Capstone Project

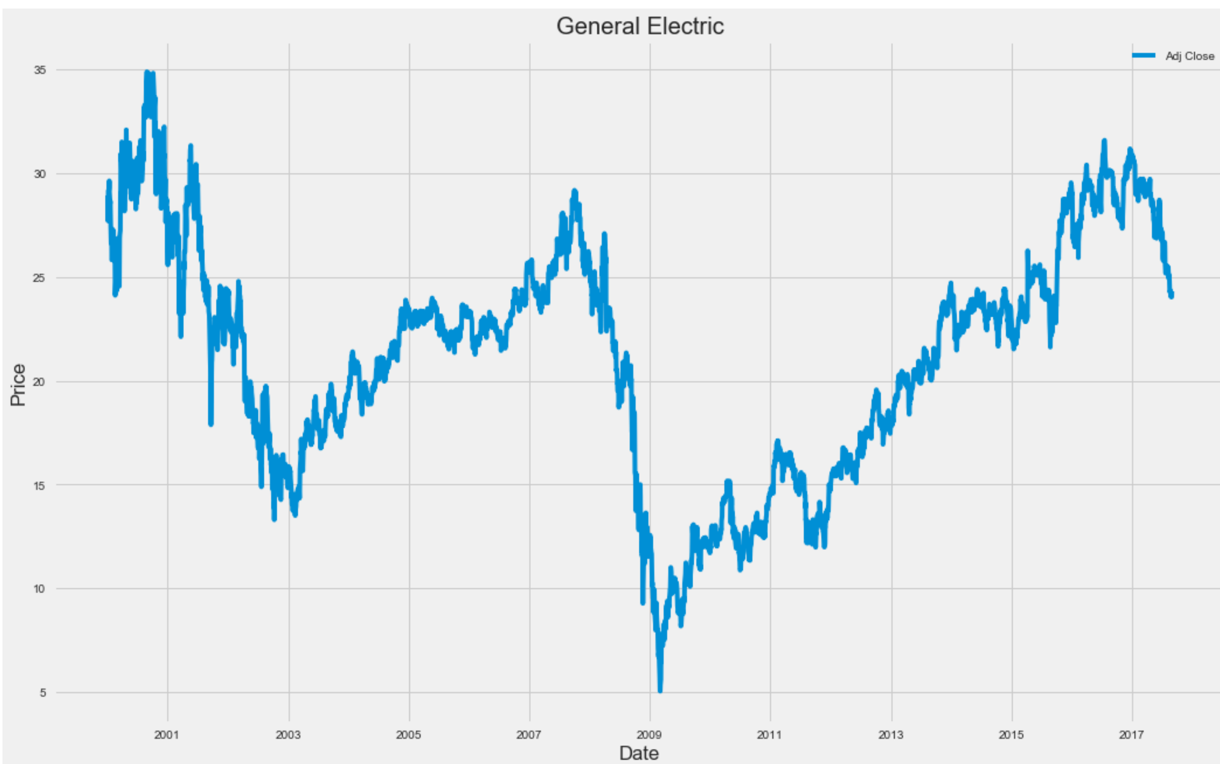
A stock or Index Price Predictor

In [1]:
```
#Importing the major libraries

import sklearn# Features various classification, regression and clustering algori
import numpy as np #Adding support for large, multi-dimensional arrays and matric
import pandas as pd #Provides fast, flexible and expressive data structures
import matplotlib.pyplot as plt#A plotting library for Python and its numerical e
import datetime as dt #A module that supplies classes for manipulating dates and
from matplotlib import style
import pandas_datareader.data as web #Getting data from the data provider's websi
import seaborn as sns  #A visualization library , provides high-level interface f
from math import sqrt #Will use this square root function to calculate RMSE
```

In [3]:
```
#Getting the data for a stock or Index



start = dt.datetime(2000,1,1)   #The start date for the data
end = dt.datetime(2017,8,31)      # The end date for the purpose of this analysis
df= web.DataReader('GE', 'yahoo', start, end)# Getting the data for a stock in th
print (df.head())# a representation of the first 5 set of data
print (df.tail())# a representation of the last 5 set of the data

df.to_csv('GE.csv') #converting the data retrieved into a csv file
```

```
                 Open       High        Low      Close  Adj Close    Volume
Date
2000-01-03  51.000000  51.229168  49.729168  50.000000  28.911114  22069800
2000-01-04  49.083332  49.333332  48.000000  48.000000  27.754667  22121400
2000-01-05  47.916668  49.000000  47.520832  47.916668  27.706484  27292800
2000-01-06  47.708332  48.979168  47.541668  48.557266  28.076889  19873200
2000-01-07  49.333332  50.625000  49.000000  50.437500  29.164083  20141400
                 Open       High        Low      Close  Adj Close    Volume
Date
2017-08-25  24.389999  24.600000  24.350000  24.490000  24.247725  22867800
2017-08-28  24.530001  24.670000  24.350000  24.469999  24.227922  23937600
2017-08-29  24.330000  24.459999  24.280001  24.440001  24.198219  23910100
2017-08-30  24.490000  24.490000  24.150000  24.280001  24.039803  33876000
2017-08-31  24.410000  24.700001  24.280001  24.549999  24.307131  55284300
```

In [4]:
```
#Visualizations



#Get the adjusted close price for the stock for the stated period for analysis
Adj_close=web.DataReader('GE', 'yahoo', start, end)['Adj Close']

#print(Adj_close)

#graphing the Data

style.use('fivethirtyeight')

#Set the size of the graph display
plt.figure(figsize=(16,10))

plt.plot(Adj_close)
plt.legend()
plt.xlabel('Date')
plt.ylabel('Price')
lw=0.1
plt.title('General Electric')
plt.show()
```



Generating Features

In [5]:
```
def generate_features(df):
    """Generating features for a chosen stock or Index based on historical price 
    the arguments passed to this function are df(dataframe with columns:"Open", "
    Function Returns:
        dataframe, data set with new features """
    df_new= pd.DataFrame()
    # The six original features

    df_new['open']= df['Open']
    df_new['Open_1']= df['Open'].shift(1) # This method shift index by 1, in orde


    df_new['close_1'] = df['Close'].shift(1)

    df_new['high_1']= df['High'].shift(1)

    df_new['low_1'] = df['Low'].shift(1)

    df_new['volume_1'] = df['Volume'].shift(1)

    # The 31 Features to Generate from the 6 original

    # Average price
    #The window sizes are rounded to 5 days, 21 days and 252 to represent the num


    df_new['avg_price_5']= pd.Series.rolling(df['Close'],window=5,center=False).m

    #rolling_mean calculates the moving average given a window {(Example [1,2,1,,

    df_new['avg_price_30']=pd.Series.rolling(df['Close'], window=21, center=False
    df_new['avg_price_365']=pd.Series.rolling(df['Close'], window=252, center=Fal


    #Ratio

    df_new['ratio_avg_price_5_30'] = df_new['avg_price_5'] / df_new['avg_price_30
    df_new['ratio_avg_price_5_365'] = df_new['avg_price_5'] / df_new['avg_price_3
    df_new['ratio_avg_price_30_365'] = df_new['avg_price_30'] / df_new['avg_price_

     # average volume
    df_new['avg_volume_5'] =pd.Series.rolling(df['Volume'], window=5, center=Fals
    df_new['avg_volume_30'] = pd.Series.rolling(df['Volume'], window=21, center=F
    df_new['avg_volume_365'] =pd.Series.rolling(df['Volume'], window=252, center=
    df_new['ratio_avg_volume_5_30'] =df_new['avg_volume_5'] / df_new['avg_volume_
    df_new['ratio_avg_volume_5_365'] =df_new['avg_volume_5'] / df_new['avg_volume
    df_new['ratio_avg_volume_30_365'] =df_new['avg_volume_30'] / df_new['avg_volu

    # standard deviation of prices

    df_new['std_price_5'] = pd.Series.rolling(df['Close'], window=5, center=False

    # rolling_mean calculates the moving standard deviation given a window
    df_new['std_price_30'] =pd.Series.rolling(df['Close'], window=21, center=Fals
    df_new['std_price_365'] =pd.Series.rolling(df['Close'], window=252, center=Fa
    df_new['ratio_std_price_5_30'] =df_new['std_price_5'] / df_new['std_price_30'
```

```
    df_new['ratio_std_price_5_365'] =df_new['std_price_5'] / df_new['std_price_36
    df_new['ratio_std_price_30_365'] =df_new['std_price_30'] / df_new['std_price_

   # standard deviation of volumes
    df_new['std_volume_5'] =pd.Series.rolling(df['Volume'], window=5,center=False
    df_new['std_volume_30'] = pd.Series.rolling(df['Volume'], window=21, center=F
    df_new['std_volume_365'] =pd.Series.rolling(df['Volume'], window=252, center=
    df_new['ratio_std_volume_5_30'] =df_new['std_volume_5'] / df_new['std_volume_
    df_new['ratio_std_volume_5_365'] =df_new['std_volume_5'] / df_new['std_volume
    df_new['ratio_std_volume_30_365'] =df_new['std_volume_30'] / df_new['std_volu

   # return
    df_new['return_1'] = ((df['Close'] - df['Close'].shift(1))/ df['Close'].shift
    df_new['return_5'] = ((df['Close'] - df['Close'].shift(5))/ df['Close'].shift
    df_new['return_30'] = ((df['Close'] -df['Close'].shift(21)) / df['Close'].shi
    df_new['return_365'] = ((df['Close'] - df['Close'].shift(252)) / df['Close'].
    df_new['moving_avg_5'] =pd.Series.rolling(df_new['return_1'], window=5, cente
    df_new['moving_avg_30'] = pd.Series.rolling(df_new['return_1'], window=21, ce
    df_new['moving_avg_365'] = pd.Series.rolling(df_new['return_1'], window=252,

   # the target
    df_new['close'] = df['Close']
    df_new = df_new.dropna(axis=0) # This will drop rows with any N/A value, whic

    return df_new
```

Applying feature engineering strategy to the GE data

In [6]:

```
raw_data=df
data=generate_features(raw_data)

data.round(decimals=2).head(3)
```

Out[6]:

Date	open	Open_1	close_1	high_1	low_1	volume_1	avg_price_5	avg_price_30	avg_price_3
2001-01-03	44.25	46.75	43.75	46.88	42.62	36837700.0	47.52	50.70	51
2001-01-04	47.31	44.25	47.81	47.94	43.81	39205800.0	47.22	50.55	51
2001-01-05	47.75	47.31	48.06	48.75	47.12	26926400.0	47.20	50.38	51

3 rows × 38 columns

Selecting data for training and testing

In [7]:
```
import datetime

#All the fields in the datatframe 'data' are feature columns while 'Close' is the

start_train =datetime.datetime(2000,1,1,0,0)
end_train =datetime.datetime(2017,8,31,0,0)
data_train =data.loc[start_train:end_train]

#print (data_train)
```

In [8]:
```
#Partitioning the data between training and testing sets

# We will be using the TimeSeriesSplit

"""TimeSeriesSplit Provides train/test indices to split time series data samples
   in train/test sets. In each split, test indices must be higher than before, an
   validator is inappropriate."""


from sklearn.model_selection import TimeSeriesSplit

X,y= data_train.iloc[:, 1:].values, data_train.iloc[:,0].values #Assigning values
#print(X)
#print(y)

dataList=TimeSeriesSplit(n_splits=3)


print(dataList)




for train_index, test_index in dataList.split(X):
        print("TRAIN:", train_index, "TEST:", test_index)
        X_train, X_test = X[train_index], X[test_index]
        y_train, y_test = y[train_index], y[test_index]


X_train.shape
y_train.shape
y_test.shape
```

```
TimeSeriesSplit(n_splits=3)
TRAIN: [   0    1    2 ..., 1045 1046 1047] TEST: [1048 1049 1050 ..., 2093 209
4 2095]
TRAIN: [   0    1    2 ..., 2093 2094 2095] TEST: [2096 2097 2098 ..., 3141 314
2 3143]
TRAIN: [   0    1    2 ..., 3141 3142 3143] TEST: [3144 3145 3146 ..., 4189 419
0 4191]
```

Out[8]: (1048,)

Preprocessing the data

In [9]:
```
from sklearn.preprocessing import StandardScaler

sc=StandardScaler() #Using stantardization

sc.fit(X_train)

#Rescaling both sets using the trained scaler; feature scaling is a crucial steep


X_scaled_train=sc.transform(X_train)
X_scaled_test=sc.transform(X_test)

X_test.shape
```

Out[9]: (1048, 37)

Implementation of the Linear Regression Model

In [10]:
```
#Using a Stochastic Gradient Descent(SGD)-based Linear Rregression

from sklearn import linear_model
from sklearn.grid_search import GridSearchCV
from sklearn.metrics import mean_squared_error , r2_score

#Setting the optimal set of parameters for the regression
Lr=linear_model.SGDRegressor(alpha=0.0001, penalty='l2', n_iter=1000, eta0=0.01)

"""Implementing the Optimization parameter 'grid search' that can further improve
    the Optimal combinaton of hyperparameters"""

#A list of dictionaies that have the parameters that we want to tune
param_grid={"alpha":[3e-06, 1e-05, 3e-5],"eta0":[0.01,0.03,0.1]}


grid_search=GridSearchCV(Lr,param_grid=param_grid, cv=5, scoring='neg_mean_square
grid_search.fit(X_scaled_train, y_train)

print(grid_search.best_params_)
```

```
C:\Users\delis\Anaconda3\lib\site-packages\sklearn\cross_validation.py:44: Depr
ecationWarning: This module was deprecated in version 0.18 in favor of the mode
l_selection module into which all the refactored classes and functions are move
d. Also note that the interface of the new CV iterators are different from that
of this module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
C:\Users\delis\Anaconda3\lib\site-packages\sklearn\grid_search.py:43: Deprecati
onWarning: This module was deprecated in version 0.18 in favor of the model_sel
ection module into which all the refactored classes and functions are moved. Th
is module will be removed in 0.20.
  DeprecationWarning)
```

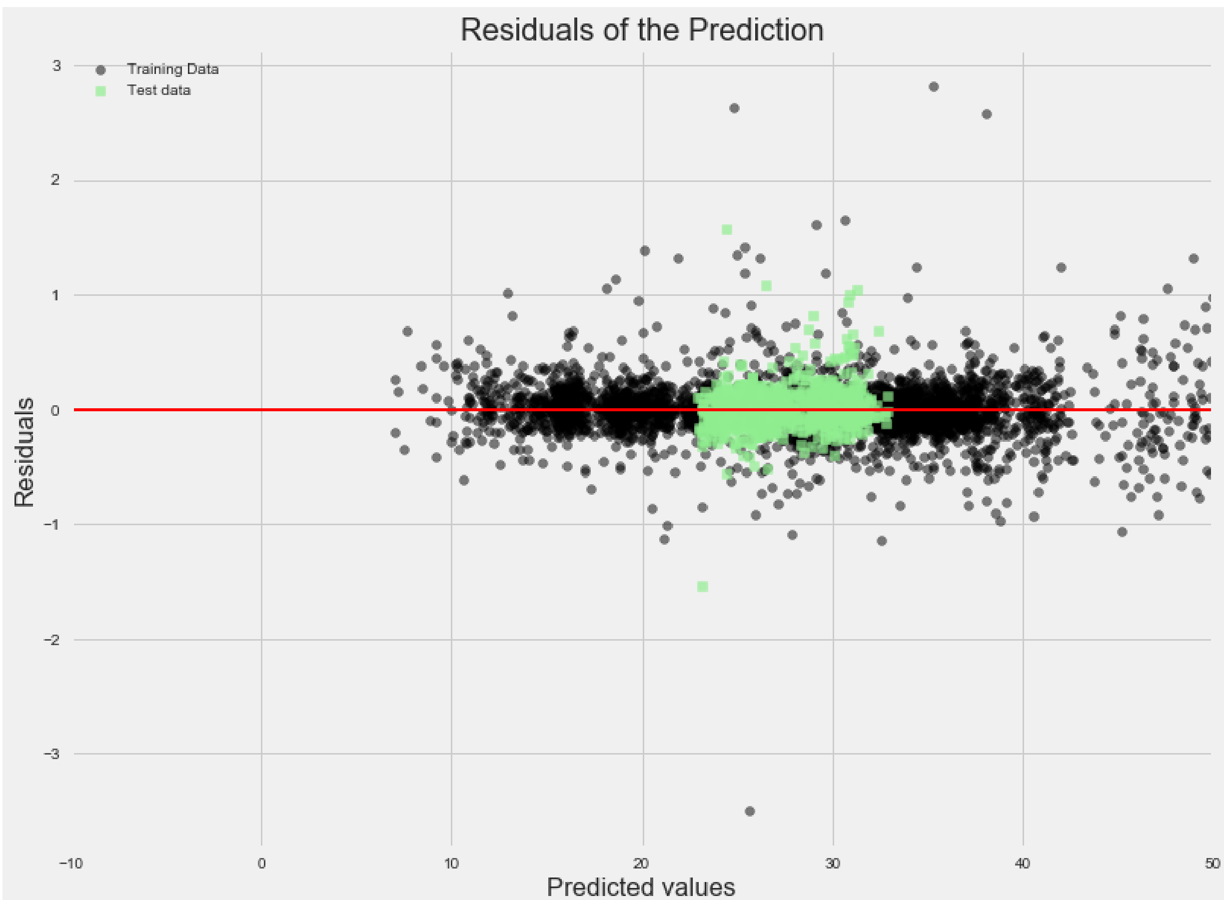
```
{'alpha': 3e-06, 'eta0': 0.03}
```

Implementing the Prediction and Measuring its performance

In [11]:
```
Lr_best = grid_search.best_estimator_

y_train_pred=Lr_best.predict(X_scaled_train)
y_test_pred1=Lr_best.predict(X_scaled_test)

#rmse=sqrt(mean_squared_error(y_test,y_test_pred1))

#The Mean Squared Error and R^2

#Coefficient of Determination (R^2, this is the fraction of response variance tha

#

print('MSE train: %.3f, test:%.3f' %(mean_squared_error(y_train, y_train_pred), m

print('RMSE train: %.3f, test:%.3f' %(sqrt(mean_squared_error(y_train, y_train_pr

print('R^2 train: %.7f, test: %.7f' % (r2_score(y_train, y_train_pred), r2_score(


print(y_test_pred1)
```

```
MSE train: 0.068, test:0.027
RMSE train: 0.260, test:0.166
R^2 train: 0.9992260, test: 0.9951264
[ 23.27383518  23.4668783   23.65255756 ...,  24.4542678   24.36308018
  24.34792929]
```

In [11]:
```
#Visualizations of the Residuals of the Prediction

plt.figure(figsize=(12,9))

plt.scatter(y_train_pred, y_train_pred -y_train, c='black', marker='o', s=35, alp

plt.scatter(y_test_pred1, y_test_pred1-y_test, c='lightgreen', marker='s', s=35, 



plt.title('Residuals of the Prediction')
plt.xlabel('Predicted values')
plt.ylabel('Residuals')
plt.legend(loc='upper left')
plt.hlines(y=0, xmin=-10, xmax=100, lw=2, color='red')
plt.xlim([-10, 50])

plt.show()
```



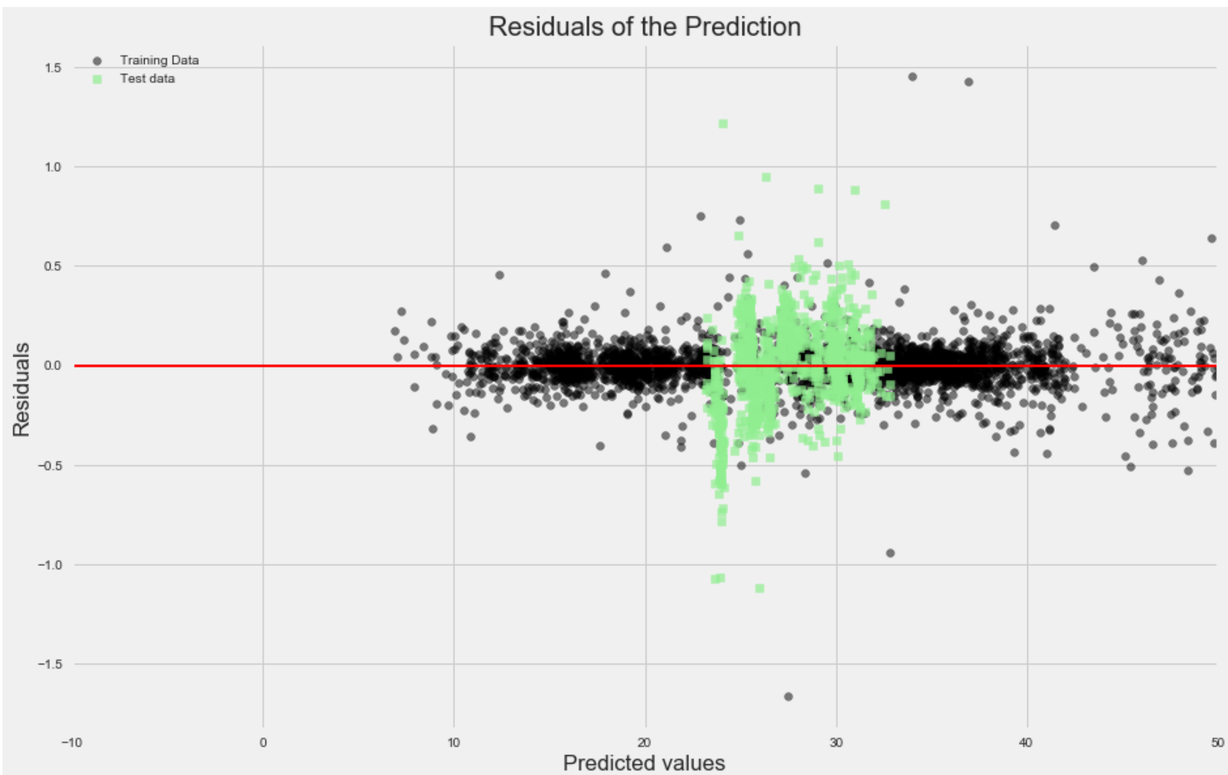
Implementation of the Random Forest Algorithm

In [12]:
```
from sklearn.ensemble import RandomForestRegressor

"""A random forest, is an ensemble of multiple decision tree. Here we are subdivi
   will become more manageable."""

#Assigning parameters for tuning the regressor

forest=RandomForestRegressor(n_estimators=1000, random_state=1, n_jobs=1, max_dep

forest.fit(X_scaled_train, y_train)

y_train_pred=forest.predict(X_scaled_train)
y_test_pred2=forest.predict(X_scaled_test)

#The Mean Squared Error and R^2
print('MSE train: %.3f, test:%.3f' %(mean_squared_error(y_train, y_train_pred), m
print('RMSE train: %.3f, test:%.3f' %(sqrt(mean_squared_error(y_train, y_train_pr
print('R^2 train: %.3f, test: %.3f' % (r2_score(y_train, y_train_pred), r2_score(
```

```
MSE train: 0.012, test:0.050
RMSE train: 0.112, test:0.224
R^2 train: 1.000, test: 0.991
```

In [13]:

```
#Visualizations of the Residuals of the Prediction

plt.figure(figsize=(14,9))

plt.scatter(y_train_pred, y_train_pred -y_train, c='black', marker='o', s=35, alp

plt.scatter(y_test_pred2, y_test_pred2-y_test, c='lightgreen', marker='s', s=35, 



plt.title('Residuals of the Prediction')
plt.xlabel('Predicted values')
plt.ylabel('Residuals')
plt.legend(loc='upper left')
plt.hlines(y=0, xmin=-10, xmax=50, lw=2, color='red')
plt.xlim([-10, 50])

plt.show()
```

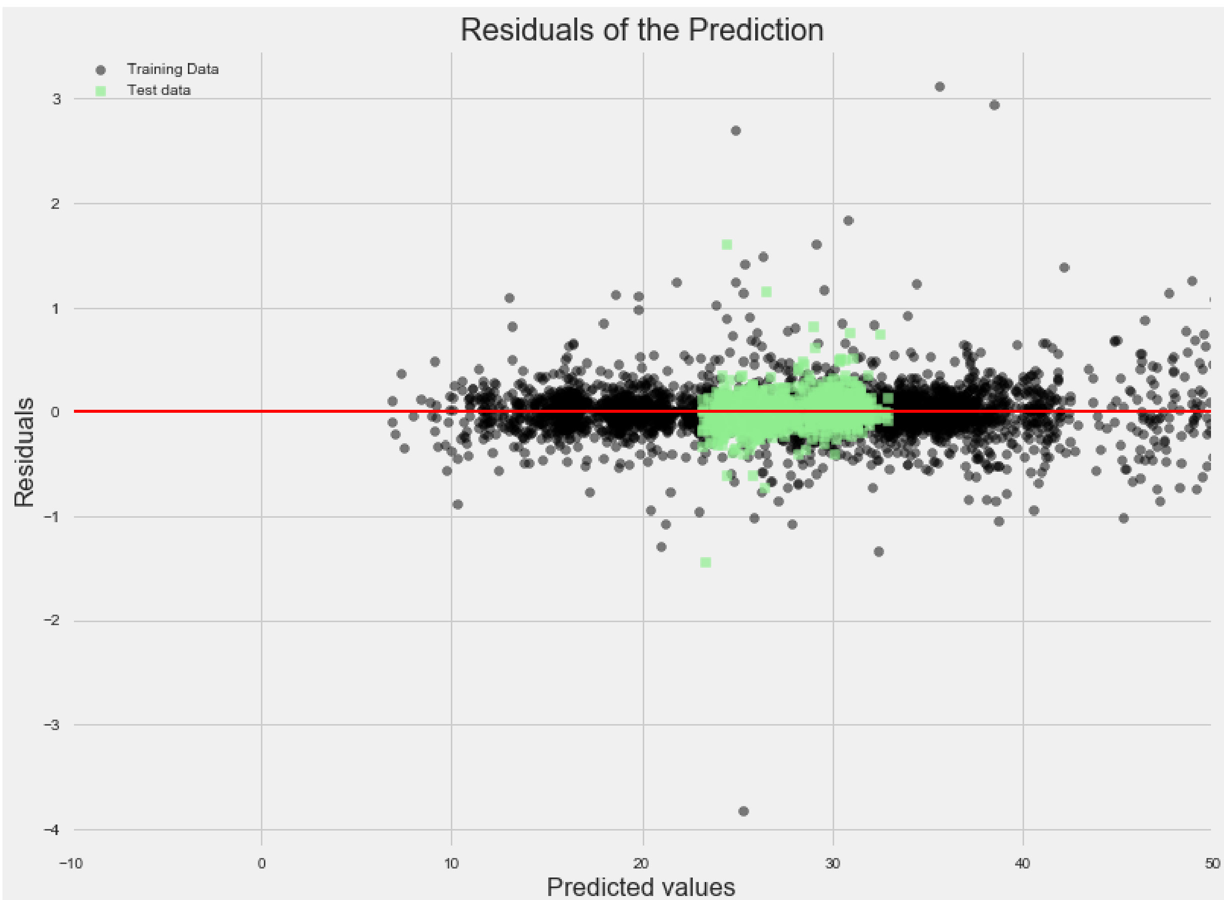


Implementation of the Support Vector Machine(SVM) Algorithm

In [14]:
```
from sklearn.svm import SVR

svr=SVR(kernel='linear', gamma=100.0, C=1.0)
svr.fit(X_scaled_train, y_train)

y_train_pred=svr.predict(X_scaled_train)
y_test_pred3=svr.predict(X_scaled_test)

#The Mean Squared Error, RMSE and R^2
print('MSE train: %.3f, test:%.3f' %(mean_squared_error(y_train, y_train_pred), m
print('RMSE train: %.3f, test:%.3f' %(sqrt(mean_squared_error(y_train, y_train_pr
print('R^2 train: %.7f, test: %.7f' % (r2_score(y_train, y_train_pred), r2_score(


#print(y_test_pred2)
```

```
MSE train: 0.067, test:0.025
RMSE train: 0.260, test:0.157
R^2 train: 0.9992302, test: 0.9956108
```

In [15]:
```
#Visualizations of the Residuals of the Prediction

plt.figure(figsize=(12,9))

plt.scatter(y_train_pred, y_train_pred -y_train, c='black', marker='o', s=35, alp

plt.scatter(y_test_pred3, y_test_pred3-y_test, c='lightgreen', marker='s', s=35,



plt.title('Residuals of the Prediction')
plt.xlabel('Predicted values')
plt.ylabel('Residuals')
plt.legend(loc='upper left')
plt.hlines(y=0, xmin=-10, xmax=100, lw=2, color='red')
plt.xlim([-10, 50])

plt.show()
```



The Benchmark (Using a Naive Forecast)

In [16]:
```
"""I will be using a Naive forecast, this forecasting method is suitable for Time
we will be using a seasonal naive approach with the autoregressive integrated mov
generalization of an autoregressive moving average (ARMA) model. Both of these mod
better understand the data or to predict future points in the series (forecasting

from statsmodels.tsa.arima_model import ARIMA

series=Adj_close #Using the adjusted close for the dates(January 1, 2000 - August
X=series.values #Getthing the Adjusted closing prices ffrom the data
#print(X)

#Partitioning the data for trainign and testing
size=int(len(X)*0.77)

train, test=X,  X[size:len(X)]

history=[values for values in train] #parsing through the training data

predict=list()

for t in range(len(test)):
    model=ARIMA(history, order=(5,1,0))#Initializing the ARIMA module; 5,1,0 repr
    model_fit=model.fit(disp=0)
    output=model_fit.forecast()#Using the ARIMA for making forecasts
    y_t=output[0]
    predict.append(y_t)
    obs = test[t]
    history.append(obs)

error=mean_squared_error(test, predict)
RMSE=sqrt(mean_squared_error(test,predict))
R_2 = r2_score(test, predict)


print('Test MSE: %.3f' %error)
print('Test RMSE: %.3f'%RMSE)
print('Test R_2: %.3f' %R_2)
```

```
C:\Users\delis\Anaconda3\lib\site-packages\statsmodels\compat\pandas.py:56: Fut
ureWarning: The pandas.core.datetools module is deprecated and will be removed
 in a future version. Please use the pandas.tseries module instead.
  from pandas.core import datetools
C:\Users\delis\Anaconda3\lib\site-packages\statsmodels\base\model.py:496: Conve
rgenceWarning: Maximum Likelihood optimization failed to converge. Check mle_re
tvals
  "Check mle_retvals", ConvergenceWarning)
C:\Users\delis\Anaconda3\lib\site-packages\statsmodels\base\model.py:496: Conve
rgenceWarning: Maximum Likelihood optimization failed to converge. Check mle_re
tvals
  "Check mle_retvals", ConvergenceWarning)

Test MSE: 0.089
Test RMSE: 0.299
Test R_2: 0.990
```

Plot Comparison

In [17]:
```
import seaborn as sns

plt.figure(figsize=(16,9))
sns.set_context(font_scale=3)

plt.xlim([0.0, 1100])
plt.ylim([0.0, 60])
lw=1
plt.title('Stock price prediction Models vs Benchmark[Naive-Forecast(ARIMA)]')

# Set figure width to 12 and height to 9




plt.xlabel('Number of Testing instance')
plt.ylabel('Price')

plt.plot(y_test_pred1, c='black',marker='o', lw=0.75,alpha=0.5, label='Linear Reg
plt.plot(y_test_pred2, c='red', marker='x', lw=3, label='RandomForest')
plt.plot(y_test_pred3, c='yellow', lw=1, label='SVR')
plt.plot(predict,c='green', lw=0.5, label='Benchmark-Naive-Forecast(ARIMA)')


plt.legend(loc='lower left')
plt.show()
```