Q. Prepare a prediction model for profit of 50_startups data. Do transformations for getting better predictions of profit and make a table containing R^2 value for each prepared model.

1. Import Necessary Libraries

In [1]:
```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings("ignore")

from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error,mean_absolute_error

import statsmodels.formula.api as smf
```

2. Import data Or Data Collection

In [2]:
```
startups_data = pd.read_csv(r"E:\Data Science by John\Assignments\Assignment 5- Multi Linear Regression\50_Startups.csv"
startups_data
```

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
5	131876.90	99814.71	362861.36	New York	156991.12
6	134615.46	147198.87	127716.82	California	156122.51
7	130298.13	145530.06	323876.68	Florida	155752.60
8	120542.52	148718.95	311613.29	New York	152211.77
9	123334.88	108679.17	304981.62	California	149759.96
10	101913.08	110594.11	229160.95	Florida	146121.95
11	100671.96	91790.61	249744.55	California	144259.40
12	93863.75	127320.38	249839.44	Florida	141585.52
13	91992.39	135495.07	252664.93	California	134307.35
14	119943.24	156547.42	256512.92	Florida	132602.65
15	114523.61	122616.84	261776.23	New York	129917.04
16	78013.11	121597.55	264346.06	California	126992.93
17	94657.16	145077.58	282574.31	New York	125370.37
18	91749.16	114175.79	294919.57	Florida	124266.90
19	86419.70	153514.11	0.00	New York	122776.86
20	76253.86	113867.30	298664.47	California	118474.03
21	78389.47	153773.43	299737.29	New York	111313.02
22	73994.56	122782.75	303319.26	Florida	110352.25
23	67532.53	105751.03	304768.73	Florida	108733.99

	R&D Spend	Administration	Marketing Spend	State	Profit
24	77044.01	99281.34	140574.81	New York	108552.04
25	64664.71	139553.16	137962.62	California	107404.34
26	75328.87	144135.98	134050.07	Florida	105733.54
27	72107.60	127864.55	353183.81	New York	105008.31
28	66051.52	182645.56	118148.20	Florida	103282.38
29	65605.48	153032.06	107138.38	New York	101004.64
30	61994.48	115641.28	91131.24	Florida	99937.59
31	61136.38	152701.92	88218.23	New York	97483.56
32	63408.86	129219.61	46085.25	California	97427.84
33	55493.95	103057.49	214634.81	Florida	96778.92
34	46426.07	157693.92	210797.67	California	96712.80
35	46014.02	85047.44	205517.64	New York	96479.51
36	28663.76	127056.21	201126.82	Florida	90708.19
37	44069.95	51283.14	197029.42	California	89949.14
38	20229.59	65947.93	185265.10	New York	81229.06
39	38558.51	82982.09	174999.30	California	81005.76
40	28754.33	118546.05	172795.67	California	78239.91
41	27892.92	84710.77	164470.71	Florida	77798.83
42	23640.93	96189.63	148001.11	California	71498.49
43	15505.73	127382.30	35534.17	New York	69758.98
44	22177.74	154806.14	28334.72	California	65200.33
45	1000.23	124153.04	1903.93	New York	64926.08
46	1315.46	115816.21	297114.46	Florida	49490.75
47	0.00	135426.92	0.00	California	42559.73
48	542.05	51743.15	0.00	New York	35673.41
49	0.00	116983.80	45173.06	California	14681.40

3. Data Understanding

3.1 Perform Initial Analysis

In [3]:
```
startups_data.shape
```

Out[3]:
```
(50, 5)
```

In [4]:
```
startups_data.dtypes
```

Out[4]:
```
R&D Spend          float64
Administration     float64
Marketing Spend    float64
State               object
Profit             float64
dtype: object
```

In [5]:
```
startups_data.describe()
```

Out[5]:

	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 [6]:
```
startups_data.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
```

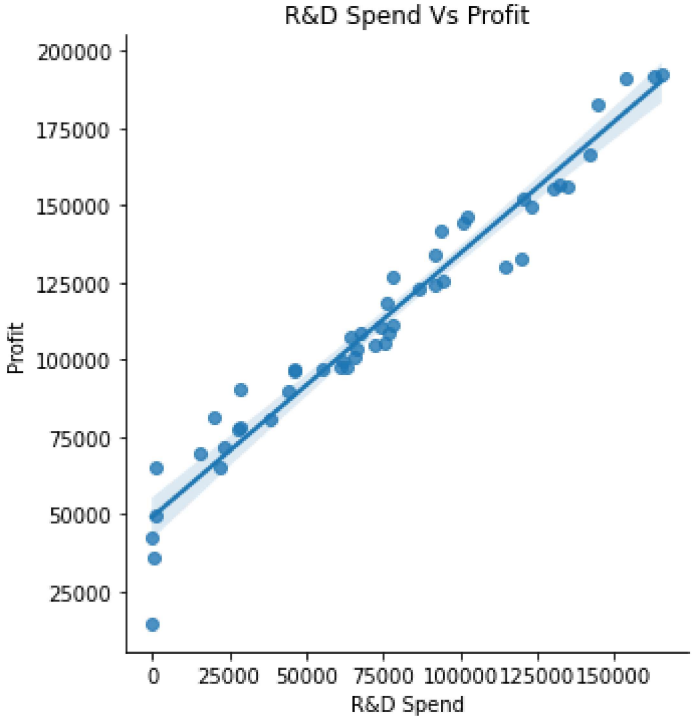
In [7]:
```
startups_data.isna().sum()
```

Out[7]:
```
R&D Spend          0
Administration     0
Marketing Spend    0
State              0
Profit             0
dtype: int64
```

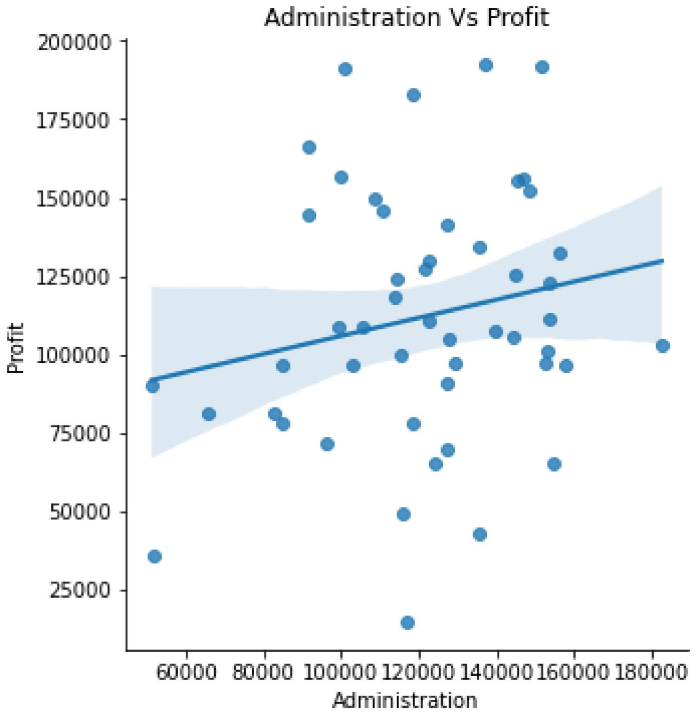
3.2 Assumptions Check

1. Linearity Check

In [8]:
```
sns.lmplot(x="R&D Spend", y="Profit", data=startups_data)
plt.title("R&D Spend Vs Profit")
plt.show()
```



In [9]:
```
sns.lmplot(x="Administration", y="Profit", data=startups_data)
plt.title("Administration Vs Profit")
plt.show()
```

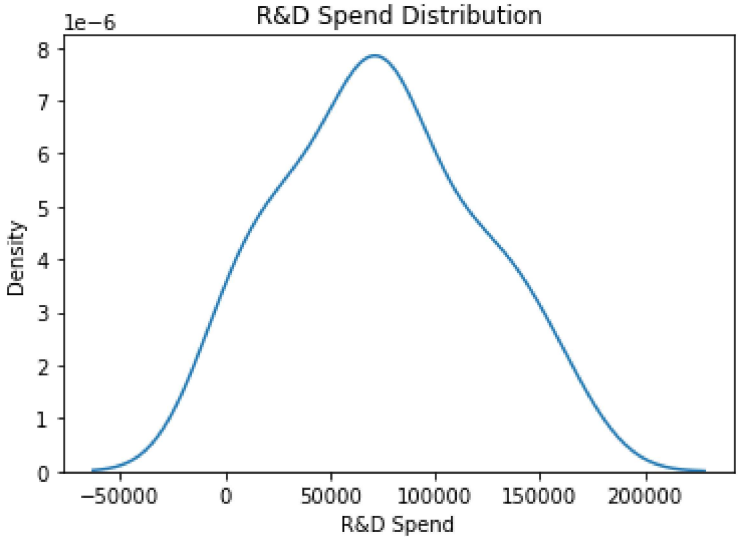


In [10]:
```
sns.lmplot(x="Marketing Spend", y="Profit", data=startups_data)
plt.title("Marketing Spend Vs Profit")
plt.show()
```

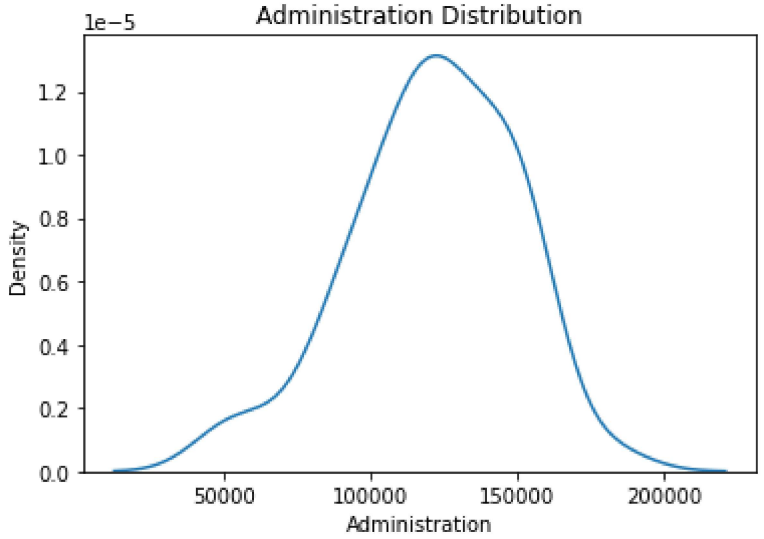
Linearity Test is Failed

2. Normality Test

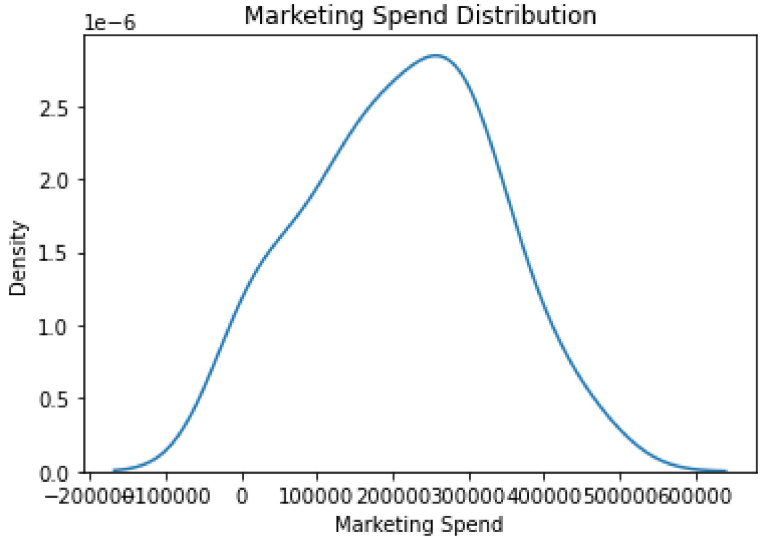
In [11]:
```
sns.kdeplot(data = startups_data, x='R&D Spend')
plt.title('R&D Spend Distribution')
plt.show()
```



In [12]:
```
sns.kdeplot(x=startups_data['Administration'])
plt.title('Administration Distribution')
plt.show()
```



In [13]:
```
sns.kdeplot(x=startups_data['Marketing Spend'])
plt.title('Marketing Spend Distribution')
plt.show()
```



Normality Test is Failed

3. No AutoRegression : No any feature is in DataTime data format so this test is passed

4. Multicollinearity

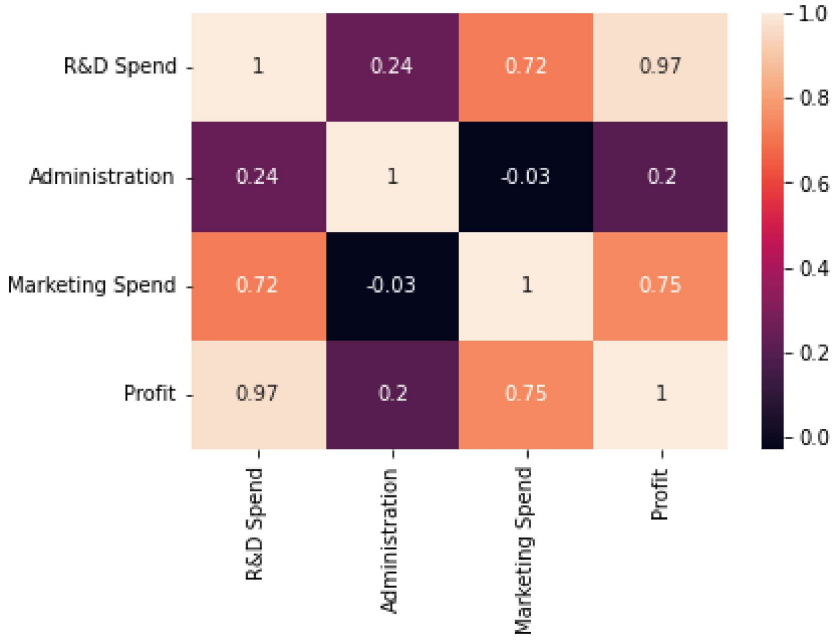
4.1 Correlation Matrix

In [14]:
```
corr_matrix = startups_data.corr().round(2)
corr_matrix
```

Out[14]:

	R&D Spend	Administration	Marketing Spend	Profit
R&D Spend	1.00	0.24	0.72	0.97
Administration	0.24	1.00	-0.03	0.20
Marketing Spend	0.72	-0.03	1.00	0.75
Profit	0.97	0.20	0.75	1.00

In [15]:
```
sns.heatmap(data = corr_matrix,annot = True)
plt.show()
```



MultiCollinearity Test is Failed

There is multicollinearity in the inputs in our data.

5. Homoscedasticity Check II 6. Zero Residual Check

This will be performed post Model Training beacuse we need the errors

4. Data Preparation

In [16]:
```
startups_data.drop(labels = ["State"], axis = 1,inplace = True)
```

5. Model Building

In [17]:
```
x = startups_data.drop("Profit",axis=1)
y = startups_data[["Profit"]]
```

6. Model Training

In [18]:
```
linear_model = LinearRegression()
```

In [19]:
```
linear_model.fit(x,y)
```

Out[19]:
```
LinearRegression()
```

In [20]:
```
linear_model.coef_
```

Out[20]:
```
array([[ 0.80571505, -0.02681597,  0.02722806]])
```

In [21]:
```
linear_model.intercept_
```

Out[21]:
```
array([50122.19298987])
```

7. Model Testing

In [22]:
```
y.head()
```

Out[22]:

	Profit
0	192261.83
1	191792.06
2	191050.39
3	182901.99
4	166187.94

In [23]:
```
y_pred = linear_model.predict(x)
y_pred
```

Out[23]:
```
array([[192521.25289008],
       [189156.76823227],
       [182147.2790962 ],
       [173696.70002553],
       [172139.51418327],
       [163580.7805712 ],
       [158114.09666865],
       [160021.36304781],
       [151741.69969865],
       [154884.68410995],
       [135509.01636714],
       [135573.71296074],
       [129138.05418243],
       [127487.99166275],
       [149548.64633453],
       [146235.1599852 ],
       [116915.40540144],
       [130192.44720781],
       [129014.2268059 ],
       [115635.21636716],
       [116639.6692309 ],
       [117319.45164029],
       [114706.98171695],
       [109996.61522126],
       [113362.96611314],
       [102237.72506481],
       [110600.5753503 ],
       [114408.07145684],
       [101660.02600497],
       [101794.98345176],
       [ 99452.37293606],
       [ 97687.85627575],
       [ 99001.32898549],
       [ 97915.00780465],
       [ 89039.27374116],
       [ 90511.59956753],
       [ 75286.17458546],
       [ 89619.5377079 ],
```

```
[ 69697.43064804],
[ 83729.01197692],
[ 74815.95399105],
[ 74802.55623866],
[ 70620.41182056],
[ 60167.03996335],
[ 64611.3549157 ],
[ 47650.64968691],
[ 56166.20685261],
[ 46490.58898335],
[ 49171.38815763],
[ 48215.1341113 ]])
```

8. Model Evaluation

In [24]:
```
error = y - y_pred
error
```

Out[24]:

	Profit
0	-259.422890
1	2635.291768
2	8903.110904
3	9205.289974
4	-5951.574183
5	-6589.660571
6	-1991.586669
7	-4268.763048
8	470.070301
9	-5124.724110
10	10612.933633
11	8685.687039
12	12447.465818
13	6819.358337
14	-16945.996335
15	-16318.119985
16	10077.524599
17	-4822.077208
18	-4747.326806
19	7141.643633
20	1834.360769
21	-6006.431640
22	-4354.731717
23	-1262.625221

	Profit
24	-4810.926113
25	5166.614935
26	-4867.035350
27	-9399.761457
28	1622.353995
29	-790.343452
30	485.217064
31	-204.296276
32	-1573.488985
33	-1136.087805
34	7673.526259
35	5967.910432
36	15422.015415
37	329.602292
38	11531.629352
39	-2723.251977
40	3423.956009
41	2996.273761
42	878.078179
43	9591.940037
44	588.975084
45	17275.430313
46	-6675.456853
47	-3930.858983
48	-13497.978158
49	-33533.734111

.....back to Assumption Check

5. Homoscedasticity Check

In [25]:
```
x
```

Out[25]:

	R&D Spend	Administration	Marketing Spend
0	165349.20	136897.80	471784.10
1	162597.70	151377.59	443898.53
2	153441.51	101145.55	407934.54
3	144372.41	118671.85	383199.62
4	142107.34	91391.77	366168.42
5	131876.90	99814.71	362861.36
6	134615.46	147198.87	127716.82
7	130298.13	145530.06	323876.68
8	120542.52	148718.95	311613.29
9	123334.88	108679.17	304981.62
10	101913.08	110594.11	229160.95
11	100671.96	91790.61	249744.55
12	93863.75	127320.38	249839.44
13	91992.39	135495.07	252664.93
14	119943.24	156547.42	256512.92
15	114523.61	122616.84	261776.23
16	78013.11	121597.55	264346.06
17	94657.16	145077.58	282574.31
18	91749.16	114175.79	294919.57
19	86419.70	153514.11	0.00
20	76253.86	113867.30	298664.47
21	78389.47	153773.43	299737.29
22	73994.56	122782.75	303319.26
23	67532.53	105751.03	304768.73

	R&D Spend	Administration	Marketing Spend
24	77044.01	99281.34	140574.81
25	64664.71	139553.16	137962.62
26	75328.87	144135.98	134050.07
27	72107.60	127864.55	353183.81
28	66051.52	182645.56	118148.20
29	65605.48	153032.06	107138.38
30	61994.48	115641.28	91131.24
31	61136.38	152701.92	88218.23
32	63408.86	129219.61	46085.25
33	55493.95	103057.49	214634.81
34	46426.07	157693.92	210797.67
35	46014.02	85047.44	205517.64
36	28663.76	127056.21	201126.82
37	44069.95	51283.14	197029.42
38	20229.59	65947.93	185265.10
39	38558.51	82982.09	174999.30
40	28754.33	118546.05	172795.67
41	27892.92	84710.77	164470.71
42	23640.93	96189.63	148001.11
43	15505.73	127382.30	35534.17
44	22177.74	154806.14	28334.72
45	1000.23	124153.04	1903.93
46	1315.46	115816.21	297114.46
47	0.00	135426.92	0.00
48	542.05	51743.15	0.00
49	0.00	116983.80	45173.06

In [26]:
```
std_scaler = StandardScaler()
scaled_x = std_scaler.fit_transform(x)
scaled_x = pd.DataFrame(scaled_x,columns=['R&D Spend','Administration','Marketing Spend'])
scaled_x
```

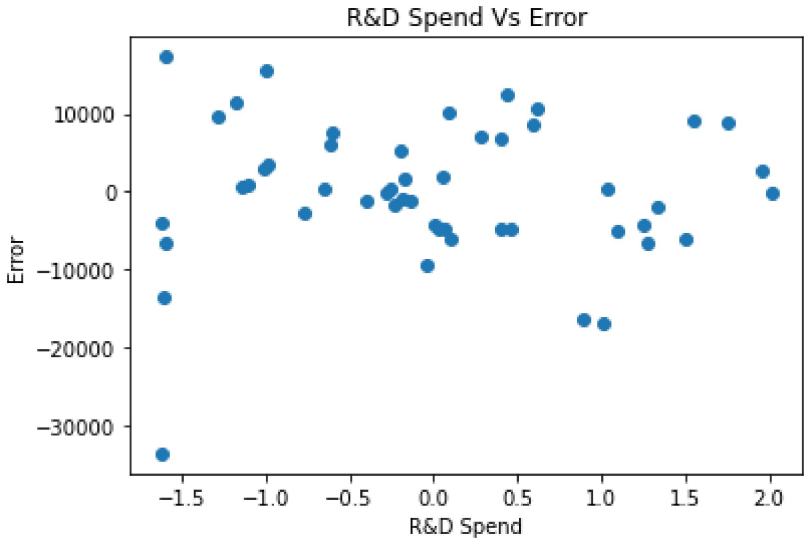
Out[26]:

	R&D Spend	Administration	Marketing Spend
0	2.016411	0.560753	2.153943
1	1.955860	1.082807	1.923600
2	1.754364	-0.728257	1.626528
3	1.554784	-0.096365	1.422210
4	1.504937	-1.079919	1.281528
5	1.279800	-0.776239	1.254210
6	1.340066	0.932147	-0.688150
7	1.245057	0.871980	0.932186
8	1.030369	0.986952	0.830887
9	1.091819	-0.456640	0.776107
10	0.620398	-0.387599	0.149807
11	0.593085	-1.065540	0.319834
12	0.443260	0.215449	0.320617
13	0.402078	0.510179	0.343957
14	1.017181	1.269199	0.375742
15	0.897913	0.045868	0.419219
16	0.094441	0.009118	0.440446
17	0.460720	0.855666	0.591017
18	0.396725	-0.258465	0.692992
19	0.279442	1.159837	-1.743127
20	0.055726	-0.269588	0.723926
21	0.102724	1.169186	0.732788

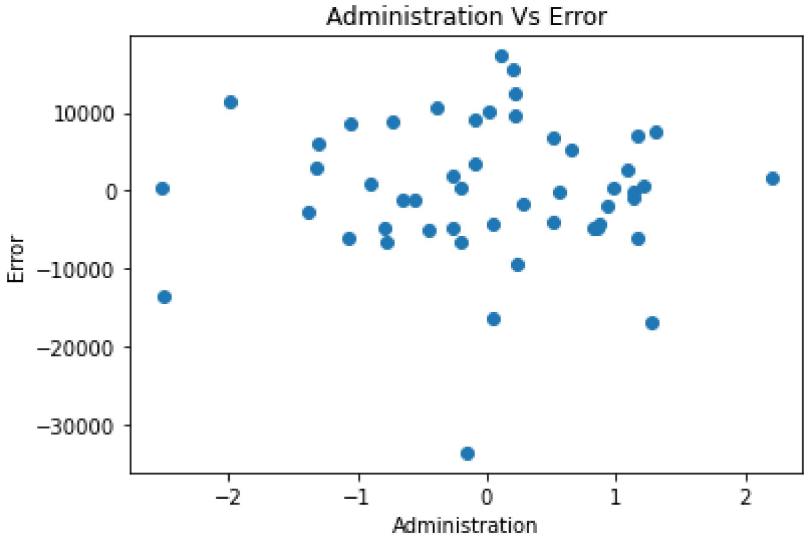
	R&D Spend	Administration	Marketing Spend
22	0.006007	0.051850	0.762376
23	-0.136201	-0.562211	0.774349
24	0.073115	-0.795469	-0.581939
25	-0.199312	0.656489	-0.603517
26	0.035370	0.821718	-0.635835
27	-0.035519	0.235069	1.174271
28	-0.168793	2.210141	-0.767189
29	-0.178609	1.142457	-0.858134
30	-0.258074	-0.205629	-0.990357
31	-0.276958	1.130554	-1.014419
32	-0.226949	0.283924	-1.362450
33	-0.401129	-0.659324	0.029817
34	-0.600682	1.310535	-0.001879
35	-0.609750	-1.308658	-0.045493
36	-0.991570	0.205925	-0.081763
37	-0.652532	-2.525994	-0.115608
38	-1.177178	-1.997270	-0.212785
39	-0.773820	-1.383122	-0.297583
40	-0.989577	-0.100900	-0.315786
41	-1.008534	-1.320796	-0.384552
42	-1.102106	-0.906938	-0.520596
43	-1.281134	0.217682	-1.449605
44	-1.134305	1.206419	-1.509074
45	-1.600350	0.101254	-1.727400
46	-1.593413	-0.199322	0.711122
47	-1.622362	0.507722	-1.743127

	R&D Spend	Administration	Marketing Spend
48	-1.610433	-2.509409	-1.743127
49	-1.622362	-0.157226	-1.369985

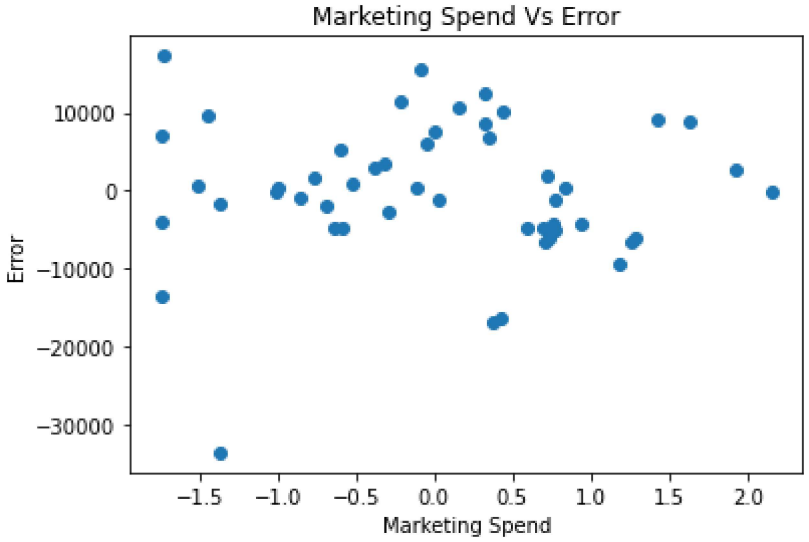
In [27]:
```
plt.scatter(x=scaled_x['R&D Spend'],y=error)
plt.title('R&D Spend Vs Error')
plt.xlabel('R&D Spend')
plt.ylabel('Error')
plt.show()
```



In [28]:
```
plt.scatter(x=scaled_x['Administration'],y=error)
plt.title('Administration Vs Error')
plt.xlabel('Administration')
plt.ylabel('Error')
plt.show()
```



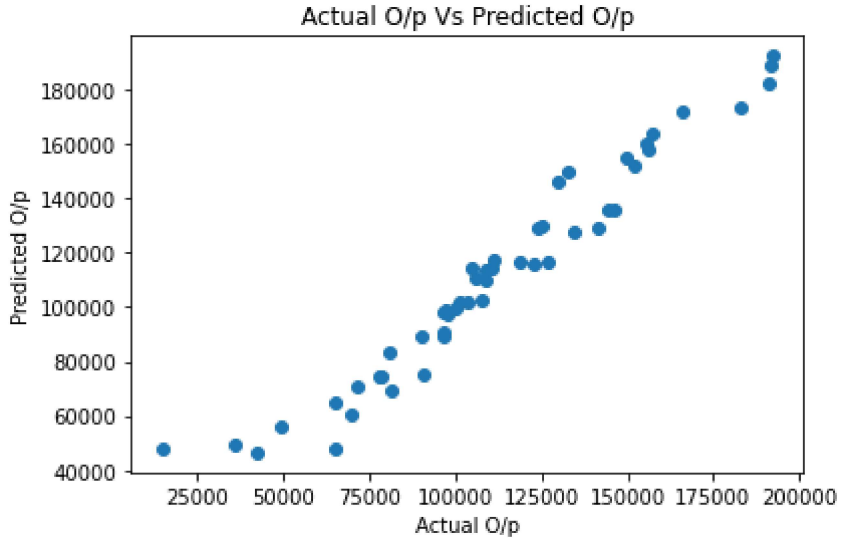
In [29]:
```
plt.scatter(x=scaled_x['Marketing Spend'],y=error)
plt.title('Marketing Spend Vs Error')
plt.xlabel('Marketing Spend')
plt.ylabel('Error')
plt.show()
```



Homoscedasticity Test is Failed

6. Zero Residual Mean Across the Fitted Line

In [30]:
```
plt.scatter(x=y,y=y_pred)
plt.title('Actual O/p Vs Predicted O/p')
plt.xlabel('Actual O/p')
plt.ylabel('Predicted O/p')
plt.show()
```



Zero Residual Mean Test is also Failed

Build Linear Regression using StatsModels

In [31]:
```
startups_data.head()
```

Out[31]:

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

In [32]:
```
startups_data.rename(columns = ({'R&D Spend':'R&D_Spend','Marketing Spend':'Marketing_Spend'}),inplace=True)
startups_data.head()
```

Out[32]:

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

In [33]:
```
linear_model_stats = smf.ols('Profit~Marketing_Spend + Administration + Q("R&D_Spend")',data = startups_data).fit()
```

8.1 Evaluation Metrics of Linear Regression

In [34]:
```
print('R2Score     :',linear_model_stats.rsquared.round(4))
print('Adj.R2Score :',linear_model_stats.rsquared_adj.round(4))
print('AIC Value   :',linear_model_stats.aic.round(4))
print('BIC Value   :',linear_model_stats.bic.round(4))
print('P-Value     :\n',linear_model_stats.pvalues)
```

```
R2Score     : 0.9507
Adj.R2Score : 0.9475
AIC Value   : 1058.7715
BIC Value   : 1066.4196
P-Value     :
 Intercept          1.057379e-09
Marketing_Spend    1.047168e-01
Administration     6.017551e-01
Q("R&D_Spend")     2.634968e-22
dtype: float64
```

In [35]:
```
linear_model_stats_1 = smf.ols('Profit~Q("R&D_Spend")',data = startups_data).fit()
print('R2Score     :',linear_model_stats_1.rsquared.round(4))
print('Adj.R2Score :',linear_model_stats_1.rsquared_adj.round(4))
print('AIC Value   :',linear_model_stats_1.aic.round(4))
print('BIC Value   :',linear_model_stats_1.bic.round(4))
print('P-Value     :\n',linear_model_stats_1.pvalues)
```

```
R2Score     : 0.9465
Adj.R2Score : 0.9454
AIC Value   : 1058.873
BIC Value   : 1062.6971
P-Value     :
 Intercept         2.782697e-24
Q("R&D_Spend")    3.500322e-32
dtype: float64
```

In [36]:
```
linear_model_stats_2 = smf.ols('Profit~Q("R&D_Spend")+ Administration',data = startups_data).fit()
print('R2Score     :',linear_model_stats_2.rsquared.round(4))
print('Adj.R2Score :',linear_model_stats_2.rsquared_adj.round(4))
print('AIC Value   :',linear_model_stats_2.aic.round(4))
print('BIC Value   :',linear_model_stats_2.bic.round(4))
print('P-Value     :\n',linear_model_stats_2.pvalues)
```

```
R2Score     : 0.9478
Adj.R2Score : 0.9456
AIC Value   : 1059.6637
BIC Value   : 1065.3998
P-Value     :
 Intercept         5.695336e-12
Q("R&D_Spend")    2.278348e-31
Administration    2.888932e-01
dtype: float64
```

In [37]:
```
linear_model_stats_3 = smf.ols('Profit~Marketing_Spend + Q("R&D_Spend")',data = startups_data).fit()
print('R2Score     :',linear_model_stats_3.rsquared.round(4))
print('Adj.R2Score :',linear_model_stats_3.rsquared_adj.round(4))
print('AIC Value   :',linear_model_stats_3.aic.round(4))
print('BIC Value   :',linear_model_stats_3.bic.round(4))
print('P-Value     :\n',linear_model_stats_3.pvalues)
```

```
R2Score     : 0.9505
Adj.R2Score : 0.9483
AIC Value   : 1057.0708
BIC Value   : 1062.8068
P-Value     :
 Intercept          3.504062e-22
Marketing_Spend    6.003040e-02
Q("R&D_Spend")     6.040433e-24
dtype: float64
```

In [38]:
```
linear_model_stats_4 = smf.ols('Profit~Marketing_Spend + Administration',data = startups_data).fit()
print('R2Score     :',linear_model_stats_4.rsquared.round(4))
print('Adj.R2Score :',linear_model_stats_4.rsquared_adj.round(4))
print('AIC Value   :',linear_model_stats_4.aic.round(4))
print('BIC Value   :',linear_model_stats_4.bic.round(4))
print('P-Value     :\n',linear_model_stats_4.pvalues)
```

```
R2Score     : 0.6097
Adj.R2Score : 0.5931
AIC Value   : 1160.2648
BIC Value   : 1166.0009
P-Value     :
 Intercept          2.589341e-01
Marketing_Spend    9.727245e-11
Administration     1.729198e-02
dtype: float64
```

In [39]:
```
linear_model_stats = smf.ols('Profit~Marketing_Spend + Administration + Q("R&D_Spend")',data = startups_data).fit()
print('R2Score     :',linear_model_stats.rsquared.round(4))
print('Adj.R2Score :',linear_model_stats.rsquared_adj.round(4))
print('AIC Value   :',linear_model_stats.aic.round(4))
print('BIC Value   :',linear_model_stats.bic.round(4))
print('P-Value     :\n',linear_model_stats.pvalues)
```

```
R2Score     : 0.9507
Adj.R2Score : 0.9475
AIC Value   : 1058.7715
BIC Value   : 1066.4196
P-Value     :
 Intercept          1.057379e-09
Marketing_Spend    1.047168e-01
Administration     6.017551e-01
Q("R&D_Spend")     2.634968e-22
dtype: float64
```

In [40]:
```
mean_squared_error(y,y_pred)
```

Out[40]:
```
78417126.01913083
```

In [41]:
```
mean_absolute_error(y,y_pred)
```

Out[41]:
```
6471.450396104808
```

9. MODEL OPTIMIZATION

In [42]:
```
startups_data_2 = startups_data.copy()
startups_data_2.head()
```

Out[42]:

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

In [43]:
```
startups_data_2['log_R&D_Spend']       = np.log(startups_data_2['R&D_Spend'])
startups_data_2['log_Administration'] = np.log(startups_data_2['Administration'])
startups_data_2['log_Marketing_Spend']= np.log(startups_data_2['Marketing_Spend'])
startups_data_2.head()
```

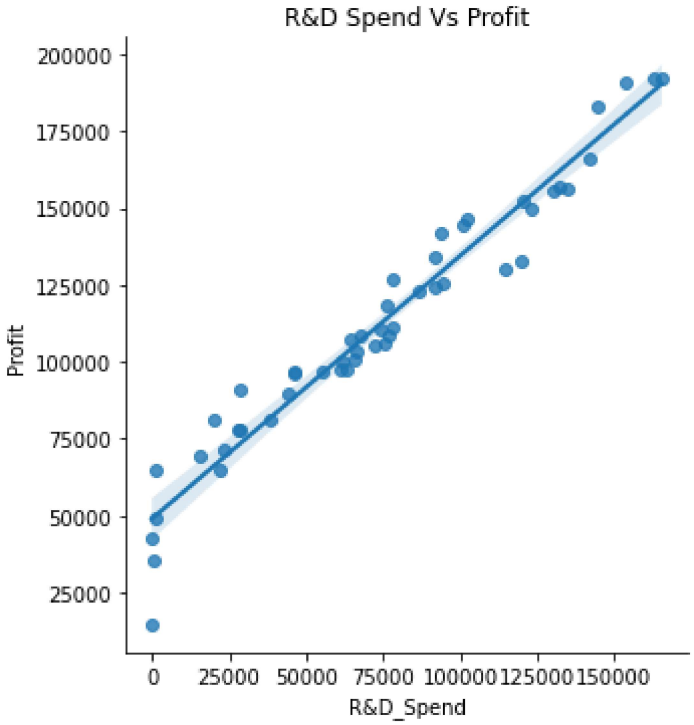
Out[43]:

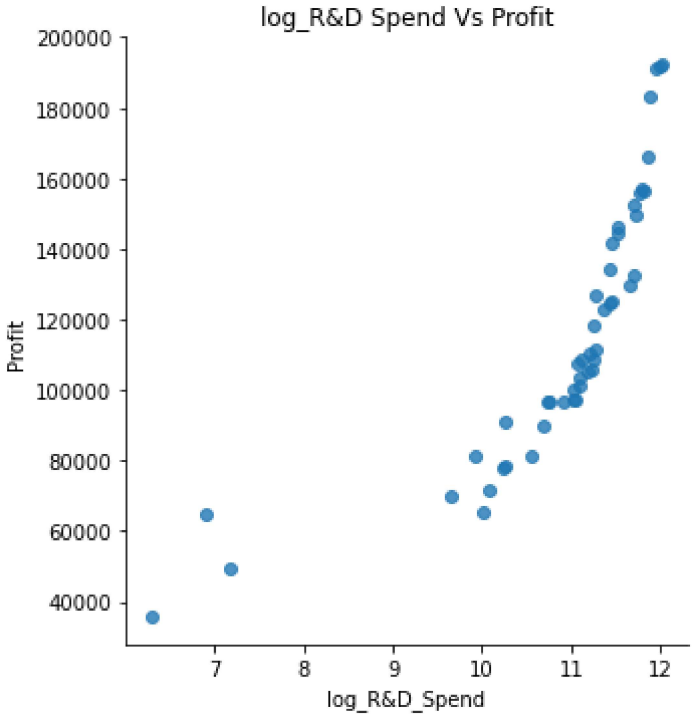
	R&D_Spend	Administration	Marketing_Spend	Profit	log_R&D_Spend	log_Administration	log_Marketing_Spend
0	165349.20	136897.80	471784.10	192261.83	12.015815	11.826990	13.064277
1	162597.70	151377.59	443898.53	191792.06	11.999034	11.927533	13.003351
2	153441.51	101145.55	407934.54	191050.39	11.941075	11.524316	12.918862
3	144372.41	118671.85	383199.62	182901.99	11.880151	11.684117	12.856311
4	142107.34	91391.77	366168.42	166187.94	11.864338	11.422911	12.810849

3.2 Assumptions Check

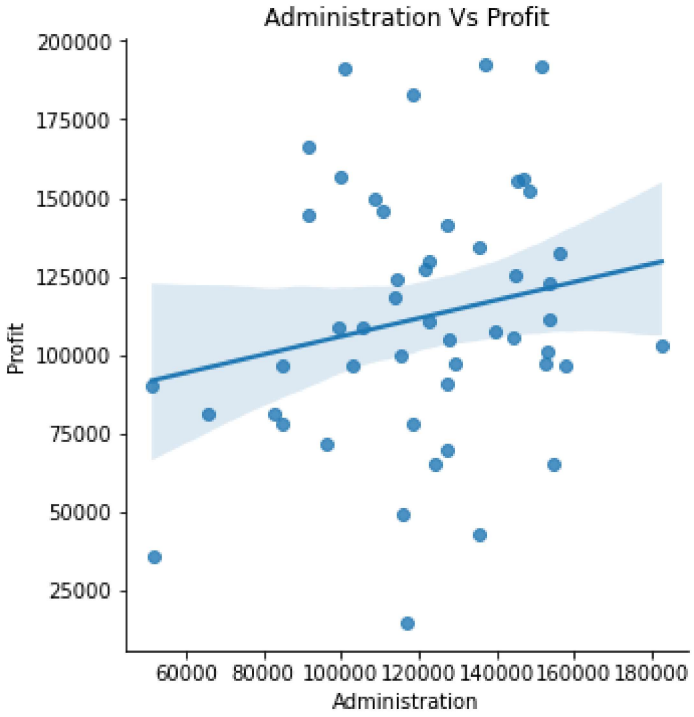
1. Linearity Check

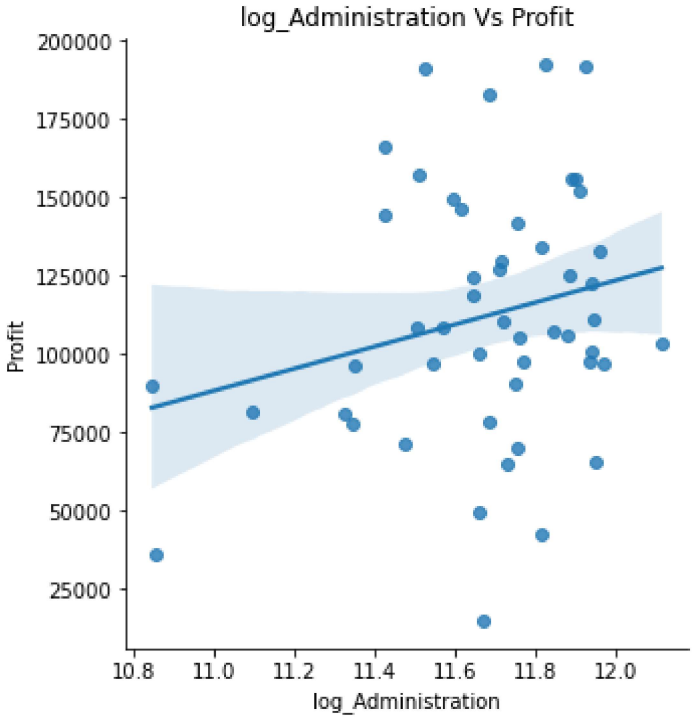
In [44]:
```
sns.lmplot(x="R&D_Spend", y="Profit", data=startups_data_2)
plt.title("R&D Spend Vs Profit")

sns.lmplot(x="log_R&D_Spend", y="Profit", data=startups_data_2)
plt.title("log_R&D Spend Vs Profit")
plt.show()
```



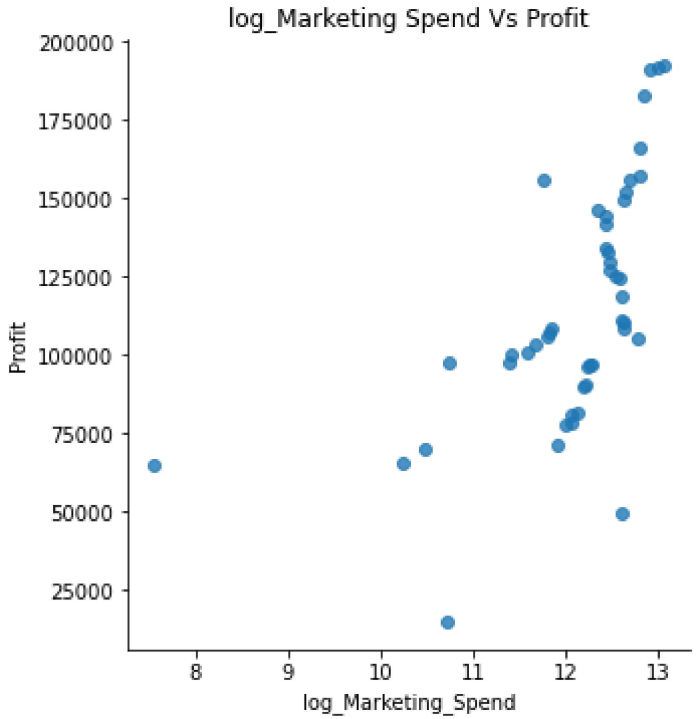

log_R&D Spend Vs Profit
Profit
log_R&D_Spend
200000
180000
160000
140000
120000
100000
80000
60000
40000
7
8
9
10
11
12

In [45]:
```
sns.lmplot(x="Administration", y="Profit", data=startups_data_2)
plt.title("Administration Vs Profit")

sns.lmplot(x="log_Administration", y="Profit", data=startups_data_2)
plt.title("log_Administration Vs Profit")
plt.show()
```




log_Administration Vs Profit
Profit
200000
175000
150000
125000
100000
75000
50000
25000
10.8
11.0
11.2
11.4
11.6
11.8
12.0
log_Administration

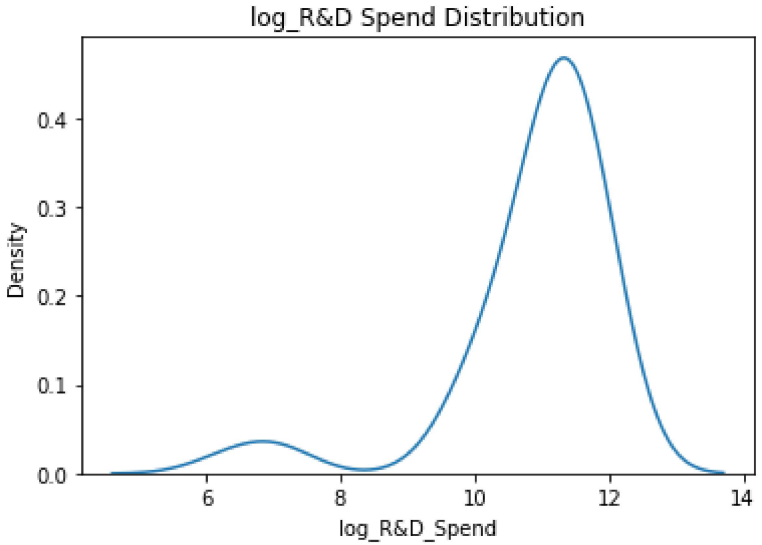
In [46]:
```
sns.lmplot(x="Marketing_Spend", y="Profit", data=startups_data_2)
plt.title("Marketing Spend Vs Profit")

sns.lmplot(x="log_Marketing_Spend", y="Profit", data=startups_data_2)
plt.title("log_Marketing Spend Vs Profit")
plt.show()
```



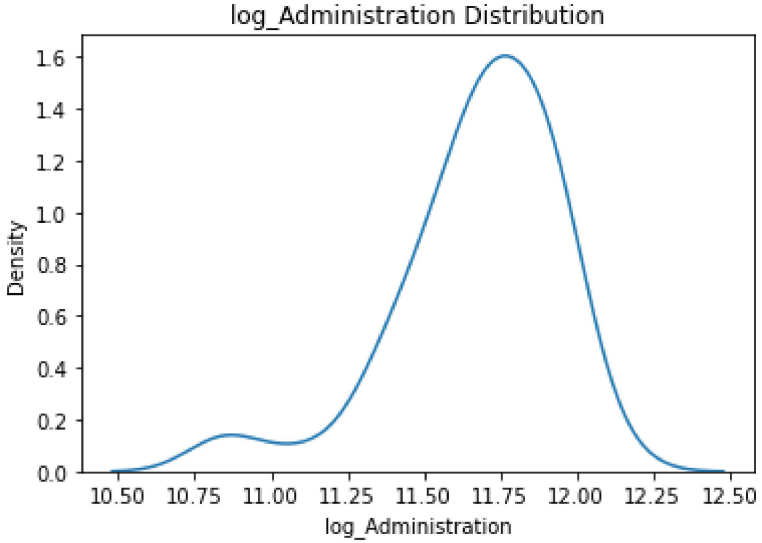
Linearity Test is Failed

2. Normality Test

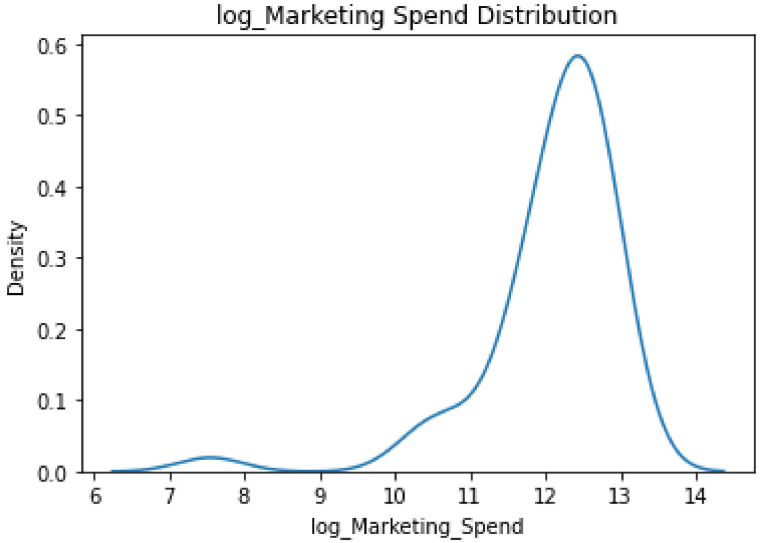
In [47]:
```
sns.kdeplot(data = startups_data_2, x='log_R&D_Spend')
plt.title('log_R&D Spend Distribution')
plt.show()
```



In [48]:
```
sns.kdeplot(x=startups_data_2['log_Administration'])
plt.title('log_Administration Distribution')
plt.show()
```



In [49]:
```
sns.kdeplot(x=startups_data_2['log_Marketing_Spend'])
plt.title('log_Marketing Spend Distribution')
plt.show()
```



Normality Test is Failed

Model Building || Training || Evaluation using Statsmodels

In [50]:
```
linear_model_stats_5 = smf.ols('Profit~log_Administration',data = startups_data_2).fit()
print('R2Score     :',linear_model_stats_5.rsquared.round(4))
print('Adj.R2Score :',linear_model_stats_5.rsquared_adj.round(4))
print('AIC Value   :',linear_model_stats_5.aic.round(4))
print('BIC Value   :',linear_model_stats_5.bic.round(4))
print('P-Value     :\n',linear_model_stats_5.pvalues)
```

```
R2Score     : 0.054
Adj.R2Score : 0.0343
AIC Value   : 1202.5319
BIC Value   : 1206.3559
P-Value     :
 Intercept             0.234300
log_Administration    0.104253
dtype: float64
```

After transformation model performance is not so good.

10. Model Finalization & Model Testing

In [51]:
```
y.head()
```

Out[51]:

	Profit
0	192261.83
1	191792.06
2	191050.39
3	182901.99
4	166187.94

In [54]:
```
X_test = pd.DataFrame(data=startups_data.drop(["Profit","Administration"],axis=1))
X_test.head()
```

Out[54]:

	R&D_Spend	Marketing_Spend
0	165349.20	471784.10
1	162597.70	443898.53
2	153441.51	407934.54
3	144372.41	383199.62
4	142107.34	366168.42

In [56]:
```
y_pred_stat_3 = linear_model_stats_3.predict(X_test)
y_pred_stat_3.head()
```

Out[56]:
```
0    192800.458625
1    189774.659480
2    181405.378097
3    173441.308842
4    171127.623218
dtype: float64
```