

```

1 import os
2 print(os.getcwd()) # This will print your current working directory
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4

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1 # from google.colab import drive
2 # drive.mount('/content/drive',force_remount=True)
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```

3  " convert 'datetime64[ns, UTC]' to 'datetime64[ns, UTC]' "
4  df.index = df.index.tz_localize(None).normalize()
5  return df
6
7  def log_returns(df):
8      df = np.log(df)
9      df = df - df.shift(1)
10     #df.index.name = None
11     return df
12
13 def L_func_2(df, pred_col='predicted', params=[]):
14     t_conditions = [ df[pred_col] <= 0, df[pred_col] > 0 ]
15     t_positions = [ params[0], params[1] ]
16     return np.select(t_conditions, t_positions, default=np.nan) # Apply trading logic here
17
18 def L_func_3(df, pred_col='preds_index', params=[]):
19     t_conditions = [
20         (df[pred_col].between(0.00, 0.25)),
21         (df[pred_col].between(0.25, 0.50)),
22         (df[pred_col].between(0.50, 0.75)),
23         (df[pred_col].between(0.75, 1.00))
24     ]
25     t_positions = params
26     return np.select(t_conditions, t_positions, default=np.nan)
27
28 def L_func_4(ds, params=[]):
29     t_conditions = [
30         (ds.between(0.00, 0.25)),
31         (ds.between(0.25, 0.50)),
32         (ds.between(0.50, 0.75)),
33         (ds.between(0.75, 1.00))
34     ]
35     t_positions = params
36     return np.select(t_conditions, t_positions, default=np.nan)
37
38 def sim_stats(regout_list, sweep_tags, author='CG', trange = None):
39     df = pd.DataFrame()
40     df.index.name = 'teo'
41     print('SIMULATION RANGE: ', 'from ', trange.start, 'to ', trange.stop)
42     for n, testlabel in enumerate(sweep_tags):
43         reg_out = regout_list[n].loc[trange,:]
44         df.loc['return', testlabel] = mean = 252*reg_out.perf_ret.mean()
45         df.loc['stdev', testlabel] = std = (np.sqrt(252))*reg_out.perf_ret.std()
46         df.loc['sharpe', testlabel] = mean / std
47         df.loc['avg_beta', testlabel] = reg_out.leverage.mean()
48         df.loc['beta_1_return', testlabel] = df.loc['return', testlabel] / reg_out.leverage.mean()
49         df.loc['pos_bet_ratio', testlabel] = np.sum(np.isfinite(reg_out['prediction']) & (reg_out['prediction'] > 0)) / np.sum(np.isfinite(reg_out['prediction']))
50         df.loc['rmse', testlabel] = np.sqrt(rmse(reg_out.prediction, reg_out.actual))
51         df.loc['mae', testlabel] = mae(reg_out.prediction, reg_out.actual)
52         #df.loc['evs', testlabel] = evs(reg_out.prediction, reg_out.actual)
53         df.loc['r2', testlabel] = r_squared(reg_out.actual, reg_out.prediction)
54         df.loc['benchmark return', testlabel] = bench_ret = 252*reg_out.actual.mean()
55         df.loc['benchmark std', testlabel] = bench_std = (np.sqrt(252))*reg_out.actual.std()
56         df.loc['benchmark sharpe', testlabel] = bench_ret / bench_std
57         df.loc['beg_pred', testlabel] = min(reg_out.prediction.index).date()
58         df.loc['end_pred', testlabel] = max(reg_out.prediction.index).date()
59         #df.loc['train window', testlabel] = window=call['regression_est_window']
60         #df.loc['z_score_window', testlabel] = call['z_score_window']
61         df.loc['sim_time', testlabel] = datetime.now(pytz.timezone(local_timezone)).strftime("%x %I:%m%p")
62         df.loc['author', testlabel] = author
63     return df
64
65 def p_by_slice(X, y, t_list, t_list_labels):
66     feat_stats = pd.DataFrame(index=X.columns)
67
68     for n, idx in enumerate(t_list):
69         X_fit = X.loc[idx,:].dropna()
70         y_fit = y.reindex(X_fit.index)
71         feat_stats.loc[:, t_list_labels[n]] = r_regression(X_fit, y_fit, center=True)
72
73     print('from ', X_fit.index.min(), ' to ', X_fit.index.max())
74     return feat_stats
75
76 def p_by_year(X, y, sort_by = 'p_value', t_list=None):
77     feat_stats = pd.DataFrame(index=X.columns)
78
79     for year in X.index.year.unique():
80         X_fit = X.loc[str(year),:].dropna()
81         y_fit = y.reindex(X_fit.index)
82         feat_stats.loc[:, str(year)] = r_regression(X_fit, y_fit, center=True)
83
84     print('from ', X_fit.index.min(), ' to ', X_fit.index.max())
85     return feat_stats
86
87 def feature_profiles(X, y, sort_by = 'pearson', t_slice=None):
88     if not t_slice:
89         t_slice = slice(X.index.min(), X.index.max())
90         print(t_slice)
91
92     if t_slice != None:
93         X_fit = X.loc[t_slice,:].dropna().ravel()
94         y_fit = y.reindex(X_fit.index).ravel()
95     else:
96         X_fit=X.ravel()
97         y_fit=y.ravel()
98
99     pear_test = r_regression(X_fit, y_fit, center=True)
100    abs_pear_test = np.abs(pear_test)

```

```

101 f_test, p_value = f_regression(X_fit, y_fit, center=False)
102 t_test = np.sqrt(f_test)/np.sqrt(1)
103 mi = mutual_info_regression(X_fit, y_fit)
104 nobs = X_fit.count().unique()[0]
105 feat_stats = pd.DataFrame({'nobs':nobs,
106                            'mutual_info':mi,
107                            'p_value':p_value,
108                            't_test':t_test,
109                            'pearson':pear_test,
110                            'abs_pearson':abs_pear_test},
111                            index=X.columns)
112 print('from ',X_fit.index.min(), ' to ',X_fit.index.max())
113 return feat_stats.sort_values(by=[sort_by],ascending=False)
114
115 def generate_train_predict_calender(df, window_type = None, window_size=None):
116     date_ranges = []
117     index = df.index
118     num_days = len(index)
119
120     if window_type == 'fixed':
121         for i in range(0, num_days - window_size):
122             train_start_date = index[i]
123             train_end_date = index[i + window_size - 1]
124             prediction_date = index[i + window_size]
125             date_ranges.append([train_start_date, train_end_date, prediction_date])
126
127     if window_type == 'expanding':
128         for i in range(0, num_days - window_size):
129             train_start_date = index[0]
130             train_end_date = index[i + window_size - 1]
131             prediction_date = index[i + window_size]
132             date_ranges.append([train_start_date, train_end_date, prediction_date])
133
134     return date_ranges
135
136 def graph_df(df,w=10,h=15):
137     fig, axes = plt.subplots(nrows=len(df.columns), ncols=1, figsize=(w, h))
138
139     # Loop through columns and create a plot for each
140     for i, col in enumerate(df.columns):
141         axes[i].plot(df[col])
142         axes[i].set_title(col)
143
144     # Adjust layout
145     plt.tight_layout()
146     plt.show()
147
148 from sklearn.base import BaseEstimator, TransformerMixin, RegressorMixin
149 class StatsModelsWrapper_with_OLS(BaseEstimator, RegressorMixin):
150     def __init__(self, exog, endog):
151         self.exog = exog
152         self.endog = endog
153
154     def fit(self, X_fit, y_fit):
155         X_with_const = add_constant(X_fit, has_constant='add') # Add constant to the features
156         self.model_ = OLS(y_fit, X_with_const)
157         self.results_ = self.model_.fit()
158         return self
159
160     def predict(self, X_pred):
161         X_pred_constant = add_constant(X_pred, has_constant='add')
162         return self.results_.predict(X_pred_constant)
163
164     def summary(self,title):
165         if title is not None:
166             return self.results_.summary(title=title)
167         else:
168             generic_title = f"OLS Estimation Summary"
169             return self.results_.summary(title=generic_title)
170
171
172 class EWMTransformer(BaseEstimator, TransformerMixin):
173     def __init__(self, halfLife=3):
174         self.halfLife = halfLife
175
176     def fit(self, X, y=None):
177         return self
178
179     def set_output(self, as_dataframe=True):
180         self.output_as_dataframe = as_dataframe
181         return self
182
183     def transform(self, X):
184         # Convert to DataFrame if not already one
185         if not isinstance(X, pd.DataFrame):
186             X = pd.DataFrame(X)
187
188         # Apply the EWM transformation
189         X_transformed = X.ewm(halfLife=self.halfLife).mean()
190
191         # If output_as_dataframe is False, convert to NumPy array
192         if not self.output_as_dataframe:
193             return X_transformed.values
194         return X_transformed
195
196
197

```

198  
---

```

1 all_etfs = ['SPY', 'AOA', 'AOK', 'AOM', 'AOR', 'IAGG', 'IDEV', 'IEMG', 'IJH', 'IJR', 'IUSB', 'IVV']
2 spdr_etfs = ['SPY', 'XLK', 'XLF', 'XLV', 'XLP', 'XLE', 'XLI', 'XLB', 'XLU']
3 target_risk_etfs = ['AOA', 'AOK', 'AOM', 'AOR']
4 component_etfs = ['IAGG', 'IDEV', 'IEMG', 'IJH', 'IJR', 'IUSB', 'IVV']
5 #X.loc[:,component_etfs].dropna().describe()

```

Double-click (or enter) to edit

```

1 # Convert index to feature teo's by datetime index and expand time stamp in inclue NYC closing time -- then convert to UTC. (TEO = Time of Effective Observation)
2
3 all_etf_closing_prices_df = yf.download(spdr_etfs)['Close']
4 etf_features_df = log_returns(all_etf_closing_prices_df).dropna()
5 etf_features_df.index = etf_features_df.index.tz_localize('America/New_York').map(lambda x: x.replace(hour=16, minute=00)).tz_convert('UTC')
6 etf_features_df.index.name = 'teo'
7 #print(etf_features_df)
8
9 # convert teo's to target teos by shifting the time to the beginning of the return window
10
11 etf_targets_df = etf_features_df.copy()
12 etf_targets_df.loc[:, 'teo_original'] = etf_targets_df.index
13 etf_targets_df.loc[:, 'teo'] = etf_targets_df['teo_original'].shift(1)
14 etf_targets_df.set_index('teo', inplace=True)
15 etf_targets_df = etf_targets_df.drop(['teo_original'], axis=1).dropna()
16 etf_targets_df = etf_targets_df.iloc[1:, :]
17 etf_targets_df
18
19 # Sync dates between features and targets
20
21 common_dates = etf_features_df.index.intersection(etf_targets_df.index)
22 #print(common_dates)
23 etf_features_df = etf_features_df.loc[common_dates]
24 etf_targets_df = etf_targets_df.loc[common_dates]
25
26 # Now that features and targets are aligned we can simplify to date format
27
28 etf_targets_df = simplify_teos(etf_targets_df)
29 etf_features_df = simplify_teos(etf_features_df)
30 #print(etf_features_df)

```

🔄 YF.download() has changed argument auto\_adjust default to True  
 [\*\*\*\*\*100%\*\*\*\*\*] 10 of 10 completed

```

1 # ROLL FORWARD SIMULATOR - 1) TRAIN UP TO T-1, 2) PREDICT AT T, 3) Store predictions in 'regout' and list of 'fit_obj' for each fit date in fit_list which contains in-sample
2
3 def Simulate(X,y>window_size=400>window_type='expanding',pipe_steps={}, param_grid={}, tag = None):
4     regout = pd.DataFrame(index=y.index)
5     #attrs_df = pd.DataFrame(0, index=X.index, columns=X.columns)
6     fit_list = []
7
8     date_ranges = generate_train_predict_calender(X, window_type=window_type>window_size = window_size)
9
10    fit_obj = Pipeline(steps=pipe_steps).set_output(transform="pandas") #### NOTE THAT .SET_OUTPUT IS NEEDED IF YOU WANT TO SEE FEATURE NAMES IN .SUMMARY() BUT IT WILL SLOW D
11    fit_obj.set_params(**param_grid)
12    fit_obj
13
14    for n, dates in enumerate(date_ranges):
15
16        start_training, end_training, prediction_date = dates[0], dates[1], dates[2]
17
18        fit_X = X[start_training:end_training]
19        fit_y = y[start_training:end_training]
20        pred_X = X[prediction_date:prediction_date]
21        trange = slice(fit_X.index[0].strftime('%Y-%m-%d'), fit_X.index[-1].strftime('%Y-%m-%d'), None)
22        title = tag + trange.start + ' to ' + trange.stop
23
24
25        #if n%252 == 0 and n != 0:
26        if n == 1000 and n != 0:
27            print('tag=', tag, ' ', prediction_date.floor('D'), " ", n, ' ', prediction )
28
29        if n%22 == 0:
30            #print(fit_X, fit_y)
31            with warnings.catch_warnings():
32                warnings.simplefilter(action='ignore')
33                fit_obj.fit(fit_X, fit_y)
34
35        if hasattr(fit_obj.predict(pred_X), 'values'):
36            prediction = np.round(fit_obj.predict(pred_X).values[0], 5)
37        else:
38            prediction = np.round(fit_obj.predict(pred_X)[0], 5)
39
40        if hasattr(fit_obj, 'summary'):
41            print('has summary')
42            tuple = (tag, prediction_date, fit_obj['final_estimator'].summary(title=title))
43        else:
44            tuple = (tag, prediction_date, fit_obj)
45
46        fit_list.append(tuple)
47
48        regout.loc[prediction_date, 'prediction'] = prediction

```

```
49
50 return regout.dronna(). fit list

1 # Wrapper to Roll the Simulator and save in Results_xr
2 learner_tag = 'OLS'
3 #sweep_tags = ['HT '+learner_tag,'BW '+learner_tag, 'Both '+learner_tag] #,'Both '+learner_tag]
4 n_ewa_lags_list = [1,2,3,4,5,6,7]
5 sweep_tags = ['ewa_halfllife_n =' +str(x) for x in n_ewa_lags_list ]
6
7 X = etf_features_df.drop(['SPY'],axis=1)
8 y = etf_targets_df['SPY']
9
10 X_list = [X.ewm(halfllife=n,min_periods=n).mean().dropna() for n in n_ewa_lags_list]
11 y_list = [y[X_list[n].index] for n in range(len(X_list))]
12
13 regout_list = []
14 xr_list = []
15 Results_xr = xr.Dataset()
16 sweep_fit_list = []
17
18 for n, tag in enumerate(sweep_tags):
19
20     title_prefix = sweep_tags[n]
21     y.index.name = 'teo'
22
23     pipe_steps=[
24         ('scaler', StandardScaler()),
25         #('final_estimator', LinearRegression()),
26         ('final_estimator', StatsModelsWrapper_with_OLS(X,y))
27     ]
28
29     #param_grid = {'ewm_halfllife' : n_ewa_lags_list[n]}
30
31     regout_df, fit_list = Simulate(X_list[n],
32                                   y_list[n],
33                                   window_size=400,
34                                   window_type='expanding',
35                                   pipe_steps=pipe_steps,
36                                   param_grid={},
37                                   tag=sweep_tags[n])
38
39     regout_list.append(regout_df)
40
41     sweep_fit_list.append(fit_list)
```

```
tag= ewa_halfllife_n =1      2004-07-22 00:00:00      1000      0.00021
tag= ewa_halfllife_n =2      2004-07-23 00:00:00      1000      0.00015
tag= ewa_halfllife_n =3      2004-07-26 00:00:00      1000      0.00022
tag= ewa_halfllife_n =4      2004-07-27 00:00:00      1000      0.00024
tag= ewa_halfllife_n =5      2004-07-28 00:00:00      1000      0.00022
tag= ewa_halfllife_n =6      2004-07-29 00:00:00      1000      4e-05
tag= ewa_halfllife_n =7      2004-07-30 00:00:00      1000     -0.00011
```

```
1 print(sweep_fit_list[3][100][2]['final_estimator'].summary(title='test title here'))
```


test title here

Dep. Variable:	SPY	R-squared:	0.010			
Model:	OLS	Adj. R-squared:	0.008			
Method:	Least Squares	F-statistic:	7.207			
Date:	Tue, 08 Apr 2025	Prob (F-statistic):	1.74e-10			
Time:	14:59:08	Log-Likelihood:	19776.			
No. Observations:	6604	AIC:	-3.953e+04			
Df Residuals:	6594	BIC:	-3.946e+04			
Df Model:	9					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	0.0003	0.000	2.001	0.045	6.04e-06	0.001
XLB	0.0003	0.000	0.829	0.407	-0.000	0.001
XLE	-0.0005	0.000	-2.177	0.030	-0.001	-4.71e-05
XLF	-0.0006	0.000	-2.046	0.041	-0.001	-2.37e-05
XLI	0.0007	0.000	1.740	0.082	-8.81e-05	0.001
XLK	-0.0006	0.000	-2.377	0.017	-0.001	-9.93e-05
XLP	-0.0002	0.000	-0.844	0.399	-0.001	0.000
XLU	-0.0005	0.000	-2.712	0.007	-0.001	-0.000
XLV	-0.0007	0.000	-2.784	0.005	-0.001	-0.000
XLY	0.0007	0.000	2.249	0.025	8.76e-05	0.001
Omnibus:	1441.113	Durbin-Watson:	2.079			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	29384.087			
Skew:	-0.520	Prob(JB):	0.00			
Kurtosis:	13.281	Cond. No.	7.33			




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

Lisa

1 regout\_df



	prediction
teo	
2000-08-03	0.00382
2000-08-04	0.00508
2000-08-07	0.00215
2000-08-08	0.00307
2000-08-09	0.00472
...	...
2025-04-01	0.00008
2025-04-02	0.00016
2025-04-03	0.00039
2025-04-04	0.00342
2025-04-07	0.00340



6206 rows x 1 columns

Next steps:

[Generate code with regout\\_df](#)


[View recommended plots](#)

[New interactive sheet](#)



Double-click (or enter) to edit

```
1 xr_list = []
2 for n, tag in enumerate(sweep_tags):
3     regout_df = regout_list[n]
4     fit_tuple = fit_list[n]
5
6     regout_df['preds_index'] = norm.cdf(zscaler.fit_transform(regout_df[['prediction']]))
7     regout_df['actual'] = etf_targets_df['SPY'].loc[regout_df.prediction.index].dropna()
8     regout_df['leverage'] = L_func_3(regout_df, pred_col='preds_index', params=[0, .5, 1.5, 2])
9     regout_df['perf_ret'] = regout_df['leverage']*regout_df['actual']
10    regout_df['avg_beta'] = regout_df['leverage'].expanding().mean()
11    regout_df.index.name = 'teo'
12
13
14    xr_list.append(regout_df.to_xarray().expand_dims(tag=[sweep_tags[n]]))
15    regout_list[n] = regout_df
16    sweep_fit_list.append(fit_list)
```

1 pd.DataFrame(y)



	SPY
teo	
1998-12-23	-0.004321
1998-12-24	-0.002550
1998-12-28	0.015709
1998-12-29	-0.008076
1998-12-30	0.000000
...	...
2025-04-01	0.006308
2025-04-02	-0.050537
2025-04-03	-0.060327
2025-04-04	-0.001783
2025-04-07	0.031191



6612 rows x 1 columns

```
1 Results_xr = xr.Dataset()
2 Results_xr = xr.merge(xr_list)
```

```
3 Results_xr = xr.merge([Results_xr,pd.DataFrame(y).to_xarray().expand_dims(tag=['SP500']).rename({'SPY':'perf_ret'})])
4 Results_xr
```

xarray.Dataset

► Dimensions: (teo: 6612, tag: 8)

▼ Coordinates: teo (teo) datetime64[ns] 1998-12-23 ... 2025-04-07 tag (tag) object 'SP500' ... 'ewa\_halflife\_n =7'

▼ Data variables: prediction (tag, teo) float64 nan nan nan ... 0.00342 0.0034 preds\_index (tag, teo) float64 nan nan nan ... 0.549 0.9881 0.9877 actual (tag, teo) float64 nan nan nan ... -0.001783 0.03119 leverage (tag, teo) float64 nan nan nan nan ... 0.5 1.5 2.0 2.0 perf\_ret (tag, teo) float64 -0.004321 -0.00255 ... 0.06238 avg\_beta (tag, teo) float64 nan nan nan ... 0.9157 0.9159

► Indexes: (2)

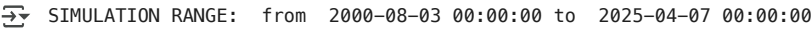
► Attributes: (0)

```
1 Results_xr['perf_ret'].sel(teo=slice('2010-01-01','2024-11-28')).cumsum(dim='teo').plot.line(x='teo')
2 plt.title("Chart_2")
```



Double-click (or enter) to edit


```
1
2 trange = slice(regout_list[-1].index[0],regout_list[-1].index[-1])
3
4 sim_stats(regout_list,sweep_tags,author='CG',trange = trange)
```





	ewa_halflife_n =1	ewa_halflife_n =2	ewa_halflife_n =3	ewa_halflife_n =4	ewa_halflife_n =5	ewa_halflife_n =6	ewa_halflife_n =7
teo							
return	0.129281	0.127278	0.115437	0.110636	0.111914	0.105734	0.10093
stdev	0.267514	0.275753	0.277365	0.282408	0.284253	0.286627	0.286417
sharpe	0.483267	0.461566	0.416192	0.391759	0.393713	0.368891	0.352389
avg_beta	0.959878	0.943281	0.937077	0.934499	0.930551	0.922172	0.915888
beta_1_return	0.134685	0.134932	0.123188	0.118391	0.120267	0.114658	0.110199
pos_bet_ratio	0.533999	0.51853	0.514341	0.509507	0.51418	0.519497	0.526587
rmse	0.012132	0.012139	0.012153	0.012171	0.01217	0.012173	0.012176
mae	0.008056	0.00805	0.008047	0.00805	0.008046	0.008045	0.008044
r2	0.002871	0.001599	-0.000588	-0.003588	-0.003513	-0.003995	-0.004361
benchmark return	0.069934	0.069934	0.069934	0.069934	0.069934	0.069934	0.069934
benchmark std	0.192877	0.192877	0.192877	0.192877	0.192877	0.192877	0.192877
benchmark sharpe	0.362585	0.362585	0.362585	0.362585	0.362585	0.362585	0.362585
beg_pred	2000-08-03	2000-08-03	2000-08-03	2000-08-03	2000-08-03	2000-08-03	2000-08-03
end_pred	2025-04-07	2025-04-07	2025-04-07	2025-04-07	2025-04-07	2025-04-07	2025-04-07

1 p\_by\_year(X\_list[0],y\_list[0],sort\_by = 'p\_value',t\_list=None).T



 from 2025-01-02 00:00:00 to 2025-04-07 00:00:00

Ticker	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLV	XLV	
1998	-0.587210	-0.374294	-0.506994	-0.280492	-0.177197	-0.502744	-0.209148	-0.700171	-0.533026		
1999	-0.071519	-0.061252	0.059149	-0.018341	-0.044764	0.011468	-0.058285	-0.005569	-0.027985		
2000	0.044946	0.036438	0.015815	-0.081600	-0.095882	-0.006675	0.004315	-0.038148	-0.002018		
2001	-0.010815	0.052548	-0.083981	-0.033722	-0.045207	0.037237	-0.020312	-0.013132	-0.005674		
2002	-0.054589	-0.048429	-0.056093	-0.064544	-0.045041	-0.013822	-0.054438	-0.003021	-0.063441		
2003	-0.088468	-0.078263	-0.047911	-0.057864	-0.050468	0.007877	-0.014729	-0.175393	-0.060857		
2004	0.069259	-0.052878	-0.029115	0.028633	-0.026441	-0.032288	0.034724	-0.049986	0.018488		
2005	-0.032689	-0.025743	-0.101314	-0.091652	-0.041514	-0.177229	-0.157255	-0.128898	-0.093580		
2006	-0.092085	-0.107380	-0.057890	-0.032647	0.037901	-0.070698	-0.107961	-0.064684	-0.013032		
2007	-0.186103	-0.280784	-0.065470	-0.110744	-0.119056	-0.051921	-0.105277	-0.044397	-0.061188		
2008	-0.162453	-0.248657	-0.098522	-0.163903	-0.109947	-0.130863	-0.206661	-0.271083	-0.050044		
2009	-0.064311	-0.062385	-0.094716	-0.042322	-0.073561	-0.066924	0.020160	0.029804	-0.065518		
2010	0.023578	-0.020579	-0.035487	-0.022676	-0.060134	-0.048782	-0.045703	-0.096340	-0.021732		