Liner Regression on Global Warming

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

In [2]:
```
data = pd.read_csv("GlobalWarming.csv")
data.head()
#raw=data
```

Out[2]:

	Year	Month	MEI	CO2	CH4	N2O	CFC-11	CFC-12	TSI	Aerosols	Temp
0	1983	5	2.556	345.96	1638.59	303.677	191.324	350.113	1366.1024	0.0863	0.109
1	1983	6	2.167	345.52	1633.71	303.746	192.057	351.848	1366.1208	0.0794	0.118
2	1983	7	1.741	344.15	1633.22	303.795	192.818	353.725	1366.2850	0.0731	0.137
3	1983	8	1.130	342.25	1631.35	303.839	193.602	355.633	1366.4202	0.0673	0.176
4	1983	9	0.428	340.17	1648.40	303.901	194.392	357.465	1366.2335	0.0619	0.149

In [3]:
```
#checking any null values are there.oops there's no null values
data.isnull().sum()
```

Out[3]:
```
Year        0
Month       0
MEI         0
CO2         0
CH4         0
N2O         0
CFC-11      0
CFC-12      0
TSI         0
Aerosols    0
```

```
Temp        0
dtype: int64
```

In [4]:
```
#checking the datatypes
data.dtypes
```

Out[4]:
```
Year           int64
Month          int64
MEI          float64
CO2          float64
CH4          float64
N2O          float64
CFC-11       float64
CFC-12       float64
TSI          float64
Aerosols     float64
Temp         float64
dtype: object
```

In [5]:
```
#shape of the dataframe
data.shape
```

Out[5]:
```
(308, 11)
```

In [6]:
```
data.Year.unique()
```

Out[6]:
```
array([1983, 1984, 1985, 1986, 1987, 1988, 1989, 1990, 1991, 1992, 199
3,
       1994, 1995, 1996, 1997, 1998, 1999, 2000, 2001, 2002, 2003, 200
4,
       2005, 2006, 2007, 2008])
```

In [7]:
```
#summary statistics
data.describe()
```

Out[7]:

	Year	Month	MEI	CO2	CH4	N2O	CFC-11	
count	308.000000	308.000000	308.000000	308.000000	308.000000	308.000000	308.000000	3C

	Year	Month	MEI	CO2	CH4	N2O	CFC-11	
mean	1995.662338	6.551948	0.275555	363.226753	1749.824513	312.391834	251.973068	49
std	7.423197	3.447214	0.937918	12.647125	46.051678	5.225131	20.231783	5
min	1983.000000	1.000000	-1.635000	340.170000	1629.890000	303.677000	191.324000	35
25%	1989.000000	4.000000	-0.398750	353.020000	1722.182500	308.111500	246.295500	47
50%	1996.000000	7.000000	0.237500	361.735000	1764.040000	311.507000	258.344000	52
75%	2002.000000	10.000000	0.830500	373.455000	1786.885000	316.979000	267.031000	54
max	2008.000000	12.000000	3.001000	388.500000	1814.180000	322.182000	271.494000	54

In [8]:

```
##corr table
data.corr()
```

Out[8]:

	Year	Month	MEI	CO2	CH4	N2O	CFC-11	CFC-12	
Year	1.000000	-0.025789	-0.145345	0.985379	0.910563	0.994850	0.460965	0.870067	
Month	-0.025789	1.000000	-0.016345	-0.096287	0.017558	0.012395	-0.014914	-0.001084	-
MEI	-0.145345	-0.016345	1.000000	-0.152911	-0.105555	-0.162375	0.088171	-0.039836	-
CO2	0.985379	-0.096287	-0.152911	1.000000	0.872253	0.981135	0.401284	0.823210	
CH4	0.910563	0.017558	-0.105555	0.872253	1.000000	0.894409	0.713504	0.958237	
N2O	0.994850	0.012395	-0.162375	0.981135	0.894409	1.000000	0.412155	0.839295	
CFC-11	0.460965	-0.014914	0.088171	0.401284	0.713504	0.412155	1.000000	0.831381	
CFC-12	0.870067	-0.001084	-0.039836	0.823210	0.958237	0.839295	0.831381	1.000000	
TSI	0.022353	-0.032754	-0.076826	0.017867	0.146335	0.039892	0.284629	0.189270	
Aerosols	-0.361884	0.014845	0.352351	-0.369265	-0.290381	-0.353499	-0.032302	-0.243785	
Temp	0.755731	-0.098016	0.135292	0.748505	0.699697	0.743242	0.380111	0.688944	

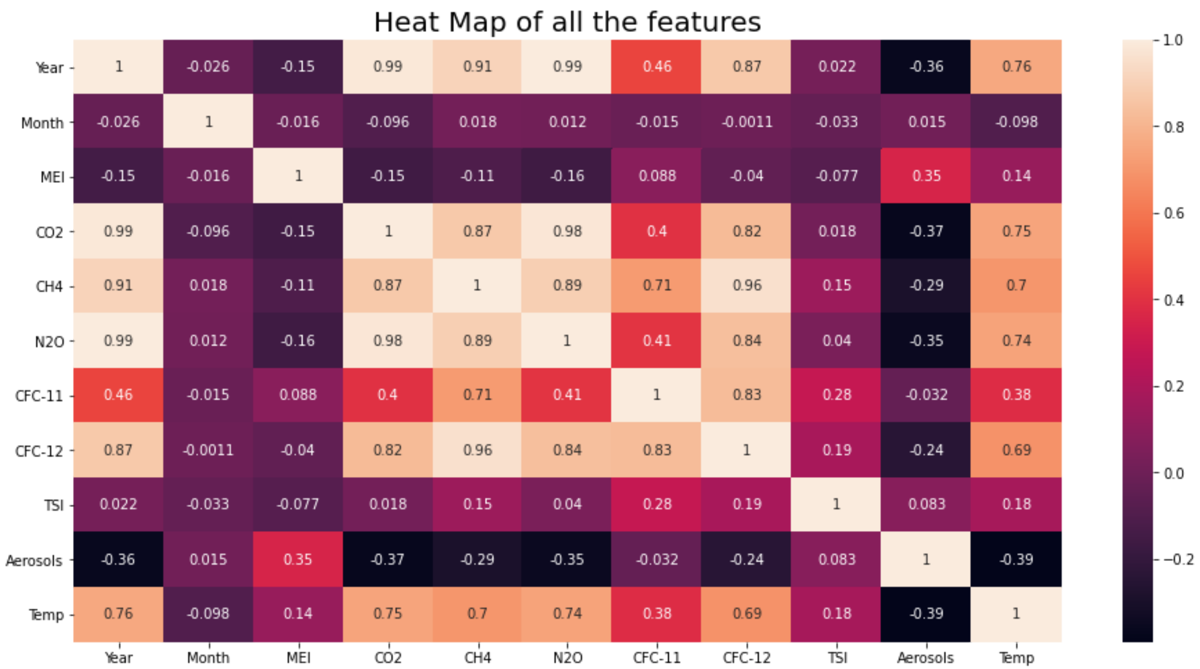
In [9]:

```
# Importing matplotlib and seaborn
```

```python
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

Heat Map

In [10]:
```python
plt.figure(figsize = (16,8))
plt.title("Heat Map of all the features", size = 20)
sns.heatmap(data.corr(),annot = True)
plt.show()
```



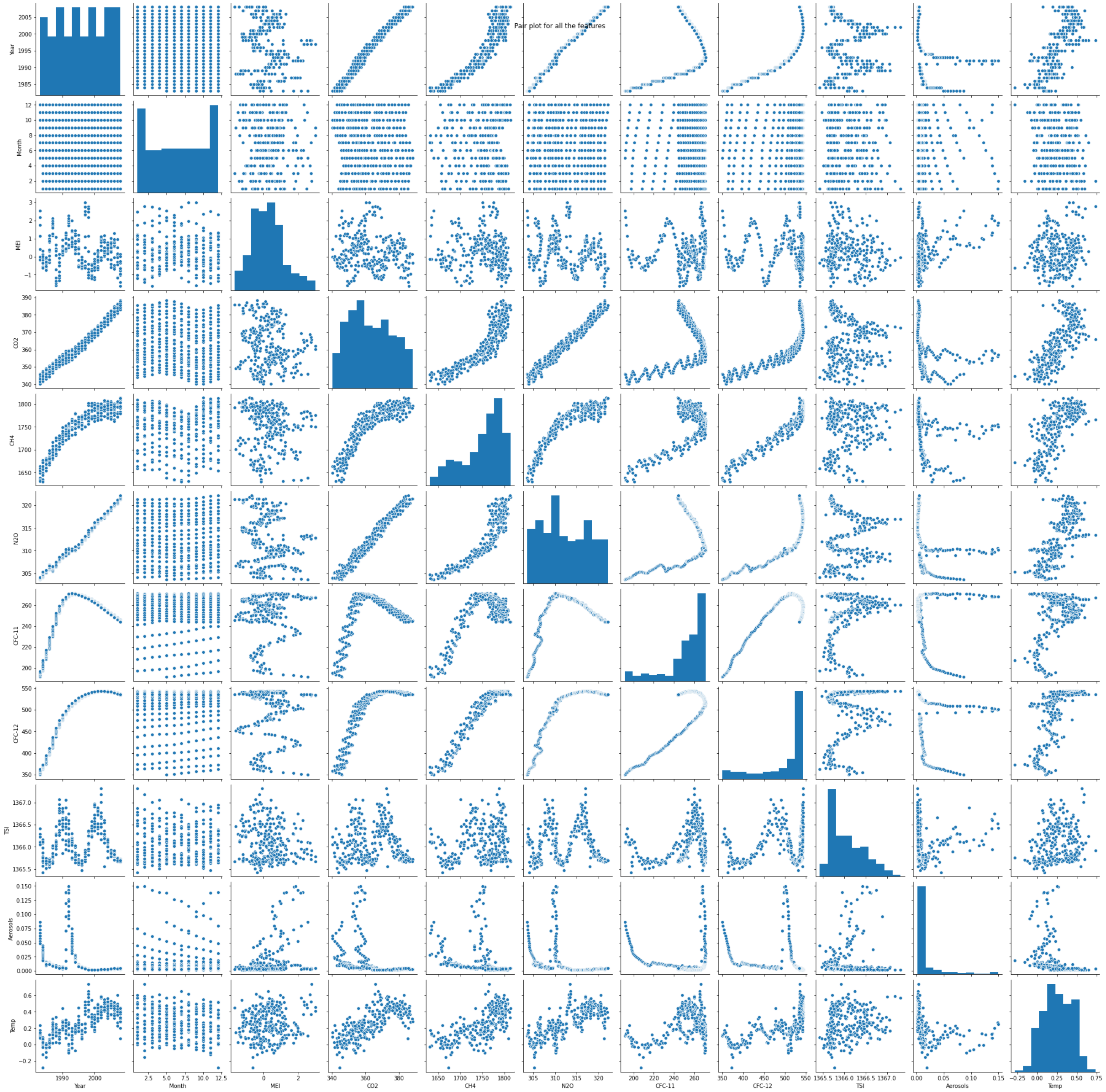
From the heatmap, there is high correlation of temperature with CO2 with corr rate 0.75 folloed by N2O with 0.74.

CH4 has correlation rate of 0.7 with temp

Checking for Multicollinearity

In [11]:
```
# let us plot pair plot for our understanding

g = sns.pairplot(data)
g.fig.suptitle("Pair plot for all the features")
```

Out[11]:
```
Text(0.5, 0.98, 'Pair plot for all the features')
```



In [12]:
```
#columns
data.columns
```

```
Out[12]: Index(['Year', 'Month', 'MEI', 'CO2', 'CH4', 'N2O', 'CFC-11', 'CFC-12',
'TSI',
       'Aerosols', 'Temp'],
      dtype='object')
```

```
In [13]: raw=data.copy()
raw.columns=['Year','Month','MEI','CO2','CH4','N2O','CFC11','CFC12','TS
I','Aerosols','Temp']
raw.head()
```

Out[13]:

	Year	Month	MEI	CO2	CH4	N2O	CFC11	CFC12	TSI	Aerosols	Temp
0	1983	5	2.556	345.96	1638.59	303.677	191.324	350.113	1366.1024	0.0863	0.109
1	1983	6	2.167	345.52	1633.71	303.746	192.057	351.848	1366.1208	0.0794	0.118
2	1983	7	1.741	344.15	1633.22	303.795	192.818	353.725	1366.2850	0.0731	0.137
3	1983	8	1.130	342.25	1631.35	303.839	193.602	355.633	1366.4202	0.0673	0.176
4	1983	9	0.428	340.17	1648.40	303.901	194.392	357.465	1366.2335	0.0619	0.149

```
In [14]: import statsmodels.formula.api as smf
from patsy import dmatrices
import patsy
```

```
In [15]: model1 = smf.ols('Temp ~ MEI+CO2+CH4+N2O +CFC11 +CFC12+ TSI+Aerosols',
data=raw).fit()
```

```
In [16]: #library for vif
from statsmodels.stats.outliers_influence import variance_inflation_fac
tor

variables = model1.model.exog

vif1 = [variance_inflation_factor(variables, i) for i in range(variable
s.shape[1])]
vif1
```

```
Out[16]: [13454981.483446594,
```

```
 1.2256958636480464,
 27.99610328105419,
 19.129507584320763,
 61.03745302018548,
 31.829321263531924,
 93.49818247345564,
 1.1409763102539896,
 1.35447009956284]
```

We can observe that the features are collinear with other features. Therefore, we pop the features to remove the collinearity

In [17]:
```
model2 = smf.ols('Temp ~ MEI+CO2+CH4+N2O +CFC11 + TSI+Aerosols', data=raw).fit()
```

In [18]:
```
#library for vif
from statsmodels.stats.outliers_influence import variance_inflation_factor

variables = model2.model.exog

vif2 = [variance_inflation_factor(variables, i) for i in range(variables.shape[1])]
vif2
```

Out[18]:
```
[13294463.802566227,
 1.2082133502180714,
 27.828286590155134,
 18.069706730342357,
 39.81368759362757,
 4.613597995435398,
 1.1402527516910357,
 1.329244557506287]
```

In [19]:
```
model3 = smf.ols('Temp ~ MEI+CO2+CH4 +CFC11 + TSI+Aerosols', data=raw).fit()
```

In [20]:
```
#library for vif
from statsmodels.stats.outliers_influence import variance_inflation_fac
tor

variables = model3.model.exog

vif3 = [variance_inflation_factor(variables, i) for i in range(variable
s.shape[1])]
vif3
```

Out[20]:
```
[13286575.242852286,
 1.2071761873041988,
 7.312001000991996,
 12.479762713790219,
 3.768725049987,
 1.1345838246892797,
 1.3184259273416337]
```

In [21]:
```
model4 = smf.ols('Temp ~ MEI+CO2 +CFC11 + TSI+Aerosols', data=raw).fit
()
```

In [22]:
```
#library for vif
from statsmodels.stats.outliers_influence import variance_inflation_fac
tor

variables = model4.model.exog

vif3 = [variance_inflation_factor(variables, i) for i in range(variable
s.shape[1])]
vif3
```

Out[22]:
```
[13284513.442577127,
 1.1921076240252628,
 1.425480977449902,
 1.369342140936699,
 1.1338806590781065,
 1.3169186245140256]
```

- We have removed the features with high collinearity

In [23]:
```
raw1=raw.iloc[:,2:11]
```

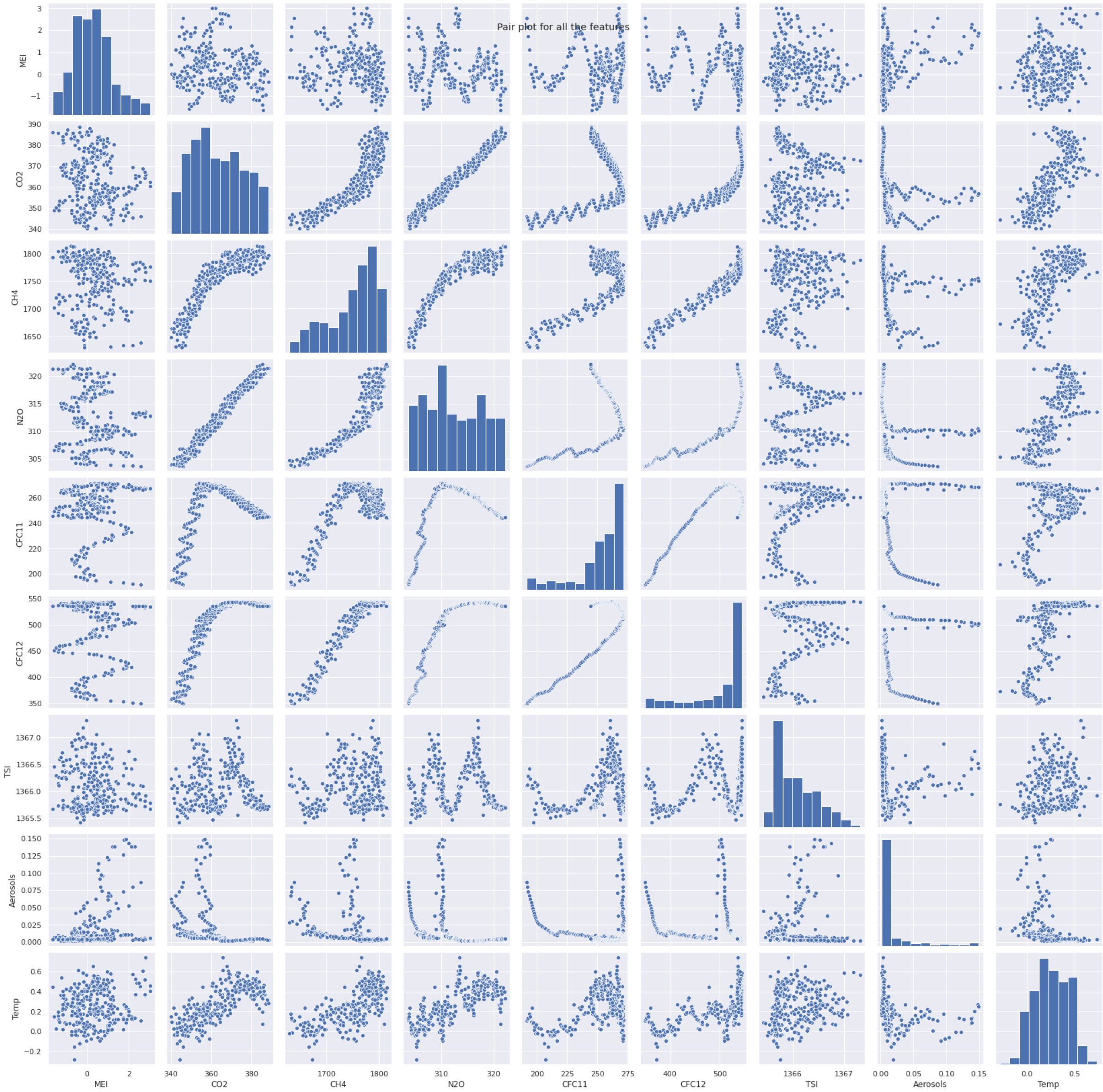
In [24]:
```
raw1.head()
```

Out[24]:

	MEI	CO2	CH4	N2O	CFC11	CFC12	TSI	Aerosols	Temp
0	2.556	345.96	1638.59	303.677	191.324	350.113	1366.1024	0.0863	0.109
1	2.167	345.52	1633.71	303.746	192.057	351.848	1366.1208	0.0794	0.118
2	1.741	344.15	1633.22	303.795	192.818	353.725	1366.2850	0.0731	0.137
3	1.130	342.25	1631.35	303.839	193.602	355.633	1366.4202	0.0673	0.176
4	0.428	340.17	1648.40	303.901	194.392	357.465	1366.2335	0.0619	0.149

In [25]:
```
sns.set()
sns.pairplot(raw1).fig.suptitle("Pair plot for all the features")
```

Out[25]:
```
Text(0.5, 0.98, 'Pair plot for all the features')
```



STATS MODELS - OLS

MODEL-1

In [26]:
```
model1 = 'Temp ~ MEI+CO2+CH4+N2O +CFC11 +CFC12+ TSI+Aerosols'

result = smf.ols(formula = model1, data = raw1).fit()
```

In [27]:
```
print(result.summary())
```

```
                            OLS Regression Results

==============================================================================
=======
Dep. Variable:                   Temp   R-squared:
  0.744
Model:                            OLS   Adj. R-squared:
  0.737
Method:                 Least Squares   F-statistic:
  108.6
Date:                Fri, 04 Dec 2020   Prob (F-statistic):
8.21e-84
Time:                        13:11:46   Log-Likelihood:
303.02
No. Observations:                 308   AIC:
-588.0
Df Residuals:                     299   BIC:
-554.5
Df Model:                           8

Covariance Type:            nonrobust

==============================================================================
=======
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-------
Intercept   -127.6958     19.191     -6.654      0.000    -165.462
```

```
-89.929
MEI              0.0663      0.006     10.722      0.000       0.054
  0.078
CO2              0.0052      0.002      2.375      0.018       0.001
  0.010
CH4           6.371e-05      0.000      0.128      0.898      -0.001
  0.001
N2O             -0.0169      0.008     -2.161      0.032      -0.032
-0.002
CFC11           -0.0073      0.001     -4.980      0.000      -0.010
-0.004
CFC12            0.0043      0.001      4.875      0.000       0.003
  0.006
TSI              0.0959      0.014      6.844      0.000       0.068
  0.123
Aerosols        -1.5818      0.210     -7.535      0.000      -1.995
-1.169
=======================================================================
=======
Omnibus:                        6.703   Durbin-Watson:
  0.978
Prob(Omnibus):                  0.035   Jarque-Bera (JB):
  8.299
Skew:                           0.191   Prob(JB):
0.0158
Kurtosis:                       3.708   Cond. No.
8.58e+06
=======================================================================
=======

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 8.58e+06. This might indicate that t
here are
strong multicollinearity or other numerical problems.
```

- The P value of CH4 is greater than 0.05. Therefore this feature needs to be removed.

MODEL1 RESULTS

In [28]:
```
print("MSE: ", result.ssr/len(raw1))
print("RMSE: ", np.sqrt(result.ssr/len(raw1)))
print("R2: ", result.rsquared)
print("R2adj: ", result.rsquared_adj)
print("AIC: ", result.aic)
print("BIC: ", result.bic)
```

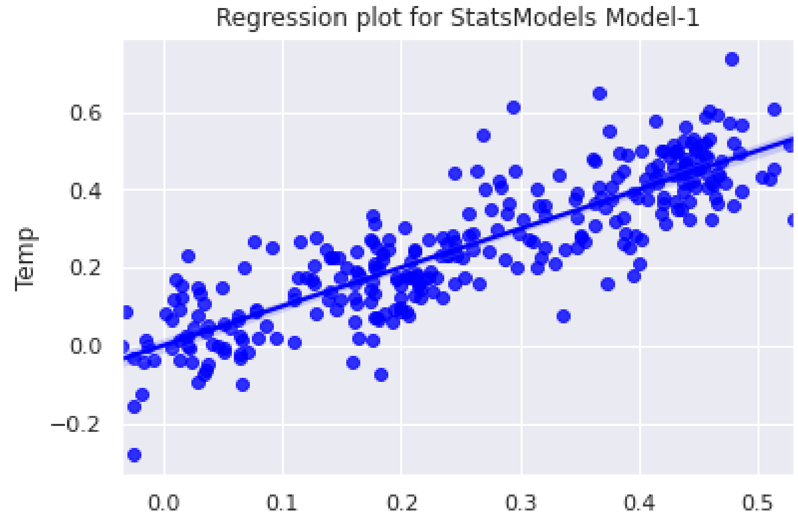
```
MSE:  0.008184260128792465
RMSE:  0.09046690073608395
R2:  0.7439939571287729
R2adj:  0.7371442971188404
AIC:  -588.0409430107441
BIC:  -554.4700449639819
```

In [29]:
```
pred1 =  result.predict(raw1)
pred1.head()
```

Out[29]:
```
0    0.163070
1    0.148257
2    0.140195
3    0.113494
4    0.048863
dtype: float64
```

Regression PLOT

In [30]:
```
import seaborn as sns

sns.regplot(x= pred1, y= data.Temp, color = 'blue')
plt.title("Regression plot for StatsModels Model-1")
plt.show()
```



since p value of ch4 is more than 0.05, it means there is no significance dependency on respnce variable.

We delete that feature (CH4)

MODEL-2

In [31]:
```
model2 = 'Temp ~ MEI+CO2+N2O +CFC11 +CFC12+ TSI+Aerosols'

result = smf.ols(formula = model2, data = raw1).fit()
```

In [32]:
```
print(result.summary())
```

```
                            OLS Regression Results

==============================================================================
=======
Dep. Variable:                   Temp   R-squared:
```

```
  0.744
Model:                            OLS   Adj. R-squared:
  0.738
Method:                 Least Squares   F-statistic:
  124.5
Date:                Fri, 04 Dec 2020   Prob (F-statistic):
7.14e-85
Time:                        13:11:46   Log-Likelihood:
303.01
No. Observations:                 308   AIC:
-590.0
Df Residuals:                     300   BIC:
-560.2
Df Model:                           7

Covariance Type:            nonrobust

========================================================================
=======
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------
-------
Intercept   -127.6250     19.151     -6.664      0.000    -165.313
-89.937
MEI            0.0662      0.006     10.783      0.000       0.054
  0.078
CO2            0.0052      0.002      2.380      0.018       0.001
  0.009
N2O           -0.0166      0.007     -2.227      0.027      -0.031
-0.002
CFC11         -0.0073      0.001     -4.998      0.000      -0.010
-0.004
CFC12          0.0043      0.001      5.055      0.000       0.003
  0.006
TSI            0.0958      0.014      6.854      0.000       0.068
  0.123
Aerosols      -1.5830      0.209     -7.559      0.000      -1.995
-1.171
```

```
==============================================================================
=======
Omnibus:                        6.603   Durbin-Watson:
  0.976
Prob(Omnibus):                  0.037   Jarque-Bera (JB):
  8.077
Skew:                           0.192   Prob(JB):
0.0176
Kurtosis:                       3.694   Cond. No.
5.69e+06
==============================================================================
=======

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 5.69e+06. This might indicate that t
here are
strong multicollinearity or other numerical problems.
```

- The Model-2 has good RMSE values and the P values are less than 0.05

RESULTS

In [33]:

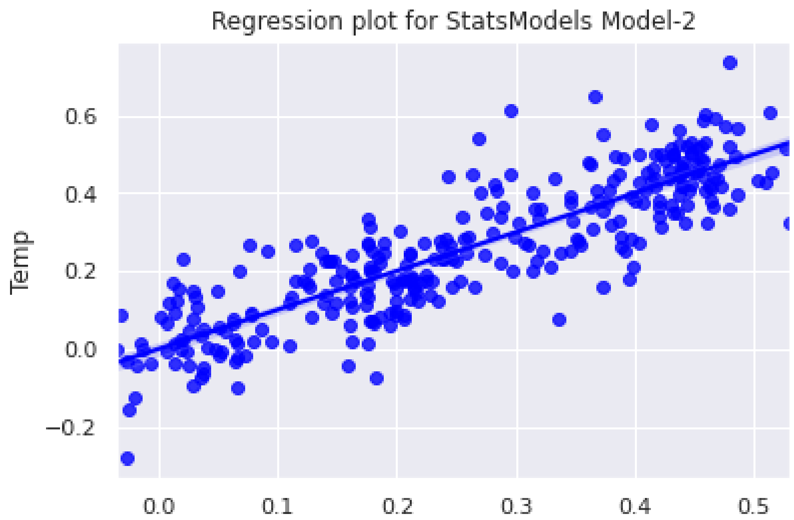
```
print("MSE: ", result.ssr/len(raw1))
print("RMSE: ", np.sqrt(result.ssr/len(raw1)))
print("R2: ", result.rsquared)
print("R2adj: ", result.rsquared_adj)
print("AIC: ", result.aic)
print("BIC: ", result.bic)
```

```
MSE:  0.00818470866133402
RMSE:  0.09046937968911924
R2:  0.7439799269001077
R2adj:  0.7380061251944435
AIC:  -590.0240637528502
BIC:  -560.1832654890617
```

In [34]:
```
pred2 =  result.predict(raw1)
pred2.head()
```

Out[34]:
```
0    0.162886
1    0.148515
2    0.140639
3    0.114243
4    0.048742
dtype: float64
```

In [35]:
```
sns.regplot(pred2, data.Temp, color = 'blue')
plt.title("Regression plot for StatsModels Model-2")
plt.show()
```



MODEL 3

In [36]:
```
model3 = 'Temp ~ MEI+CO2+CFC11 + TSI+Aerosols'

result = smf.ols(formula = model3, data = raw1).fit()
```

```
In [37]: print(result.summary())
```

```
                            OLS Regression Results                            
==============================================================================
=======
Dep. Variable:                   Temp   R-squared:
  0.719
Model:                            OLS   Adj. R-squared:
  0.714
Method:                 Least Squares   F-statistic:
  154.5
Date:                Fri, 04 Dec 2020   Prob (F-statistic):
5.08e-81
Time:                        13:11:47   Log-Likelihood:
288.64
No. Observations:                 308   AIC:
-565.3
Df Residuals:                     302   BIC:
-542.9
Df Model:                           5

Covariance Type:            nonrobust

==============================================================================
=======
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-------
Intercept   -138.8416     19.881     -6.984      0.000    -177.964
-99.719
MEI            0.0683      0.006     10.735      0.000       0.056
  0.081
CO2            0.0099      0.001     19.151      0.000       0.009
  0.011
CFC11      -2.964e-05      0.000     -0.094      0.925      -0.001
  0.001
TSI            0.0992      0.015      6.815      0.000       0.071
```

```
  0.128
Aerosols      -1.7201      0.216     -7.970      0.000      -2.145
-1.295
==============================================================================
Omnibus:                      11.534   Durbin-Watson:
  0.912
Prob(Omnibus):                 0.003   Jarque-Bera (JB):
15.097
Skew:                          0.312   Prob(JB):
0.000527
Kurtosis:                      3.887   Cond. No.
5.23e+06
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 5.23e+06. This might indicate that t
here are
strong multicollinearity or other numerical problems.
```

- We can observe that the RMSE value is low. But, the P value for CFC-11 is more than 0.05. Therefore we need to pop the feature.

MODEL3 RESULTS

In [38]:

```
print("MSE: ", result.ssr/len(raw1))
print("RMSE: ", np.sqrt(result.ssr/len(raw1)))
print("R2: ", result.rsquared)
print("R2adj: ", result.rsquared_adj)
print("AIC: ", result.aic)
print("BIC: ", result.bic)
```

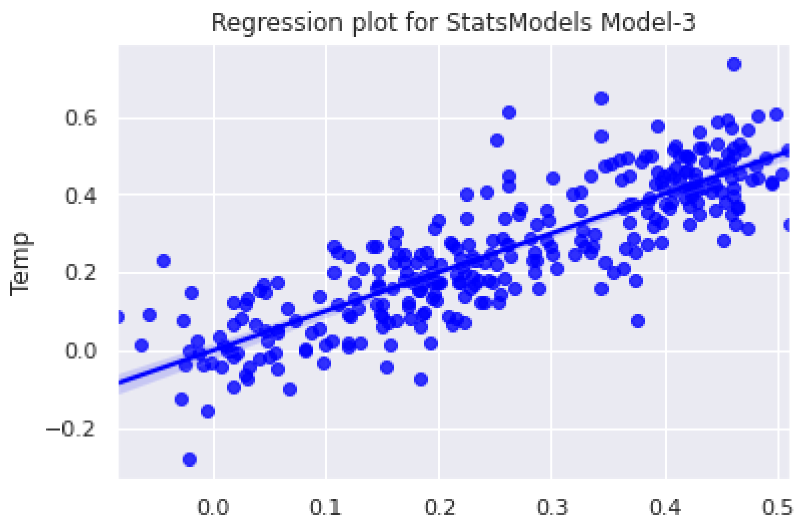
```
MSE:  0.008985275872117466
RMSE:  0.09479069507139119
```

```
R2:  0.7189379511491043
R2adj:  0.7142846059694536
AIC:  -565.2816246669481
BIC:  -542.9010259691066
```

In [39]:
```python
pred3 =  result.predict(raw1)
pred3.head()
```

Out[39]:
```
0    0.127063
1    0.109831
2    0.094318
3    0.057201
4   -0.020530
dtype: float64
```

In [40]:
```python
sns.regplot(pred3, data.Temp, color = 'blue')
plt.title("Regression plot for StatsModels Model-3")
plt.show()
```



MODEL 4

```
In [41]: model4 = 'Temp ~ MEI+CO2 + TSI+Aerosols'

         result = smf.ols(formula = model4, data = raw1).fit()
```

```
In [42]: print(result.summary())
```

```
                            OLS Regression Results

=======================================================================
=======
Dep. Variable:                   Temp   R-squared:
  0.719
Model:                            OLS   Adj. R-squared:
  0.715
Method:                 Least Squares   F-statistic:
  193.8
Date:                Fri, 04 Dec 2020   Prob (F-statistic):
3.44e-82
Time:                        13:11:48   Log-Likelihood:
288.64
No. Observations:                 308   AIC:
-567.3
Df Residuals:                     303   BIC:
-548.6
Df Model:                           4

Covariance Type:            nonrobust

=======================================================================
=======
                 coef    std err          t      P>|t|      [0.025
0.975]
-----------------------------------------------------------------------
-------
Intercept   -138.2575     18.849     -7.335      0.000    -175.349    -
101.166
MEI            0.0682      0.006     10.897      0.000       0.056
  0.080
CO2            0.0099      0.000     21.205      0.000       0.009
```

```
  0.011
TSI              0.0988       0.014       7.156       0.000        0.072
  0.126
Aerosols        -1.7212       0.215      -7.998       0.000       -2.145
-1.298
==============================================================================
=======
Omnibus:                       11.490   Durbin-Watson:
  0.911
Prob(Omnibus):                  0.003   Jarque-Bera (JB):
14.999
Skew:                           0.312   Prob(JB):
0.000553
Kurtosis:                       3.883   Cond. No.
4.89e+06
==============================================================================
=======

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 4.89e+06. This might indicate that t
here are
strong multicollinearity or other numerical problems.
```

- The P values are less than 0.05 and the RMSE values are also less

In [43]:

```
print("MSE: ", result.ssr/len(raw1))
print("RMSE: ", np.sqrt(result.ssr/len(raw1)))
print("R2: ", result.rsquared)
print("R2adj: ", result.rsquared_adj)
print("AIC: ", result.aic)
print("BIC: ", result.bic)
```

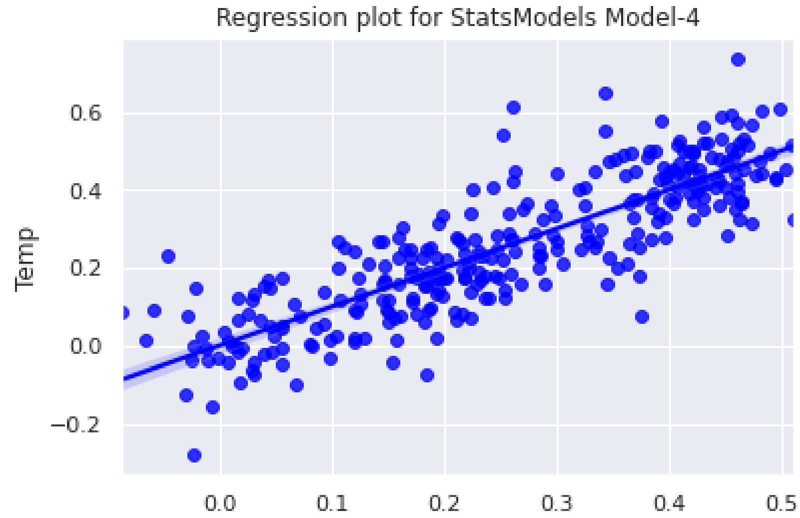
```
MSE:  0.008985537581110689
RMSE:  0.09479207551852997
R2:  0.7189297648154975
R2adj:  0.7152192666612467
```

```
AIC:  -567.2726538576824
BIC:  -548.6221549428145
```

In [44]:
```
pred4 =  result.predict(raw1)
pred4.head()
```

Out[44]:
```
0    0.125307
1    0.108145
2    0.092663
3    0.055619
4   -0.021889
dtype: float64
```

In [45]:
```
sns.regplot(pred4, data.Temp, color = 'blue')
plt.title("Regression plot for StatsModels Model-4")
plt.show()
```



SUMMARY

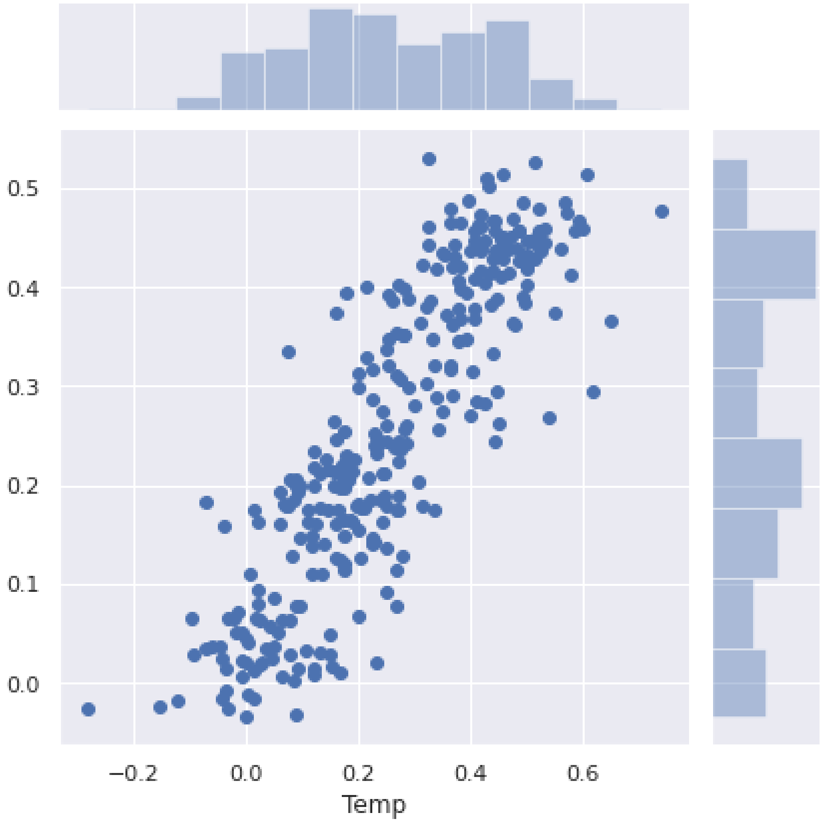
- From the above 4 models, we can observe that the Model-1 and Model-2 have almost similar RMSE values.

- The Model-1 has lowest RMSE values among all the models

Correlation between actual and predicted values

In [46]:
```
sns.jointplot(data.Temp,pred1)
```

Out[46]: <seaborn.axisgrid.JointGrid at 0x7efffebe4610>



- We can observe that the features are positively correlated

In [47]:
```
correlation = raw1.Temp.corr(pred4)
correlation
```
Out[47]: 0.8478972607665969

- Our predictions are 84% correlated with actual values

In [48]:
```
r2=np.square(correlation)
r2
```
Out[48]: 0.7189297648154984

SK-LEARN LINEAR REGRESSION WITH TEST-TRAIN SPLIT

In [49]:
```
data.head()
```
Out[49]:

	Year	Month	MEI	CO2	CH4	N2O	CFC-11	CFC-12	TSI	Aerosols	Temp
0	1983	5	2.556	345.96	1638.59	303.677	191.324	350.113	1366.1024	0.0863	0.109
1	1983	6	2.167	345.52	1633.71	303.746	192.057	351.848	1366.1208	0.0794	0.118
2	1983	7	1.741	344.15	1633.22	303.795	192.818	353.725	1366.2850	0.0731	0.137
3	1983	8	1.130	342.25	1631.35	303.839	193.602	355.633	1366.4202	0.0673	0.176
4	1983	9	0.428	340.17	1648.40	303.901	194.392	357.465	1366.2335	0.0619	0.149

In [50]:
```
data.shape
```
Out[50]: (308, 11)

MODEL -1

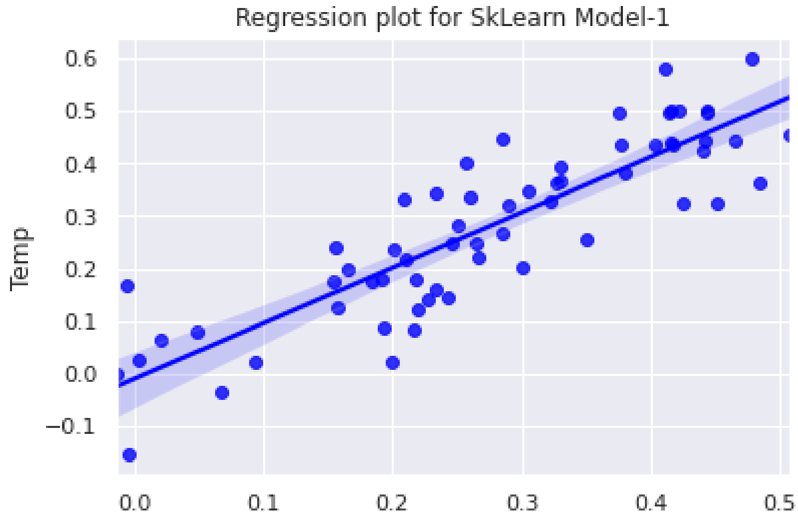
In [51]:
```
X = data.iloc[:, :-1]
y = data.iloc[:, 10]
```

In [52]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.2, random_state = 5)
```

In [53]:
```
# Fitting Multiple Linear Regression to the Training set
from sklearn.linear_model import LinearRegression
from sklearn import linear_model, metrics

regressor = LinearRegression()
regressor.fit(X_train, y_train)

# Predicting the Test set results
y_pred = regressor.predict(X_test)

from sklearn.metrics import r2_score
score=r2_score(y_test,y_pred)
print("R2 SCORE: ",score)

print("MSE: ",metrics.mean_squared_error(y_test, regressor.predict(X_te
st)))
```

```
R2 SCORE:  0.7500893204365684
MSE:  0.006844221344486302
```

In [54]:
```
sns.regplot(y_pred, y_test, color = 'blue')
plt.title("Regression plot for SkLearn Model-1")
plt.show()
```



MODEL 2

In [55]:
```
X = data[['MEI', 'CO2', 'N2O', 'CFC-11', 'CFC-12', 'TSI','Aerosols']]
```

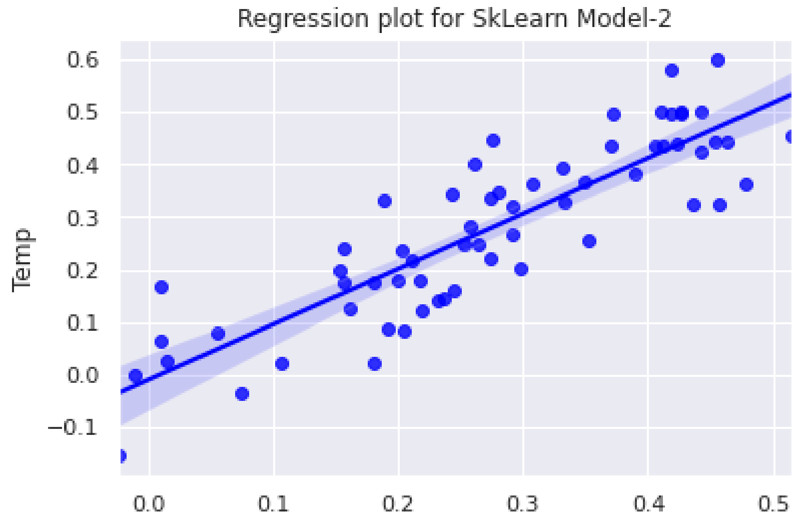
In [56]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.2, random_state = 5)
```

In [57]:
```
# Fitting Multiple Linear Regression to the Training set
from sklearn.linear_model import LinearRegression
from sklearn import linear_model, metrics

regressor = LinearRegression()
regressor.fit(X_train, y_train)

# Predicting the Test set results
y_pred = regressor.predict(X_test)

from sklearn.metrics import r2_score
score=r2_score(y_test,y_pred)
```

```
print("R2 SCORE: ",score)

print("MSE: ",metrics.mean_squared_error(y_test, regressor.predict(X_te
st)))
```

```
R2 SCORE:  0.747657806782692
MSE:  0.006910812406854 4335
```

In [58]:
```
sns.regplot(y_pred, y_test, color = 'blue')
plt.title("Regression plot for SkLearn Model-2")
plt.show()
```



MODEL-3

In [59]:
```
X = data[['MEI', 'CO2', 'CFC-11','TSI','Aerosols']]
```

In [60]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.2, random_state = 5)
```

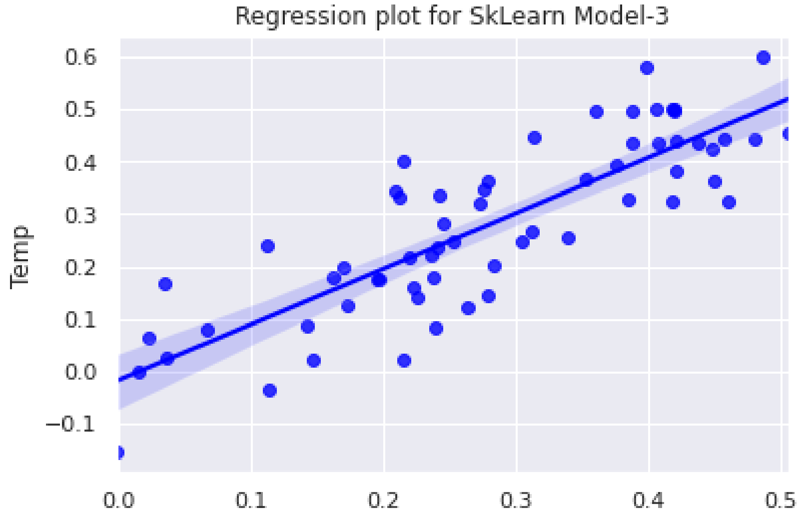
In [61]:

```
# Fitting Multiple Linear Regression to the Training set
from sklearn.linear_model import LinearRegression
from sklearn import linear_model, metrics

regressor = LinearRegression()
regressor.fit(X_train, y_train)

# Predicting the Test set results
y_pred = regressor.predict(X_test)

from sklearn.metrics import r2_score
score=r2_score(y_test,y_pred)
print("R2 SCORE: ",score)

print("MSE: ",metrics.mean_squared_error(y_test, regressor.predict(X_te
st)))
```

```
R2 SCORE:  0.7045015220984228
MSE:  0.008092719339766566
```

In [62]:

```
sns.regplot(y_pred, y_test, color = 'blue')
plt.title("Regression plot for SkLearn Model-3")
plt.show()
```



MODEL-4

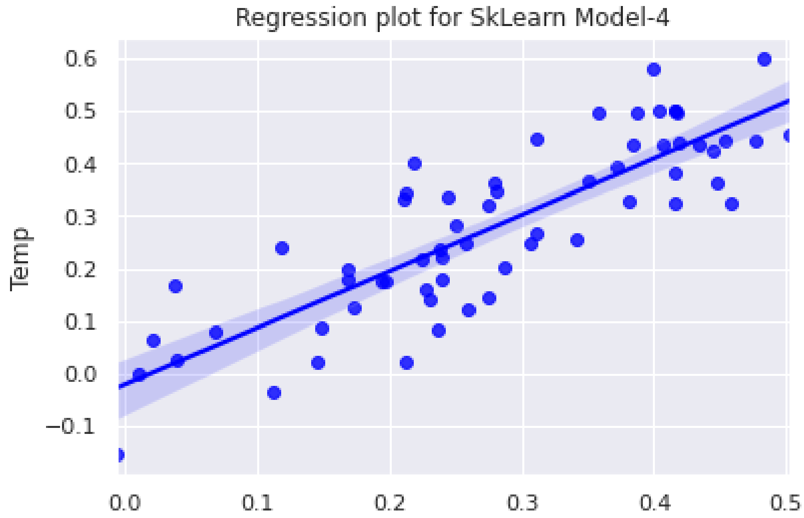
In [63]:
```
X = data[['MEI', 'CO2', 'TSI','Aerosols']]
```

In [64]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.2, random_state = 5)
```

In [65]:
```
# Fitting Multiple Linear Regression to the Training set
from sklearn.linear_model import LinearRegression
from sklearn import linear_model, metrics

regressor = LinearRegression()
regressor.fit(X_train, y_train)

# Predicting the Test set results
y_pred = regressor.predict(X_test)

from sklearn.metrics import r2_score
score=r2_score(y_test,y_pred)
print("R2 SCORE: ",score)

print("MSE: ",metrics.mean_squared_error(y_test, regressor.predict(X_te
st)))
```

```
R2 SCORE:  0.7088104354889706
MSE:  0.00797471255009816
```

In [66]:
```
sns.regplot(y_pred, y_test, color = 'blue')
plt.title("Regression plot for SkLearn Model-4")
plt.show()
```



Conclusion Sklearn Test-Train Split:

Model-1 & Model-2 has almost similar MSE scores

Model 1 has least Mean Squared Error

The results are similar to the Stats Models

LINEAR REGRESSION WITH CROSSVALIDATION

MODEL - 1

In [67]:
```
from sklearn.model_selection import cross_val_score
-cross_val_score(regressor, X, y, cv = 10, scoring = 'neg_mean_squared_
```

```
error').mean()
```

Out[67]: 0.010077575559097907

MODEL - 2

In [68]:
```
X = data[['MEI', 'CO2', 'N2O', 'CFC-11', 'CFC-12', 'TSI','Aerosols']]
-cross_val_score(regressor, X, y, cv = 10, scoring = 'neg_mean_squared_
error').mean()
```

Out[68]: 0.009984286154481034

MODEL - 3

In [69]:
```
X = data[['MEI', 'CO2', 'CFC-11','TSI','Aerosols']]
-cross_val_score(regressor, X, y, cv = 10, scoring = 'neg_mean_squared_
error').mean()
```

Out[69]: 0.010951233415290813

MODEL - 4

In [70]:
```
X = data[['MEI', 'CO2','TSI','Aerosols']]
-cross_val_score(regressor, X, y, cv = 10, scoring = 'neg_mean_squared_
error').mean()
```

Out[70]: 0.010077575559097907

Conclusions:

Model 2 has least Mean Squared Error

While Model 1 & Model 2 has almost similar scores

From the above three implementations of Linear Regression, all the three implemenations are giving similar results.

We can say that our models are working well as all the approaches are giving similar results

Time Series Forecasting on Avocado Prices

Data Loading

In [71]:

```
import warnings
warnings.filterwarnings("ignore")

import itertools
import pandas as pd
import numpy as np
from pylab import rcParams
import statsmodels.api as sm
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure

df = pd.read_csv("avocado.csv")
df.head(3)
```

Out[71]:

	Unnamed: 0	Date	AveragePrice	Total Volume	4046	4225	4770	Total Bags	Small Bags	Larg Bag
0	0	2015-12-27	1.33	64236.62	1036.74	54454.85	48.16	8696.87	8603.62	93.2
1	1	2015-12-20	1.35	54876.98	674.28	44638.81	58.33	9505.56	9408.07	97.4

	Unnamed: 0	Date	AveragePrice	Total Volume	4046	4225	4770	Total Bags	Small Bags	Larg Bag
2	2	2015-12-13	0.93	118220.22	794.70	109149.67	130.50	8145.35	8042.21	103.1

In [72]:
```
# Index and sort data by Date
df = df.set_index("Date")
df.index = pd.to_datetime(df.index)
df.sort_values(by=['Date'], inplace=True)
```

In [73]:
```
df.head()
```

Out[73]:

Date	Unnamed: 0	AveragePrice	Total Volume	4046	4225	4770	Total Bags	Small Bags	Larg Bag
2015-01-04	51	1.75	27365.89	9307.34	3844.81	615.28	13598.46	13061.10	537.3
2015-01-04	51	1.49	17723.17	1189.35	15628.27	0.00	905.55	905.55	0.0
2015-01-04	51	1.68	2896.72	161.68	206.96	0.00	2528.08	2528.08	0.0
2015-01-04	51	1.52	54956.80	3013.04	35456.88	1561.70	14925.18	11264.80	3660.3
2015-01-04	51	1.64	1505.12	1.27	1129.50	0.00	374.35	186.67	187.6

In [74]:
```
r = df.rolling(30)
r
```

Out[74]: Rolling [window=30,center=False,axis=0]

In [75]:
```
df['Close_avg_price'] = r.AveragePrice.mean()
```

```
df[['AveragePrice', 'Close_avg_price']].head(5)
```

Out[75]:

Date	AveragePrice	Close_avg_price
2015-01-04	1.75	NaN
2015-01-04	1.49	NaN
2015-01-04	1.68	NaN
2015-01-04	1.52	NaN
2015-01-04	1.64	NaN

In [76]:

```
fig = plt.figure(figsize = (18,10))
df.AveragePrice.rolling(150).quantile(.9).plot(color = 'red')
plt.title('Rolling window of prices', fontsize = 20)
```

Out[76]:

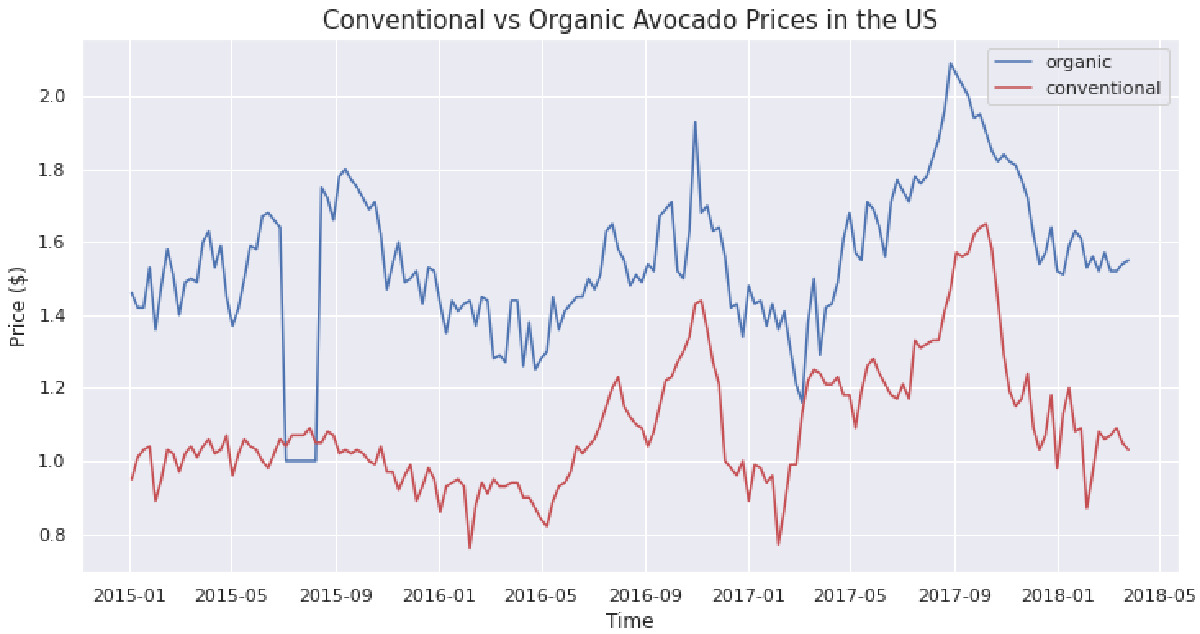
```
Text(0.5, 1.0, 'Rolling window of prices')
```

Data Exploration

Comparison of Organic and Conventional Avocado Prices

In [77]:
```
organic = df.loc[(df['region'] == "TotalUS") & (df['type'] == "organic"
)]
conv = df.loc[(df['region'] == "TotalUS") & (df['type'] == "conventiona
l")]

plt.figure(figsize=(12,6))
plt.plot(organic.index, organic['AveragePrice'], label="organic", color
='b')
plt.plot(conv.index, conv['AveragePrice'], label="conventional", color=
'r')
plt.legend()
```

```
plt.title("Conventional vs Organic Avocado Prices in the US", fontsize=
15)
plt.xlabel("Time")
plt.ylabel("Price ($)")
plt.show()
```



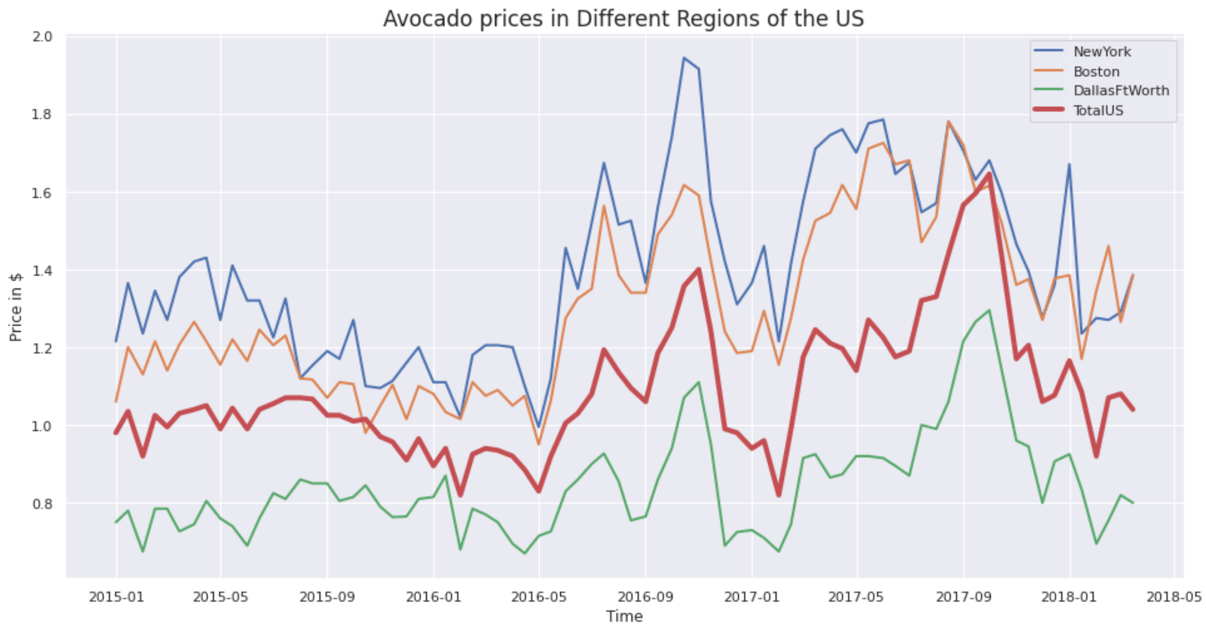
We can observe that:

1. Generally, organic and conventional avocado prices have similar fluctuations.
2. There is a sudden drop in organic prices in August 2015.

Comparison of Prices for Avocado in New York, Boston, Dallas and Total US

In [78]:
```
conventional = df.loc[df['type'] == "conventional"]
```

```
plt.figure(figsize=(16,8))

cities = ["NewYork", "Boston", "DallasFtWorth", "TotalUS"]
for c in cities:
    data = conventional.loc[conventional['region'] == c]
    data = data['AveragePrice'].resample("SMS").mean()
    if c == "TotalUS":
        linewidth = 4
    else:
        linewidth = 2
    plt.plot(data.index, data, label=c, linewidth=linewidth)

plt.legend()
plt.title("Avocado prices in Different Regions of the US", fontsize=17)
plt.xlabel("Time")
plt.ylabel("Price in $")
plt.show()
```



- New York has the highest prices

- Dallas has the lowest prices

Time-series Analysis

In [79]:
```
conv.index.min()
```

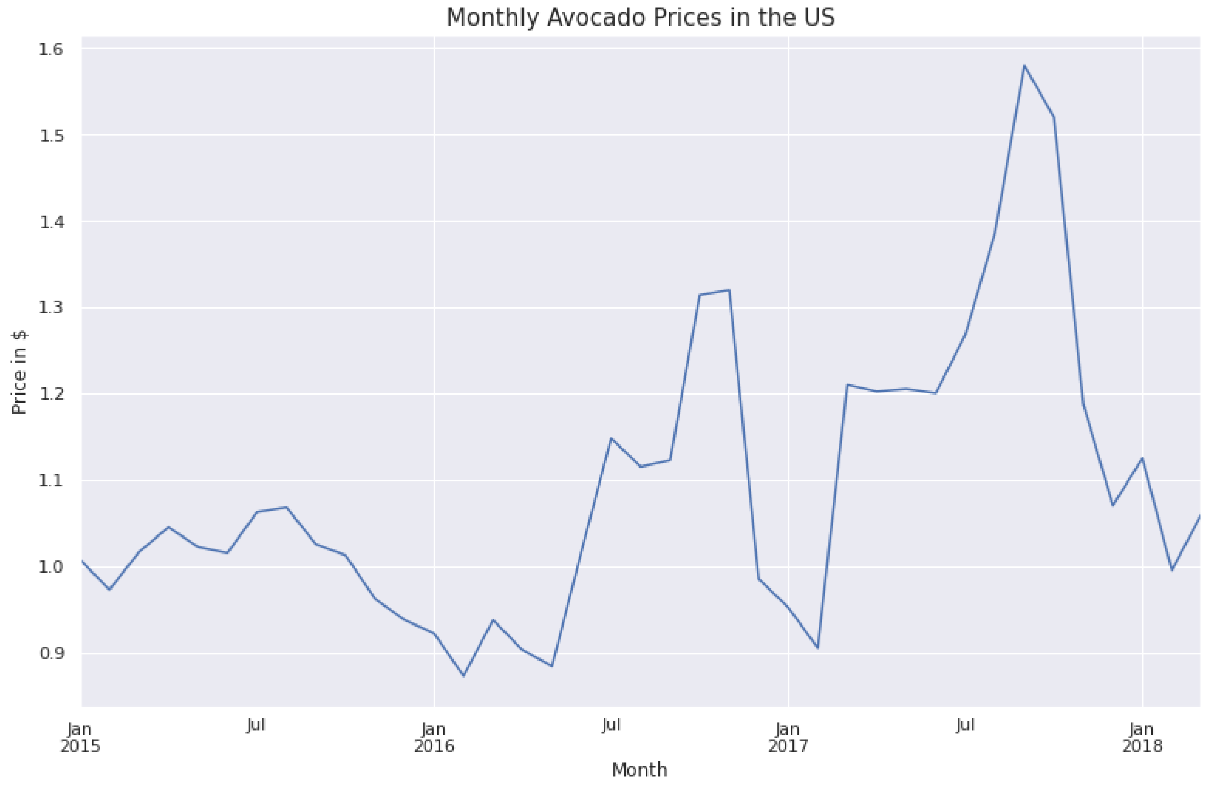
Out[79]: Timestamp('2015-01-04 00:00:00')

In [80]:
```
conv.index.max()
```

Out[80]: Timestamp('2018-03-25 00:00:00')

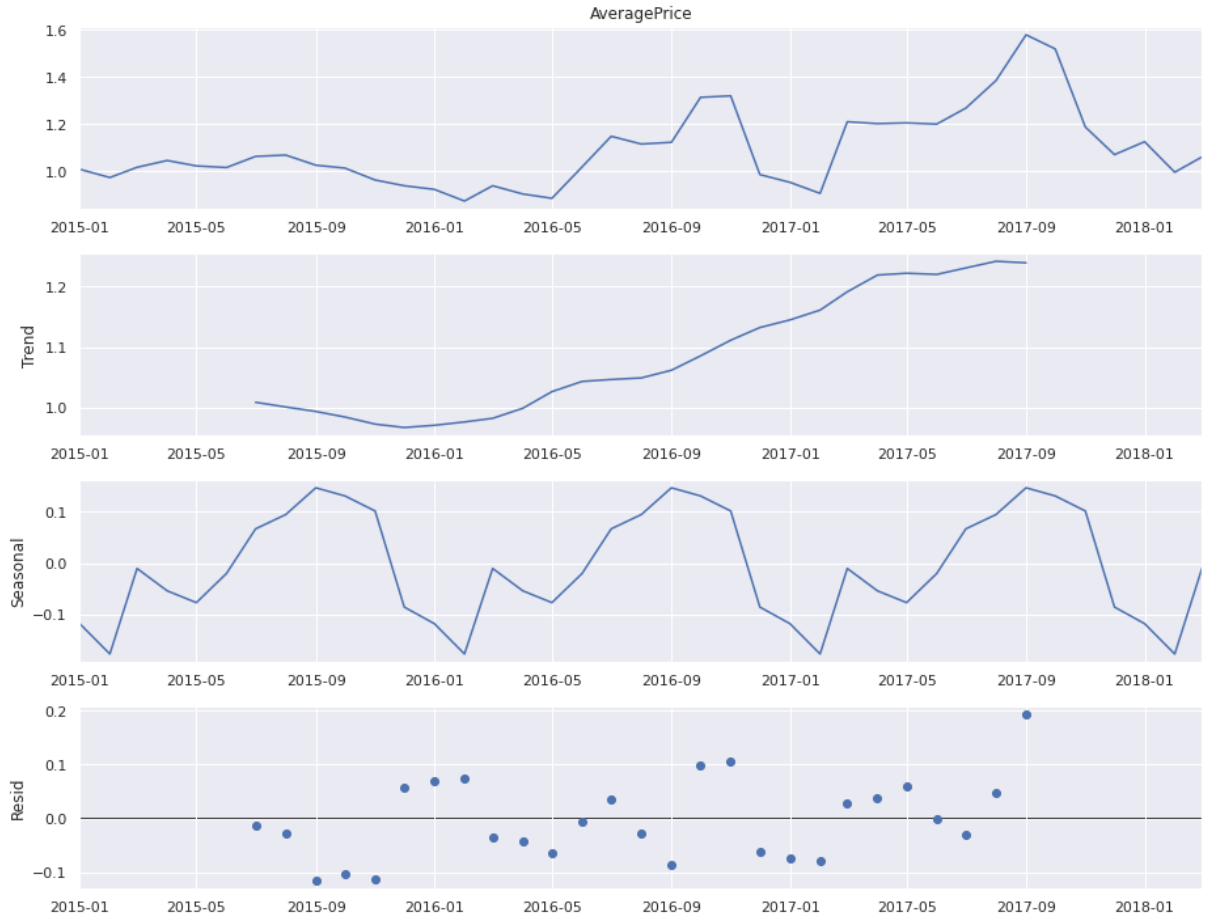
- Date range: Jan 2015 to March 2018

In [81]:
```
y = conv['AveragePrice'].resample("MS").mean()
plt.figure(figsize=(13,8))
y.plot()
plt.title("Monthly Avocado Prices in the US", fontsize=15)
plt.xlabel("Month")
plt.ylabel("Price in $")
plt.show()
```



Seasonal decomposition

In [82]:
```
rcParams['figure.figsize'] = 13, 10

decomposition = sm.tsa.seasonal_decompose(y, model='additive')
fig = decomposition.plot()
plt.show()
```



We can observe that

- The fluctuation in prices is *seasonal*
- The trend in price is overall *increasing*

ARIMA Model

In [83]:
```
conventional = df[(df.region == 'TotalUS')&(df.type == 'conventional')]
```

```
conventional = conventional.drop(columns = ['Total Volume', '4046', '42
25', '4770', 'Total Bags',
       'Small Bags', 'Large Bags', 'XLarge Bags', 'type', 'year', 'regi
on'])
```

In [84]:
```
#ARIMA
# evaluate an ARIMA model for a given order (p,d,q)
def evaluate_arima_model(X, arima_order):
    # prepare training dataset
    train_size = int(len(X) * 0.66)
    train, test = X[0:train_size], X[train_size:]
    history = [x for x in train]
    # make predictions
    predictions = list()
    for t in range(len(test)):
        model = ARIMA(history, order=arima_order)
        model_fit = model.fit(disp=0)
        yhat = model_fit.forecast()[0]
        predictions.append(yhat)
        history.append(test[t])
    # calculate out of sample error
    error = mean_squared_error(test, predictions)
    return error

# evaluate combinations of p, d and q values for an ARIMA model
def evaluate_models(dataset, p_values, d_values, q_values):
    dataset = dataset.astype('float32')
    best_score, best_cfg = float("inf"), None
    for p in p_values:
        for d in d_values:
            for q in q_values:
                order = (p,d,q)
                try:
                    mse = evaluate_arima_model(dataset, order)
                    if mse < best_score:
                        best_score, best_cfg = mse, order
                    print('ARIMA%s MSE=%.3f' % (order,mse))
                except:
                    continue
```

```
    print('Best ARIMA%s MSE=%.3f' % (best_cfg, best_score))

# evaluate parameters
p_values = range(0, 4)
d_values = range(0, 4)
q_values = range(0, 4)
warnings.filterwarnings("ignore")
evaluate_models(conventional.values, p_values, d_values, q_values)
```

```
Best ARIMANone MSE=inf
```

In [85]:

```
from statsmodels.tsa.arima_model import ARIMA
import statsmodels.api as sm

from sklearn.metrics import mean_squared_error

# instantiate the ARIMA model
model = ARIMA(conventional['AveragePrice'], order = (1, 0, 0))

# fit the model
results_ARIMA = model.fit()

# collect the predicted results, rounding to two to indicate dollars an
d cents
predictions = round(results_ARIMA.predict(), 2)

# put the predictions into a DataFrame with Date and Predicted Price co
lumns
preds = pd.DataFrame(list(zip(list(predictions.index),list(predictions
))),columns=['Date',
'PredictedPrice']).set_index('Date')

# combine the original data set with the predicted data
predicted_df = pd.merge(conventional[1:], preds, left_index=True, right
_index=True)
```

In [86]:

```
print("\tMean Squared Error:", mean_squared_error(predicted_df['Average
Price'], predicted_df['PredictedPrice']))
print("\tRoot Mean Squared Error:", np.sqrt(mean_squared_error(predicte
```

```
d_df['AveragePrice'],
predicted_df['PredictedPrice'])))
```

```
Mean Squared Error: 0.004301785714285715
Root Mean Squared Error: 0.06558799977347773
```

In [87]:
```
results_ARIMA.plot_predict(start='2015-01-11', end = '2018-12-30')
plt.show()
```

In [88]:
```
# grab the forecast from the model out 40 steps to 2018-12-30, and crea
te a Series out of the data
```

```
ARIMA_forecast = pd.Series(results_ARIMA.forecast(steps = 40)[0])

# create an index from the end of the data out to the length of the for
ecast on a weekly basis
idx = pd.date_range('2018-04-01', '2018-12-30', freq='W')

# create a DataFrame combining the index above and the forecast prices
ARIMA_forecast = pd.DataFrame(list(zip(list(idx),list(ARIMA_forecast
))),columns=['Date','ForecastPrice']).set_index('Date')
```

In [89]:

```
#SARIMAX
# instantiate the model using the ARIMA order we had earlier
mod = sm.tsa.statespace.SARIMAX(conventional['AveragePrice'], order=(1,
 0, 0), seasonal_order=(1, 0, 0, 52), enforce_stationarity=False, enfor
ce_invertibility=False)

# fit the model
SARIMAX_results = mod.fit()

# store the predictions from the model rounding to two for dollars and
 cents
SARIMAX_predictions = round(SARIMAX_results.predict(), 2)

# create a DataFrame with Date and Predicted Price
SARIMAX_preds = pd.DataFrame(list(zip(list(SARIMAX_predictions.index),l
ist(SARIMAX_predictions))), columns=['Date','PredictedPrice']).set_inde
x('Date')

# merge the original DataFrame with the predictions
SARIMAX_predicted_df = pd.merge(conventional[1:], SARIMAX_preds, left_i
ndex=True, right_index=True)
```

In [90]:

```
print("\tMean Squared Error:", mean_squared_error(SARIMAX_predicted_df[
'AveragePrice'], SARIMAX_predicted_df['PredictedPrice']))
print("\tRoot Mean Squared Error:", np.sqrt(mean_squared_error(SARIMAX_
predicted_df['AveragePrice'], SARIMAX_predicted_df['PredictedPrice'])))
```

```
	Mean Squared Error: 0.006040476190476l9
	Root Mean Squared Error: 0.07772050045178679
```

In [91]:
```
SARIMAX_forecast = pd.DataFrame(round(SARIMAX_results.forecast(steps =
40), 2), columns = ['Forecasted Price'])
SARIMAX_forecast
```

Out[91]:

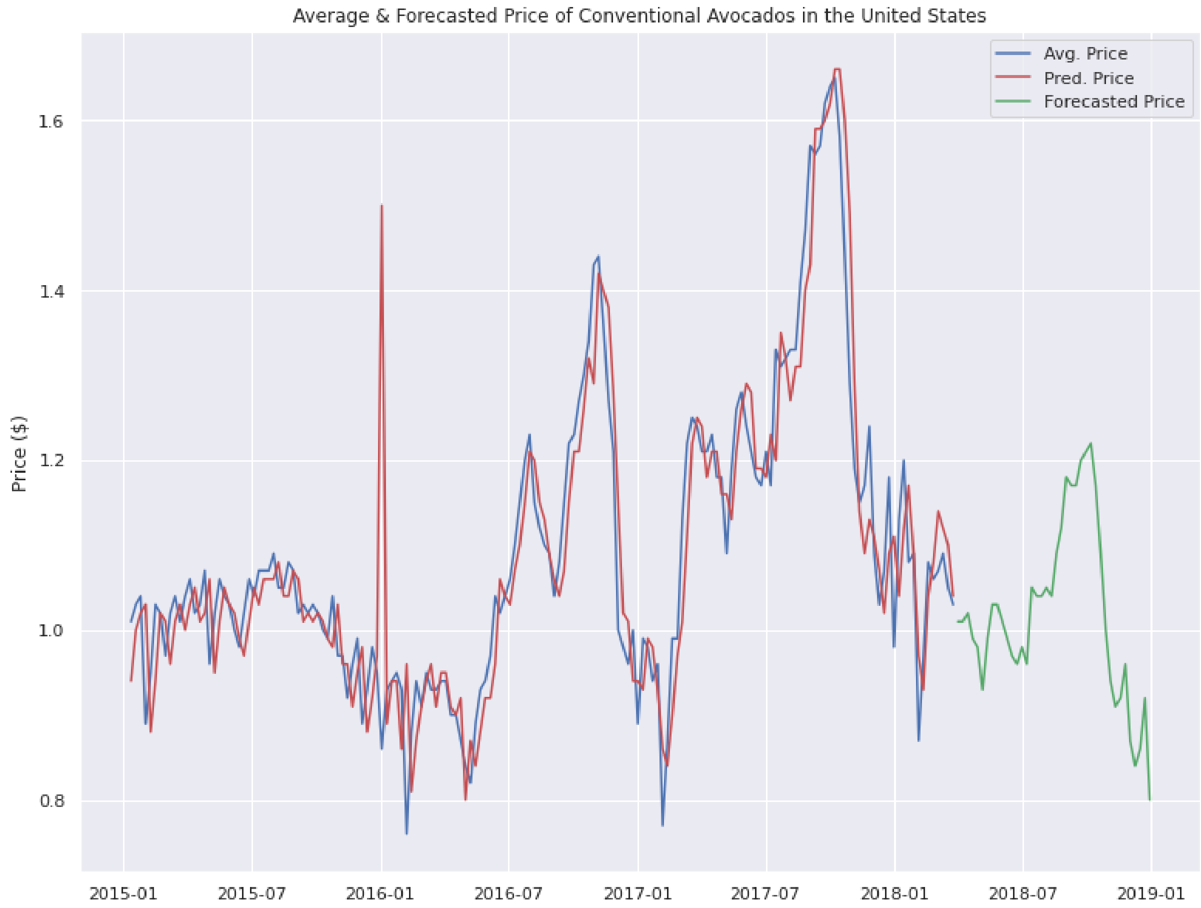
	Forecasted Price
2018-04-01	1.01
2018-04-08	1.01
2018-04-15	1.02
2018-04-22	0.99
2018-04-29	0.98
2018-05-06	0.93
2018-05-13	0.99
2018-05-20	1.03
2018-05-27	1.03
2018-06-03	1.01
2018-06-10	0.99
2018-06-17	0.97
2018-06-24	0.96
2018-07-01	0.98
2018-07-08	0.96
2018-07-15	1.05
2018-07-22	1.04
2018-07-29	1.04
2018-08-05	1.05
2018-08-12	1.04
2018-08-19	1.09

	Forecasted Price
2018-08-26	1.12
2018-09-02	1.18
2018-09-09	1.17
2018-09-16	1.17
2018-09-23	1.20
2018-09-30	1.21
2018-10-07	1.22
2018-10-14	1.17
2018-10-21	1.09
2018-10-28	1.00
2018-11-04	0.94
2018-11-11	0.91
2018-11-18	0.92
2018-11-25	0.96
2018-12-02	0.87
2018-12-09	0.84
2018-12-16	0.86
2018-12-23	0.92
2018-12-30	0.80

In [92]:

```
fig=plt.figure()
fig.show()
ax=fig.add_subplot(111)

ax.plot(SARIMAX_predicted_df['AveragePrice'],c='b',label='Avg. Price')
ax.plot(SARIMAX_predicted_df['PredictedPrice'],c='r', label='Pred. Pric
e')
```

```
ax.plot(SARIMAX_forecast['Forecasted Price'],c='g', label='Forecasted P
rice')

plt.legend(loc='best')
plt.ylabel('Price ($)')
plt.title('Average & Forecasted Price of Conventional Avocados in the U
nited States')
plt.draw()
```



In [93]:
```
model = sm.tsa.statespace.SARIMAX(y,
                                order=(1, 1, 1),
```

```
                                    seasonal_order=(1, 1, 0, 12),
                                    enforce_stationarity=True,
                                    enforce_invertibility=False)
results = model.fit()
results.summary().tables[1]
```

Out[93]:

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.7217	0.315	2.289	0.022	0.104	1.340
ma.L1	-1.0004	45.347	-0.022	0.982	-89.880	87.879
ar.S.L12	-0.6012	0.312	-1.926	0.054	-1.213	0.011
sigma2	0.0125	0.569	0.022	0.983	-1.102	1.127

In [94]:

```
# Check for convergence
results.mle_retvals
```

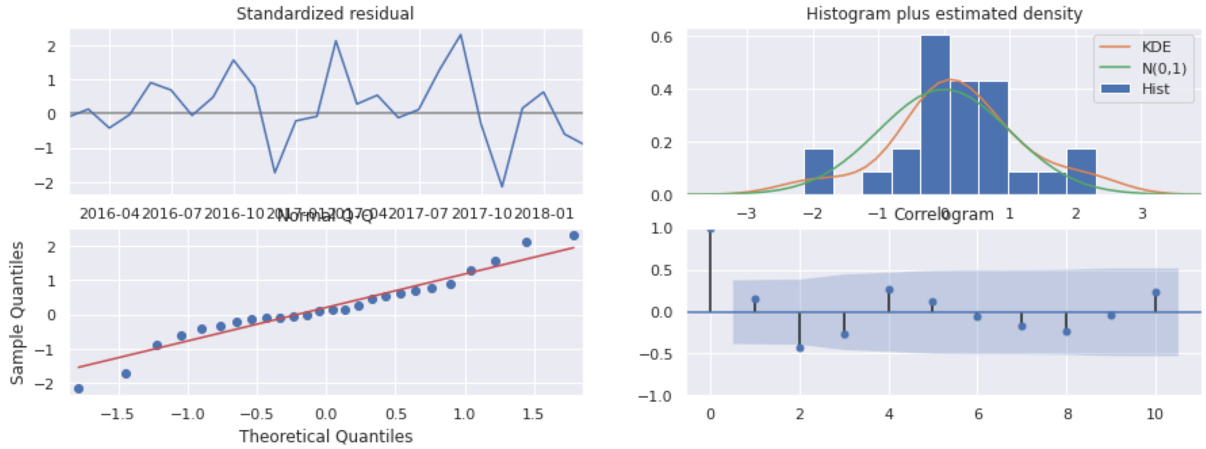
Out[94]:

```
{'fopt': -0.41771917968696004,
 'gopt': array([ 6.46773690e-05, -1.42826051e-04,  7.95428556e-05,  2.5
0577975e-04]),
 'fcalls': 195,
 'warnflag': 0,
 'converged': True,
 'iterations': 26}
```

After 27 iterations, the model converged with the optimal values (1, 1, 1) x (1, 1, 0, 12). We will use this for our predictive model.

In [95]:

```
results.plot_diagnostics(figsize=(15, 5))
plt.show()
```

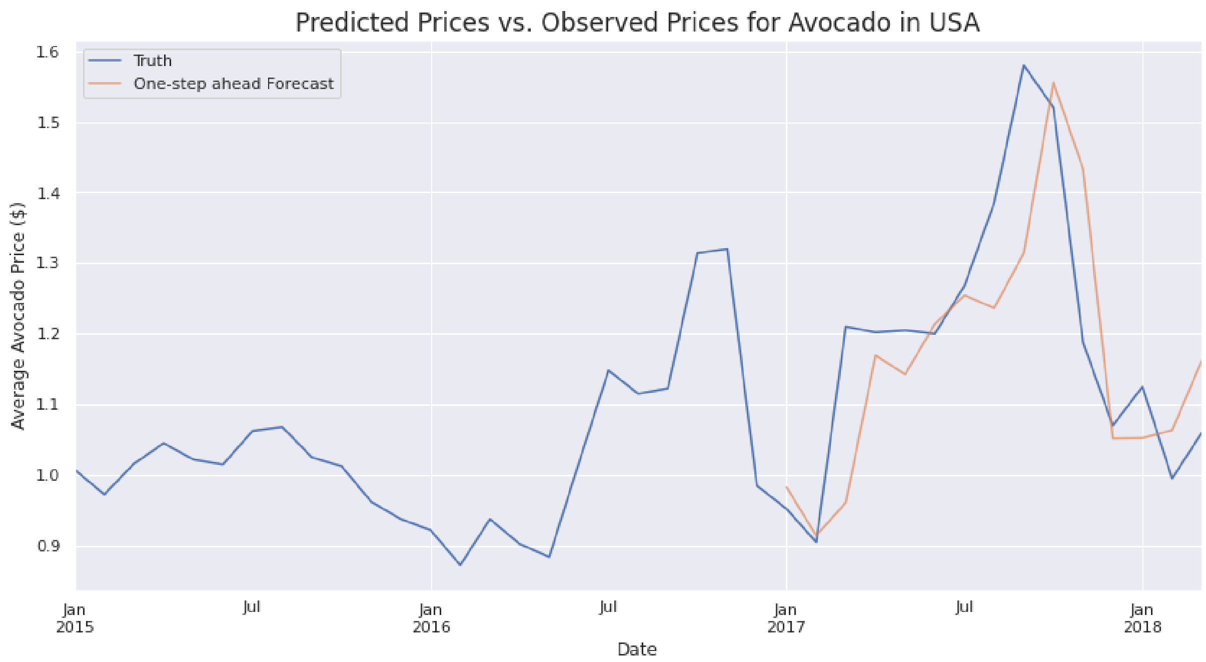


The model residuals almost follow a normal distribution

Comparison of Predicted prices and True prices for Avocaodos

In [96]:

```
pred_date = '2017-01-01'
pred = results.get_prediction(start=pd.to_datetime(pred_date), dynamic=
False)
pred_ci = pred.conf_int()
ax = y['2015':].plot(label='Truth')
pred.predicted_mean.plot(ax=ax, label='One-step ahead Forecast', alpha
=.7, figsize=(14, 7))
#ax.fill_between(pred_ci.index,
#                pred_ci.iloc[:, 0],
#                pred_ci.iloc[:, 1], color='k', alpha=.2)
ax.set_xlabel('Date')
ax.set_ylabel('Average Avocado Price ($)')
plt.title("Predicted Prices vs. Observed Prices for Avocado in USA", fo
ntsize=17)
plt.legend()
plt.show()
```



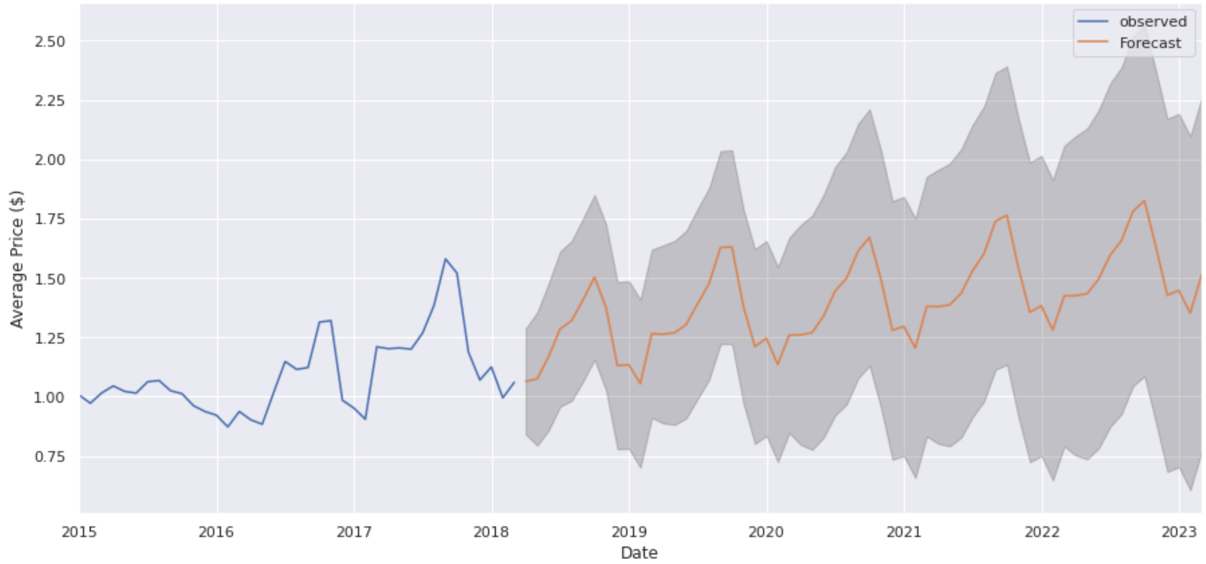
Although the forecasted values are not exactly the same, they follow the upward then downward trend of the observed data.

Evaluation

Future Forecasting

In [97]:
```
pred_uc = results.get_forecast(steps=60)
pred_ci = pred_uc.conf_int()
ax = y.plot(label='observed', figsize=(15, 7))
pred_uc.predicted_mean.plot(ax=ax, label='Forecast')
ax.fill_between(pred_ci.index,
```

```
                pred_ci.iloc[:, 0],
                pred_ci.iloc[:, 1], color='k', alpha=.2)
ax.set_xlabel('Date')
ax.set_ylabel('Average Price ($)')
plt.legend()
plt.show()
```



The predictive model captures both the seasonality and the overall increasing trend of the price values.