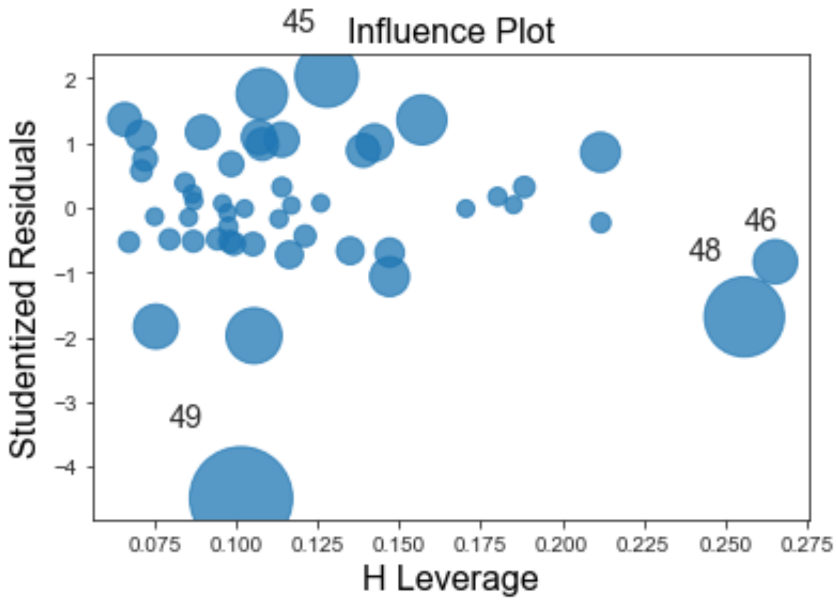
	variables	vif
0	rd	2.495511
1	admin	1.177766
2	ms	2.416797
3	sc	1.335061
4	sf	1.361299

the vif values is small so no probleam so lets check the if data has any influential value

In [16]:
```
from statsmodels.graphics.regressionplots import influence_plot
influence_plot(model)
```

Out[16]:





index 49 is showing high influence so we can exclude this entire row

In [17]:
```
df2 = df1.drop(df1.index[49],axis=0)
df2.tail(5)
```

Out[17]:

	rd	admin	ms	Profit	sc	sf
44	22177.74	154806.14	28334.72	65200.33	1	0
45	1000.23	124153.04	1903.93	64926.08	0	0
46	1315.46	115816.21	297114.46	49490.75	0	1
47	0.00	135426.92	0.00	42559.73	1	0
48	542.05	51743.15	0.00	35673.41	0	0

In [18]:
```
m1=smf.ols("Profit~admin+rd+ms+sc+sf",data=df2).fit()
m1.summary()
```

Out[18]:

OLS Regression Results

Dep. Variable:	Profit	**R-squared:**	0.962
Model:	OLS	**Adj. R-squared:**	0.957
Method:	Least Squares	**F-statistic:**	216.6
Date:	Mon, 05 Dec 2022	**Prob (F-statistic):**	2.51e-29
Time:	16:25:35	**Log-Likelihood:**	-505.97
No. Observations:	49	**AIC:**	1024.
Df Residuals:	43	**BIC:**	1035.
Df Model:	5		
Covariance Type:	nonrobust		

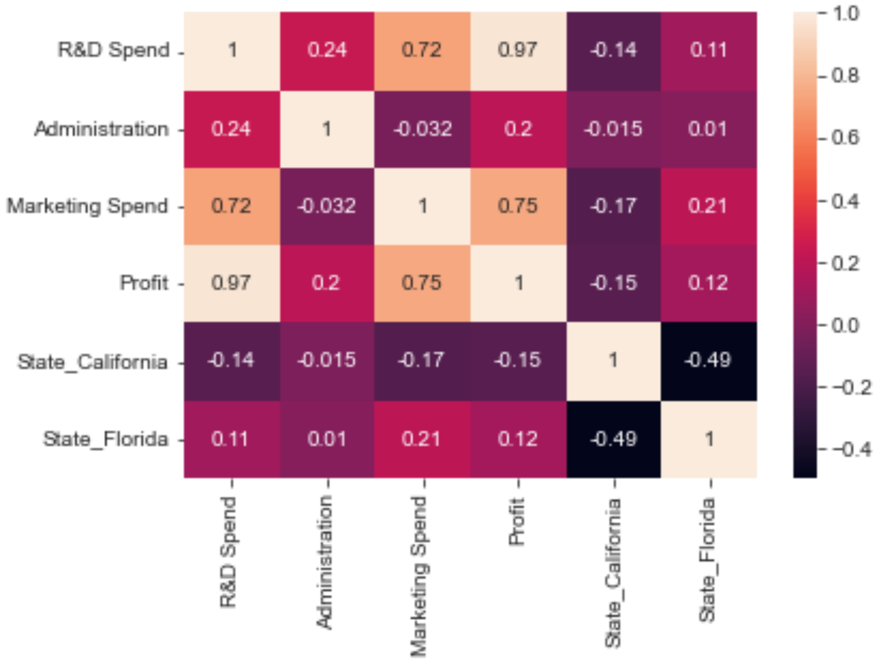
	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	5.143e+04	5812.919	8.847	0.000	3.97e+04	6.31e+04
admin	-0.0220	0.044	-0.505	0.616	-0.110	0.066
rd	0.7836	0.039	20.056	0.000	0.705	0.862
ms	0.0258	0.014	1.804	0.078	-0.003	0.055
sc	1954.0177	2751.932	0.710	0.482	-3595.783	7503.818
sf	389.7935	2788.050	0.140	0.889	-5232.845	6012.432

Omnibus:	0.051	**Durbin-Watson:**	1.667
Prob(Omnibus):	0.975	**Jarque-Bera (JB):**	0.207
Skew:	0.061	**Prob(JB):**	0.902
Kurtosis:	2.705	**Cond. No.**	1.47e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.47e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

In [19]:
```
sns.heatmap(df.corr(), annot = True)
```

Out[19]: <AxesSubplot:>



In [20]:
```
m2 = smf.ols('Profit~rd', df2).fit()
m2.summary()
```

Out[20]:

OLS Regression Results

Dep. Variable:	Profit	**R-squared:**	0.957
Model:	OLS	**Adj. R-squared:**	0.956
Method:	Least Squares	**F-statistic:**	1055.
Date:	Mon, 05 Dec 2022	**Prob (F-statistic):**	7.56e-34
Time:	16:25:36	**Log-Likelihood:**	-508.68
No. Observations:	49	**AIC:**	1021.
Df Residuals:	47	**BIC:**	1025.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	5.172e+04	2229.914	23.195	0.000	4.72e+04	5.62e+04
rd	0.8278	0.025	32.477	0.000	0.777	0.879

Omnibus:	0.070	**Durbin-Watson:**	1.372
Prob(Omnibus):	0.966	**Jarque-Bera (JB):**	0.203
Skew:	-0.080	**Prob(JB):**	0.903
Kurtosis:	2.728	**Cond. No.**	1.71e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.71e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

In [21]:
```
m3 =  smf.ols('Profit~ms', df2).fit()
m3.summary()
```

Out[21]:

OLS Regression Results

Dep. Variable:	Profit	**R-squared:**	0.547
Model:	OLS	**Adj. R-squared:**	0.537
Method:	Least Squares	**F-statistic:**	56.66
Date:	Mon, 05 Dec 2022	**Prob (F-statistic):**	1.30e-09
Time:	16:25:36	**Log-Likelihood:**	-566.59
No. Observations:	49	**AIC:**	1137.
Df Residuals:	47	**BIC:**	1141.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	6.406e+04	7601.574	8.428	0.000	4.88e+04	7.94e+04
ms	0.2329	0.031	7.527	0.000	0.171	0.295

Omnibus:	4.458	**Durbin-Watson:**	1.140
Prob(Omnibus):	0.108	**Jarque-Bera (JB):**	4.096
Skew:	-0.303	**Prob(JB):**	0.129
Kurtosis:	4.281	**Cond. No.**	5.03e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.03e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

In [22]:
```
m4 = smf.ols('Profit~sc', df2).fit()
m4.summary()
```

Out[22]:

OLS Regression Results

Dep. Variable:	Profit	**R-squared:**	0.007
Model:	OLS	**Adj. R-squared:**	-0.014
Method:	Least Squares	**F-statistic:**	0.3281
Date:	Mon, 05 Dec 2022	**Prob (F-statistic):**	0.570
Time:	16:25:36	**Log-Likelihood:**	-585.79
No. Observations:	49	**AIC:**	1176.
Df Residuals:	47	**BIC:**	1179.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	1.162e+05	6691.764	17.363	0.000	1.03e+05	1.3e+05
sc	-6707.5503	1.17e+04	-0.573	0.570	-3.03e+04	1.69e+04

Omnibus:	0.566	**Durbin-Watson:**	0.036
Prob(Omnibus):	0.753	**Jarque-Bera (JB):**	0.671
Skew:	0.225	**Prob(JB):**	0.715
Kurtosis:	2.644	**Cond. No.**	2.41

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

In [23]:
```
m5 = smf.ols('Profit~admin', df2).fit()
m5.summary()
```

Out[23]:

OLS Regression Results

Dep. Variable:	Profit	**R-squared:**	0.042
Model:	OLS	**Adj. R-squared:**	0.022
Method:	Least Squares	**F-statistic:**	2.080
Date:	Mon, 05 Dec 2022	**Prob (F-statistic):**	0.156
Time:	16:25:36	**Log-Likelihood:**	-584.90
No. Observations:	49	**AIC:**	1174.
Df Residuals:	47	**BIC:**	1178.
Df Model:	1		
Covariance Type:	nonrobust		

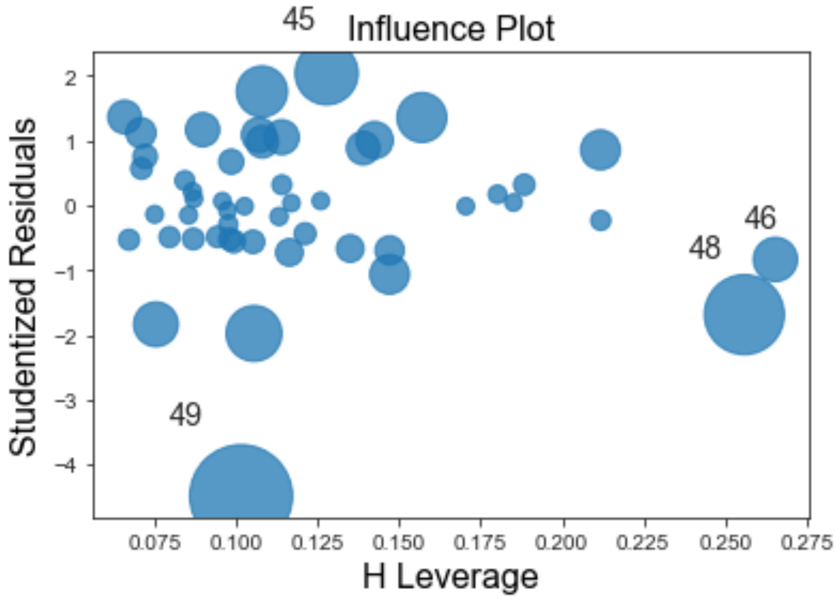
	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	8.029e+04	2.4e+04	3.346	0.002	3.2e+04	1.29e+05
admin	0.2776	0.193	1.442	0.156	-0.110	0.665

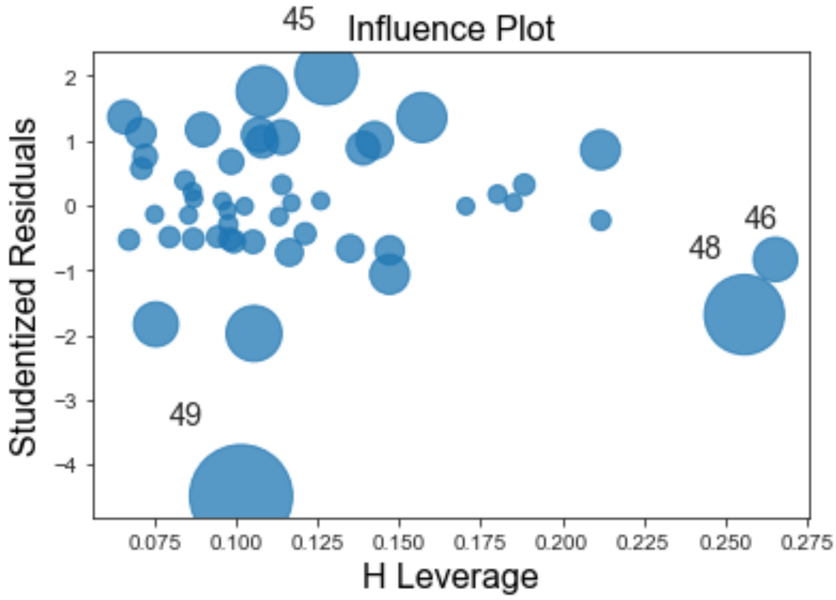
Omnibus:	1.016	**Durbin-Watson:**	0.084
Prob(Omnibus):	0.602	**Jarque-Bera (JB):**	1.052
Skew:	0.310	**Prob(JB):**	0.591
Kurtosis:	2.639	**Cond. No.**	5.54e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.54e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

In [24]:
```
from statsmodels.graphics.regressionplots import influence_plot
influence_plot(model)
```

Out[24]:





In [25]:
```
df2 = df1.drop(df1.index[49],axis=0)
df2
```

Out[25]:

	rd	admin	ms	Profit	sc	sf
0	165349.20	136897.80	471784.10	192261.83	0	0
1	162597.70	151377.59	443898.53	191792.06	1	0
2	153441.51	101145.55	407934.54	191050.39	0	1
3	144372.41	118671.85	383199.62	182901.99	0	0

4	142107.34	91391.77	366168.42	166187.94	0	1
5	131876.90	99814.71	362861.36	156991.12	0	0
6	134615.46	147198.87	127716.82	156122.51	1	0
7	130298.13	145530.06	323876.68	155752.60	0	1
8	120542.52	148718.95	311613.29	152211.77	0	0
9	123334.88	108679.17	304981.62	149759.96	1	0
10	101913.08	110594.11	229160.95	146121.95	0	1
11	100671.96	91790.61	249744.55	144259.40	1	0
12	93863.75	127320.38	249839.44	141585.52	0	1
13	91992.39	135495.07	252664.93	134307.35	1	0
14	119943.24	156547.42	256512.92	132602.65	0	1
15	114523.61	122616.84	261776.23	129917.04	0	0
16	78013.11	121597.55	264346.06	126992.93	1	0
17	94657.16	145077.58	282574.31	125370.37	0	0
18	91749.16	114175.79	294919.57	124266.90	0	1
19	86419.70	153514.11	0.00	122776.86	0	0
20	76253.86	113867.30	298664.47	118474.03	1	0
21	78389.47	153773.43	299737.29	111313.02	0	0
22	73994.56	122782.75	303319.26	110352.25	0	1
23	67532.53	105751.03	304768.73	108733.99	0	1
24	77044.01	99281.34	140574.81	108552.04	0	0
25	64664.71	139553.16	137962.62	107404.34	1	0
26	75328.87	144135.98	134050.07	105733.54	0	1
27	72107.60	127864.55	353183.81	105008.31	0	0
28	66051.52	182645.56	118148.20	103282.38	0	1
29	65605.48	153032.06	107138.38	101004.64	0	0
30	61994.48	115641.28	91131.24	99937.59	0	1
31	61136.38	152701.92	88218.23	97483.56	0	0
32	63408.86	129219.61	46085.25	97427.84	1	0
33	55493.95	103057.49	214634.81	96778.92	0	1
34	46426.07	157693.92	210797.67	96712.80	1	0
35	46014.02	85047.44	205517.64	96479.51	0	0
36	28663.76	127056.21	201126.82	90708.19	0	1
37	44069.95	51283.14	197029.42	89949.14	1	0

38	20229.59	65947.93	185265.10	81229.06	0	0
39	38558.51	82982.09	174999.30	81005.76	1	0
40	28754.33	118546.05	172795.67	78239.91	1	0
41	27892.92	84710.77	164470.71	77798.83	0	1
42	23640.93	96189.63	148001.11	71498.49	1	0
43	15505.73	127382.30	35534.17	69758.98	0	0
44	22177.74	154806.14	28334.72	65200.33	1	0
45	1000.23	124153.04	1903.93	64926.08	0	0
46	1315.46	115816.21	297114.46	49490.75	0	1
47	0.00	135426.92	0.00	42559.73	1	0
48	542.05	51743.15	0.00	35673.41	0	0

In [26]:
```
m1=smf.ols("Profit~admin+rd+ms+sc+sf",data=df2).fit()
m1.summary()
```

Out[26]:

OLS Regression Results

Dep. Variable:	Profit	**R-squared:**	0.962
Model:	OLS	**Adj. R-squared:**	0.957
Method:	Least Squares	**F-statistic:**	216.6
Date:	Mon, 05 Dec 2022	**Prob (F-statistic):**	2.51e-29
Time:	16:35:43	**Log-Likelihood:**	-505.97
No. Observations:	49	**AIC:**	1024.
Df Residuals:	43	**BIC:**	1035.
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	5.143e+04	5812.919	8.847	0.000	3.97e+04	6.31e+04
admin	-0.0220	0.044	-0.505	0.616	-0.110	0.066
rd	0.7836	0.039	20.056	0.000	0.705	0.862
ms	0.0258	0.014	1.804	0.078	-0.003	0.055
sc	1954.0177	2751.932	0.710	0.482	-3595.783	7503.818
sf	389.7935	2788.050	0.140	0.889	-5232.845	6012.432

Omnibus:	0.051	**Durbin-Watson:**	1.667
Prob(Omnibus):	0.975	**Jarque-Bera (JB):**	0.207
Skew:	0.061	**Prob(JB):**	0.902
Kurtosis:	2.705	**Cond. No.**	1.47e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.47e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

residual analysis

In [27]:
```
res=m1.resid
res
```

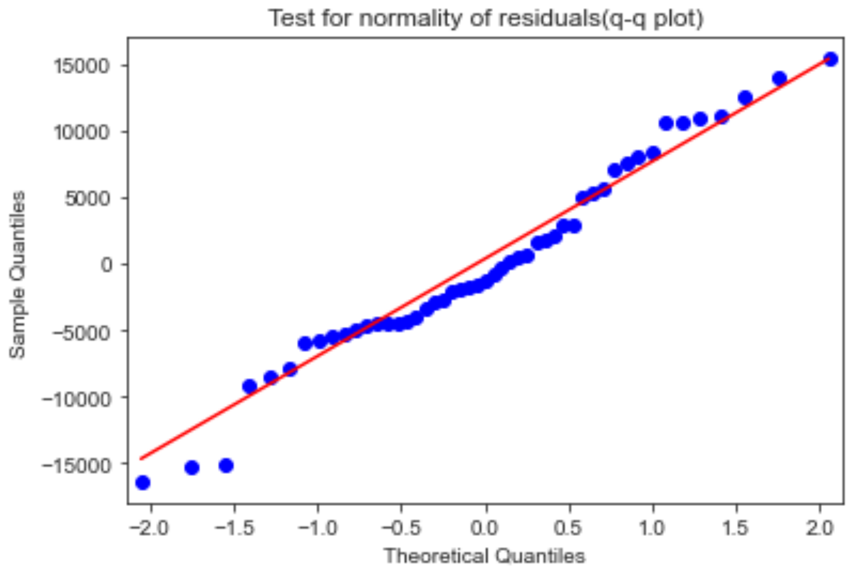
Out[27]:
```
0      2103.543815
1      2874.720587
2     10694.367621
3     11066.868378
4     -4423.099177
5     -4942.775088
6     -2796.090299
7     -3320.587404
8      1559.651080
9     -5744.777225
10    10967.282206
11     7567.444947
12    12572.633164
13     5303.686160
14   -16374.515563
15   -15306.706646
16     8335.604545
17    -4328.626135
18    -4542.513614
19     7014.838789
20      138.854192
21    -5890.450112
22    -4572.189923
23    -1539.378722
24    -4687.432233
25     2865.472822
26    -5395.474562
27    -9223.381138
28      681.678987
29    -1224.630972
30     -262.046827
31     -762.501777
32    -3982.146650
33    -1793.100995
34     4984.357361
35     5564.445851
36    14037.325081
37    -1920.986205
38    10620.728755
39    -5278.728239
40      477.979569
41     1745.939803
42    -2108.753231
43     8071.376720
44    -2879.569187
45    15402.088726
46    -8476.320071
47    -7837.069144
48   -15037.038014
dtype: float64
```

In [28]:
```
res.mean()
```

Out[28]:
```
1.667887067460284e-07
```

In [29]:
```
import statsmodels.api as sm
qqplot=sm.qqplot(res,line="q")
plt.title("Test for normality of residuals(q-q plot)")
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)
```



In [30]:
```
list(np.where(m1.resid<-15000))
```

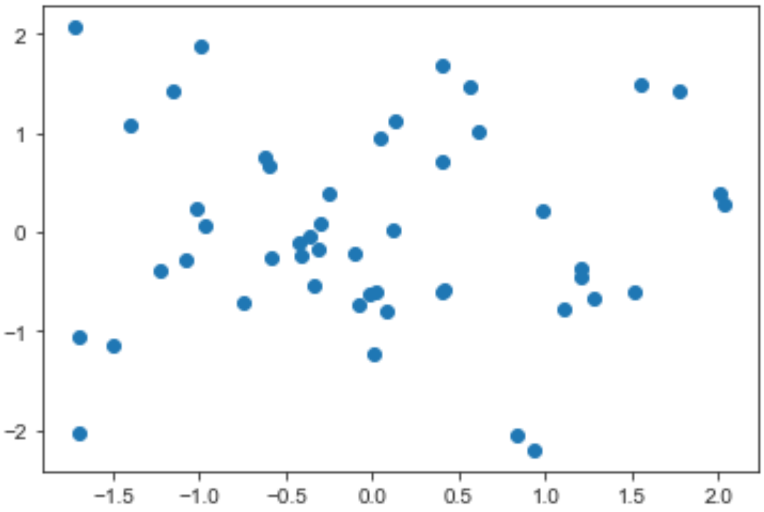
Out[30]:
```
[array([14, 15, 48])]
```

residual plot for homosceasity

In [31]:
```
def get_Stardardized_values(vals):
    return(vals - vals.mean())/(vals.std())
```

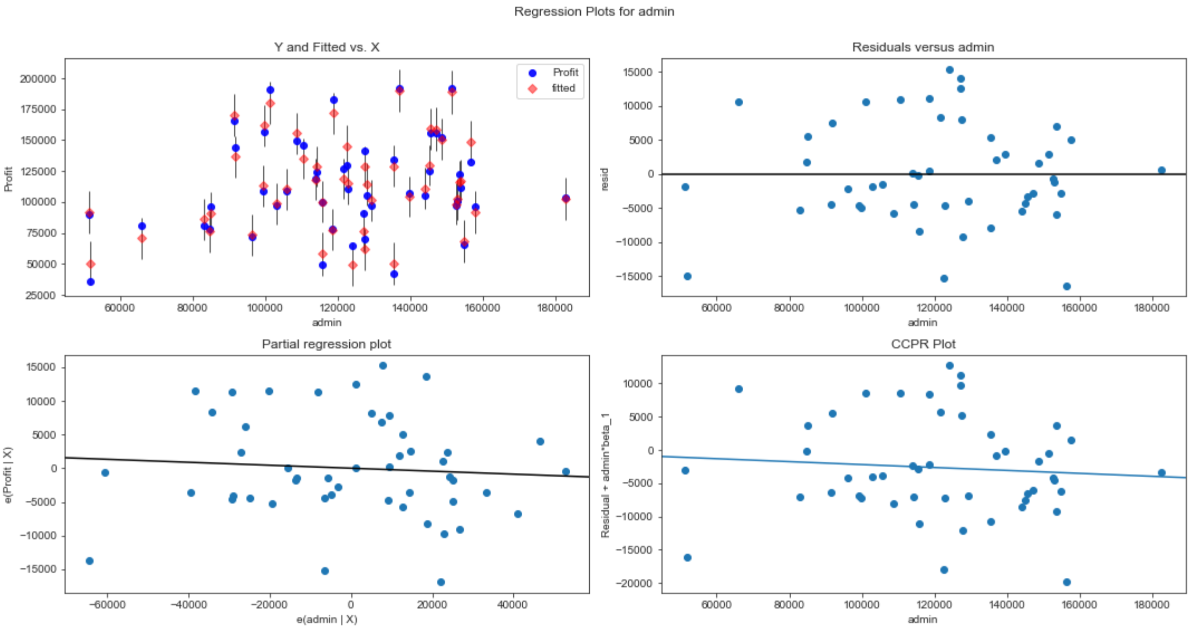
In [32]:
```
plt.scatter(get_Stardardized_values(m1.fittedvalues),
            get_Stardardized_values(m1.resid))
```

Out[32]: <matplotlib.collections.PathCollection at 0x7fa2dd896610>

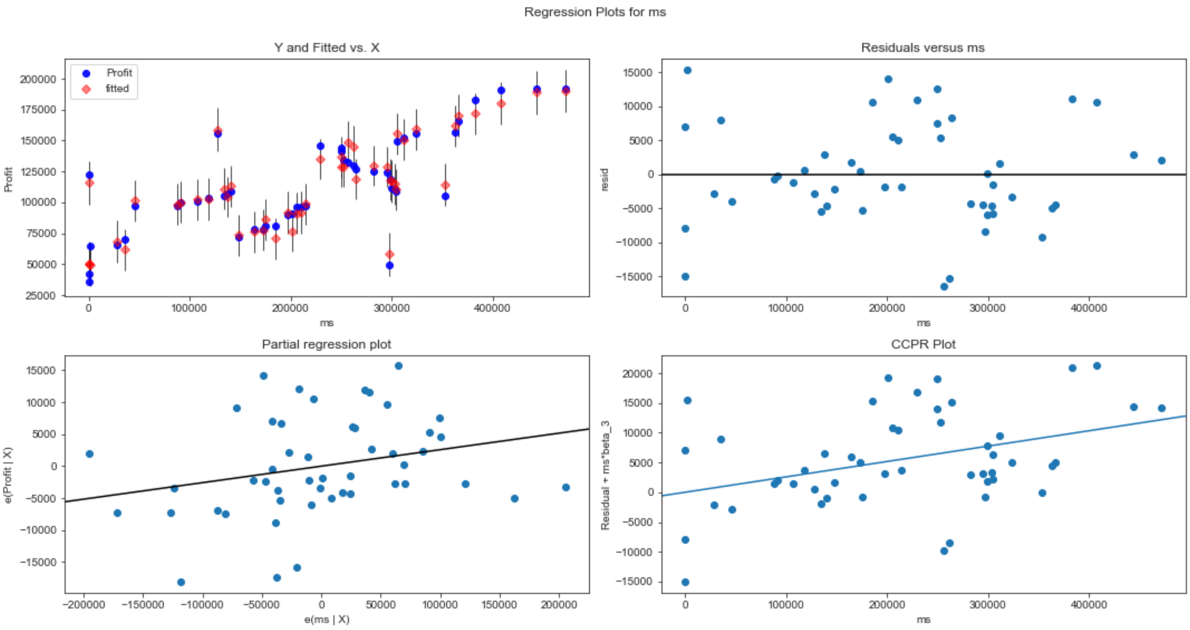


residual vs Regressor

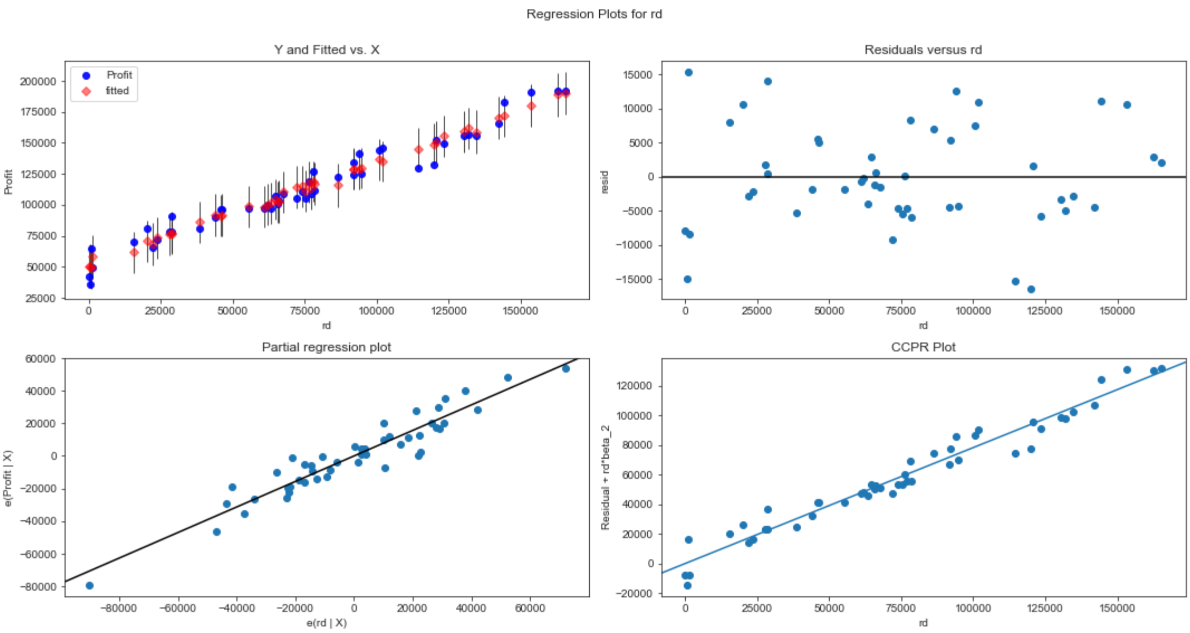
In [33]:
```
fig= plt.figure(figsize=(15,8))
fig=sm.graphics.plot_regress_exog(m1,'admin',fig=fig)
plt.show()
```



In [34]:
```
fig= plt.figure(figsize=(15,8))
fig=sm.graphics.plot_regress_exog(m1,'ms',fig=fig)
plt.show()
```

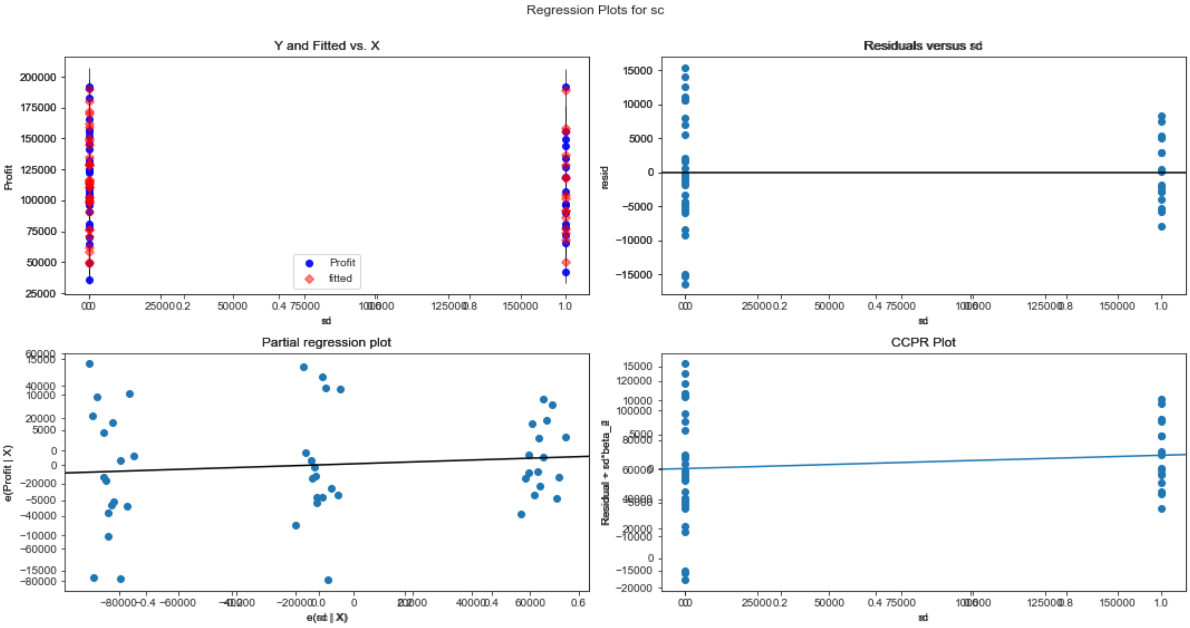


In [35]:
```
fig= plt.figure(figsize=(15,8))
fig=sm.graphics.plot_regress_exog(m1,'rd',fig=fig)
plt.show()
```



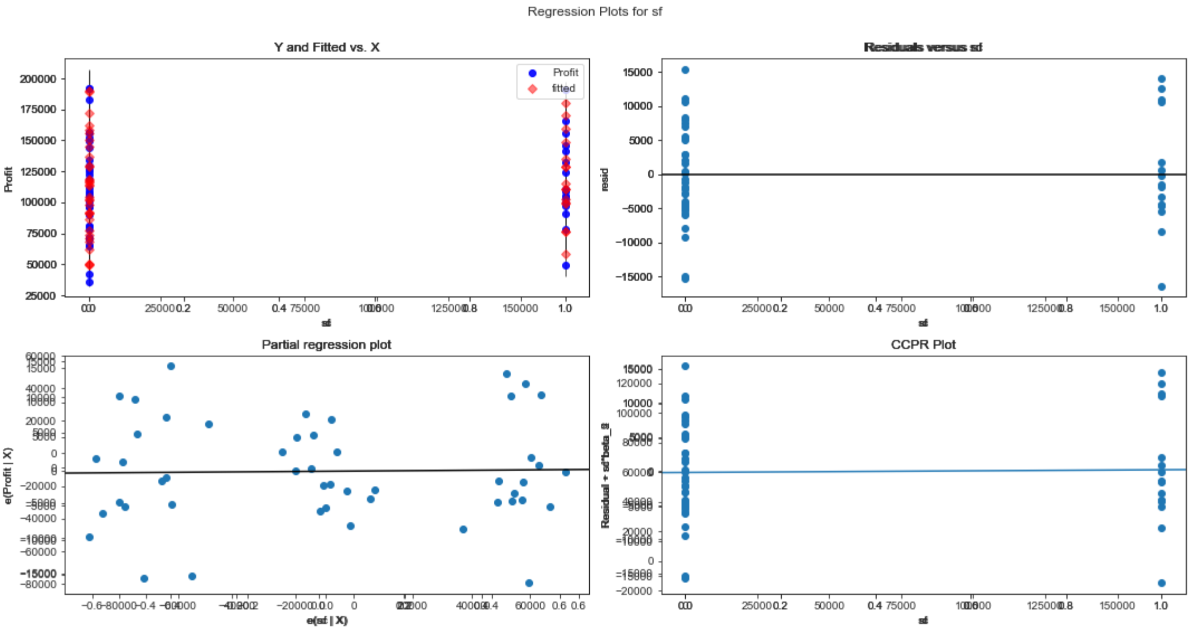
In [36]:
```python
sm.graphics.plot_regress_exog(m1,"sc",fig=fig)
```

Out[36]:



In [37]:
```python
sm.graphics.plot_regress_exog(m1,"sf",fig=fig)
```

Out[37]:



model deletion diagnostic

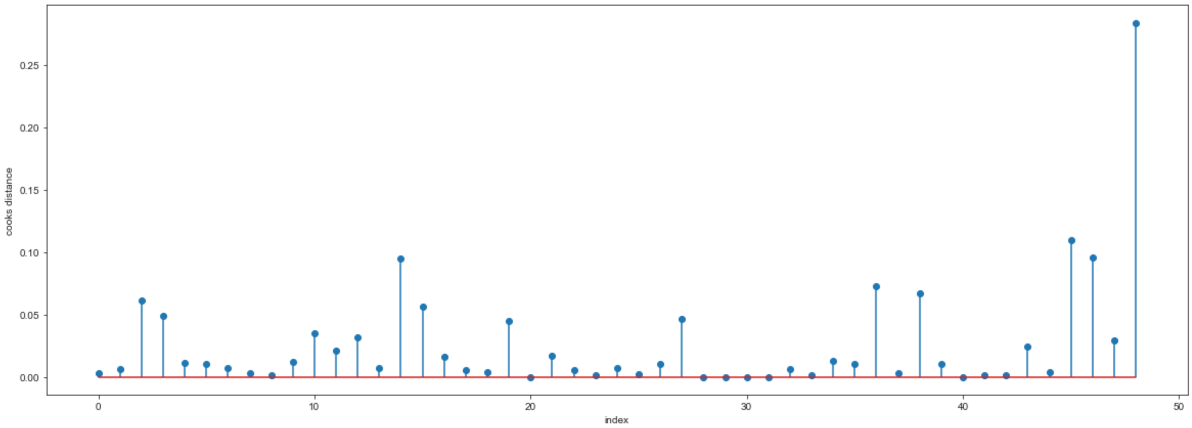
In [38]:
```python
from statsmodels.graphics.regressionplots import influence_plot
model_influence = m1.get_influence()
(c, _)= model_influence.cooks_distance
```

In [39]:
```
c
```

Out[39]:
```
array([3.03867206e-03, 6.34213501e-03, 6.10907745e-02, 4.89969621e
-02,
       1.08296207e-02, 9.96640531e-03, 7.18257664e-03, 3.43906612e
-03,
       7.71896400e-04, 1.16791482e-02, 3.50252773e-02, 2.11128062e
-02,
       3.19794651e-02, 6.51681649e-03, 9.52677666e-02, 5.59931284e
-02,
       1.59297138e-02, 5.24377171e-03, 4.27707492e-03, 4.50057058e
-02,
       5.55348982e-06, 1.67935282e-02, 5.26498586e-03, 6.49142710e
-04,
       7.10541515e-03, 1.94064299e-03, 9.56819087e-03, 4.61390479e
-02,
       3.35515812e-04, 4.81929683e-04, 2.77054838e-05, 1.99386901e
-04,
       6.44240628e-03, 7.58291881e-04, 1.32227858e-02, 1.00900380e
-02,
       7.27039884e-02, 2.85158478e-03, 6.73063867e-02, 9.56592291e
-03,
       6.78841259e-05, 1.20050726e-03, 1.37273222e-03, 2.39875939e
-02,
       4.04204676e-03, 1.10116060e-01, 9.62426496e-02, 2.92982414e
-02,
       2.84116205e-01])
```

In [40]:
```
fig=plt.subplots(figsize=(20,7))
plt.stem(np.arange(len(df2)),np.round(c,3))
plt.xlabel("index")
plt.ylabel("cooks distance")
```

Out[40]:
```
Text(0, 0.5, 'cooks distance')
```



In [41]:
```
np.argmax(c),np.max(c)
```

Out[41]:
```
(48, 0.28411620500588586)
```

In [42]:
```
new_data=df2.drop(df2.index[[48]],axis=0).reset_index()
```

In [43]:
```
new_data.head()
```

Out[43]:

	index	rd	admin	ms	Profit	sc	sf
0	0	165349.20	136897.80	471784.10	192261.83	0	0
1	1	162597.70	151377.59	443898.53	191792.06	1	0
2	2	153441.51	101145.55	407934.54	191050.39	0	1
3	3	144372.41	118671.85	383199.62	182901.99	0	0
4	4	142107.34	91391.77	366168.42	166187.94	0	1

In [44]:
```
data2=new_data.copy()
data2.head()
```

Out[44]:

	index	rd	admin	ms	Profit	sc	sf
0	0	165349.20	136897.80	471784.10	192261.83	0	0
1	1	162597.70	151377.59	443898.53	191792.06	1	0
2	2	153441.51	101145.55	407934.54	191050.39	0	1
3	3	144372.41	118671.85	383199.62	182901.99	0	0
4	4	142107.34	91391.77	366168.42	166187.94	0	1

In [45]:
```
final_m=smf.ols("Profit~rd+admin+ms+sc+sf",data=data2).fit()
final_m.summary()
```

Out[45]:

OLS Regression Results

Dep. Variable:	Profit	**R-squared:**	0.963
Model:	OLS	**Adj. R-squared:**	0.958
Method:	Least Squares	**F-statistic:**	217.6
Date:	Mon, 05 Dec 2022	**Prob (F-statistic):**	7.02e-29
Time:	16:43:10	**Log-Likelihood:**	-493.23
No. Observations:	48	**AIC:**	998.5
Df Residuals:	42	**BIC:**	1010.
Df Model:	5		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	5.872e+04	6363.927	9.228	0.000	4.59e+04	7.16e+04
rd	0.7888	0.037	21.160	0.000	0.714	0.864
admin	-0.0621	0.045	-1.381	0.174	-0.153	0.029
ms	0.0179	0.014	1.275	0.209	-0.010	0.046
sc	665.7875	2678.779	0.249	0.805	-4740.208	6071.783
sf	-484.4021	2681.751	-0.181	0.858	-5896.395	4927.591

Omnibus:	0.267	**Durbin-Watson:**	1.835
Prob(Omnibus):	0.875	**Jarque-Bera (JB):**	0.453
Skew:	0.108	**Prob(JB):**	0.797
Kurtosis:	2.576	**Cond. No.**	1.69e+06

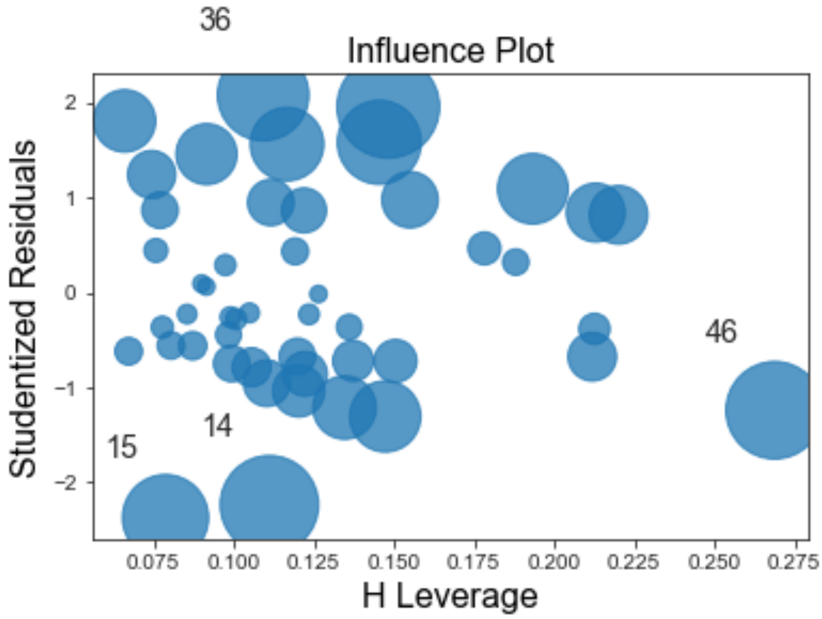
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.69e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

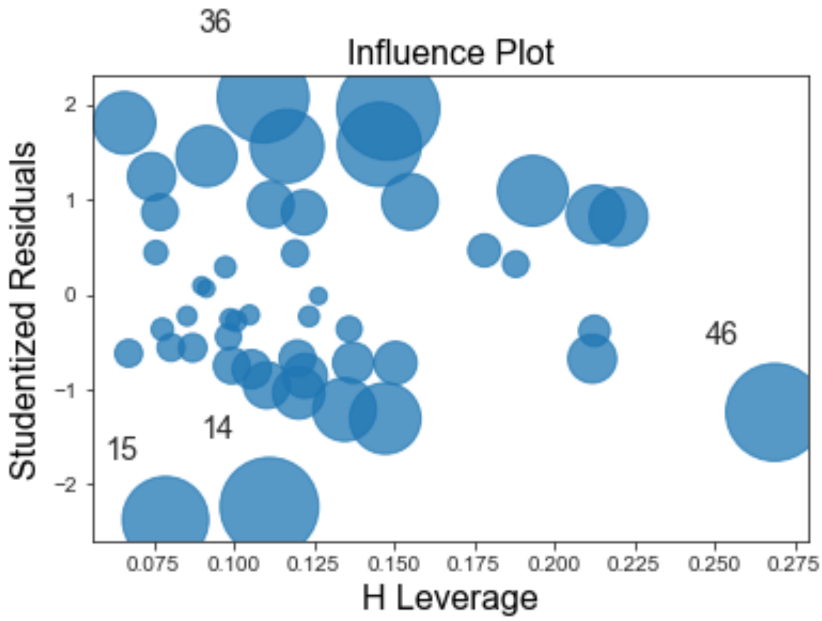
In [46]:
```
final_m.rsquared,final_m.aic
```

Out[46]: (0.9628371102993712, 998.4621953724801)

In [47]:
```
from statsmodels.graphics.regressionplots import influence_plot
influence_plot(final_m)
```

Out[47]:





prediction for new data

In [48]:
```
new_dataa=pd.DataFrame({'rd':162597.7,'admin':151377.59,'ms':443898
```

In [49]:
```
new_dataa
```

Out[49]:

	rd	admin	ms	sc	sf
1	162597.7	151377.59	443898.53	1	0

In [50]:
```
pred_y=final_m.predict(new_dataa)
```

In [51]:
```
pred_y
```

Out[51]:
```
1    186183.370112
dtype: float64
```

In [52]:
```
data2["predicted"] = final_m.fittedvalues
data2["erro"] = data2["Profit"]-data2["predicted"]
data2.head()
```

Out[52]:

	index	rd	admin	ms	Profit	sc	sf	predicted	erro
0	0	165349.20	136897.80	471784.10	192261.83	0	0	189087.074698	3174.755302
1	1	162597.70	151377.59	443898.53	191792.06	1	0	186183.370112	5608.689888
2	2	153441.51	101145.55	407934.54	191050.39	0	1	180288.581217	10761.808783
3	3	144372.41	118671.85	383199.62	182901.99	0	0	172087.545967	10814.444033
4	4	142107.34	91391.77	366168.42	166187.94	0	1	171206.768166	-5018.828166

In [ ]: