In [1048]:
```
import numpy as np
import pandas as pd
import matplotlib
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegressionCV
import sklearn.metrics as metrics
from sklearn.metrics import r2_score
from sklearn.preprocessing import PolynomialFeatures
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score
import sklearn.discriminant_analysis as da
import sklearn.neighbors as knn
from sklearn.model_selection import KFold
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LinearRegression
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_curve, auc
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.linear_model import RidgeCV
from sklearn.linear_model import LassoCV
from statsmodels.api import OLS
from statsmodels.api import add_constant
import statsmodels.api as sm
import datetime

#import pydotplus
#import io
from sklearn.tree import export_graphviz
from IPython.display import Image
from IPython.display import display
%matplotlib inline
from matplotlib import pyplot
default_dims = (13, 10)
import seaborn.apionly as sns #sets up styles and gives us more plotting
 options
sns.set_style("whitegrid")
sns.set_context("poster")
sns.reset_orig()
```

In [1280]:
```
five_factor_df = pd.read_csv('F-
F_Research_Data_5_Factors_2x3_daily.CSV', index_col = 'Date')
nan_rows = five_factor_df.isnull().T.any().T
five_factor_df = five_factor_df[~nan_rows]
print(np.shape(five_factor_df))
five_factor_df.head()
```

```
(13657, 6)
```

Out[1280]:

	Mkt-RF	SMB	HML	RMW	CMA	RF
Date						
19630701	-0.67	0.00	-0.32	0.01	0.15	0.012
19630702	0.79	-0.27	0.27	-0.08	-0.19	0.012
19630703	0.63	-0.17	-0.09	0.19	-0.33	0.012
19630705	0.40	0.08	-0.28	0.07	-0.33	0.012
19630708	-0.63	0.04	-0.17	-0.31	0.13	0.012

In [1281]:
```
five_factor_df.index = pd.to_datetime(five_factor_df.index,format='%Y%m%
d')
```

In [1282]:
```
three_factor_df = pd.read_csv('F-F_Research_Data_Factors_daily.CSV', ind
ex_col = 'Date')
nan_rows = three_factor_df.isnull().T.any().T
three_factor_df = three_factor_df[~nan_rows]
print(np.shape(three_factor_df))
three_factor_df.head()
```

```
(24077, 4)
```

Out[1282]:

	Mkt-RF	SMB	HML	RF
Date				
19260701	0.10	-0.24	-0.28	0.009
19260702	0.45	-0.32	-0.08	0.009
19260706	0.17	0.27	-0.35	0.009
19260707	0.09	-0.59	0.03	0.009
19260708	0.21	-0.36	0.15	0.009

In [1283]:
```
three_factor_df.index = pd.to_datetime(three_factor_df.index,format='%Y%
m%d')
```

In [1284]:
```
three_factors = [x for x in three_factor_df.columns if x != 'Date' and x
 != 'RF']
five_factors = [x for x in five_factor_df.columns if x != 'Date' and x !
= 'RF']
```

In [1285]:
```
stocks_held = ['USAK', 'RHDGF', 'DXLG', 'NUSMF', 'LEE', 'AXLE']
# stocks_held = ['USAK', 'RHDGF', 'DXLG', 'NUSMF', 'LEE']
```

In [1286]:
```
quantities = [180, 110, 1000, 8000, 425, 2000]
# quantities = [180, 110, 1000, 8000, 425]
```

In [1287]:
```
ptf_dict = {stocks_held[i]: quantities[i] for i in
range(len(quantities))}
```

In [1290]:
```
dfs = []
for stock in stocks_held:
    if stock != 'AXLE':
        stock_df = pd.read_csv('{}.csv'.format(stock), index_col = None)
        stock_df['Stock'] = stock
        dfs.append(stock_df)

# Adds in last dataframe at the end to keep them in order
df = pd.concat(dfs)
df.head()
```

Out[1290]:

	Date	Open	High	Low	Close	Adj Close	Volume	Stock
0	1992-03-19	7.5	7.5	7	7.125	7.125	1256400	USAK
1	1992-03-20	7.375	7.625	7.125	7.25	7.25	262800	USAK
2	1992-03-23	7.25	7.625	7.25	7.25	7.25	43800	USAK
3	1992-03-24	7.5	7.625	7.25	7.5	7.5	73600	USAK
4	1992-03-25	7.625	7.625	7.25	7.625	7.625	28000	USAK

In [1291]:
```
df['Date'] = pd.to_datetime(df['Date'])
```

In [1292]:
```
df = df.convert_objects(convert_numeric=True)
```

```
/anaconda/lib/python3.6/site-packages/ipykernel_launcher.py:1: FutureWa
rning: convert_objects is deprecated.  Use the data-type specific conve
rters pd.to_datetime, pd.to_timedelta and pd.to_numeric.
  """Entry point for launching an IPython kernel.
```

In [1293]:
```
df.index = range(len(df))
df['Open'] = [df['Open'][i] * ptf_dict[df['Stock'][i]] for i in range(le
n(df))]
df['Close'] = [df['Close'][i] * ptf_dict[df['Stock'][i]] for i in
range(len(df))]
df.head()
```

Out[1293]:

	Date	Open	High	Low	Close	Adj Close	Volume	Stock
0	1992-03-19	1350.0	7.500	7.000	1282.5	7.125	1256400.0	USAK
1	1992-03-20	1327.5	7.625	7.125	1305.0	7.250	262800.0	USAK
2	1992-03-23	1305.0	7.625	7.250	1305.0	7.250	43800.0	USAK
3	1992-03-24	1350.0	7.625	7.250	1350.0	7.500	73600.0	USAK
4	1992-03-25	1372.5	7.625	7.250	1372.5	7.625	28000.0	USAK

In [1294]:
```
AXLE_df = pd.read_csv('AXLE.csv', index_col = None)
```

In [1295]:
```
AXLE_df['Stock'] = 'AXLE'
AXLE_df['Date'] = pd.to_datetime(AXLE_df['Date'])
AXLE_df = AXLE_df.convert_objects(convert_numeric=True)
```

```
/anaconda/lib/python3.6/site-packages/ipykernel_launcher.py:3: FutureWa
rning: convert_objects is deprecated.  Use the data-type specific conve
rters pd.to_datetime, pd.to_timedelta and pd.to_numeric.
  This is separate from the ipykernel package so we can avoid doing imp
orts until
```

In [1296]:
```
AXLE_df['Last Price'] = ptf_dict['AXLE'] * AXLE_df['Last Price']
return_list = [np.log(AXLE_df['Last Price'][i]) - np.log(AXLE_df['Last P
rice'][i + 1]) for i in range(len(AXLE_df) - 1)]
AXLE_df = AXLE_df.drop(AXLE_df.index[-1])
AXLE_df['Returns'] = return_list
```

In [1299]:
```
df['Returns'] = np.log(df['Close']) - np.log(df['Open'])
```

In [1300]:
```
df = pd.concat([df, AXLE_df])
```

In [1301]:
```
df = df[df['Date'] >= datetime.datetime(2012, 10, 19)]
```

In [1302]:
```
three_factor_df = three_factor_df[three_factor_df.index >= datetime.date
time(2012, 10, 19)]
```

In [1303]:
```
five_factor_df = five_factor_df[five_factor_df.index >= datetime.datetim
e(2012, 10, 19)]
```

In [1304]:
```
grouped_by_stock = df.groupby('Stock')
```

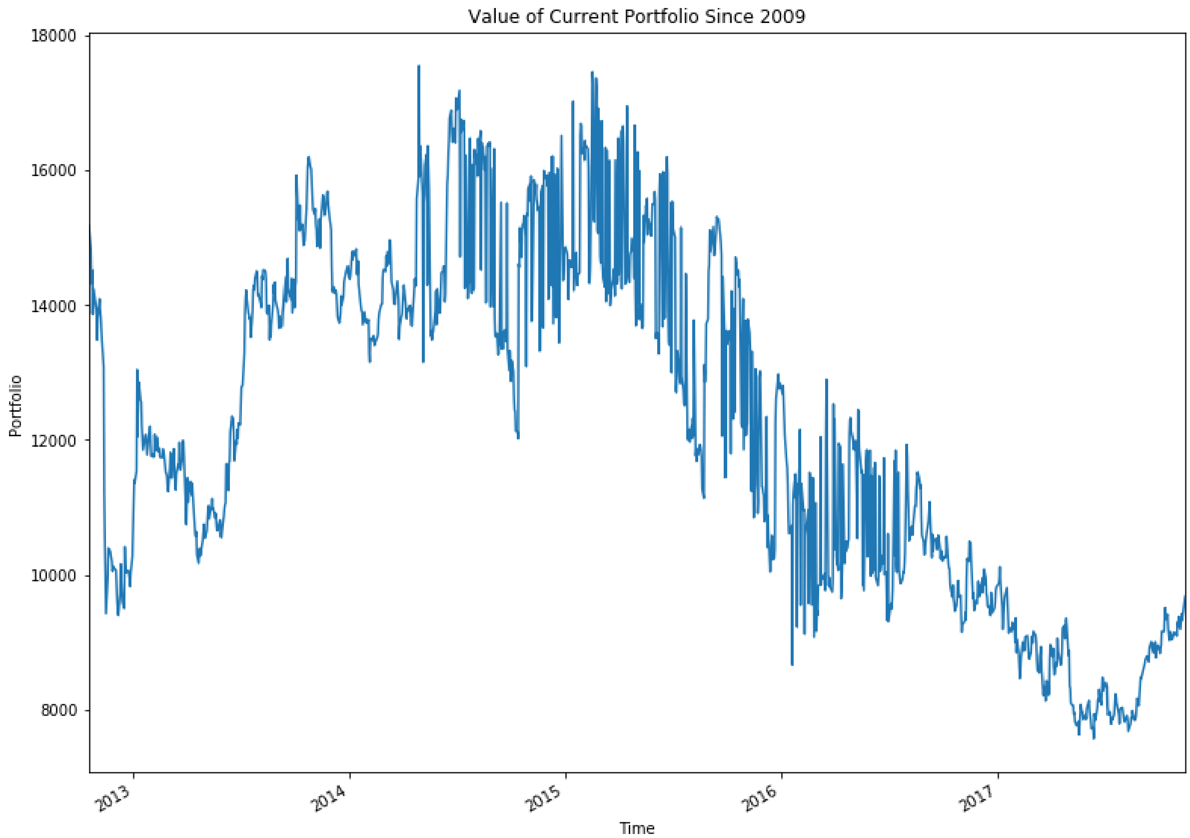
In [1305]:
```
grouped_by_date = df.groupby('Date')
```

In [1306]:
```
portfolio_values = grouped_by_date.sum()
portfolio_values.head()
```

Out[1306]:

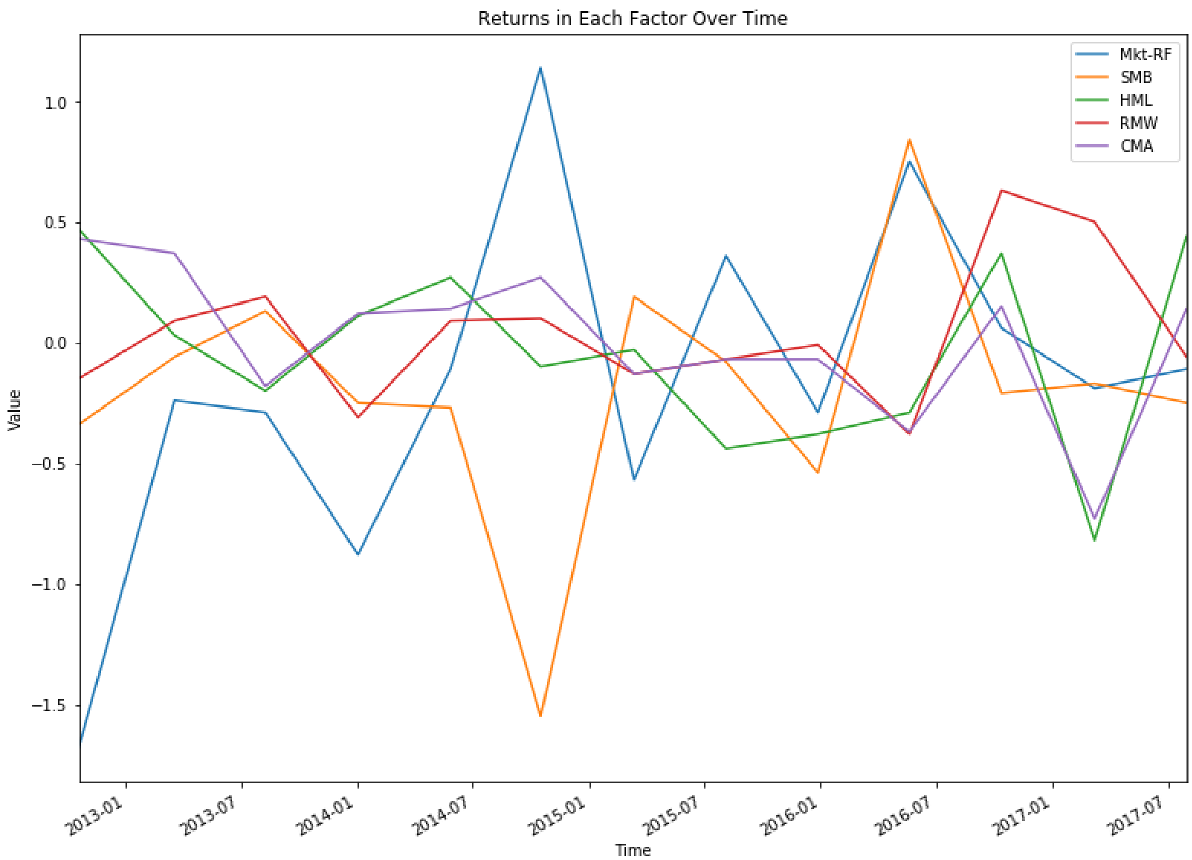
	Adj Close	Close	High	Last Price	Low	Open	Returns	SMAVG (15)	Volume
Date									
2012-10-19	26.674713	14931.25	32.10	NaN	30.18	15167.15	-0.050744	NaN	1373082.0
2012-10-22	26.554713	14442.40	30.71	NaN	30.16	14835.85	-0.052136	NaN	316500.0
2012-10-23	26.574713	14286.30	30.49	NaN	30.12	14322.25	0.035713	NaN	192200.0
2012-10-24	27.710764	13846.70	31.97	NaN	31.59	14510.35	-0.061278	NaN	270100.0
2012-10-25	27.610764	13912.65	31.79	NaN	31.59	13862.30	-0.008985	NaN	181500.0

In [1307]:
```
fig, ax = plt.subplots(figsize=default_dims)
portfolio_values['Open'].plot();
ax.set_xlabel('Time');
ax.set_ylabel('Portfolio');
ax.set_title('Value of Current Portfolio Since 2009');
```

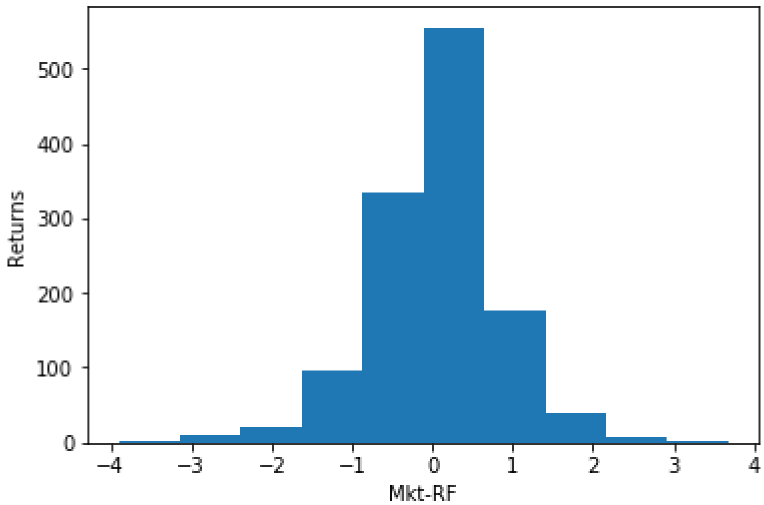


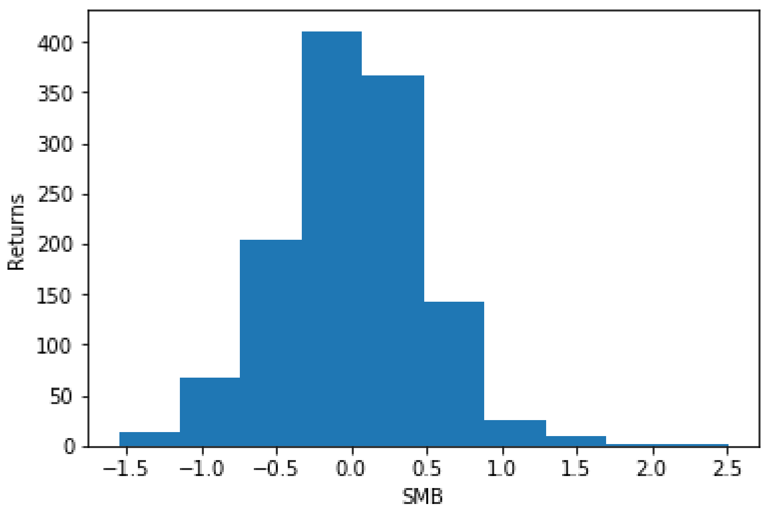
In [1308]:

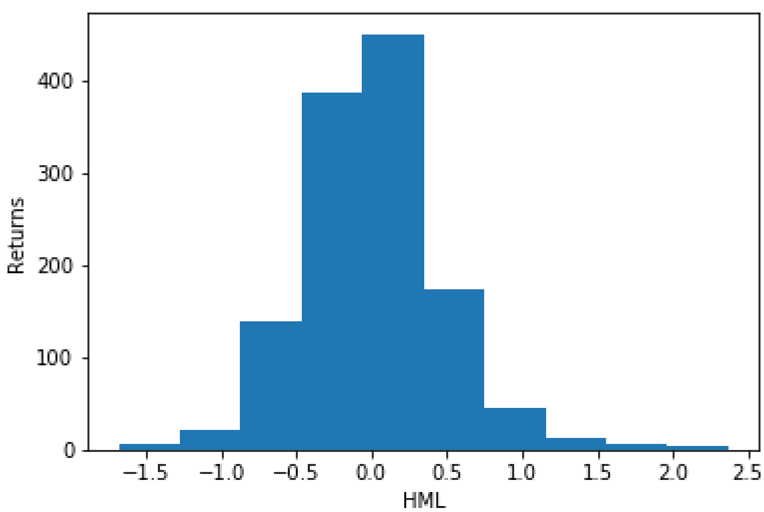
```
msk = [True if i % 100 ==0 else False for i in
range(len(three_factor_df))]
fig, ax = plt.subplots(figsize=default_dims)
for factor in five_factors:
    five_factor_df[factor][msk].plot(legend = True);
ax.set_xlabel('Time');
ax.set_ylabel('Value');
ax.set_title('Returns in Each Factor Over Time');
```

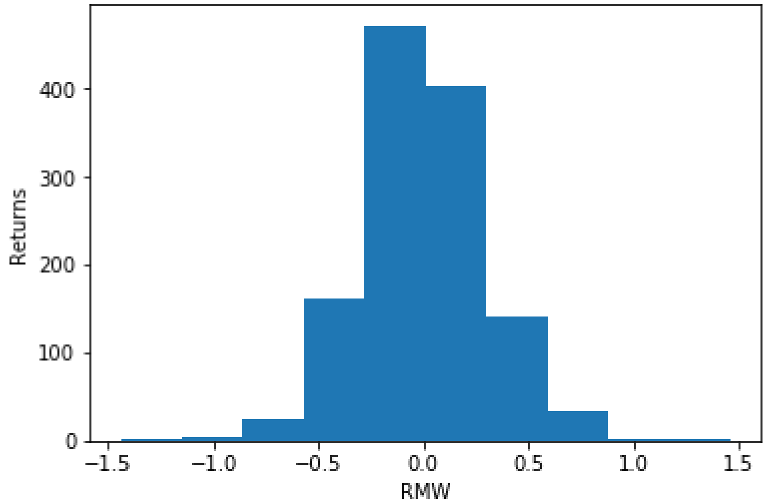


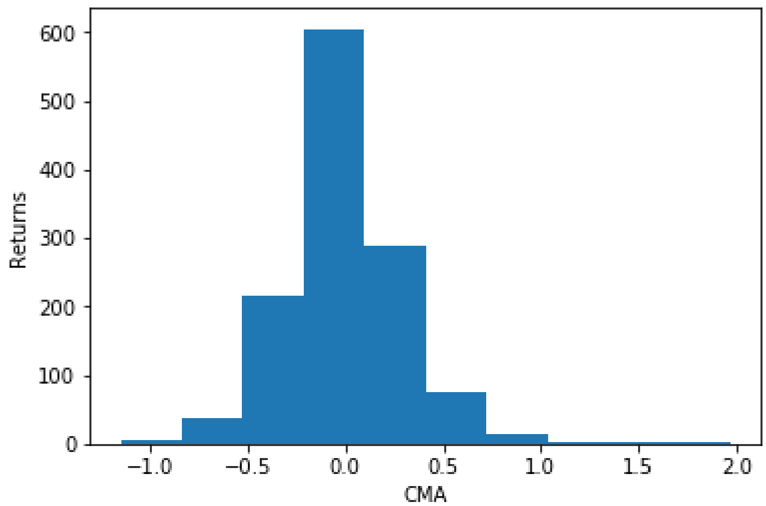
In [1309]:
```
for factor in five_factors:
    fig, ax = pyplot.subplots()
    plt.hist(five_factor_df[factor])
    ax.set_xlabel(factor);
    ax.set_ylabel('Returns');
```


Returns
Mkt-RF


Returns
SMB


Returns
HML





In [1310]:
```
three_factors
```

Out[1310]:
```
['Mkt-RF', 'SMB', 'HML']
```

In-sample evaluation

In [1311]:
```
df_three = pd.concat([portfolio_values, three_factor_df], axis=1,
join='inner')
```

In [1312]:
```
df_five = pd.concat([portfolio_values, five_factor_df], axis=1, join='in
ner')
```

In [1313]:
```
x_three = sm.add_constant(df_three[three_factors])
```

In [1314]:
```
x_five = sm.add_constant(df_five[five_factors])
```

In [1315]:
```
y = df_three['Returns']
```

In [1316]:
```
three_factor_OLS = sm.OLS(y, x_three.values)
three_factor_results = three_factor_OLS.fit()
three_factor_results.summary(xname = ['const'] + three_factors)
```

Out[1316]:

OLS Regression Results

Dep. Variable:	Returns	**R-squared:**	0.055
Model:	OLS	**Adj. R-squared:**	0.053
Method:	Least Squares	**F-statistic:**	24.10
Date:	Thu, 16 Nov 2017	**Prob (F-statistic):**	3.70e-15
Time:	15:49:31	**Log-Likelihood:**	1011.8
No. Observations:	1244	**AIC:**	-2016.
Df Residuals:	1240	**BIC:**	-1995.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-0.0015	0.003	-0.498	0.619	-0.008	0.004
Mkt-RF	0.0235	0.004	5.910	0.000	0.016	0.031
SMB	0.0295	0.006	4.581	0.000	0.017	0.042
HML	0.0021	0.007	0.323	0.747	-0.011	0.015

Omnibus:	630.208	**Durbin-Watson:**	2.022
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	21747.027
Skew:	1.702	**Prob(JB):**	0.00
Kurtosis:	23.198	**Cond. No.**	2.33

In [1317]:
```
five_factor_OLS = sm.OLS(y, x_five.values)
five_factor_results = five_factor_OLS.fit()
five_factor_results.summary(xname = ['const'] + five_factors)
```

Out[1317]:

OLS Regression Results

Dep. Variable:	Returns	**R-squared:**	0.065
Model:	OLS	**Adj. R-squared:**	0.061
Method:	Least Squares	**F-statistic:**	17.13
Date:	Thu, 16 Nov 2017	**Prob (F-statistic):**	2.07e-16
Time:	15:49:31	**Log-Likelihood:**	1018.2
No. Observations:	1244	**AIC:**	-2024.
Df Residuals:	1238	**BIC:**	-1994.
Df Model:	5		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-0.0015	0.003	-0.485	0.628	-0.007	0.004
Mkt-RF	0.0275	0.004	6.537	0.000	0.019	0.036
SMB	0.0326	0.007	4.853	0.000	0.019	0.046
HML	-0.0173	0.008	-2.047	0.041	-0.034	-0.001
RMW	0.0107	0.011	0.971	0.332	-0.011	0.032
CMA	0.0423	0.014	3.095	0.002	0.015	0.069

Omnibus:	644.306	**Durbin-Watson:**	2.021
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	22861.537
Skew:	1.751	**Prob(JB):**	0.00
Kurtosis:	23.707	**Cond. No.**	4.99

In [1318]:
```
capm_df = pd.read_csv('SPY.csv',index_col = 'Date')
```

In [1319]:
```
capm_df.index = pd.to_datetime(capm_df.index)
```

In [1320]:
```
df_train_capm = portfolio_values
df_train_capm['Market'] = np.log(capm_df['Close']) - np.log(capm_df['Ope
n'])
```

In [1321]:
```
x_capm = sm.add_constant(df_train_capm['Market'])
y_capm = df_train_capm['Returns']
```

In [1322]:
```
capm_OLS = sm.OLS(y_capm, x_capm)
capm_results = capm_OLS.fit()
capm_results.summary()
```

Out[1322]:

OLS Regression Results

Dep. Variable:	Returns	**R-squared:**	0.053
Model:	OLS	**Adj. R-squared:**	0.053
Method:	Least Squares	**F-statistic:**	71.92
Date:	Thu, 16 Nov 2017	**Prob (F-statistic):**	6.12e-17
Time:	15:49:31	**Log-Likelihood:**	1049.2
No. Observations:	1277	**AIC:**	-2094.
Df Residuals:	1275	**BIC:**	-2084.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.0006	0.003	-0.206	0.837	-0.006	0.005
Market	4.1713	0.492	8.481	0.000	3.206	5.136

Omnibus:	601.310	**Durbin-Watson:**	2.030
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	19008.483
Skew:	1.553	**Prob(JB):**	0.00
Kurtosis:	21.644	**Cond. No.**	165.

Out-of-sample evaluation

In [1323]:
```
def split(x,y):
    np.random.seed(9001)
    msk = np.random.rand(len(x)) < .75
    return x[msk], x[~msk], y[msk], y[~msk]
```

In [1324]:
```
x_train_three, x_test_three, y_train, y_test = split(x_three, y)
```

In [1325]:
```
three_factor_OLS = sm.OLS(y_train, x_train_three.values)
results_sm = three_factor_OLS.fit()
print('Three factor test r2 of {}'.format(r2_score(y_test, results_sm.pr
edict(x_test_three.values))))
```

```
Three factor test r2 of 0.037517106956969415
```

In [1326]:
```
x_train_five, x_test_five, y_train, y_test = split(x_five, y)
```

In [1327]:
```
five_factor_OLS = sm.OLS(y_train, x_train_five.values)
results_sm = five_factor_OLS.fit()
print('Five factor test r2 of {}'.format(r2_score(y_test, results_sm.pre
dict(x_test_five.values))))
```

```
Five factor test r2 of 0.03861363794348216
```

In [1328]:
```
x_train_capm, x_test_capm, y_train_capm, y_test_capm = split(x_capm, y_c
apm)
```

In [1329]:
```
capm_OLS = sm.OLS(y_train_capm, x_train_capm.values)
results_sm = capm_OLS.fit()
print('CAPM test r2 of {}'.format(r2_score(y_test_capm, results_sm.predi
ct(x_test_capm.values))))
```

```
CAPM test r2 of 0.00987989942112033
```

EDA for Value Factor

In [1330]:
```
value_df = pd.read_csv('RZV.csv', index_col = 'Date')
```

In [1331]:
```
value_df.index = pd.to_datetime(value_df.index)
```

In [1332]:
```
df_value = portfolio_values
df_value['Value'] = np.log(value_df['Close']) - np.log(value_df['Open'])
df_value = df_value.dropna()
```

In [1333]:
```
x_value = sm.add_constant(df_value['Value'])
y_value = df_value['Returns']
```

In [1334]:
```
value_OLS = sm.OLS(y_value, x_value)
value_results = value_OLS.fit()
value_results.summary()
```

Out[1334]:

OLS Regression Results

Dep. Variable:	Returns	**R-squared:**	0.000
Model:	OLS	**Adj. R-squared:**	-0.006
Method:	Least Squares	**F-statistic:**	0.0001196
Date:	Thu, 16 Nov 2017	**Prob (F-statistic):**	0.991
Time:	15:49:34	**Log-Likelihood:**	38.759
No. Observations:	173	**AIC:**	-73.52
Df Residuals:	171	**BIC:**	-67.21
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	0.0113	0.015	0.762	0.447	-0.018	0.040
Value	0.0174	1.590	0.011	0.991	-3.121	3.156

Omnibus:	95.794	**Durbin-Watson:**	2.198
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	862.706
Skew:	1.833	**Prob(JB):**	4.63e-188
Kurtosis:	13.307	**Cond. No.**	108.

In [1335]:
```
x_train_value, x_test_value, y_train_value, y_test_value =
split(x_value, y_value)
value_OLS = sm.OLS(y_train_value.values, x_train_value.values)
results_sm = value_OLS.fit()
print('Value factor test r2 of {}'.format(r2_score(y_test_value, results
_sm.predict(x_test_value.values))))
```

```
Value factor test r2 of -0.02156766348128336
```

In [1336]:
```
x_value = df_five['SMB']
y_value = df_five['Returns']
```

In [1337]:
```
x_train_value, x_test_value, y_train_value, y_test_value =
split(x_value, y_value)
value_OLS = sm.OLS(y_train_value.values, x_train_value.values)
results_sm = value_OLS.fit()
print('Value factor test r2 of {}'.format(r2_score(y_test_value, results
_sm.predict(x_test_value.values))))
```

```
Value factor test r2 of 0.04018357532819217
```

In [1338]:
```
grouped_by_stock.sum()
```

Out[1338]:

	Adj Close	Close	High	Last Price	Low	Open
Stock						
AXLE	NaN	NaN	NaN	116982.6	NaN	NaN
DXLG	5971.330000	5.971330e+06	6094.660000	NaN	5844.010000	5.975170e+(
LEE	3396.350000	1.443449e+06	3484.690000	NaN	3307.860000	1.444231e+(
NUSMF	361.000000	2.888000e+06	373.870000	NaN	347.280000	2.885840e+(
RHDGF	16510.290043	2.054872e+06	18756.985110	NaN	18595.037589	2.053733e+(
USAK	17906.519996	3.223174e+06	18358.069998	NaN	17472.149995	3.221932e+(

In [1339]:
```
for stock in stocks_held:
    stock_group =
grouped_by_stock.get_group(stock).groupby('Date').sum()
    temp_df = pd.concat([stock_group, five_factor_df], axis=1, join='inn
er')
    temp_df = temp_df[five_factors + ['Returns']].dropna()
    x = sm.add_constant(temp_df[five_factors])
    y = temp_df['Returns']
    x_train, x_test, y_train, y_test = split(x, y)
    OLS = sm.OLS(y_train, x_train)
    results = OLS.fit()
    print(results.summary(title=stock))
```

USAK

```
==============================================================================
=======
Dep. Variable:                Returns   R-squared:
  0.093
Model:                            OLS   Adj. R-squared:
  0.088
Method:                 Least Squares   F-statistic:
  18.88
Date:                Thu, 16 Nov 2017   Prob (F-statistic):
 6.63e-18
Time:                        15:49:36   Log-Likelihood:
1888.7
No. Observations:                 926   AIC:
-3765.
Df Residuals:                     920   BIC:
-3736.
Df Model:                           5

Covariance Type:            nonrobust

==============================================================================
=======
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-------
const        8.11e-05      0.001      0.078      0.938      -0.002
  0.002
Mkt-RF         0.0090      0.001      6.222      0.000       0.006
  0.012
SMB            0.0135      0.002      5.932      0.000       0.009
  0.018
HML           -0.0010      0.003     -0.338      0.735      -0.007
  0.005
RMW            0.0059      0.004      1.555      0.120      -0.002
  0.013
CMA            0.0073      0.005      1.566      0.118      -0.002
  0.017
==============================================================================
=======
Omnibus:                      119.516   Durbin-Watson:
  1.861
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              1
036.383
Skew:                           0.220   Prob(JB):                      8.
96e-226
Kurtosis:                       8.164   Cond. No.
   4.98
==============================================================================
=======

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

RHDGF

```
==============================================================================
=======
Dep. Variable:                Returns   R-squared:
  0.010
Model:                            OLS   Adj. R-squared:
  0.003
Method:                 Least Squares   F-statistic:
  1.369
Date:                Thu, 16 Nov 2017   Prob (F-statistic):
  0.234
Time:                        15:49:36   Log-Likelihood:
1977.6
No. Observations:                 705   AIC:
-3943.
Df Residuals:                     699   BIC:
-3916.
Df Model:                           5

Covariance Type:            nonrobust

==============================================================================
=======
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-------
const          0.0002      0.001      0.418      0.676      -0.001
  0.001
Mkt-RF         0.0011      0.001      1.383      0.167      -0.000
  0.003
SMB            0.0009      0.001      0.699      0.485      -0.002
  0.003
HML            0.0020      0.002      1.307      0.192      -0.001
  0.005
RMW            0.0037      0.002      1.779      0.076      -0.000
  0.008
CMA           -0.0033      0.002     -1.345      0.179      -0.008
  0.002
==============================================================================
=======
Omnibus:                      490.792   Durbin-Watson:
  1.849
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             29
014.619
Skew:                           2.442   Prob(JB):
   0.00
Kurtosis:                      34.046   Cond. No.
   4.88
==============================================================================
=======

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

```
==============================================================================
=======
Dep. Variable:                Returns   R-squared:
  0.125
Model:                            OLS   Adj. R-squared:
  0.121
Method:                 Least Squares   F-statistic:
  26.36
Date:                Thu, 16 Nov 2017   Prob (F-statistic):
 6.10e-25
Time:                        15:49:36   Log-Likelihood:
2072.8
No. Observations:                 926   AIC:
-4134.
Df Residuals:                     920   BIC:
-4105.
Df Model:                           5

Covariance Type:            nonrobust

==============================================================================
=======
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-------
const         -0.0017      0.001     -1.947      0.052      -0.003
 1.36e-05
Mkt-RF         0.0058      0.001      4.889      0.000       0.003
  0.008
SMB            0.0170      0.002      9.147      0.000       0.013
  0.021
HML           -0.0037      0.002     -1.540      0.124      -0.008
  0.001
RMW            0.0077      0.003      2.467      0.014       0.002
  0.014
CMA            0.0099      0.004      2.592      0.010       0.002
  0.017
==============================================================================
=======
Omnibus:                      144.401   Durbin-Watson:
  2.084
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1
464.046
Skew:                          -0.342   Prob(JB):
   0.00
Kurtosis:                       9.122   Cond. No.
   4.98
==============================================================================
=======

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

==============================================================================
```

```
=======
Dep. Variable:                Returns   R-squared:
  0.013
Model:                            OLS   Adj. R-squared:
  0.008
Method:                 Least Squares   F-statistic:
  2.458
Date:                Thu, 16 Nov 2017   Prob (F-statistic):
0.0318
Time:                        15:49:36   Log-Likelihood:
1165.1
No. Observations:                 926   AIC:
-2318.
Df Residuals:                     920   BIC:
-2289.
Df Model:                           5

Covariance Type:            nonrobust

========================================================================
=======
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------
-------
const          0.0016      0.002      0.712      0.477      -0.003
  0.006
Mkt-RF         0.0082      0.003      2.576      0.010       0.002
  0.014
SMB           -0.0101      0.005     -2.043      0.041      -0.020
-0.000
HML           -0.0107      0.006     -1.682      0.093      -0.023
  0.002
RMW            0.0063      0.008      0.755      0.451      -0.010
  0.023
CMA            0.0121      0.010      1.179      0.239      -0.008
  0.032
========================================================================
=======
Omnibus:                      959.178   Durbin-Watson:
  2.036
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            187
513.439
Skew:                           4.362   Prob(JB):
   0.00
Kurtosis:                      72.165   Cond. No.
   4.98
========================================================================
=======

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

========================================================================
=======
```

```
Dep. Variable:                Returns   R-squared:
  0.029
Model:                            OLS   Adj. R-squared:
  0.024
Method:                 Least Squares   F-statistic:
  5.577
Date:                Thu, 16 Nov 2017   Prob (F-statistic):
 4.52e-05
Time:                        15:49:37   Log-Likelihood:
1833.4
No. Observations:                 926   AIC:
-3655.
Df Residuals:                     920   BIC:
-3626.
Df Model:                           5

Covariance Type:            nonrobust

========================================================================
=======
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------
-------
const         -0.0012      0.001     -1.070      0.285      -0.003
  0.001
Mkt-RF         0.0057      0.002      3.690      0.000       0.003
  0.009
SMB            0.0067      0.002      2.796      0.005       0.002
  0.011
HML            0.0011      0.003      0.370      0.711      -0.005
  0.007
RMW            0.0037      0.004      0.905      0.366      -0.004
  0.012
CMA            0.0007      0.005      0.131      0.896      -0.009
  0.010
========================================================================
=======
Omnibus:                       77.299   Durbin-Watson:
  1.982
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
 366.193
Skew:                           0.191   Prob(JB):
 3.04e-80
Kurtosis:                       6.057   Cond. No.
   4.98
========================================================================
=======

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

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

```
  0.047
Model:                            OLS   Adj. R-squared:
  0.008
Method:                 Least Squares   F-statistic:
  1.198
Date:                Thu, 16 Nov 2017   Prob (F-statistic):
  0.314
Time:                        15:49:37   Log-Likelihood:
77.030
No. Observations:                 127   AIC:
-142.1
Df Residuals:                     121   BIC:
-125.0
Df Model:                           5

Covariance Type:            nonrobust

==============================================================================
=======
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-------
const         -0.0023      0.012     -0.185      0.854      -0.027
  0.022
Mkt-RF         0.0192      0.018      1.087      0.279      -0.016
  0.054
SMB            0.0327      0.030      1.090      0.278      -0.027
  0.092
HML           -0.0613      0.042     -1.471      0.144      -0.144
  0.021
RMW           -0.0371      0.055     -0.672      0.503      -0.146
  0.072
CMA            0.1315      0.070      1.888      0.061      -0.006
  0.269
==============================================================================
=======
Omnibus:                        8.859   Durbin-Watson:
  2.121
Prob(Omnibus):                  0.012   Jarque-Bera (JB):
14.866
Skew:                           0.267   Prob(JB):
 0.000591
Kurtosis:                       4.588   Cond. No.
   6.76
==============================================================================
=======

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

```
In [ ]:
```