In [1]:
```
# This notebook prepares the dataframes for analysis and runs
# the Random Forest on the combined model (economic and sentiment features) and
# the economic (only) model.
```

In [2]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import TimeSeriesSplit
from sklearn.metrics import r2_score, mean_absolute_error
```

In [4]:
```
# Quick look at the first two lines of the econ CSV
with open('data/econ_vars.csv') as f:
    print(f.readline())
    next(f)
    print(f.readline())
```

```
month_date,ur,pi_gr,nyse_gr,gdp_log_diff,tb_sqrt_diff,ics_log_diff,pce_gr_diff

2011-01-01,9.1,0.002028679786119758,0.016528644263536174,-
0.0024113163305852225,0.013132595943347536,-0.004034975212179326,-
0.004803188602163777
```

In [5]:
```
# Set data types for the econ features
dts = {"month_date": str, "ur": np.float64
    , "pi_gr": np.float64, "nyse_gr": np.float64
    , "gdp_log_diff": np.float64, "tb_sqrt_diff": np.float64
    , "ics_log_diff": np.float64, "pce_gr_diff": np.float64}
```

In [6]:
```
# Import econ data
data_raw = pd.read_csv("data/econ_vars.csv"
                   , sep=","
                   , skiprows=0
                   , dtype=dts)
```

In [7]:
```
# Check the shape of the raw econ data
data_raw.shape
```

Out[7]:
```
(91, 8)
```

In [8]:
```
# Copy raw data
data = data_raw.copy()
```

In [9]:
```
# Sort and reset index
data.sort_index(ascending=False, inplace=True)
data.reset_index(drop=True, inplace=True)
```

In [10]:
```
# Check the dataframe
data.head()
```

Out[10]:

	month_date	ur	pi_gr	nyse_gr	gdp_log_diff	tb_sqrt_diff	ics_log_diff	pce_gr_diff
0	2018-06-01	4.0	0.003863	-0.001827	0.000000	0.014587	0.002039	-0.001110
1	2018-05-01	3.8	0.003728	0.000941	0.010188	0.037168	-0.008130	0.008168
2	2018-04-01	3.9	-0.004827	-0.002903	0.010188	0.022809	-0.025975	-0.008891
3	2018-03-01	4.1	0.003938	-0.015846	0.000000	0.050844	0.016907	0.007407
4	2018-02-01	4.1	0.003282	-0.053517	0.005479	0.065562	0.040947	0.001663

In [11]:
```
# Quick look at the first two lines of the sentiment CSV
with open('data/rev_means_vars_stationary.csv') as f:
    print(f.readline())
    next(f)
    print(f.readline())
```

```
date,perc_pos_rev_weighted,perc_neg_rev_weighted,perc_uncert_rev_weighted,perc_l
itig_rev_weighted,perc_modal_wk_rev_weighted,perc_modal_mod_rev_weighted,perc_co
nstrain_rev_weighted,perc_modal_str_rev_weighted_diff

2011-03-01,1.9607048390000001,0.979452392,0.957424913,0.073102265,0.387478896,0.
560045154,0.142131806,-0.0495581759999999
```

In [12]:
```
# Import sentiment data
sent_raw = pd.read_csv("data/rev_means_vars_stationary.csv"
    , sep=","
    , skiprows=0
    #, dtype=dts
    , usecols=[0,1,2,3,4,5,6,7,8]
    )
```

In [13]:
```
# Check the sentiment data types
sent_raw.dtypes
```

Out[13]:
```
date                                  object
perc_pos_rev_weighted                float64
perc_neg_rev_weighted                float64
perc_uncert_rev_weighted             float64
perc_litig_rev_weighted              float64
perc_modal_wk_rev_weighted           float64
perc_modal_mod_rev_weighted          float64
perc_constrain_rev_weighted          float64
perc_modal_str_rev_weighted_diff     float64
dtype: object
```

In [14]:
```
# Drop any observations with Nan
sent_raw.dropna(inplace=True)
```

In [15]:
```
#sort and reset index
sent_raw.sort_values(by='date', ascending=False, inplace=True)
sent_raw.reset_index(drop=True, inplace=True)
```

In [16]:
```
# Confirm the shape of the dataframe
sent_raw.shape
```

Out[16]: (89, 9)

In [17]:
```
# Check the dataframe
sent_raw.head()
```

Out[17]:

	date	perc_pos_rev_weighted	perc_neg_rev_weighted	perc_uncert_rev_weighted	perc_litig
0	2018-06-01	2.043836	0.890239	0.815790	0.094844
1	2018-05-01	1.915107	1.074677	0.803269	0.082565
2	2018-04-01	1.926137	1.068873	0.777739	0.095691
3	2018-03-01	2.016781	0.979256	0.800769	0.102810
4	2018-02-01	2.004129	0.963727	0.815629	0.098500

In [18]:
```
# Copy raw data
sent = sent_raw.copy()
```

In [19]:
```
# Filter econ observations to match the sentiment dataframe
data = data.iloc[0:89,:]
```

In [20]:
```
# Combine the econ and sentiment dataframes
data = pd.concat([data,sent], axis=1)
```

In [21]:
```
# Replace the integer index with the date column
data = data.set_index("date")
```

In [22]:
```
# Create response variable
y_true = data['pce_gr_diff']
```

In [23]:
```
# Drop the month_date column and the gdp column
data = data.drop(data.columns[[0,4,7]], axis=1)
```

In [24]:
```
# Check the dataframe
data.head()
```

Out[24]:

	ur	pi_gr	nyse_gr	tb_sqrt_diff	ics_log_diff	perc_pos_rev_weighted	perc_neg_rev
date							
2018-06-01	4.0	0.003863	-0.001827	0.014587	0.002039	2.043836	0.890239
2018-05-01	3.8	0.003728	0.000941	0.037168	-0.008130	1.915107	1.074677
2018-04-01	3.9	-0.004827	-0.002903	0.022809	-0.025975	1.926137	1.068873
2018-03-01	4.1	0.003938	-0.015846	0.050844	0.016907	2.016781	0.979256
2018-02-01	4.1	0.003282	-0.053517	0.065562	0.040947	2.004129	0.963727

In [25]:
```
# Copy econ features to econ dataframe and drop all sentiment variables
econ = data.drop(data.columns[[5,6,7,8,9,10,11,12]], axis=1)
```

In [26]:
```
# Check the dataframe
econ.head()
```

Out[26]:

	ur	pi_gr	nyse_gr	tb_sqrt_diff	ics_log_diff
date					
2018-06-01	4.0	0.003863	-0.001827	0.014587	0.002039
2018-05-01	3.8	0.003728	0.000941	0.037168	-0.008130
2018-04-01	3.9	-0.004827	-0.002903	0.022809	-0.025975
2018-03-01	4.1	0.003938	-0.015846	0.050844	0.016907
2018-02-01	4.1	0.003282	-0.053517	0.065562	0.040947

In [27]:
```
# create time series cross validation split
tscv = TimeSeriesSplit(n_splits=3)
print(tscv)
```

```
TimeSeriesSplit(max_train_size=None, n_splits=3)
```

In [28]:
```
# instantiate random forest object
rfreg = RandomForestRegressor()
```

In [29]:
```
# establish parameters for grid search object
parameters = {"n_estimators": [50, 100],
    "max_features": [3, 4, 6],
    "min_samples_leaf": [3, 5, 10],
    "max_depth": [3, None],
    "min_samples_split": [2, 5, 10],
    "bootstrap": [True],
    "random_state": [987]
    }
```

In [30]:
```
# create a grid search object
comb_model_gs = GridSearchCV(estimator=rfreg
                   , n_jobs=-1 # parallel execution -1 is all processors
                   , verbose=1 # low verbosity
                   , param_grid=parameters
                   , cv=tscv # KFolds = 3
                   , scoring="neg_mean_squared_error"
                    )
```

In [31]:
```
# fit random forest regressor
comb_model_gs.fit(data, y_true)
```

```
Fitting 3 folds for each of 108 candidates, totalling 324 fits

[Parallel(n_jobs=-1)]: Done  32 tasks      | elapsed:    0.8s
[Parallel(n_jobs=-1)]: Done 324 out of 324 | elapsed:    4.3s finished
```

Out[31]:
```
GridSearchCV(cv=TimeSeriesSplit(max_train_size=None, n_splits=3),
       error_score='raise',
       estimator=RandomForestRegressor(bootstrap=True, criterion='mse', max_dept
h=None,
           max_features='auto', max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=1, min_samples_split=2,
           min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=1,
           oob_score=False, random_state=None, verbose=0, warm_start=False),
       fit_params=None, iid=True, n_jobs=-1,
       param_grid={'n_estimators': [50, 100], 'max_features': [3, 4, 6], 'min_sa
mples_leaf': [3, 5, 10], 'max_depth': [3, None], 'min_samples_split': [2, 5,
10], 'bootstrap': [True], 'random_state': [987]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='neg_mean_squared_error', verbose=1)
```

In [32]:
```
# print grid search results sorted by mean test score
comb_model_results = pd.DataFrame(comb_model_gs.cv_results_)
headers = ['rank_test_score','mean_test_score','mean_train_score','mean_fit_time
','split0_train_score','split1_train_score','split2_train_score']
comb_model_results.sort_values(by=["rank_test_score"], inplace=True, ascending=Tru
e)
comb_model_results[headers].head(10)
```

Out[32]:

	rank_test_score	mean_test_score	mean_train_score	mean_fit_time	split0_train_score	split1_tra
93	1	-0.00002	-0.000008	0.194232	-0.000011	-0.00000
91	1	-0.00002	-0.000008	0.203017	-0.000011	-0.00000
39	3	-0.00002	-0.000010	0.182110	-0.000011	-0.00000
37	3	-0.00002	-0.000010	0.176719	-0.000011	-0.00000
43	5	-0.00002	-0.000015	0.177317	-0.000021	-0.00001
47	5	-0.00002	-0.000015	0.183128	-0.000021	-0.00001
45	5	-0.00002	-0.000015	0.175593	-0.000021	-0.00001
42	8	-0.00002	-0.000015	0.092832	-0.000020	-0.00001
44	8	-0.00002	-0.000015	0.087386	-0.000020	-0.00001
46	8	-0.00002	-0.000015	0.093360	-0.000020	-0.00001

In [33]:
```
# View the optimal random forest model parameters
comb_model_gs.best_estimator_
```

Out[33]:
```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
           max_features=6, max_leaf_nodes=None, min_impurity_decrease=0.0,
           min_impurity_split=None, min_samples_leaf=3,
           min_samples_split=2, min_weight_fraction_leaf=0.0,
           n_estimators=100, n_jobs=1, oob_score=False, random_state=987,
           verbose=0, warm_start=False)
```

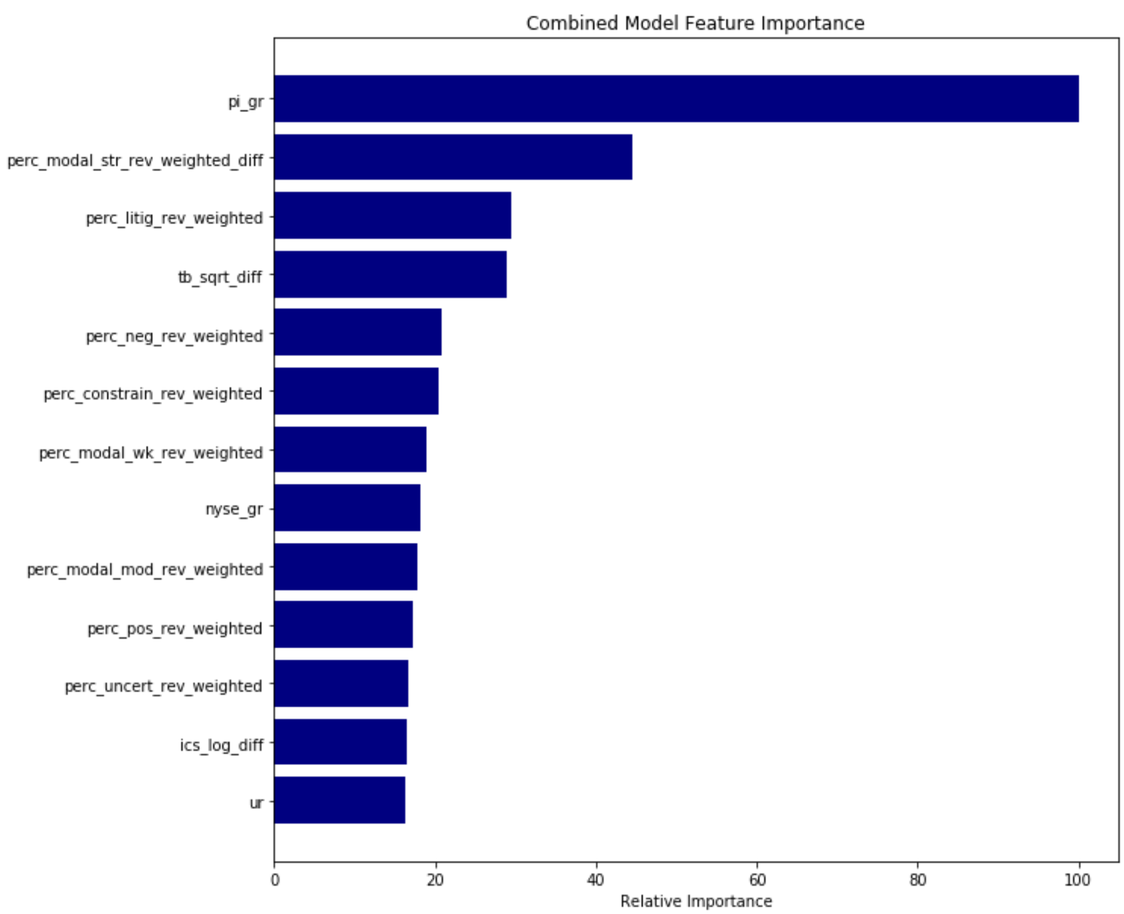
In [34]:
```
print("Combined model MSE: {}".format(comb_model_gs.best_score_))
```

```
Combined model MSE: -2.0119435819526655e-05
```

In [35]:
```
# Run a new model using the best model from the grid search
comb_best_model = comb_model_gs.best_params_
rfreg_features = RandomForestRegressor(**comb_best_model)
rfreg_features.fit(data, y_true)
```

Out[35]:
```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
           max_features=6, max_leaf_nodes=None, min_impurity_decrease=0.0,
           min_impurity_split=None, min_samples_leaf=3,
           min_samples_split=2, min_weight_fraction_leaf=0.0,
           n_estimators=100, n_jobs=1, oob_score=False, random_state=987,
           verbose=0, warm_start=False)
```

In [36]:
```
# Plot the feature importances
feature_importance = rfreg_features.feature_importances_
feature_importance = 100.0 * (feature_importance / feature_importance.max())
sorted_idx = np.argsort(feature_importance)
pos = np.arange(sorted_idx.shape[0]) + .5
plt.figure(figsize=(10, 10))
plt.barh(pos, feature_importance[sorted_idx], align='center', color='navy')
plt.yticks(pos, np.asanyarray(data.columns.tolist())[sorted_idx])  # data is X
plt.xlabel('Relative Importance')
plt.title('Combined Model Feature Importance')
plt.show()
#plt.savefig('Random Forest Feature Importance.png')
```



In [37]:
```
# establish parameters for grid search object
parameters = {"n_estimators": [50, 100],
    "max_features": [2, 3, 4],
    "min_samples_leaf": [3, 5, 10],
    "max_depth": [3, None],
    "min_samples_split": [2, 5, 10],
    "bootstrap": [True],
    "random_state": [987]
    }
```

In [38]:
```
# create a grid search object
econ_model_gs = GridSearchCV(estimator=rfreg
                   , n_jobs=-1 # parallel execution -1 is all processors
                   , verbose=1 # low verbosity
                   , param_grid=parameters
                   , cv=tscv # KFolds = 3
                   , scoring="neg_mean_squared_error"
                    )
```

In [39]:
```
# fit random forest regressor
econ_model_gs.fit(econ, y_true)
```

```
Fitting 3 folds for each of 108 candidates, totalling 324 fits

[Parallel(n_jobs=-1)]: Done  32 tasks      | elapsed:    0.8s
[Parallel(n_jobs=-1)]: Done 324 out of 324 | elapsed:    4.2s finished
```

Out[39]:
```
GridSearchCV(cv=TimeSeriesSplit(max_train_size=None, n_splits=3),
       error_score='raise',
       estimator=RandomForestRegressor(bootstrap=True, criterion='mse', max_dept
h=None,
           max_features='auto', max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=1, min_samples_split=2,
           min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=1,
           oob_score=False, random_state=None, verbose=0, warm_start=False),
       fit_params=None, iid=True, n_jobs=-1,
       param_grid={'n_estimators': [50, 100], 'max_features': [2, 3, 4], 'min_sa
mples_leaf': [3, 5, 10], 'max_depth': [3, None], 'min_samples_split': [2, 5,
10], 'bootstrap': [True], 'random_state': [987]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='neg_mean_squared_error', verbose=1)
```

In [40]:
```
# print results sorted by mean test score
econ_model_results = pd.DataFrame(econ_model_gs.cv_results_)
headers = ['rank_test_score','mean_test_score','mean_train_score','mean_fit_time
','split0_train_score','split1_train_score','split2_train_score']
econ_model_results.sort_values(by=["rank_test_score"], inplace=True, ascending=Tru
e)
econ_model_results[headers].head(10)
```

Out[40]:

	rank_test_score	mean_test_score	mean_train_score	mean_fit_time	split0_train_score	split1_tı
53	1	-0.000021	-0.000023	0.172886	-0.000033	-0.0000
105	1	-0.000021	-0.000023	0.134153	-0.000033	-0.0000
103	1	-0.000021	-0.000023	0.141396	-0.000033	-0.0000
51	1	-0.000021	-0.000023	0.174077	-0.000033	-0.0000
49	1	-0.000021	-0.000023	0.181301	-0.000033	-0.0000
107	1	-0.000021	-0.000023	0.104362	-0.000033	-0.0000
50	7	-0.000021	-0.000023	0.089039	-0.000033	-0.0000
52	7	-0.000021	-0.000023	0.093082	-0.000033	-0.0000
106	7	-0.000021	-0.000023	0.056159	-0.000033	-0.0000
48	7	-0.000021	-0.000023	0.092212	-0.000033	-0.0000

In [41]:
```
econ_model_gs.best_estimator_
```

Out[41]:
```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=3,
           max_features=4, max_leaf_nodes=None, min_impurity_decrease=0.0,
           min_impurity_split=None, min_samples_leaf=10,
           min_samples_split=2, min_weight_fraction_leaf=0.0,
           n_estimators=100, n_jobs=1, oob_score=False, random_state=987,
           verbose=0, warm_start=False)
```

In [42]:
```
print("Economic model MSE: {}".format(econ_model_gs.best_score_))
```

```
Economic model MSE: -2.0665388481727326e-05
```

In [43]:
```
# Run a new model using the best model from the grid search
econ_best_model = econ_model_gs.best_params_
rfreg_features = RandomForestRegressor(**econ_best_model)
rfreg_features.fit(econ, y_true)
```

Out[43]:
```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=3,
           max_features=4, max_leaf_nodes=None, min_impurity_decrease=0.0,
           min_impurity_split=None, min_samples_leaf=10,
           min_samples_split=2, min_weight_fraction_leaf=0.0,
           n_estimators=100, n_jobs=1, oob_score=False, random_state=987,
           verbose=0, warm_start=False)
```

In [44]:
```
# Plot the feature importances
feature_importance = rfreg_features.feature_importances_
feature_importance = 100.0 * (feature_importance / feature_importance.max())
sorted_idx = np.argsort(feature_importance)
pos = np.arange(sorted_idx.shape[0]) + .5
plt.figure(figsize=(10, 10))
plt.barh(pos, feature_importance[sorted_idx], align='center', color='maroon')
plt.yticks(pos, np.asanyarray(econ.columns.tolist())[sorted_idx])  # econ is X
plt.xlabel('Relative Importance')
plt.title('Economic Model Feature Importance')
plt.show()
#plt.savefig('Random Forest Feature Importance.png')
```