

Testing the Predictive Power of Single Alpha Directional Trading Signals

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Goal and Results

Goal:

- Test single trading signals' predict ability to return, using OLS univariate regression to see the statistical significance of each signals corresponding to each asset.

Improvement:

- Divide both side of OLS by the std of VIX to reduce the residual volatility during Covid period, following the OLS assumption about homoscedasticity of the error term.
- Check multicollinearity problem by VIF approach

Results:

- The MAXO and BB signals do not show pervasively statistical significance in asset return prediction.

Outline

- Data
- Trading Signals
- Introduce VIX index to OLS
- Feature Selection
- OLS Regression
- Result comparison
- Summary

Data

- We used 10 years worth of data from the following sector ETFs:
 - Energy: XLE
 - Materials: XLB
 - Industrials: XLI
 - Consumer Discretionary: XLY
 - Consumer Staples: XLP
 - Healthcare: XLV
 - Financials: XLF
 - Information Technology: SMH
 - Communication Services: XTL
 - Utilities: XLU
- From Bloomberg we utilized the TOT_RETURN_INDEX_GROSS_DVDS FLD in order to account for dividends through the life of the asset
- We collect [VIX index](#) from Federal Reserve Economic Data

Trading Signals

- Bollinger Bands
 - Calculate 20 day moving average and volatility to calculate upper/lower bounds of prices. We'd go long if the price drops below the lower bound and short if price moves higher than the upper bound
- MAXO(2,10), MAXO (10,60)
 - MAXO(X, Y): calculate X day and Y day moving averages and take the sign of (Xday - Yday)

Feature Selection

We apply VIF, a measure of the amount of multicollinearity in a set of multiple regression variables.

We screen out features with VIF value > 10, which shows high multicollinearity

According to results, MAXO(10,60) in most assets have multicollinearity, we decide to drop MAXO(10,60) for all assets

Screened results(VIF>10):

XLE_MAXO(10,60)_lag_1	XLI_MAXO(10,60)_lag_1
XLE_MAXO(10,60)_lag_2	XLI_MAXO(10,60)_lag_2
XLE_MAXO(10,60)_lag_3	XLI_MAXO(10,60)_lag_3
XLE_MAXO(10,60)_lag_4	XLI_MAXO(10,60)_lag_4
XLE_MAXO(10,60)_lag_5	XLI_MAXO(10,60)_lag_5
XLY_MAXO(10,60)_lag_1	XLY_MAXO(10,60)_lag_1
XLY_MAXO(10,60)_lag_2	XLY_MAXO(10,60)_lag_2
XLY_MAXO(10,60)_lag_3	XLY_MAXO(10,60)_lag_3
XLY_MAXO(10,60)_lag_4	XLY_MAXO(10,60)_lag_4
XLY_MAXO(10,60)_lag_5	XLY_MAXO(10,60)_lag_5
XLP_MAXO(10,60)_lag_1	XLP_MAXO(10,60)_lag_1
XLP_MAXO(10,60)_lag_2	XLP_MAXO(10,60)_lag_2
XLP_MAXO(10,60)_lag_3	XLP_MAXO(10,60)_lag_3
XLP_MAXO(10,60)_lag_4	XLP_MAXO(10,60)_lag_4

Data Statistics

Asset	Return Average	Return Volatility	BB Average	BB Volatility	MAXO Average	MAXO Volatility
XLE	0.04%	1.73%	1.04%	32.28%	7.68%	99.72%
XLB	0.05%	1.23%	0.38%	33.02%	15.45%	98.81%
XLI	0.05%	1.16%	0.25%	30.85%	18.33%	98.31%
XLV	0.06%	1.22%	-0.06%	30.95%	19.81%	98.03%
XLP	0.04%	0.86%	-0.38%	32.25%	21.55%	97.65%
XLV	0.06%	1.00%	-0.60%	32.00%	19.87%	98.02%
XLF	0.06%	1.30%	0.03%	32.40%	19.49%	98.10%
SMH	0.10%	1.71%	-1.42%	32.66%	23.35%	97.25%
XTL	0.03%	1.27%	0.25%	32.05%	10.08%	99.51%
XLU	0.04%	1.11%	1.86%	31.85%	16.62%	98.61%
Average	0.05%	1.26%	0.14%	32.03%	17.22%	98.40%

The daily Return Average is quite low while the average volatility over assets is higher than mean almost 25 times, which indicates the assets are quite unstable.

The BB strategy shows selective trading signals with a stronger inclination to buy XLE and XLU, and sell SMH with absolute average signal larger than 1, whereas other assets are given more neutral signals. In contrast, the MAXO strategy prefers buying than selling across all assets, demonstrating a consistently bullish stance relative to BB signals.

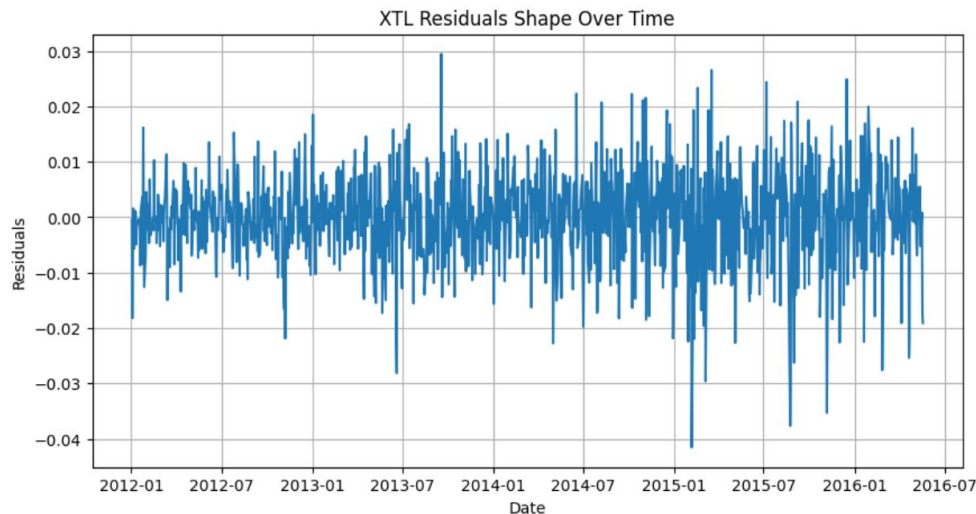
The volatility figures suggest that BB signals are relatively stable, while MAXO signals are highly volatile, implying a reactive approach that closely tracks daily market movements.

OLS Regression - Autoregressive Model

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + \epsilon_t$$

- Y_t is the value of the asset returns at time t .
 - $Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}$ are the lagged values of the asset returns, where each lag corresponds to a previous time period (e.g., Y_{t-1} is the asset return at time $t - 1$).
 - c is a constant (intercept of the model),
 - $\phi_1, \phi_2, \dots, \phi_p$ are the coefficients that measure the impact of the p lagged returns on the current return,
 - ϵ_t is the error term, representing random fluctuations that cannot be predicted by past returns.
- We initially set an upto 5 day lag, to see if there is a lag in the relationship of our signals and the actual data, since in financial data, this is often the case, and time series data often show dependency on time.

Residual Distribution



- Here we can see that our errors exhibit heteroskedasticity which means that variance is inconsistent through this time period and this doesn't align with OLS assumptions
- Our errors are compact during low vol period and very wide during periods of high vol - such as COVID
- To combat this, we will divide our data set by VIX

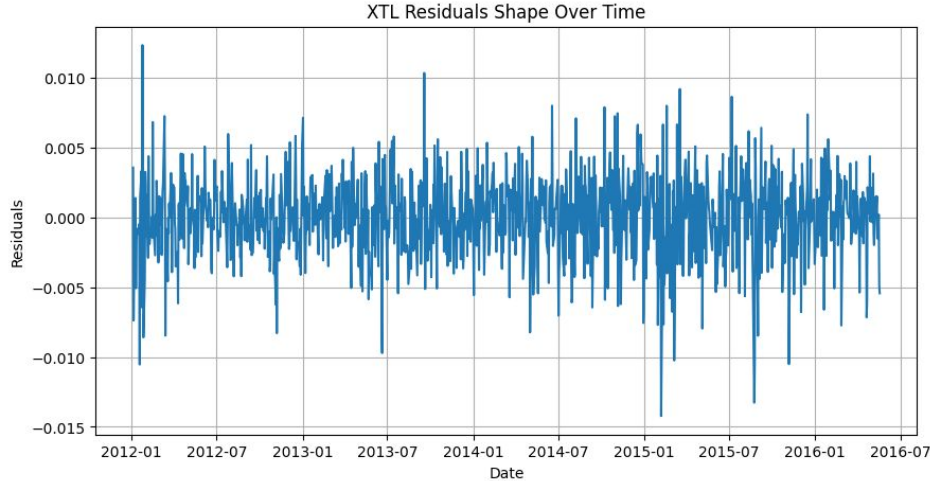
Introduce VIX Index to OLS

$$\frac{Y_t}{\sigma_{VIX,t}} = \frac{c}{\sigma_{VIX,t}} + \frac{\phi_1 Y_{t-1}}{\sigma_{VIX,t}} + \frac{\phi_2 Y_{t-2}}{\sigma_{VIX,t}} + \dots + \frac{\phi_p Y_{t-p}}{\sigma_{VIX,t}} + \frac{\epsilon_t}{\sigma_{VIX,t}}$$

For each day t, We calculate the volatility of VIX index before that day t, the historical standard deviation of mean.

- We divide both hand side by the volatility of VIX to make OLS residuals constant variance
- This make model's predictions less sensitive to periods of high volatility and allowing for a more consistent interpretation of the beta coefficients.

After VIX Division



The variance range of residual is reduced from ± 0.03 to ± 0.015 , around 2x less. This suggests that incorporating the VIX standard deviation adjustment has effectively decreased the variability in the OLS residuals, yielding a more accurate representation of the trading signals' impact.

Compare OLS Before vs. After VIX Division

Model Summary for XLE:

OLS Regression Results

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Dep. Variable:          XLE_return    R-squared:                0.002
Model:                  OLS           Adj. R-squared:           -0.001
Method:                 Least Squares  F-statistic:              0.6902
Date:                   Sun, 10 Mar 2024  Prob (F-statistic):      0.658
Time:                   02:55:44       Log-Likelihood:           5686.6
No. Observations:      1905           AIC:                     -1.136e+04
Df Residuals:          1898           BIC:                     -1.132e+04
Df Model:               6
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
const	0.0001	0.000	0.491	0.623	-0.000	0.001
XLE_BB	0.0014	0.001	1.532	0.126	-0.000	0.003
XLE_BB_lag_1	7.959e-06	0.001	0.008	0.994	-0.002	0.002
XLE_BB_lag_2	-0.0006	0.001	-0.639	0.523	-0.003	0.001
XLE_BB_lag_3	0.0002	0.001	0.227	0.820	-0.002	0.002
XLE_BB_lag_4	0.0009	0.001	0.931	0.352	-0.001	0.003
XLE_BB_lag_5	-0.0008	0.001	-0.885	0.376	-0.003	0.001

```
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Omnibus:                109.668    Durbin-Watson:            1.948
Prob(Omnibus):           0.000     Jarque-Bera (JB):         393.642
Skew:                    -0.157    Prob(JB):                 3.32e-86
Kurtosis:                5.205     Cond. No.:                4.10
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```

Model Summary for XLE:

OLS Regression Results

```
=====
Dep. Variable:          XLE_return    R-squared:                0.003
Model:                  OLS           Adj. R-squared:           -0.000
Method:                 Least Squares  F-statistic:              0.9610
Date:                   Sun, 10 Mar 2024  Prob (F-statistic):      0.450
Time:                   02:55:46       Log-Likelihood:           7483.8
No. Observations:      1833           AIC:                     -1.495e+04
Df Residuals:          1826           BIC:                     -1.491e+04
Df Model:               6
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
const	2.593e-05	9.58e-05	0.271	0.787	-0.000	0.000
XLE_BB	0.0019	0.001	1.966	0.049	4.89e-06	0.004
XLE_BB_lag_1	9.327e-05	0.001	0.094	0.925	-0.002	0.002
XLE_BB_lag_2	-0.0002	0.001	-0.252	0.801	-0.002	0.002
XLE_BB_lag_3	-8.66e-05	0.001	-0.088	0.930	-0.002	0.002
XLE_BB_lag_4	0.0011	0.001	1.084	0.279	-0.001	0.003
XLE_BB_lag_5	-0.0004	0.001	-0.436	0.663	-0.002	0.001

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Omnibus:                101.709    Durbin-Watson:            1.902
Prob(Omnibus):           0.000     Jarque-Bera (JB):         327.127
Skew:                    -0.199    Prob(JB):                 9.23e-72
Kurtosis:                5.031     Cond. No.:                12.0
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The reduction in kurtosis after adjusting for VIX suggests that incorporating market volatility helps in diminishing the prevalence of outliers in the residuals. Nonetheless, with the Omnibus probability near zero in both scenarios, indicating the residual distribution is not normally distributed, implying potential omitted variable bias, or non-linear relationship between asset's returns and the trading signal.

OLS Regression–BB Signal–Single Asset

T-value: The absolute values of t statistic are all lower than 2, so BB trading signals and its lags do not have a strong effect on the return.

F-test: its high probability 0.35 suggests that BB signals and its lags do not significantly enhance the explanation of XLE returns beyond what is captured by a simplistic model that includes only the intercept.

Durbin-Watson: It is approximately 2, indicating no autocorrelation in residuals, showing residual independence across time.

Omnibus: The almost 0 probability of omnibus implies residuals are not normal distributions, causing bias effect of BB signals toward asset's return and the bias statistical indicator.

Model Summary for XLE:

OLS Regression Results						
Dep. Variable:	XLE_return	R-squared:	0.005			
Model:	OLS	Adj. R-squared:	0.001			
Method:	Least Squares	F-statistic:	1.117			
Date:	Sun, 10 Mar 2024	Prob (F-statistic):	0.350			
Time:	02:55:56	Log-Likelihood:	5048.6			
No. Observations:	1234	AIC:	-1.008e+04			
Df Residuals:	1227	BIC:	-1.005e+04			
Df Model:	6					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	5.145e-05	0.000	0.445	0.656	-0.000	0.000
XLE_BB	7.825e-05	0.002	0.037	0.971	-0.004	0.004
XLE_BB_lag_1	-0.0024	0.002	-1.062	0.288	-0.007	0.002
XLE_BB_lag_2	0.0008	0.002	0.331	0.741	-0.004	0.005
XLE_BB_lag_3	-0.0011	0.002	-0.484	0.628	-0.006	0.003
XLE_BB_lag_4	-0.0015	0.002	-0.663	0.507	-0.006	0.003
XLE_BB_lag_5	-0.0028	0.002	-1.315	0.189	-0.007	0.001
Omnibus:	698.046	Durbin-Watson:	2.125			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	39693.621			
Skew:	-1.851	Prob(JB):	0.00			
Kurtosis:	30.537	Cond. No.	24.5			

OLS Regression–BB Signal–All Assets

Asset	intercept	Coefficient	lag_1 Coefficient	lag_2 Coefficient	lag_3 Coefficient	lag_4 Coefficient	lag_5 Coefficient	t-statistic	Durbin-Watson
XLE	0.000026	0.001858	0.000094	-0.000244	-0.000100	0.001062	-0.000402	1.966877	1.902306
XLB	0.000140	-0.000750	0.002320	0.000122	0.000954	0.000787	-0.000378	-0.927302	1.956881
XLI	0.000195	0.000276	0.001396	0.000797	-0.000049	0.002174	-0.000798	0.360926	1.965719
XLY	0.000254	0.000497	0.000095	0.001444	-0.000130	0.000778	-0.001157	0.678007	1.936123
XLP	0.000156	0.000761	-0.000198	0.000128	0.001235	-0.000568	0.000409	1.445481	1.999593
XLV	0.000227	-0.000327	0.001218	0.000160	0.001294	0.000501	-0.000250	-0.480358	2.014263
XLF	0.000245	-0.001405	0.001295	-0.000260	0.000422	0.002630	-0.000916	-1.682296	2.003054
SMH	0.000315	0.001289	0.002368	-0.000888	0.001455	0.000862	-0.001037	1.205574	1.966194
XTL	0.000160	-0.001821	0.002269	0.000593	-0.000453	0.001444	-0.000770	-2.038509	1.963050
XLU	0.000133	0.000365	0.000614	-0.000688	-0.000063	-0.001047	0.000317	0.553230	2.021098

Coefficient Values: Positive coefficients for certain assets suggest BB buy signals are associated with positive returns. Interestingly, the negative coefficients for XLB, XLV, XLF, and SMH are followed by positive coefficients at time lag 1, indicating a delayed positive market response to the BB buy signals on those assets.

T-value: T-statistics for almost all assets fall below the absolute value of 2, signifying that the BB signals lack statistical significance in predicting asset returns.

Durbin-Watson: The Durbin-Watson values are all near 2 across all assets, indicating residuals follow the OLS assumption of independent residuals over time, which is a good sign of more accurate estimation effects of factors.

OLS Regression–MAXO Signal–Single Asset

Following the same logic as BB interpretation

T-value: The major absolute values of t statistic are all lower than 2 except for MAXO with lag 3, so MAXO and its lags do not have a strong effect on the return overall.

F-test: its high probability 0.133 suggests that MAXO signals and its lags do not substantially improve the model's ability to explain XLE returns compared to a baseline model that includes only an intercept.

Durbin-Watson: It is approximately 2, indicating no autocorrelation in residuals, showing residual independence across time.

Omnibus: The almost 0 probability of omnibus implies residuals are not normal distributions, causing bias effect of MAXO signals toward asset's return and the bias statistical indicator.

Model Summary for XLE:

OLS Regression Results						
Dep. Variable:	XLE_return	R-squared:	0.008			
Model:	OLS	Adj. R-squared:	0.003			
Method:	Least Squares	F-statistic:	1.640			
Date:	Sun, 10 Mar 2024	Prob (F-statistic):	0.133			
Time:	02:55:56	Log-Likelihood:	5050.2			
No. Observations:	1234	AIC:	-1.009e+04			
Df Residuals:	1227	BIC:	-1.005e+04			
Df Model:	6					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	2.546e-05	0.000	0.220	0.826	-0.000	0.000
XLE_MAXO(2,10)	0.0004	0.001	0.374	0.709	-0.002	0.002
XLE_MAXO(2,10)_lag_1	0.0006	0.001	0.528	0.598	-0.002	0.003
XLE_MAXO(2,10)_lag_2	-0.0007	0.001	-0.600	0.548	-0.003	0.002
XLE_MAXO(2,10)_lag_3	0.0026	0.001	2.212	0.027	0.000	0.005
XLE_MAXO(2,10)_lag_4	-0.0022	0.001	-1.852	0.064	-0.004	0.000
XLE_MAXO(2,10)_lag_5	0.0010	0.001	1.090	0.276	-0.001	0.003
Omnibus:	705.775	Durbin-Watson:	2.119			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	41007.391			
Skew:	-1.877	Prob(JB):	0.00			
Kurtosis:	30.990	Cond. No.	13.3			

OLS Regression–MAXO Signal–All Assets

Asset	intercept	Coefficient	lag_1 Coefficient	lag_2 Coefficient	lag_3 Coefficient	lag_4 Coefficient	lag_5 Coefficient	t-statistic	Durbin-Watson
XLE	0.000042	0.000552	-0.000705	-0.000349	0.000107	0.000156	0.000004	1.323533	1.962746
XLB	0.000179	-0.000100	0.000071	-0.000040	0.000248	-0.001049	0.000306	-0.283838	1.935282
XLI	0.000218	0.000281	0.000188	-0.000544	-0.000051	-0.000200	0.000055	0.864717	1.984708
XLY	0.000245	0.000316	-0.000429	-0.000013	-0.000258	0.000055	0.000416	1.005185	1.968662
XLP	0.000159	-0.000089	-0.000229	0.000226	-0.000400	0.000594	-0.000224	-0.371761	2.029592
XLV	0.000234	0.000131	-0.000337	-0.000030	0.000035	-0.000393	0.000341	0.434322	2.003517
XLF	0.000235	-0.000324	0.000429	-0.000182	-0.000192	-0.000484	0.000876	-0.928358	1.951999
SMH	0.000271	0.000554	-0.000674	0.000250	-0.000041	-0.000690	0.001072	1.210727	2.000923
XTL	0.000159	0.000097	-0.000009	0.000093	0.000191	-0.000574	0.000186	0.255233	1.928586
XLU	0.000151	-0.000152	-0.000246	0.000174	-0.000163	0.000605	-0.000486	-0.550463	2.027050

Coefficients: The positive coefficients indicate that buy signals from MAXO align with positive returns. However, for assets like XLB and XLF, an immediate negative response to MAXO buy signals transitions to positive at a one-period lag, highlighting a market delay. In XLU, the highest positive effect 0.000605 surfaces at a four-period lag, suggesting the strategy's signals may be more frequent than the market's response cycle in XLU.

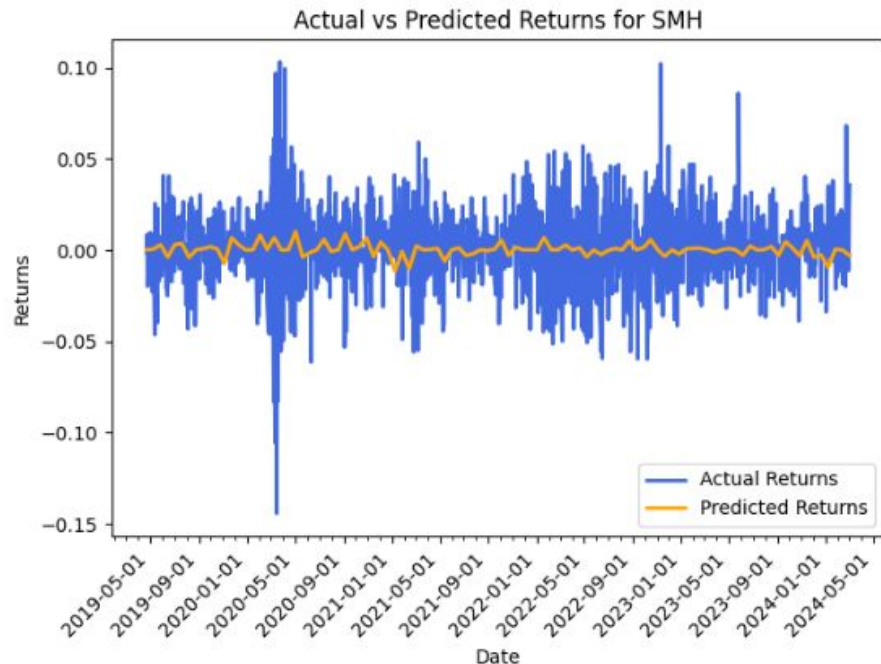
T-value: T-statistics for all assets fall below the absolute value of 2, signifying that the MAXO signals lack statistical significance in predicting asset returns.

Durbin-Watson: The Durbin-Watson values are all near 2 across all assets, indicating residuals follow the OLS assumption of independent residuals over time, which is a good sign of more accurate estimation effects of factors.

Predicted Return vs. Actual Return

Split the dataset into train : test = 60 : 40, maintaining the chronological sequence. Use the fitted model in train set to predict return in test set.

- Signal return are very weak, compared to the actual return with noise. The model fail to capture the actual returns volatility.
- The graph implies heteroskedasticity in the residuals, as actual returns exhibit greater variance than the homoscedastic predicted returns, indicating the VIX adjustment did not fully address this issue, and further transformation is needed to stabilize the variance.



P&L Analysis with XLF

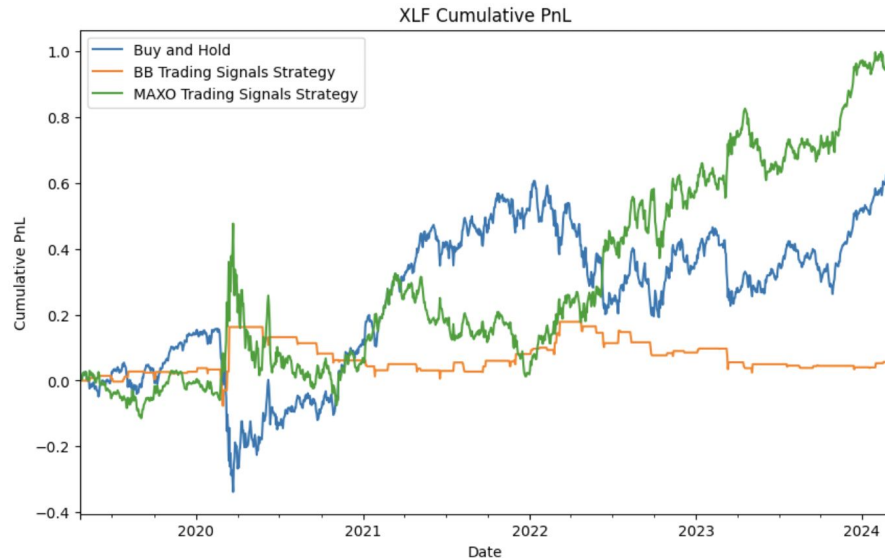
Model Summary for XLF:

OLS Regression Results

Dep. Variable:	XLF_return	R-squared:	0.007
Model:	OLS	Adj. R-squared:	0.002
Method:	Least Squares	F-statistic:	1.408
Date:	Sun, 10 Mar 2024	Prob (F-statistic):	0.208
Time:	02:55:56	Log-Likelihood:	5397.9
No. Observations:	1234	AIC:	-1.078e+04
Df Residuals:	1227	BIC:	-1.075e+04
Df Model:	6		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	2.369e-05	8.92e-05	0.266	0.791	-0.000	0.000
XLF_MAXO(2,10)	0.0004	0.001	0.498	0.619	-0.001	0.002
XLF_MAXO(2,10)_lag_1	0.0012	0.001	1.234	0.217	-0.001	0.003
XLF_MAXO(2,10)_lag_2	-0.0020	0.001	-1.990	0.047	-0.004	-2.81e-05
XLF_MAXO(2,10)_lag_3	0.0016	0.001	1.692	0.091	-0.000	0.004
XLF_MAXO(2,10)_lag_4	-0.0008	0.001	-0.782	0.435	-0.003	0.001
XLF_MAXO(2,10)_lag_5	0.0007	0.001	0.875	0.382	-0.001	0.002

Omnibus:	455.342	Durbin-Watson:	2.460
Prob(Omnibus):	0.000	Jarque-Bera (JB):	38410.469
Skew:	-0.765	Prob(JB):	0.00
Kurtosis:	30.289	Cond. No.	15.0



- When looking at the P&L of trading strategies on XLF (Financials Sector ETF) the MAXO trading signals picks up more P&L than the buy and hold strategy
- By naively looking at the chart, one might conclude that this was a successful strategy but our statistics show that it was only luck
- Although our R^2 is higher than in most other cases, it is still quite low and our t-stats show that none of the signals are significant

Possible Improvement - Single Lag or Multiple Lags?

OLS Regression Results

Dep. Variable:	XLU_return	R-squared:	0.001			
Model:	OLS	Adj. R-squared:	0.001			
Method:	Least Squares	F-statistic:	2.146			
Date:	Mon, 11 Mar 2024	Prob (F-statistic):	0.143			
Time:	02:21:37	Log-Likelihood:	6415.1			
No. Observations:	1905	AIC:	-1.283e+04			
Df Residuals:	1903	BIC:	-1.282e+04			
Df Model:	1					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

const	0.0004	0.000	2.094	0.036	2.54e-05	0.001
XLE_BB	0.0009	0.001	1.465	0.143	-0.000	0.002
=====						
Omnibus:	171.405	Durbin-Watson:	2.008			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	406.421			
Skew:	-0.531	Prob(JB):	5.58e-89			
Kurtosis:	4.998	Cond. No.	3.12			
=====						

- One thing we can see here is that adding lagged features doesn't help explain our data. We get similar results when using a single 1 day lag feature.
- We choose to keep running the regressions on multiple lags to see if we see consistent results for all assets and strategies and whether we see any patterns in specific lags
- The Adjusted R² becomes negative after adding in 5 lags, which implies the potential overfitting problem, indicating that use 1 lag shows more accurate and generalized estimation of out signals

Model Summary for XLE:

OLS Regression Results

Dep. Variable:	XLE_return	R-squared:	0.002			
Model:	OLS	Adj. R-squared:	-0.001			
Method:	Least Squares	F-statistic:	0.6902			
Date:	Sun, 10 Mar 2024	Prob (F-statistic):	0.658			
Time:	02:55:44	Log-Likelihood:	5686.6			
No. Observations:	1905	AIC:	-1.136e+04			
Df Residuals:	1898	BIC:	-1.132e+04			
Df Model:	6					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

const	0.0001	0.000	0.491	0.623	-0.000	0.001
XLE_BB	0.0014	0.001	1.532	0.126	-0.000	0.003
XLE_BB_lag_1	7.959e-06	0.001	0.008	0.994	-0.002	0.002
XLE_BB_lag_2	-0.0006	0.001	-0.639	0.523	-0.003	0.001
XLE_BB_lag_3	0.0002	0.001	0.227	0.820	-0.002	0.002
XLE_BB_lag_4	0.0009	0.001	0.931	0.352	-0.001	0.003
XLE_BB_lag_5	-0.0008	0.001	-0.885	0.376	-0.003	0.001
=====						
Omnibus:	109.668	Durbin-Watson:	1.948			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	393.642			
Skew:	-0.157	Prob(JB):	3.32e-86			
Kurtosis:	5.205	Cond. No.	4.10			
=====						

Summary

- Looking at our statistics, the t-statistic show that BB and MAXO(2, 10) signals are statistically insignificant, while the Omnibus test indicates non-normality in the residuals, prompting the exploration of alternative nonlinear modeling approaches.
- Dividing our data by VIX smoothed heteroskedasticity but not addressed it in residuals, still requiring further transformation.
- Running the regression on multiple lags allowed us to rule out the hypothesis that maybe certain day lags would better help explain the returns
 - We saw no patterns across assets or strategies
- In the cases where our signals make more money than a buy and hold strategy, we have concluded that the P&L stems from luck rather than from our signals having strong predictability power.
- In cases like this it can be easy to accept the P&L results blindly but our project shows that its important to take a look at the statistics to see the validity of the signal

Thank you !