Importing Packages and Loading Data

In [1]:
```
import warnings
import itertools
import pandas as pd

import numpy as np
import statsmodels.api as sm
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')
import seaborn as sns
from statsmodels.stats.stattools import durbin_watson
```

```
C:\Users\08486\AppData\Local\Continuum\anaconda3\lib\site-packages\statsmodel
s\compat\pandas.py:56: FutureWarning: The pandas.core.datetools module is dep
recated and will be removed in a future version. Please use the pandas.tserie
s module instead.
  from pandas.core import datetools
```

In [2]:
```
# Get current size
fig_size = plt.rcParams["figure.figsize"]

# Prints: [8.0, 6.0]
print("Current size:", fig_size)

# Set figure width to 12 and height to 9
fig_size[0] = 15
fig_size[1] = 9
plt.rcParams["figure.figsize"] = fig_size
print("Current size:", fig_size)
```

```
Current size: [6.0, 4.0]
Current size: [15, 9]
```

In [10]:
```
data = pd.Series.from_csv('Gasoline_Crack_2009_2017.csv', header=0)
```

```
C:\Users\08486\AppData\Local\Continuum\anaconda3\lib\site-packages\pandas\cor
e\series.py:2890: FutureWarning: from_csv is deprecated. Please use read_csv
(...) instead. Note that some of the default arguments are different, so plea
se refer to the documentation for from_csv when changing your function calls
  infer_datetime_format=infer_datetime_format)
```

In [9]:
```
data.head()
```

Out[9]:
```
Date
2009-01-02   -1.06
2009-01-05    0.37
2009-01-06    1.82
2009-01-07    1.65
2009-01-08    3.94
Name: Gasoline_Crack, dtype: float64
```

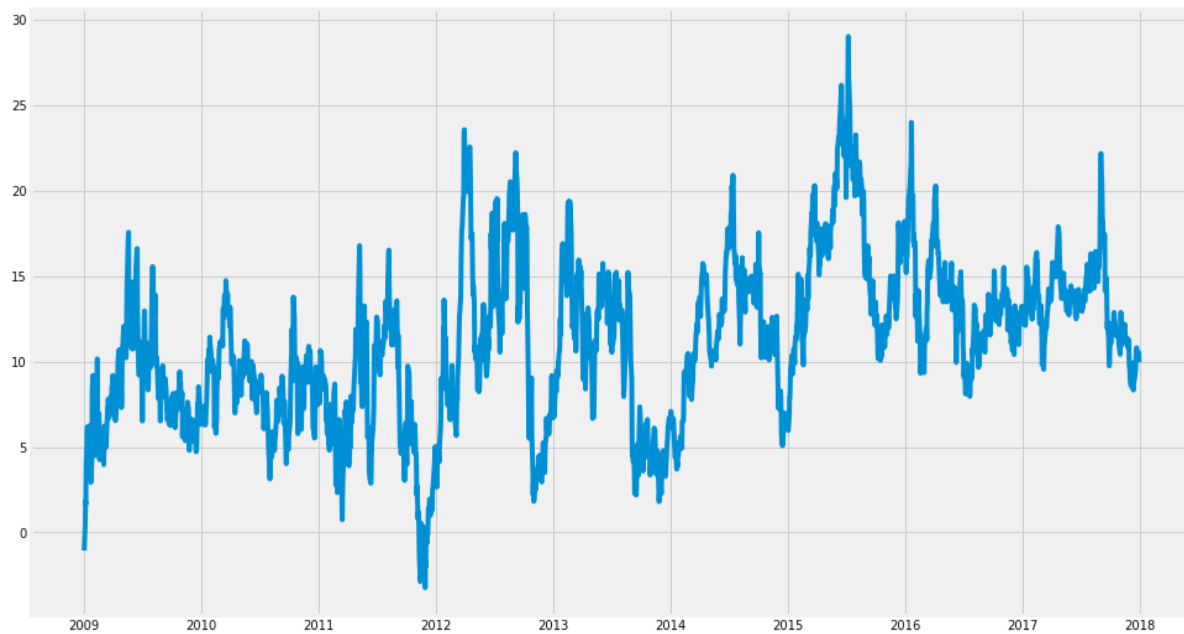
In [7]:
```
df=pd.read_csv("Gasoline_Crack_2009_2017.csv") #panda labından csv formatını o
kuma /data frame
```

In [11]:
```
df['Date']=pd.to_datetime(df['Date']) #to_datetime fonksiyonuyla texti date'e
 çevirdik
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2273 entries, 0 to 2272
Data columns (total 2 columns):
Date              2273 non-null datetime64[ns]
Gasoline_Crack    2273 non-null float64
dtypes: datetime64[ns](1), float64(1)
memory usage: 35.6 KB
```

In [12]:
```
plt.plot(df['Date'],df['Gasoline_Crack'])
```

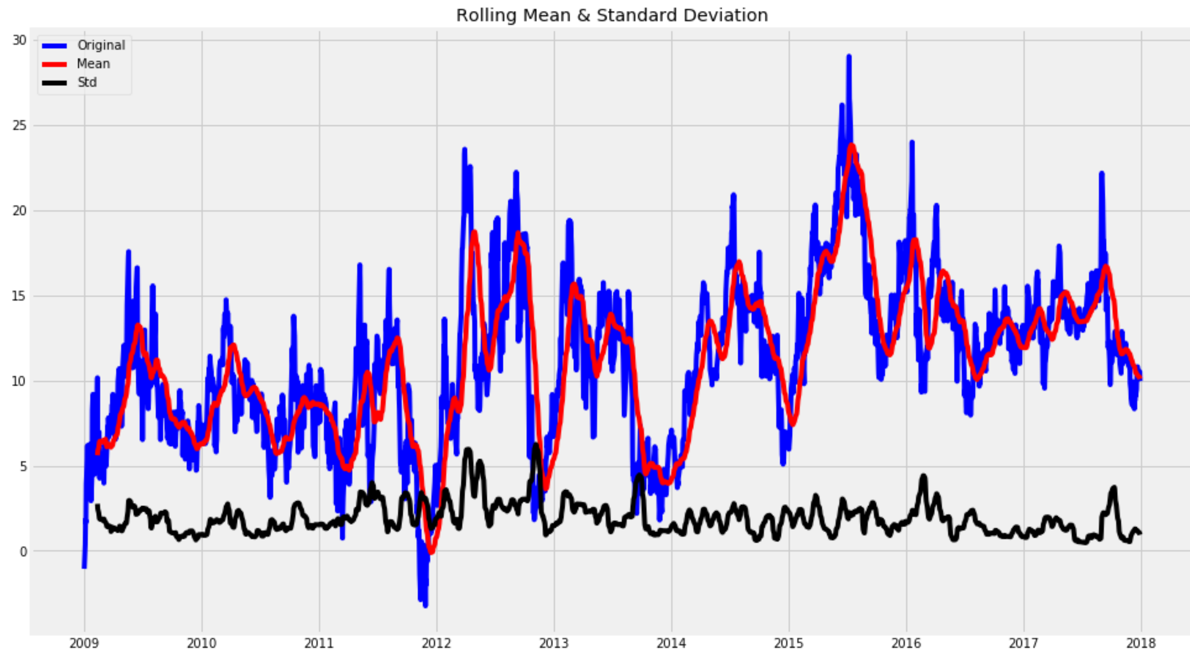
Out[12]:
```
[<matplotlib.lines.Line2D at 0x20f92ea0b38>]
```



Stationary Test - 30 days mean and standard deviation plotting

In [13]:
```
from statsmodels.tsa.stattools import adfuller

rolmean=df['Gasoline_Crack'].rolling(window=30,center=False).mean()
rolstd=df['Gasoline_Crack'].rolling(window=30,center=False).std()

plt.gca().set_color_cycle(['blue', 'red', 'black'])
plt.plot(df['Date'],df['Gasoline_Crack'])
plt.plot(df['Date'],rolmean)
plt.plot(df['Date'],rolstd)


plt.legend(['Original', 'Mean', 'Std'], loc='upper left')
plt.title('Rolling Mean & Standard Deviation')
plt.show()
```

```
C:\Users\08486\AppData\Local\Continuum\anaconda3\lib\site-packages\matplotlib
\cbook\deprecation.py:106: MatplotlibDeprecationWarning: The set_color_cycle
attribute was deprecated in version 1.5. Use set_prop_cycle instead.
  warnings.warn(message, mplDeprecation, stacklevel=1)
```



Stationary Test Continue - After seeing the mean and standard deviation do not change significantly; further testing (Augmented Dickey-Fuller Test) is applied

In [14]:
```
from statsmodels.tsa.stattools import adfuller
result = adfuller(df['Gasoline_Crack'])
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
print('Critical Values:')
for key, value in result[4].items():
        print('\t%s: %.3f' % (key, value))
```

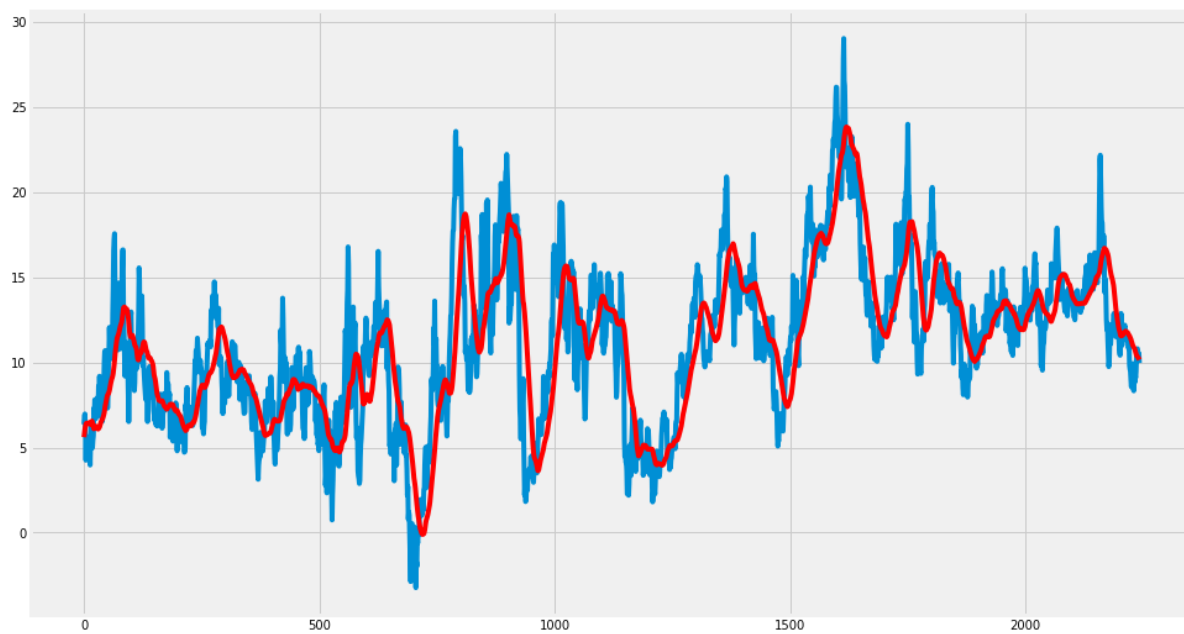
```
ADF Statistic: -5.141409
p-value: 0.000012
Critical Values:
        1%: -3.433
        5%: -2.863
        10%: -2.567
```

p-value is lower than 0.05 which means we can reject null hypothesis so data is stationary (Ho : non-stationary)

Moving Average Method

In [15]:
```
from sklearn.metrics import mean_squared_error
# prepare situation
X = df['Gasoline_Crack']
window = 30
history = [X[i] for i in range(window)]

test = [X[i] for i in range(window, len(X))]
predictions = list()
# walk forward over time steps in test
for t in range(len(test)):
    length = len(history)
    yhat = np.mean([history[i] for i in range(length-window,length)])
    obs = test[t]
    predictions.append(yhat)
    history.append(obs)
    #print('actual_value=%f, predicted=%f' % (obs, yhat))
error = mean_squared_error(test, predictions)
print('Test MSE: %.3f' % error)
print("Prediction for next period: {}".format(sum(history[-30:])/30))
# plot
plt.plot(test)
plt.plot(predictions, color='red')
plt.show()
```

```
Test MSE: 8.160
Prediction for next period: 10.086
```

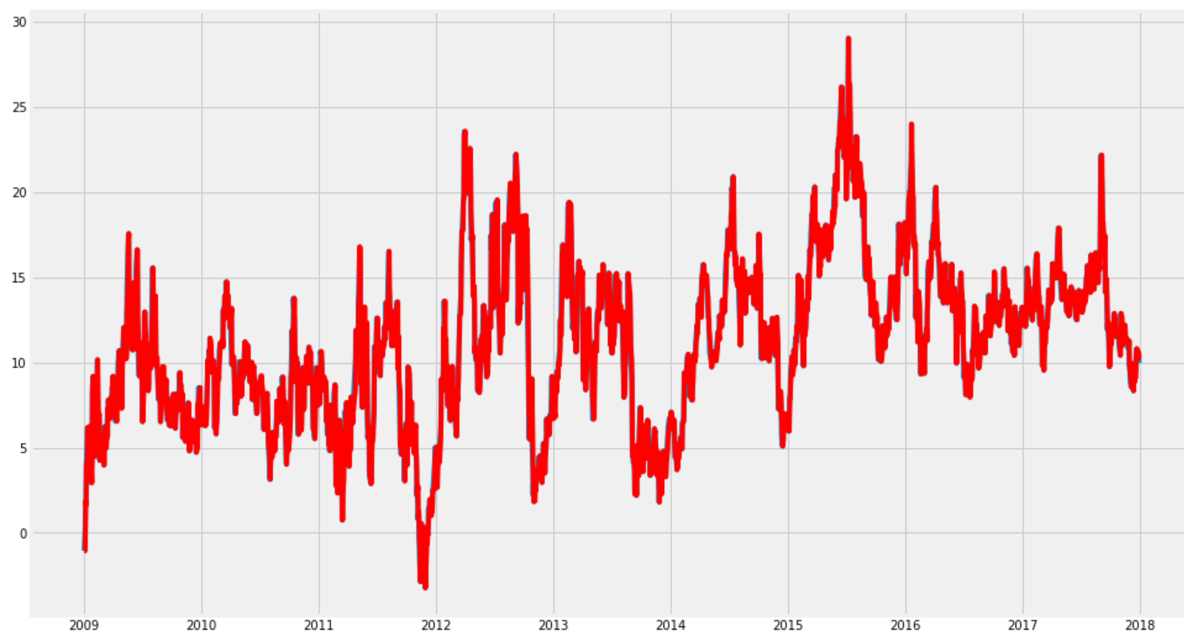


Next day predicted value is calculated by taking the average of previous 30 days and then predicted value is subtracted from the actual(real) values so that error for each day is calculated. Then mean square error (MSE) by using all of the errors is calculated.

Exponential Smoothing Method

In [20]:
```
Y = df['Gasoline_Crack']
window = 2
history = [Y[i] for i in range(window)]
predictions=list()
predictions.append(history[0])
predictions.append(history[0])
test = [Y[i] for i in range(window, len(Y))]
alpha=1
# walk forward over time steps in test
for t in range(len(test)):
    length = len(history)
    yhat = history[-1]*alpha+(1-alpha)*predictions[-1]
    obs = test[t]
    predictions.append(yhat)
    history.append(obs)
    #print('actual_value=%f, predicted=%f' % (obs, predictions[-1]))
error = mean_squared_error(history, predictions)
print('Test MSE: %.3f' % error)
print("Prediction for next period: {}".format(history[-1]*alpha+(1-alpha)*pred
ictions[-1]))

plt.plot(df['Date'],history)
plt.plot(df['Date'],predictions, color='red')
plt.show()
```

```
Test MSE: 1.015
Prediction for next period: 9.96
```



Next day predicted value is calculated by multiplying the previously predicted value and actual value by a multiplier (called as alpha) and then predicted value is subtracted from the actual(real) values so that error for each day is calculated. Then mean square error (MSE) by using all of the errors is calculated.

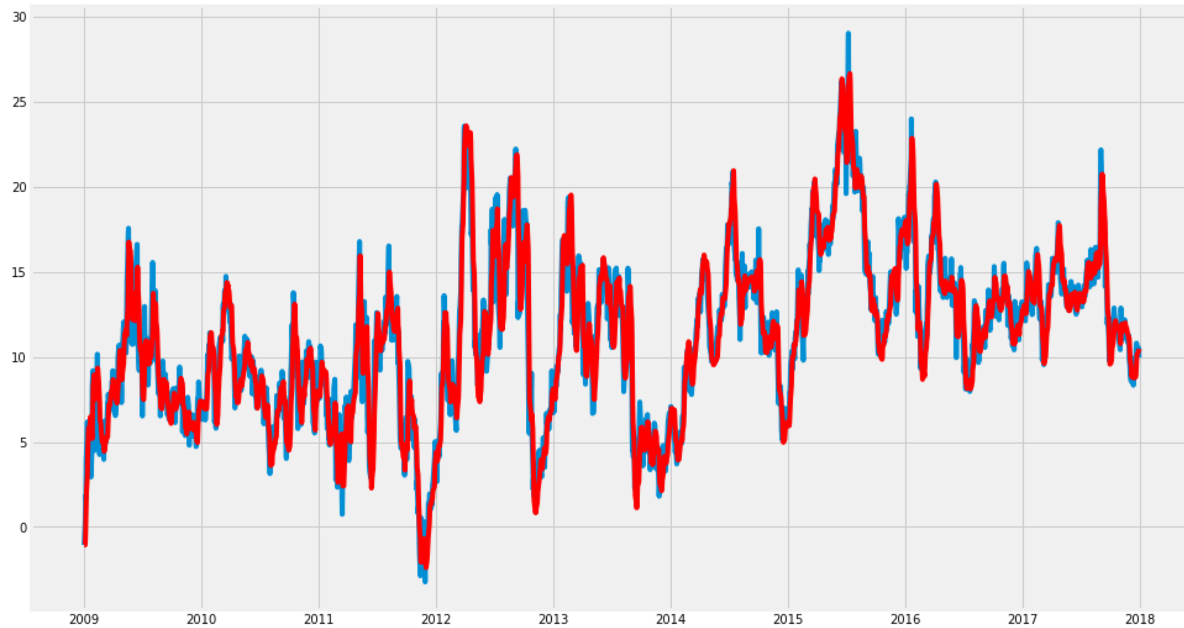
Exponentially Weighted Moving Average

Test MSE: 0.08 (Excel)

Holt-Winter's Method

In [19]:
```
Y = df['Gasoline_Crack']
window = 2
history = [Y[i] for i in range(window)]
predictions=list()
predictions_l=list()
predictions_t=list()

predictions.append(history[0])
predictions.append(history[0])

predictions_l.append(history[0])
predictions_t.append(0)

test = [Y[i] for i in range(window, len(Y))]
alpha=0.3
beta=0.1
period=1

# walk forward over time steps in test
for t in range(len(test)):
    length = len(history)
    lhat=history[-1]*alpha+(predictions_l[-1]+predictions_t[-1])*(1-alpha)
    predictions_l.append(lhat)
    that=(predictions_l[-1]-predictions_l[-2])*beta+predictions_t[-1]*(1-beta)
    predictions_t.append(that)
    yhat = predictions_l[-1]+predictions_t[-1]*period
    obs = test[t]
    predictions.append(yhat)
    history.append(obs)
    #print('actual_value=%f, predicted=%f' % (obs, predictions[-1]))
error = mean_squared_error(history, predictions)
print('Test MSE: %.3f' % error)
lhat=history[-1]*alpha+(predictions_l[-1]+predictions_t[-1])*(1-alpha)
predictions_l.append(lhat)
that=(predictions_l[-1]-predictions_l[-2])*beta+predictions_t[-1]*(1-beta)
predictions_t.append(that)


print("Prediction for next period: {}".format(predictions_l[-1]+predictions_t[
-1]*period))

plt.plot(df['Date'],history)
plt.plot(df['Date'],predictions, color='red')
plt.show()
```

```
Test MSE: 2.193
Prediction for next period: 10.363487553853824
```



Next day predicted value is calculated by using multipliers (alpha for t-2 and beta for t-1) for the previously predicted value and its "coefficients L and T" then predicted value is subtracted from the actual(real) values so that error for each day is calculated. Then mean square error (MSE) by using all of the errors is calculated.

Box Jenkins (ARIMA) Method

What needs to be identified?: Stationary, Autocorrelation, Partial Autocorrelation

1-Stationarity

Augmented Dickey-Fuller Test

In [44]:

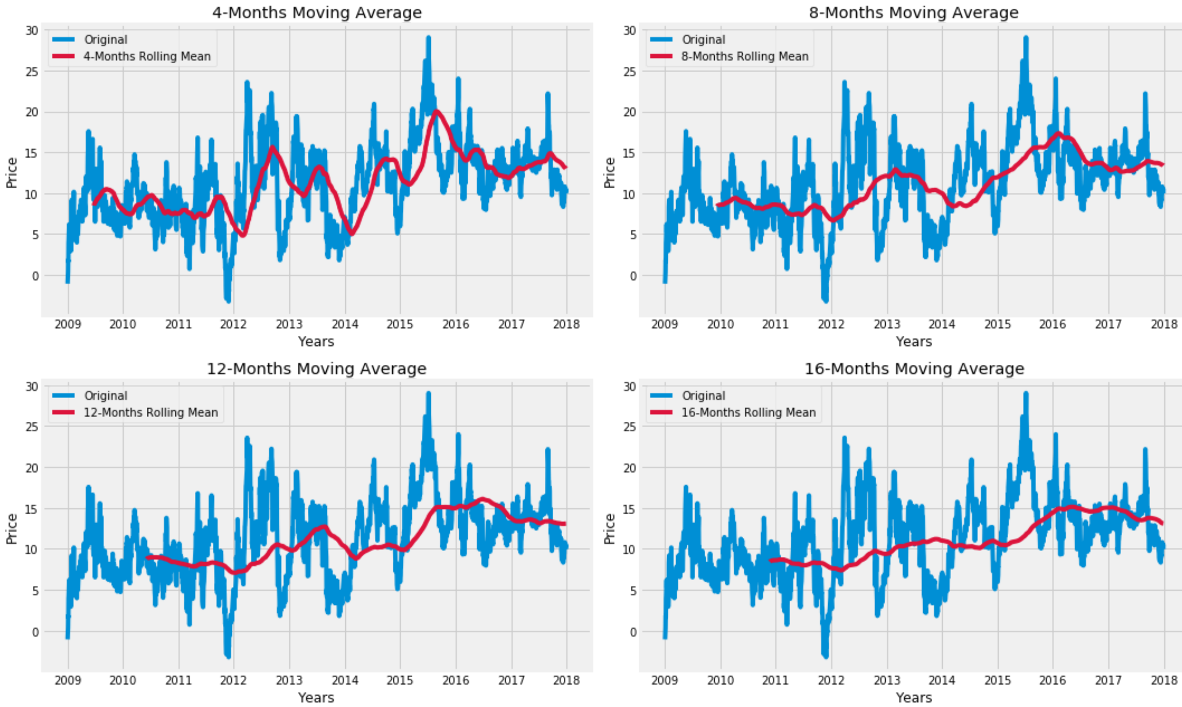
```
from statsmodels.tsa.stattools import adfuller
result = adfuller(df['Gasoline_Crack'])
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
print('Critical Values:')
for key, value in result[4].items():
        print('\t%s: %.3f' % (key, value))
```

```
ADF Statistic: -5.141409
p-value: 0.000012
Critical Values:
        1%: -3.433
        5%: -2.863
        10%: -2.567
```

Augmented Dickey-Fuller Test indicates stationarity but ARIMA did not work with p=0

Let Check Visulization Trend

In [35]:
```
# define figure and axes
fig, axes = plt.subplots(2, 2, sharey=False, sharex=False);
fig.set_figwidth(15);
fig.set_figheight(9);
y=data
# push data to each ax
#upper left
axes[0][0].plot(y.index, y, label='Original');
axes[0][0].plot(y.index, y.rolling(window=120).mean(), label='4-Months Rolling Mean', color='crimson');
axes[0][0].set_xlabel("Years");
axes[0][0].set_ylabel("Price");
axes[0][0].set_title("4-Months Moving Average");
axes[0][0].legend(loc='best');

# upper right
axes[0][1].plot(y.index, y, label='Original')
axes[0][1].plot(y.index, y.rolling(window=240).mean(), label='8-Months Rolling Mean', color='crimson');
axes[0][1].set_xlabel("Years");
axes[0][1].set_ylabel("Price");
axes[0][1].set_title("8-Months Moving Average");
axes[0][1].legend(loc='best');

# lower left
axes[1][0].plot(y.index, y, label='Original');
axes[1][0].plot(y.index, y.rolling(window=360).mean(), label='12-Months Rolling Mean', color='crimson');
axes[1][0].set_xlabel("Years");
axes[1][0].set_ylabel("Price");
axes[1][0].set_title("12-Months Moving Average");
axes[1][0].legend(loc='best');

# lower right
axes[1][1].plot(y.index, y, label='Original');
axes[1][1].plot(y.index, y.rolling(window=480).mean(), label='16-Months Rolling Mean', color='crimson');
axes[1][1].set_xlabel("Years");
axes[1][1].set_ylabel("Price");
axes[1][1].set_title("16-Months Moving Average");
axes[1][1].legend(loc='best');
plt.tight_layout();
plt.show()
```



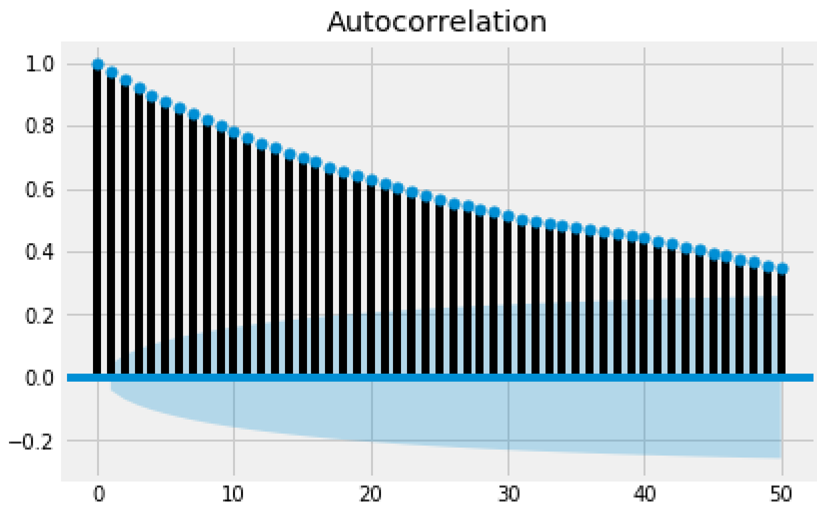
In [34]:

```
#from pandas import Series
#series = Series.from_csv('Gasoline_Crack_2009_2017.csv', header=0)
#X = series.values
X=data.values
split = int((len(X) / 2))
X1= X[0:split]
X2=X[split+1:]
mean1, mean2 = X1.mean(), X2.mean()
var1, var2 = X1.var(), X2.var()
print('mean1=%f, mean2=%f' % (mean1, mean2))
print('variance1=%f, variance2=%f' % (var1, var2))
```

```
mean1=9.314005, mean2=12.926417
variance1=18.992705, variance2=18.712366
```

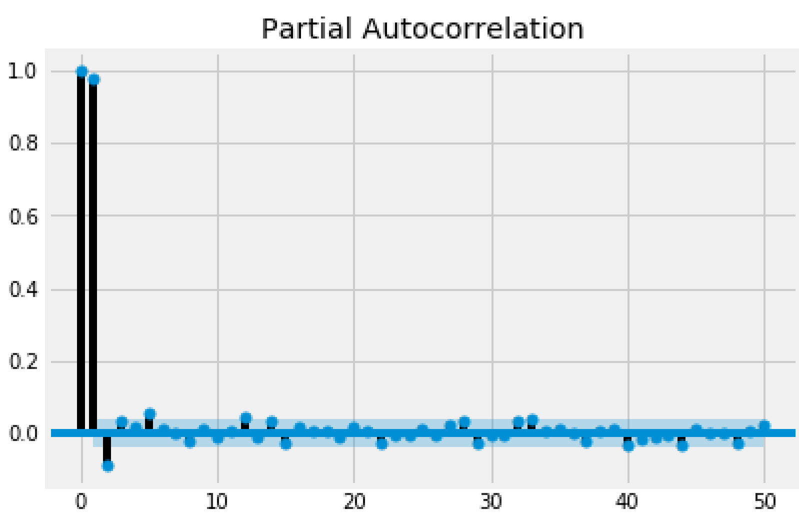
2-AutoCorrelation

In [45]:
```
from pandas import Series

from statsmodels.graphics.tsaplots import plot_acf
plot_acf(data, lags=50)
plt.show()
```



3-Partial Autocorrelation

In [46]:
```
from statsmodels.graphics.tsaplots import plot_pacf

plot_pacf(data, lags=50)
plt.show()
```



Montly Price Data

In [48]:
```
resample = data.resample('M') #the 'M' groups the data in buckets by end of th
e month, if you want bucket by start of the month use 'MS'
monthly_mean = resample.mean()
print(monthly_mean.head(13))
number_sample=monthly_mean.shape[0]
number_sample
```

```
Date
2009-01-31     4.791429
2009-02-28     6.474000
2009-03-31     6.550000
2009-04-30     8.556500
2009-05-31    12.862105
2009-06-30    12.188182
2009-07-31    10.284783
2009-08-31    10.213000
2009-09-30     7.728636
2009-10-31     7.769091
2009-11-30     6.422381
2009-12-31     6.234762
2010-01-31     8.431000
Freq: M, Name: Gasoline_Crack, dtype: float64
```

Out[48]: 108

In [50]:
```
#Create a training sample and testing sample before analyzing the series

number_data_train=int(0.95*number_sample+1)
number_data_forecast=number_sample-number_data_train
#timeseries_dataframe
ts_train=monthly_mean.iloc[:number_data_train]
ts_test=monthly_mean.iloc[number_data_train:]
print(ts_train.shape)
print(ts_test.shape)
print("Training Series:","\n",ts_train.tail(),"\n")
print("Testing Series:","\n",ts_test.head())
```

```
(103,)
(5,)
Training Series:
 Date
2017-03-31    12.270000
2017-04-30    15.893889
2017-05-31    13.743810
2017-06-30    13.429545
2017-07-31    14.269524
Freq: M, Name: Gasoline_Crack, dtype: float64

Testing Series:
 Date
2017-08-31    15.952727
2017-09-30    14.926190
2017-10-31    11.714545
2017-11-30    11.373636
2017-12-31     9.663684
Freq: M, Name: Gasoline_Crack, dtype: float64
```

In [55]:
```
import statsmodels.api as sm
import statsmodels.formula.api as smf
import statsmodels.tsa.api as smt
```

In [56]:
```
def model_resid_stats(model_results,verbose= True):
    het_method='breakvar'
    norm_method='jarquebera'
    sercor_method='ljungbox'

    (het_stat,het_p)=model_results.test_heteroskedasticity(het_method)[0]
    norm_stat,norm_p,skew,kurtosis=model_results.test_normality(norm_method)[0
]
    sercor_stat,sercor_p=model_results.test_serial_correlation(sercor_method)[
0]
    sercor_stat=sercor_stat[-1]#largest lag
    sercor_p=sercor_p[-1]#largest lag

    dw= durbin_watson(model_results.filter_results.standardized_forecasts_erro
r[0])

    #check whether roots are outside the unit circle ( we want them to be)
    #will be True when AR is not used (i.e, AR order=0)
    arroots_outside_unit_circle=np.all(np.abs(model_results.arroots)>1)
    # will be True when MA is not used (i.e., MA order=0)
    maroots_outside_unit_circle=np.all(np.abs(model_results.maroots)>1)

    if verbose:
        print("Test heteroskedasticity of residuals ({}): stat={:.3f},p={:.3f}
".format(het_method,het_stat,het_p))
        #print("\nTest normality of residuals {}: stat={:.3f},p={:.3f}").forma
t(norm_method,norm_stat,norm_p)
        print("\nTest serial correlation ({}): stat={:.3f}, p={:.3f}".format(s
ercor_method,sercor_stat,sercor_p))
        print("\nTest for durbin watson (should be between 1-3):",dw)
        print("\nTest for all AR roots outside the unit circle (>1):",arroots_
outside_unit_circle)
        print("\nTest for all MA roots outside the unit circle (>1):",maroots_
outside_unit_circle)

    stat={'durbin_watson':dw,'het_method':het_method, 'het_stat': het_stat,'he
t_p':het_p,'norm_method': norm_method,'norm_stat':norm_stat,'norm_p':norm_p,'s
kew':skew,'kurtosis':kurtosis,'sercor_method':sercor_method,'sercor_stat':serc
or_stat,'sercor_p':sercor_p,'arroots_outside_unit_circle':arroots_outside_unit
_circle,'maroots_outside_unit_circle':maroots_outside_unit_circle}
    return stat
```

In [58]:
```
def model_gridsearch(ts,p_min,d_min,q_min,p_max,d_max,q_max,enforce_stationari
ty=True,enforce_invertibility=True,simple_differencing=False, plot_diagnostics
=False,verbose=False,filter_warnings=True):
    cols=['p','d','q','enforce_stationarity','enforce_invertibility','simple_d
ifferencing','aic','bic','het_p','norm_p','secor_p','dw_stat','arroots_gt_1',
'maroots_gt_1','datetime_run']
    df_results=pd.DataFrame(columns=cols)
    mod_num=0
    for p,d,q in itertools.product(range(p_min,p_max+1),range(d_min,d_max+1),r
ange(q_min,q_max+1)):
        this_model=pd.DataFrame(index=[mod_num],columns=cols)
        if p==0 and d==0 and q==0:
            continue
        try:
            model=sm.tsa.SARIMAX(ts,order=(p,d,q),enforce_stationarity=enforce
_stationarity,enforce_invertibility=enforce_invertibility,simple_differencing=
simple_differencing)
            #if filter_warnings is True:

                #with warnings.catch_warnings():
                    #warnings.filterwarning("ignore")
                    #model_results=model.fit(disp=0)

            if True:
                model_results=model.fit()
            if verbose:
                print(model_results.summary())
            if plot_diagnostics:
                model_results.plot_diagnostics
            stat=model_resid_stats(model_results,verbose=verbose)

            this_model.loc[mod_num,'p']=p
            this_model.loc[mod_num,'d']=d
            this_model.loc[mod_num,'q']=q
            this_model.loc[mod_num,'enforce_stationarity']=enforce_stationarit
y
            this_model.loc[mod_num,'enforce_invertibility']=enforce_invertibil
ity
            this_model.loc[mod_num,'simple_differencing']=simple_differencing
            this_model.loc[mod_num,'aic']=model_results.aic
            this_model.loc[mod_num,'bic']=model_results.bic
            this_model.loc[mod_num,'het_p']=stat['het_p']
            this_model.loc[mod_num,'norm_p']=stat['norm_p']
            this_model.loc[mod_num,'secor_p']=stat['sercor_p']
            this_model.loc[mod_num,'dw_stat']=stat['durbin_watson']
            this_model.loc[mod_num,'arroots_gt_1']=stat['arroots_outside_unit_
circle']
            this_model.loc[mod_num,'maroots_gt_1']=stat['maroots_outside_unit_
circle']

            this_model.loc[mod_num,'datetime_run']=pd.to_datetime('today').str
ftime('%Y-%m-%d')

            df_results=df_results.append(this_model)
            mod_num+=1
        except:
```

```
                continue
        return df_results
```

In [59]:
```
df_results=model_gridsearch(ts_train,0,0,0,2,2,2,enforce_stationarity=True,enforce_invertibility=True,simple_differencing=False, plot_diagnostics=False,verbose=False,filter_warnings=True)
df_results.sort_values(by='bic')
```

Out[59]:

	p	d	q	enforce_stationarity	enforce_invertibility	simple_differencing	aic	b
9	1	1	2	True	True	False	514.024	524.5
15	2	1	2	True	True	False	515.164	528.3
2	0	1	2	True	True	False	522.267	530.1
1	0	1	1	True	True	False	525.127	530.3
8	1	1	0	True	True	False	525.13	530.3
3	0	2	1	True	True	False	525.557	530.8
14	2	1	0	True	True	False	525.115	533.0
4	0	2	2	True	True	False	527.518	535.4
11	1	2	1	True	True	False	527.528	535.4
5	1	0	0	True	True	False	530.961	536.2
17	2	2	1	True	True	False	527.762	538.3
12	1	2	2	True	True	False	529.093	539.6
6	1	0	1	True	True	False	532.875	540.7
13	2	0	0	True	True	False	532.896	540.8
7	1	0	2	True	True	False	531.58	542.1
18	2	2	2	True	True	False	529.776	542.9
16	2	2	0	True	True	False	563.289	571.1
10	1	2	0	True	True	False	570.195	575.4
0	0	0	1	True	True	False	697.8	703.0

In [60]:
```
arima112=sm.tsa.SARIMAX(ts_train, order=(1,1,2))
model_results=arima112.fit()
model_results.summary()
```

Out[60]:

Statespace Model Results

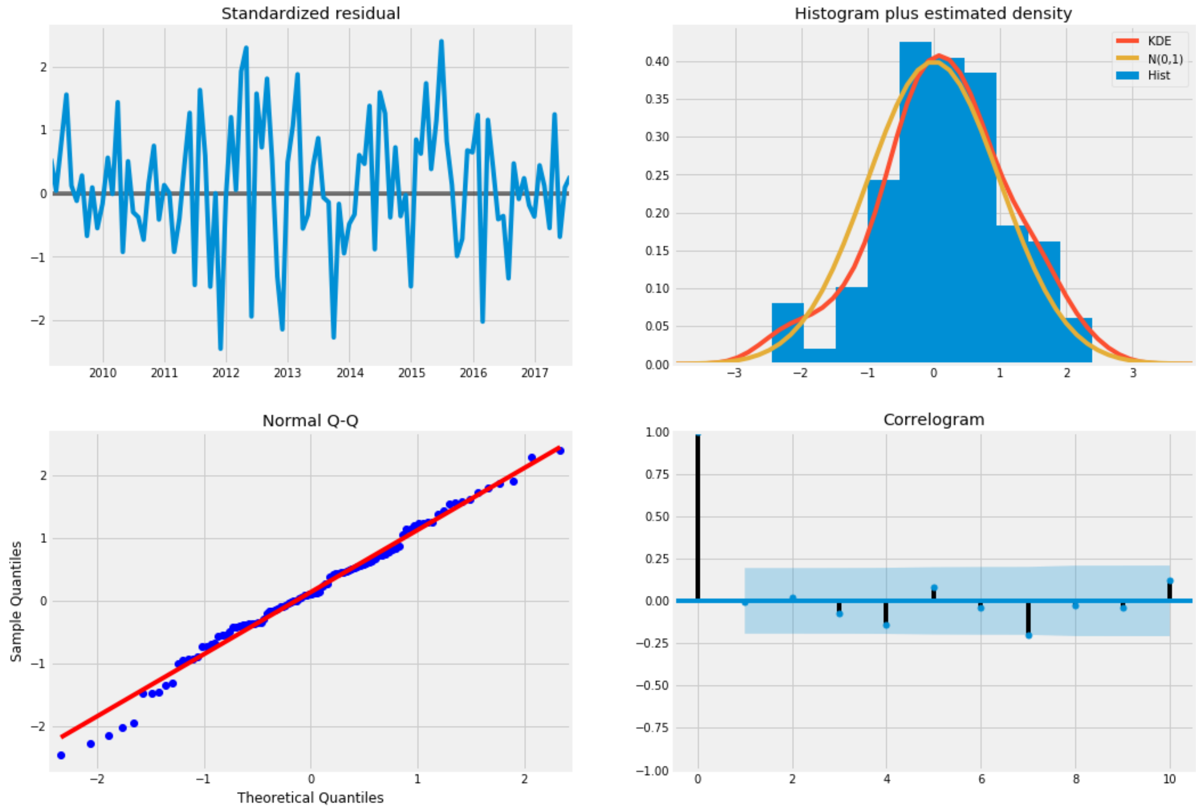
Dep. Variable:	Gasoline_Crack	**No. Observations:**	103
Model:	SARIMAX(1, 1, 2)	**Log Likelihood**	-253.012
Date:	Thu, 24 May 2018	**AIC**	514.024
Time:	00:23:20	**BIC**	524.563
Sample:	01-31-2009	**HQIC**	518.293
	- 07-31-2017		
Covariance Type:	opg		

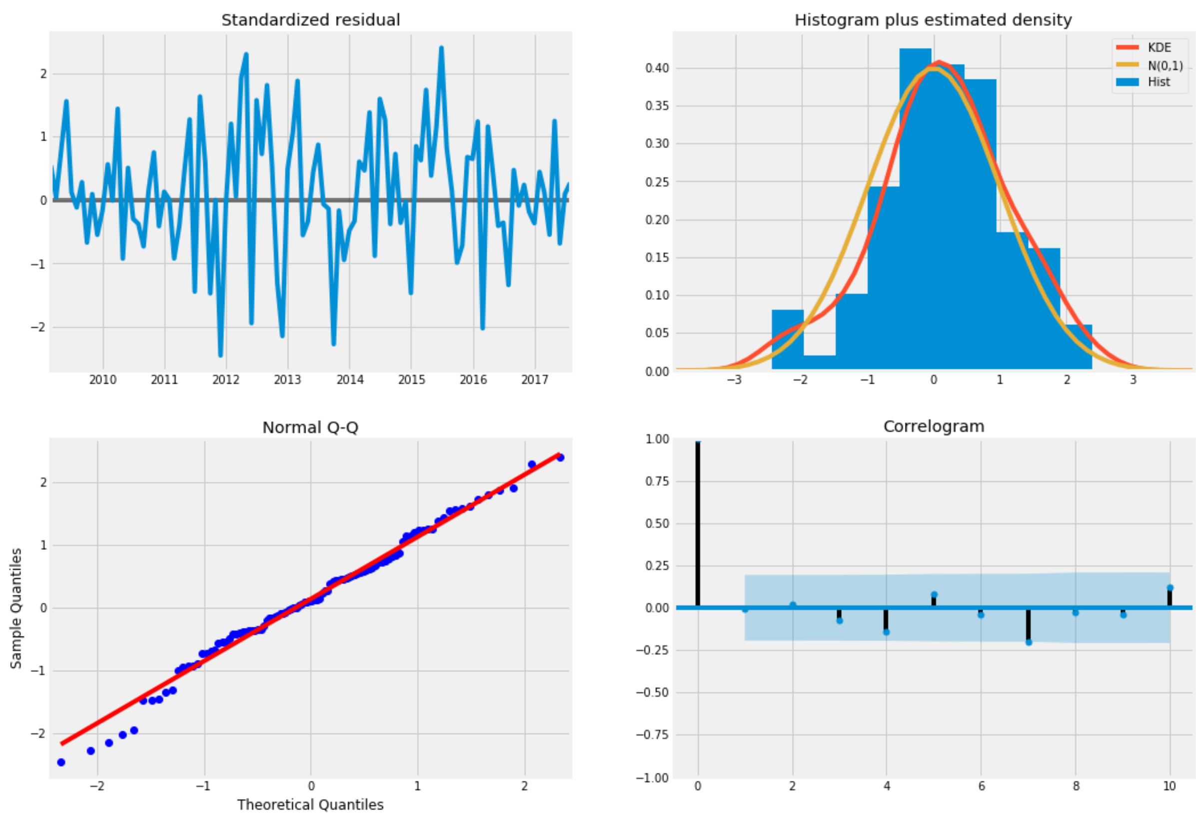
	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ar.L1	0.5538	0.150	3.702	0.000	0.261	0.847
ma.L1	-0.7078	0.160	-4.414	0.000	-1.022	-0.394
ma.L2	-0.2207	0.126	-1.757	0.079	-0.467	0.025
sigma2	8.2776	1.231	6.722	0.000	5.864	10.691

Ljung-Box (Q):	54.89	**Jarque-Bera (JB):**	0.91
Prob(Q):	0.06	**Prob(JB):**	0.63
Heteroskedasticity (H):	1.14	**Skew:**	-0.23
Prob(H) (two-sided):	0.70	**Kurtosis:**	3.07

In [61]:
```
model_results.plot_diagnostics(figsize=(16,12))
```

Out[61]:



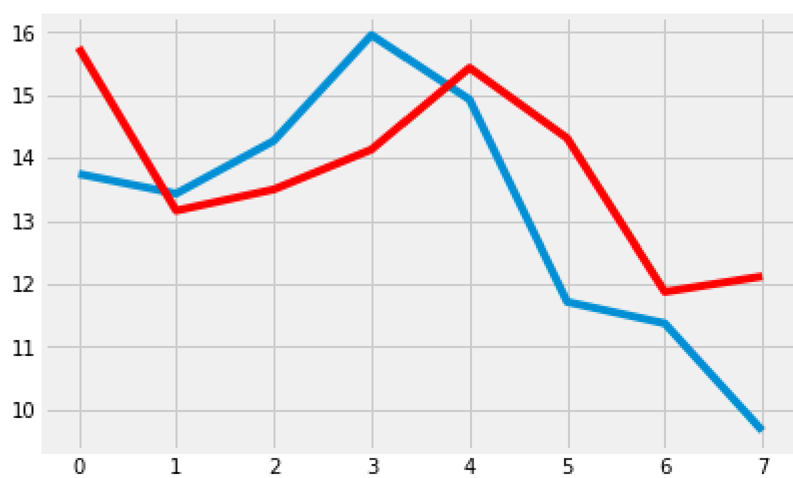


In [62]:
```
import warnings
from pandas import Series
from statsmodels.tsa.arima_model import ARIMA
from sklearn.metrics import mean_squared_error

# 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) * 0.93)
    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 = sm.tsa.SARIMAX(history, order=arima_order)
        model_fit = model.fit()
        yhat = model_fit.get_forecast(steps=1)
        yhat = yhat.predicted_mean
        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))

# load dataset
series = Series.from_csv('Gasoline_Crack_2009_2017.csv', header=0)
resample = data.resample('M')
monthly_mean = resample.mean()
# evaluate parameters
p_values = [0, 1, 2]
d_values = range(0, 3)
q_values = range(0, 3)
warnings.filterwarnings("ignore")
timeseries=monthly_mean.values
evaluate_models(timeseries, p_values, d_values, q_values)
```

```
ARIMA(0, 1, 1) MSE=2.863
ARIMA(0, 1, 2) MSE=3.138
ARIMA(0, 2, 1) MSE=2.990
ARIMA(0, 2, 2) MSE=3.030
ARIMA(1, 0, 0) MSE=2.293
ARIMA(1, 0, 1) MSE=2.324
ARIMA(1, 0, 2) MSE=2.773
ARIMA(1, 1, 0) MSE=2.854
ARIMA(1, 1, 2) MSE=2.665
ARIMA(1, 2, 0) MSE=4.849
ARIMA(1, 2, 1) MSE=3.018
ARIMA(1, 2, 2) MSE=3.073
ARIMA(2, 0, 0) MSE=2.314
ARIMA(2, 1, 0) MSE=2.963
ARIMA(2, 1, 2) MSE=2.663
ARIMA(2, 2, 0) MSE=4.169
ARIMA(2, 2, 1) MSE=3.143
ARIMA(2, 2, 2) MSE=3.137
Best ARIMA(1, 0, 0) MSE=2.293
```

In [63]:

```
series = Series.from_csv('Gasoline_Crack_2009_2017.csv', header=0)
resample = data.resample('M')
monthly_mean = resample.mean()
order = (1,1,2)
X=monthly_mean.values

train_size = int(len(X) * 0.93)
train, test = X[0:train_size], X[train_size:]
history = [x for x in train]
predictions = list()
for t in range(len(test)):
    model = sm.tsa.SARIMAX(history, order=order)
    model_fit = model.fit()
    yhat = model_fit.get_forecast(steps=1)
    yhat = yhat.predicted_mean[0]
    obs = test[t]
    predictions.append(yhat)
    history.append(obs)
plt.plot(test)
plt.plot(predictions, color='red')
plt.show()
```



Seasonality - SARIMA

In [65]:
```
series= pd.read_csv('Gasoline_Crack_2009_2017.csv')
series['Date']=pd.to_datetime(series['Date'])
series['Month']=series['Date'].dt.month
series['Year'] = series['Date'].dt.year
series2= series.drop(['Date'],axis=1,inplace=False)
data1=series[series['Month']==1]['Gasoline_Crack']
data2=series[series['Month']==2]['Gasoline_Crack']
data3=series[series['Month']==3]['Gasoline_Crack']
data4=series[series['Month']==4]['Gasoline_Crack']
data5=series[series['Month']==5]['Gasoline_Crack']
data6=series[series['Month']==6]['Gasoline_Crack']
data7=series[series['Month']==7]['Gasoline_Crack']
data8=series[series['Month']==8]['Gasoline_Crack']
data9=series[series['Month']==9]['Gasoline_Crack']
data10=series[series['Month']==10]['Gasoline_Crack']
data11=series[series['Month']==11]['Gasoline_Crack']
data12=series[series['Month']==12]['Gasoline_Crack']
data_to_plot=[data1,data2,data3,data4,data5,data6,data7,data8,data9,data10,dat
a11,data12]
```

In [66]:
```
fig = plt.figure(1, figsize=(16, 9))
ax = fig.add_subplot(111)
bp = ax.boxplot(data_to_plot)

bp = ax.boxplot(data_to_plot, patch_artist=True)
for box in bp['boxes']:
    # change outline color
    box.set( color='#7570b3', linewidth=2)
    # change fill color
    box.set( facecolor = '#1b9e77' )

for whisker in bp['whiskers']:
    whisker.set(color='#7570b3', linewidth=2)

for cap in bp['caps']:
    cap.set(color='#7570b3', linewidth=2)

for median in bp['medians']:
    median.set(color='#b2df8a', linewidth=2)

for flier in bp['fliers']:
    flier.set(marker='o', color='#e7298a', alpha=0.5)

ax.set_xticklabels(['Jan', 'Feb', 'Mar', 'Apr','May','Jun','Jul','Aug','Sep',
'Oct','Nov','Dec'])
ax.get_xaxis().tick_bottom()
ax.get_yaxis().tick_left()
ax.set_xlabel('Price')
ax.set_ylabel('Months')
```

Out[66]:
```
Text(0,0.5,'Months')
```