Submission Number: 3

Group Number: 01

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Statement of integrity: By typing the names of all group members in the text box below, you confirm that the assignment submitted is original work produced by the group (*excluding any non-contributing members identified with an "X" above*).

David Akanji, Baris Kaya, Thanakorn Seasim

Use the box below to explain any attempts to reach out to a non-contributing member. Type (N/A) if all members contributed.

** Note, you may be required to provide proof of your outreach to non-contributing members upon request.*

1.1. Data Import

Date	XLB	VOX	XLE	XLF	XLI	XLK	XLP	IYR	XLU	XLV	XLY
2013-12-31	39.781387	72.149460	66.326424	15.372337	45.100849	31.869316	35.226295	48.451271	29.487286	49.048355	60.550556
2014-01-02	39.462929	71.528519	65.382210	15.287949	44.470848	31.557217	34.791908	48.374454	29.036858	48.774105	60.269672
2014-01-03	39.368259	71.321556	65.142441	15.393431	44.591675	31.405630	34.726334	48.658653	28.943678	48.889114	60.106598
2014-01-06	39.153088	71.571640	65.232361	15.407503	44.332764	31.352112	34.595215	48.858345	28.990271	48.685623	59.735107
2014-01-07	39.084229	72.080452	65.726936	15.414529	44.608921	31.637468	34.783710	49.027328	29.246548	49.198750	60.097538
...	...	...	...	...	...	...	...	...	...	...	...
2019-12-24	59.291908	92.998398	55.247555	29.654032	79.649132	89.694038	60.466576	88.187439	60.928539	99.836365	122.781921
2019-12-26	59.553837	93.719543	55.229717	29.818348	79.834190	90.362526	60.524250	88.658531	61.033138	99.768501	124.280457
2019-12-27	59.330715	93.541725	54.997887	29.741024	79.765999	90.352684	60.793369	88.898865	61.213787	99.797585	124.270607
2019-12-30	59.146400	92.652634	54.824322	29.654032	79.395897	89.831657	60.476181	88.966171	61.204285	99.198448	123.472038
2019-12-31	59.582932	92.790939	55.136555	29.750689	79.347214	90.116753	60.533855	89.485313	61.441986	99.393600	123.649498

1511 rows × 11 columns

Calculate Returns

Date	XLB	VOX	XLE	XLF	XLI	XLK	XLP	IYR	XLU	XLV	XLY
2014-01-02	-0.008005	-0.008606	-0.014236	-0.005490	-0.013969	-0.009793	-0.012331	-0.001585	-0.015275	-0.005591	-0.004639
2014-01-03	-0.002399	-0.002893	-0.003667	0.006900	0.002717	-0.004804	-0.001885	0.005875	-0.003209	0.002358	-0.002706
2014-01-06	-0.005466	0.003506	0.001380	0.000914	-0.005806	-0.001704	-0.003776	0.004104	0.001610	-0.004162	-0.006181
2014-01-07	-0.001759	0.007109	0.007582	0.000456	0.006229	0.009102	0.005449	0.003459	0.008840	0.010540	0.006067
2014-01-08	0.005946	-0.001196	-0.006955	0.003194	-0.001741	0.000000	-0.007540	-0.001567	-0.005311	0.008812	-0.002714
...	...	...	...	...	...	...	...	...	...	...	...
2019-12-24	0.001147	-0.000955	-0.000484	0.002287	-0.004019	0.000329	0.001273	0.002733	0.001406	-0.001261	0.002253
2019-12-26	0.004418	0.007754	-0.000323	0.005541	0.002323	0.007453	0.000954	0.005342	0.001717	-0.000680	0.012205
2019-12-27	-0.003747	-0.001897	-0.004198	-0.002593	-0.000854	-0.000109	0.004446	0.002711	0.002960	0.000292	-0.000079
2019-12-30	-0.003107	-0.009505	-0.003156	-0.002925	-0.004640	-0.005767	-0.005217	0.000757	-0.000155	-0.006004	-0.006426
2019-12-31	0.007381	0.001493	0.005695	0.003259	-0.000613	0.003174	0.000954	0.005835	0.003884	0.001967	0.001437

1510 rows × 11 columns

Robust Method for Calculation of Efficient Frontiers for all 165 combinations using 2019 data

Date	XLB	VOX	XLE	XLF	XLI	XLK	XLP	IYR	XLU	XLV	XLY
2019-01-02	0.005146	0.013096	0.019704	0.008396	0.005123	0.000645	-0.005908	-0.021617	-0.017196	-0.015143	0.007575
2019-01-03	-0.028358	-0.013460	-0.009918	-0.022481	-0.030429	-0.050468	-0.005745	0.006410	-0.000192	-0.020305	-0.021652
2019-01-04	0.039319	0.041470	0.034024	0.033220	0.037916	0.044320	0.021319	0.010706	0.014808	0.029831	0.033094
2019-01-07	0.003510	0.009338	0.014865	0.001237	0.008135	0.008943	-0.001366	0.010056	-0.006822	0.003839	0.022612
2019-01-08	0.010494	0.016962	0.007735	0.000823	0.013703	0.008380	0.009181	0.018187	0.012402	0.007765	0.011056
...	...	...	...	...	...	...	...	...	...	...	...
2019-12-24	0.001147	-0.000955	-0.000484	0.002287	-0.004019	0.000329	0.001273	0.002733	0.001406	-0.001261	0.002253
2019-12-26	0.004418	0.007754	-0.000323	0.005541	0.002323	0.007453	0.000954	0.005342	0.001717	-0.000680	0.012205
2019-12-27	-0.003747	-0.001897	-0.004198	-0.002593	-0.000854	-0.000109	0.004446	0.002711	0.002960	0.000292	-0.000079
2019-12-30	-0.003107	-0.009505	-0.003156	-0.002925	-0.004640	-0.005767	-0.005217	0.000757	-0.000155	-0.006004	-0.006426
2019-12-31	0.007381	0.001493	0.005695	0.003259	-0.000613	0.003174	0.000954	0.005835	0.003884	0.001967	0.001437

252 rows × 11 columns

MScFE 640 Portfolio Theory and Asset Pricing

Group #: 01 Submission #: 3

2.1. Assignment 2 & 3 – Portfolios for all combinations

	Portfolio	weight_assset_1	weight_assset_2	weight_assset_3	return	std_dev	sharpe_ratio
0	(XLB, VOX, XLE)	1.00000	1.00000	-1.00000	0.142993	0.205146	0.599537
1	(XLB, VOX, XLF)	0.17104	-0.17104	1.00000	0.121087	0.170271	0.593686
2	(XLB, VOX, XLI)	0.12640	-0.12640	1.00000	0.102262	0.155520	0.528951
3	(XLB, VOX, XLK)	0.15999	-0.15999	1.00000	0.193726	0.170330	1.019937
4	(XLB, VOX, XLP)	0.21781	-0.21781	1.00000	0.100412	0.120848	0.665400
5	(XLB, VOX, IYR)	0.30196	-0.30196	1.00000	0.115923	0.139859	0.685857

2.2. Determine the EF under no constraints as in 4.2.

	Annual_Return	Annual_Volatility	Sharpe_Ratio
0	0.142993	0.205146	0.599537
1	0.121087	0.170271	0.593686
2	0.102262	0.155520	0.528951
3	0.193726	0.170330	1.019937
4	0.100412	0.120848	0.665400
5	0.115923	0.139859	0.685857
6	0.138362	0.143671	0.823840
7	0.130027	0.153852	0.715145
8	0.132068	0.151032	0.742018
9	0.216601	0.217362	0.904487
10	0.198976	0.210454	0.850425

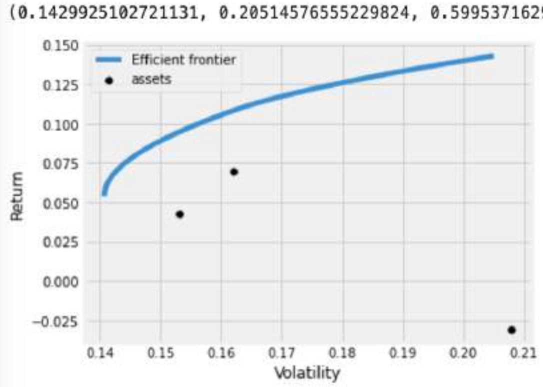
Calculate Average of Annual Return, Volatility and Sharpe Ratio

```
Annual_Return        0.173182
Annual_Volatility    0.158158
Sharpe_Ratio         0.953812
```

Select portfolio of XLB, VOX, and XLE for displaying EF

```
OrderedDict([('XLB', 1.0), ('VOX', 1.0), ('XLE', -1.0)])
Expected annual return: 14.3%
Annual volatility: 20.5%
Sharpe Ratio: 0.60
```

```
(0.1429925102721131, 0.20514576555229824, 0.5995371629582008)
```



2.3. Determine the Efficient Frontier under long-only constraints

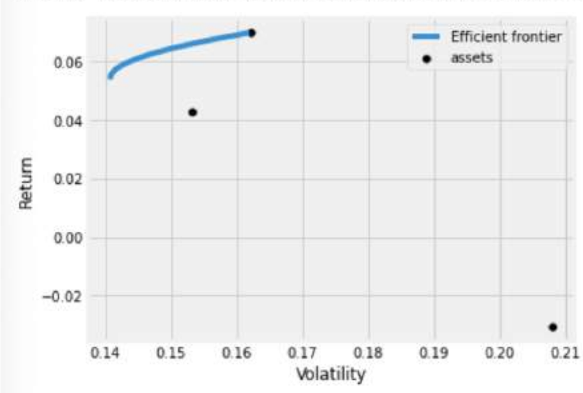
	Annual_Return	Annual_Volatility	Sharpe_Ratio
0	0.069742	0.162142	0.306781
1	0.116493	0.164120	0.587943
2	0.098867	0.150020	0.525713
3	0.189429	0.167580	1.011030
4	0.094562	0.115833	0.643705
5	0.107261	0.133510	0.653593
6	0.122533	0.128485	0.798021
7	0.125097	0.149049	0.705120
8	0.126542	0.146281	0.728342
9	0.116492	0.164120	0.587936
10	0.098867	0.150020	0.525713

Calculate Average of Annual Return, Volatility and Sharpe Ratio

```
Annual_Return        0.133766
Annual_Volatility    0.134716
Sharpe_Ratio         0.841062
```

Select portfolio of XLB, VOX, and XLE for displaying EF

```
OrderedDict([('XLB', 1.0), ('VOX', 0.0), ('XLE', 0.0)])
Expected annual return: 7.0%
Annual volatility: 16.2%
Sharpe Ratio: 0.31
(0.06974201293274092, 0.16214188256379525, 0.30678077832955813)
```

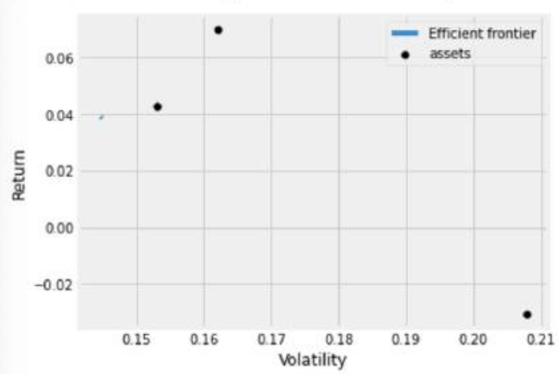


2.4. Determine the EF under box constraints of a minimum weight of 10% and a maximum weight of 40%

	Annual_Return	Annual_Volatility	Sharpe_Ratio
0	0.038977	0.144692	0.131157
1	0.083071	0.143521	0.439454
2	0.076021	0.141664	0.395447
3	0.112245	0.145202	0.635290
4	0.074299	0.120678	0.449945
5	0.079599	0.123569	0.482313
6	0.088609	0.115834	0.592306
7	0.086513	0.134775	0.493506
8	0.087091	0.137983	0.486223
9	0.068421	0.153699	0.315037
10	0.061371	0.152145	0.271916

Calculate Average of Annual Return, Volatility and Sharpe Ratio

```
OrderedDict([('XLB', 0.4), ('VOX', 0.4), ('XLE', 0.2)])
Expected annual return: 3.9%
Annual volatility: 14.5%
Sharpe Ratio: 0.13
(0.038977376971547247, 0.14469156949262407, 0.13115744779114208)
```



2.5. Discussion on the impacts under constraints.

	no_constraint	long_only	weight_constraint
Annual_Return	0.173182	0.133766	0.106981
Annual_Volatility	0.158158	0.134716	0.127704
Sharpe_Ratio	0.953812	0.841062	0.688679

a) We observed that non-constraint portfolios have the highest value in expected annual return, average annual volatilities, and average Sharpe ratio in case of no constraints.

b) In the case of long-only constraints, we observed that portfolios have the highest value in expected annual return, average annual volatilities, and average Sharpe ratio.

c) In the case of weight constraints(minimum weight of 10% and a maximum weight of 40% are imposed), we observed that portfolios have the lowest value in expected annual return, average annual volatilities, and average Sharpe ratio.

As a result;

- Each investor should choose the constraints that best suit their needs – high return or low risk.
- If we require low risk, we should select weight constraints and consider several weights to show their impact on the optimized portfolio weights. We think that it may be helpful to complete the analysis to get the lowest risk.
- We may verify that its weight constraints are compatible with its views on volatilities, risk factors, Sharpe Ratios, etc.

3.1.

Dear Portfolio Manager,

We want to share the report of our findings on the optimization of 3 security portfolios. In the analysis process, we applied a robust method of calculating the efficient frontier used to calculate the three selected SPDRs portfolios using the daily returns of 2019 data. Fixed amounts of risk were assumed where the EF of each portfolio was used to calculate each of the three securities (XLB, XLC, XLRE).

We have studied and analyzed the other constraints to the portfolios. The three types of other constraints analyzed are as follows:

1. No constraints

2. Long only constraints

3. Weight constraints of a minimum weight of 10% and a maximum weight of 40%.

After studying, we get the result as follows:

	no_constraint	long_only	weight_constraint
Annual_Return	0.173182	0.133766	0.106981
Annual_Volatility	0.158158	0.134716	0.127704
Sharpe_Ratio	0.953812	0.841062	0.688679

From the result in the table above, we deduced that:

1. In case of no constraints, We observed that non-constraint portfolios have the highest value in expected annual return, average annual volatility, and average Sharpe ratio (17.3%, 15.8%, and 0.95, respectively).

2. In the case of long-only constraints, we observed that portfolios have the highest value in expected annual return, average annual volatility, and average Sharpe ratio (13.4%, 13.5%, and 0.84, respectively).

3. In case of weight constraints (minimum weight of 10% and a maximum weight of 40% are imposed), we observed that portfolios have the lowest value in expected annual return, average annual volatility, and average Sharpe ratio (10.7%, 12.8%, and 0.69, respectively).

Based on our key findings, we came to conclusions that:

1. Each investor should choose the constraints that best suit their needs (high return or low risk).

2. If we require low risk, we should select weight constraints. And we should study more and consider several weights constraints and show their impact on the optimized portfolio weights. We think that it may be helpful to complete this analysis to get the lowest risk.

3. We may verify that its weights constraints are compatible with its views on volatilities, risk factors, Sharpe ratios.

Best regards,

WQU Group 01 Team.

3.2 Group work collaboration

We have divided the work equally between the group members.

1. Working on the program code was carried out by Thanakorn Seasim

2. Collaborating with David Akanji and Baris Kaya reviewed the code and commented on each code.

3. Report writing was carried out in collaboration with all the members of the team.

4. Report to the Quant Team Manager and Model Validation Team

To: Team Manager and Model Validation team

Dear Team Manager,

We are delighted to report on the final result of the models explored on the 11 ETF Select Sector fund index and the suitable indexed portfolio securities that can benefit our firm.

Our team has explored the Machine learning model, impact of the economic indicator, and extensive Efficient Frontier models to investigate the chosen portfolio securities formed from the selected 11 ETF Select Sector.

Python Programming Language (PPL) was used to analyze the report. Below are details of all our research insight and approaches adopted for the analysis with recommendations on the findings:

STAGE I: Exploring the Composite Economic Indicators on the 11 Select Sector SPDRs

1. Importing the 11 Select sector SPDR index and the U.S Composite Economic Indicator Index
The 11 Select sector SPDR index, which includes the XLY, XLP, XLE, XLF, XLV, XLI, XLB, XLK, XLU, XLRE, XLC, were imported using the yfinance python library. In contrast, the U.S. Composite Economic indicator was imported using FRED and Quandl python tools.

The daily record dataset used for this analysis were converted to a monthly time series dataset due to the problem of missing data for some days as regarding the XLC, XLRE, and also the LEI, LAG of our economic indicator

2. We implemented a linear regression (OLS) model that considers the historical imported data of composite economic index as our features in each 11 SPDRs index prediction.

For each ETF, we have run 11 regression models for the ETF returns on the Leading EI factors using the given weights.

We have imported six (6) indicators and utilize PCA. And the LCI is the first principal component of the selected indicators.

The cumulated form of the LCI can be compared directly with the levels of LEI and CEI. The cumulation procedure is also helpful in the interpretation of the LCI as a business cycle indicator.

	weekly_hours	initial claims	new orders	ISM	new orders excl. aircraft	Building permits	SP500	Leading Credit Index	10yrTbill less federal funds	consumer expectations
XLB	0.0667531	0.169421	-0.438696	0.28406	0.126121	-0.416829	1.23984	-0.328363	0.685368	-0.211109
VOX	0.0305156	0.205803	-0.246456	0.351048	0.0574486	-0.698317	1.34479	-0.596524	0.714378	-0.0316608
XLE	0.121977	0.22201	-0.417246	0.202516	0.21571	-0.00341715	0.834125	-0.250312	0.560364	-0.239595
XLF	0.0731577	-0.0450821	-0.640448	0.253923	0.0094173	-0.670579	1.98328	-0.230625	1.13014	-0.582
XLI	0.0522263	0.0329492	-0.620192	0.375661	0.156693	-0.561779	1.65478	-0.366209	0.990244	-0.401321

Thus, we check the performance of each model result using the R-Squared, Mean Squared Error, AIC metrics from sklearn. We noticed that the R-Squared was generally performing poorly for all different indicators as their values were below 50% for almost all targeted SDPR indexes.

	ETFS	RSquared	MSE	AIC
0	XLB	0.261913	0.003814	-244.181675
1	XLRE	0.172981	0.001212	-288.671601
2	XLC	0.298573	0.001202	-340.417741
3	XLE	0.209116	0.004838	-205.872135
4	XLF	0.488972	0.007095	-270.908108
5	XLI	0.417375	0.005336	-270.590391
6	XLK	0.502958	0.006997	-275.943046
7	XLP	0.254577	0.001927	-290.577663
8	XLU	0.150342	0.001429	-264.746582
9	XLV	0.412110	0.004396	-282.970412
10	XLY	0.471481	0.005695	-281.697389

Repeated regressions models using the 7 Lagging EI factors

	ETFS	RSquared	MSE	AIC
0	XLB	0.261913	0.003814	-244.181675
1	XLRE	0.172981	0.001212	-288.671601
2	XLC	0.298573	0.001202	-340.417741
3	XLE	0.209116	0.004838	-205.872135
4	XLF	0.488972	0.007095	-270.908108
5	XLI	0.417375	0.005336	-270.590391
6	XLK	0.502958	0.006997	-275.943046
7	XLP	0.254577	0.001927	-290.577663
8	XLU	0.150342	0.001429	-264.746582
9	XLV	0.412110	0.004396	-282.970412
10	XLY	0.471481	0.005695	-281.697389

Repeated regressions models using the 4 Coincidental EI factors.

	ETFS	RSquared	MSE	AIC
0	XLB	0.056576	0.002060	-238.508991
1	XLRE	0.052795	0.000925	-290.902054
2	XLC	0.027591	0.000278	-328.898263
3	XLE	0.082314	0.004761	-207.165424
4	XLF	0.089058	0.003231	-241.288210
5	XLI	0.079303	0.002535	-249.644121
6	XLK	0.140651	0.004892	-248.523030
7	XLP	0.067135	0.001271	-286.427491
8	XLU	0.093368	0.002219	-272.073636
9	XLV	0.077070	0.002055	-262.497413
10	XLY	0.089522	0.002703	-254.537313

The R-squared results on the CEI OLS model were all below 20%. Repeated regression models using all 21 EI factors.

	ETFS	RSquared	MSE	AIC
0	XLB	0.424037	0.002941	-240.039011
1	XLRE	0.293541	0.000979	-278.016087
2	XLC	0.471695	0.000904	-338.825665
3	XLE	0.462738	0.005098	-211.712023
4	XLF	0.692368	0.004784	-285.449683
5	XLI	0.542073	0.003300	-265.930472
6	XLK	0.632910	0.004193	-275.763993
7	XLP	0.440077	0.001586	-289.180653
8	XLU	0.251276	0.001138	-251.851969
9	XLV	0.465856	0.002367	-267.873390
10	XLY	0.553348	0.003183	-271.815038

Also, we explored the combination of all 21 composite economic indicators as features and ran the OLS model to predict the SPDR indexes. The new result obtained showed overall improvements above each composite economic indicator OLS model. However, as shown above, only four SPDR indexes (XLI, XLK, XLF, XLY) surpass 50% R- squared.

We then use the MSE metrics as our performance metrics to further analyze our model prediction and assign the economic indicator that best predicts the ETF index. The resulting economic indicators that best singly indicate the ETF is the Lagging Economic indicators as it predicts all the 11 SPDR excluding the XLU, which had the Leading Economic indicators.

We observed that the XLC was the best fit for each economic OLS model and the performance metrics MSE.

Selecting the best models for each ETF:

	LEI	LAG	CEI	Best Model
0	1.773690	2.557347	3.883912	LEI
1	1.688224	2.390243	3.594885	LEI
2	2.141780	3.091575	4.805869	LEI
3	1.905101	2.696841	4.069021	LEI
4	2.187904	3.123130	4.785837	LEI
5	2.240254	3.126220	4.835633	LEI
6	3.344753	4.723209	7.295427	LEI
7	1.635398	2.306568	3.509741	LEI
8	2.190551	3.095676	4.627901	LEI
9	2.776048	3.888749	5.886170	LEI
10	2.457091	3.459235	5.428374	LEI

From the table above, we have:

The best fit for LEI is IYR, with an MSE score of 1.6353.

The best fit for LAG is IYR, with an MSE score of 2.3065.

The best fit for CEI is IYR, with an MSE score of 3.5097

3. Machine learning algorithm, which includes Linear regression, Lasso, and Decision Tree, was used in consideration with all economics indicators to predict each ETF data. Our findings deduce that three model predictions were different except for the Communication select sector SPDRs XLC, which yielded a similar result. XLC appears to perform well on all models tested.

In addition, Lasso Regression's natural feature selection characteristic was beneficial for this experiment as it helped identify the best features to reach low MSE to the other models.

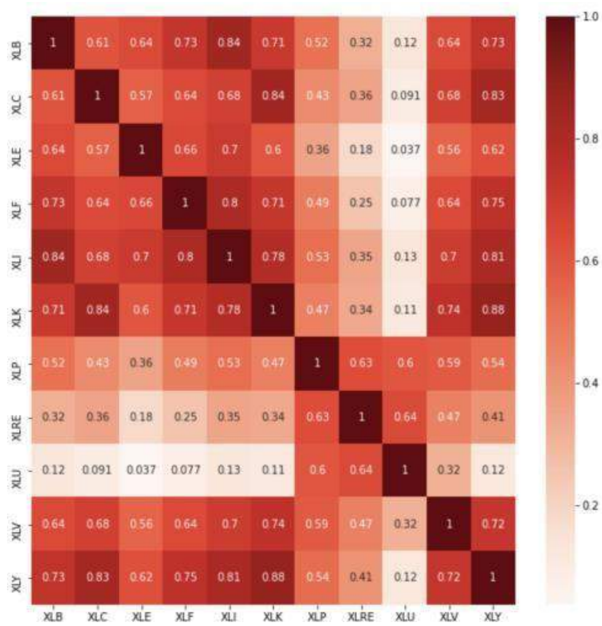
LASSO regression on each ETF using 21 economic indicators.

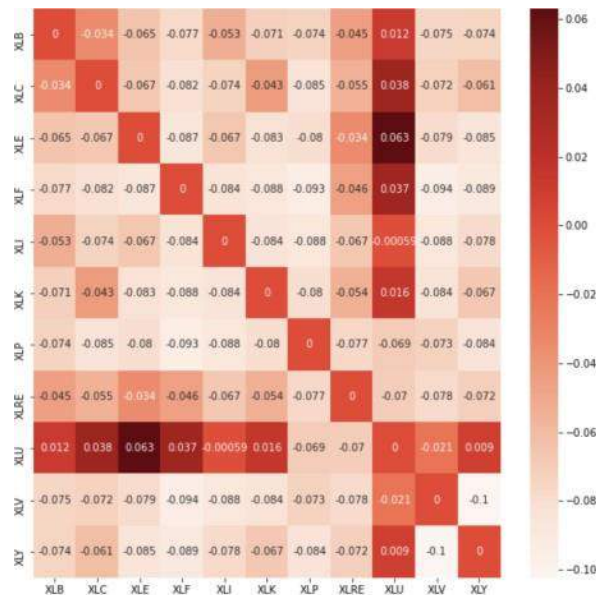
	ETFs	MSE_lasso
0	XLB	0.002152
1	VOX	0.001734
2	XLE	0.004165
3	XLF	0.002583
4	XLI	0.003161
5	XLK	0.002666
6	XLP	0.001113
7	IYR	0.001269
8	XLU	0.000579
9	XLV	0.001827
10	XLY	0.002216

	ETFs	MSE_lasso	MSE_combined_data	Lasso_rank	combined_data
8	XLU	0.000579	1.062673	1.0	5.0
6	XLP	0.001113	1.618475	2.0	11.0
7	IYR	0.001269	0.803297	3.0	1.0
1	VOX	0.001734	0.831178	4.0	2.0
9	XLV	0.001827	1.338407	5.0	10.0
0	XLB	0.002152	0.877570	6.0	3.0
10	XLY	0.002216	1.204320	7.0	9.0

Cluster Analysis

Using daily returns, we computed a distance matrix from the correlation or covariance matrix.





We also computed the correlation matrix of distances to the cluster centers are as follows:

	To_cluster1	To_cluster2	To_cluster3
0	0.024469	0.031884	0.062187
1	0.046578	0.012540	0.034702
2	0.042048	0.012855	0.038196
3	0.065033	0.023584	0.018291
4	0.047729	0.016194	0.036139

	To_cluster1	To_cluster2	To_cluster3
To_cluster1	1.000000	0.365502	-0.506606
To_cluster2	0.365502	1.000000	0.558440
To_cluster3	-0.506606	0.558440	1.000000

Tree Models

For each ETF, we are using decision trees for modeling:

ETFs	MSE_lasso	MSE_combined_data	Lasso_rank	combined_data	MSE_dt	dt_rank
XLV	0.001827	1.338407	5.0	10.0	0.002321	1.0
XLK	0.002666	1.111501	9.0	8.0	0.003071	2.0
XLF	0.002583	0.944457	8.0	4.0	0.003202	3.0
XLU	0.000579	1.062673	1.0	5.0	0.004174	4.0
XLY	0.002216	1.204320	7.0	9.0	0.004423	5.0
VOX	0.001734	0.831178	4.0	2.0	0.004750	6.0
XLI	0.003161	1.083156	10.0	7.0	0.005482	7.0
XLP	0.001113	1.618475	2.0	11.0	0.006923	8.0
IYR	0.001269	0.803297	3.0	1.0	0.008051	9.0
XLB	0.002152	0.877570	6.0	3.0	0.010213	10.0
XLE	0.004165	1.076608	11.0	6.0	0.016554	11.0

Based on the metrics above, it is evident that there is a difference between the previous and Tree rankings. However, XLU and XLC can make a similar ranking to that of last.

STAGE II: Implementation of Efficient Frontier on the 11 SPDRs indexes

Regarding the definition of Efficient Frontier, a powerful tool that can be used to quantify the best portfolio assets to choose that will yield an optimal return at different levels of volatilities.

In this stage, we explore our 11 SPDRs securities on an Efficient frontier model to decide on the best portfolio of two and three securities. We also determine the resulting targeted weighted proportion of the ETFs in the chosen portfolio. The breakdown of the task is detailed as follow;

To decide on the best portfolio of two and three securities, 11 SPDRs securities on an Efficient frontier model were explored and determined the resulting targeted weighted proportion of the ETFs in the chosen portfolio.

This approach is detailed below:

We chose two individual securities, XLF and XLK, with standard deviations of 16.42% and 16.76%, respectively. The correlation among those securities is 0.71. The average return for these securities on a standalone basis is 11.11% and 17.53%, respectively. When we combined these two assets in an equal-weight portfolio, we observed the portfolio return at 14.33%, whereas the portfolio standard deviation was at 15.34% and a Sharpe ratio of 0.85.

```
Standard Deviation of XLF is 16.42 %
Standard Deviation of XLF is 16.76 %

Portfolio Return is: 0.1433

Portfolio Standard Deviation is: 0.1534
```

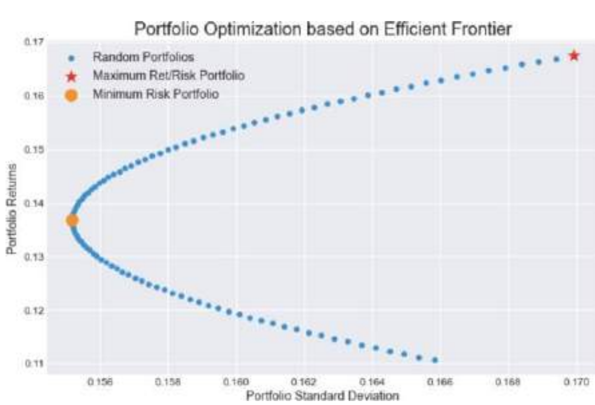
XLF and XLK are selected, 50%-50% equally weight portfolio generated.

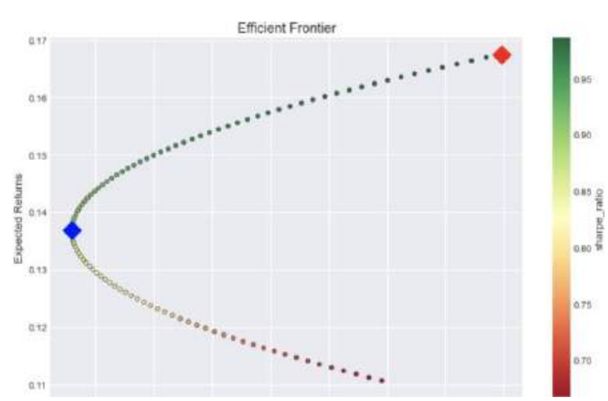
Date	XLF	XLK
2014-01-02	-0.005490	-0.009793
2014-01-03	0.006900	-0.004804
2014-01-06	0.000914	-0.001704
2014-01-07	0.000456	0.009102
2014-01-08	0.003194	0.000000
...	...	...
2019-12-24	0.002287	0.000329
2019-12-26	0.005541	0.007453
2019-12-27	-0.002593	-0.000109
2019-12-30	-0.002925	-0.005767
2019-12-31	0.003259	0.003174

1510 rows × 2 columns

Forming two asset portfolios with trimmed data pretty much yielded similar results. Portfolio standard deviation stood at 15.4%, whereas the portfolio return was slightly lower at 13.8%, with a Sharpe ratio of 0.81.

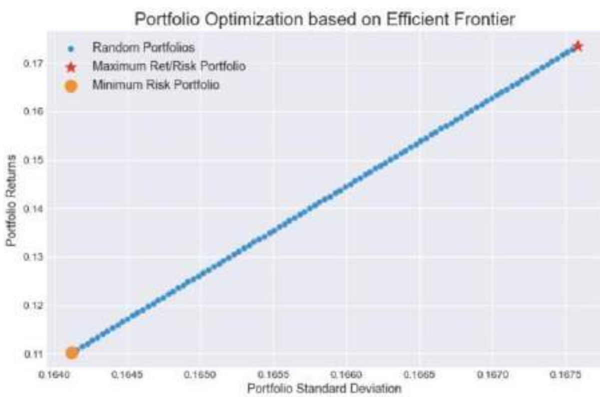
5% Trim applied to the data and recomputed the correlations and Efficient Frontier.

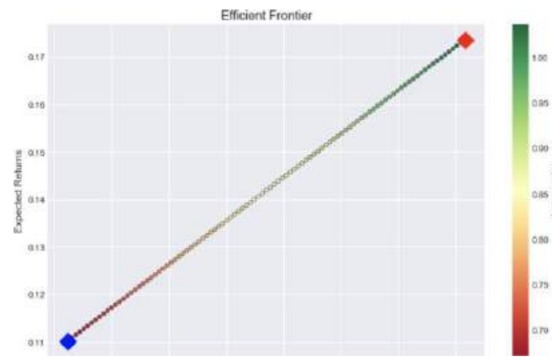




In assuming different correlations between the assets, correlation of -1 shows the portfolio return moving down to 11.1%, standard deviation up to 16.41%, and Sharpe ratio down to 0.70 from 0.85.

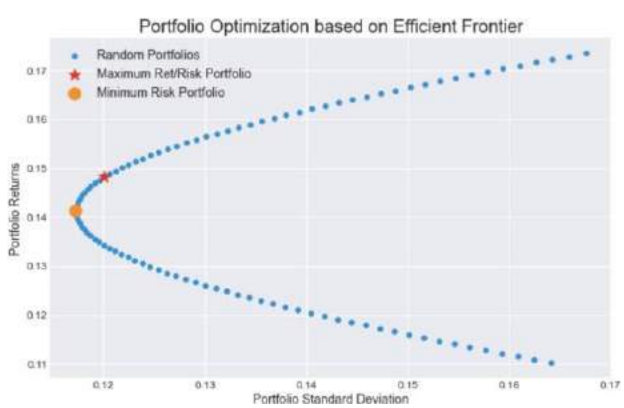
Correlation between the XLF and XLK is supposed to = -1

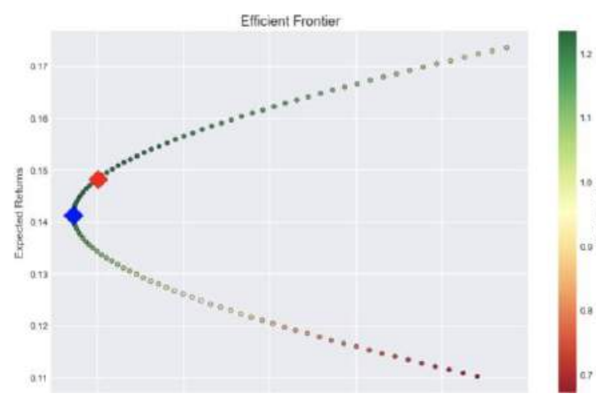




A correlation of 0 shows the two assets and the portfolio returns similar to the original portfolio at 14.2%. However, there is an improvement in the standard deviation down to 11.7% from the 15.34% level earlier. Sharpe ratio also improved from 0.85 to 1.03.

Correlation between the XLF and XLK is supposed = 0





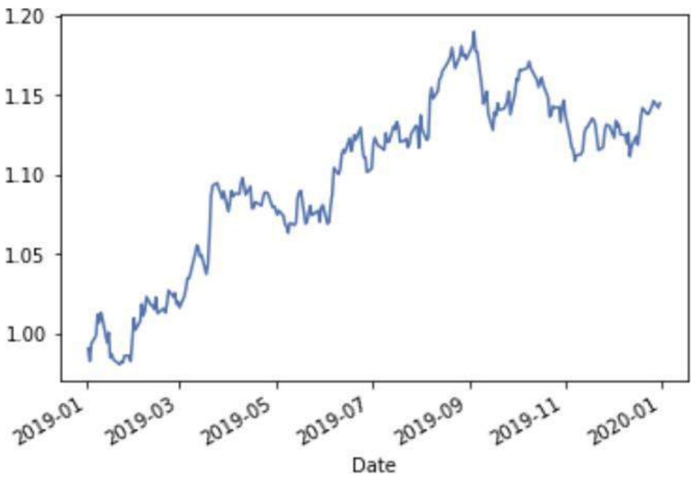
Using a robust method with three securities, we reached a return of 19.2% with a standard deviation also a bit higher at 16.8%. Sharpe ratio was at 1.02.

Using a fixed risk rate of 16% leveraging 2019 data, a portfolio consisting of the XLE, XLK, and XLU assets had a return of 45.55%. In contrast, the same combination of the assets has reached a 54.51% return using 2020 data. Sharpe ratio was also noticeably higher at 1.57.

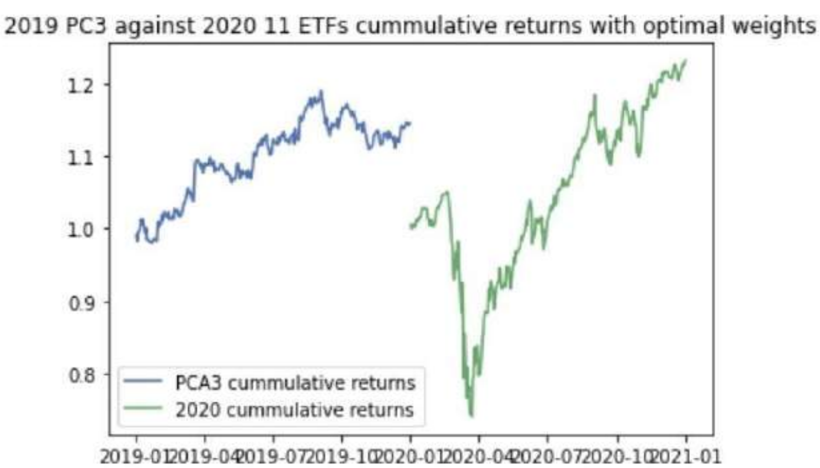
We have also used economic indicators of LEI, LAG, and CEI and had the following results. Looking at the best 20 combinations according to the best Sharpe ratio using 2020 data, we had the XLB, XLE, and XLY assets outperforming the other combinations with a Sharpe ratio of 1.57.

Finally, we have experimented with a four asset portfolio using Principal Component Analysis and the first three principal components. Our results showed that the returns for the portfolio using the first three main components leveraging 2019 data had reached a return of 36.89%, assuming a fixed risk of 30%, whereas 11 ETFs portfolio leveraging 2020 data showed a return of 25.2% return vs. a fixed risk of 30%.

Assuming a 30% fixed risk, calculation of the 3 Principal Components portfolio returns



Comparison of PCA portfolio return vs. the 2020 3-Security portfolio



Conclusion: From all analysis indicators, we can recommend PCA Portfolio has the most suitable for the risk-averse investor who wants an optimal portfolio at lower risk.

Stage III: Constraint EF

In the Constraint EF, our objective is to apply weight constraint methods in optimizing our Efficient Frontiers.

The data used was pulled using Yahoo Finance. All the returns of each EFT were calculated. A robust method of calculating the efficient frontier was used to calculate the three selected SPDRs portfolios using the daily returns of 2019 data. A fixed amount of risk was assumed where the EF of each portfolio was used to calculate the weight of each of the three securities (XLB, XLC, XLRE).

Below are the Efficient Frontiers for optimix=zation that was performed in the analysis

1. **Determine the EF under no constraints**:

This efficient frontier was developed, and we applied no constraint to our optimization method to indicate that the weight of the calculated EF is between -1 and 1

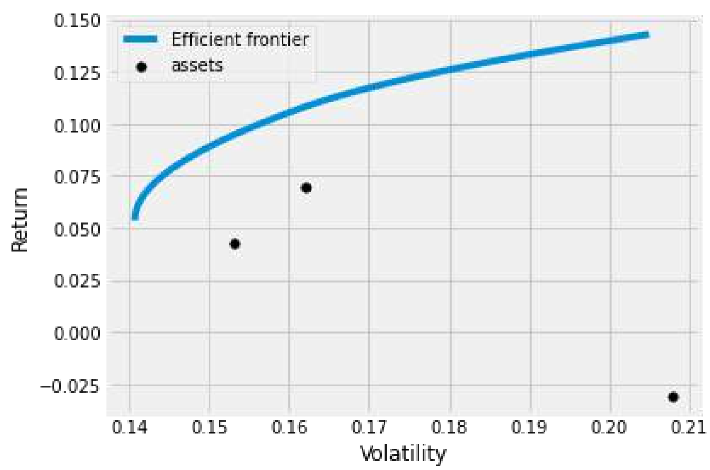


Figure 1: 3 portfolios all combinations with no constraint

Figure 1 above shows that the three portfolios combination without constraint plot has an Efficient long frontier.

2. **Determine the EF under long-only constraints**:

An optimization model based on long-only constraint was calculated, and each of the weights of the calculated EF is between 0 and 1, which is all positive.

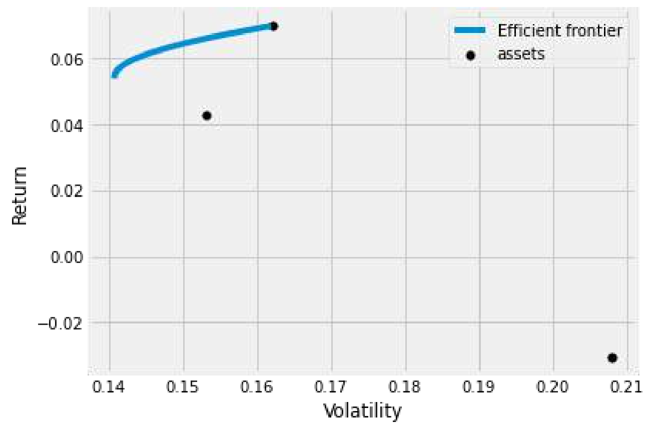


Figure 2: 3 portfolios all combinations with the long-only constraint

Figure 2 above shows that the three portfolios combination constraint plot has an Efficient long frontier. The value of the expected annual returns and Sharpe ratio of the long constraint is 17.8% and 0.65, respectively, which is lower than EF with no constraint.

3. **Determine the EF under box constraints of a minimum weight of 10% and a maximum weight of 40%**:

In determining the EF under box constraints, we set the weight of the EF to 0.1 and 0.4, i.e., 10% to 40%, respectively.

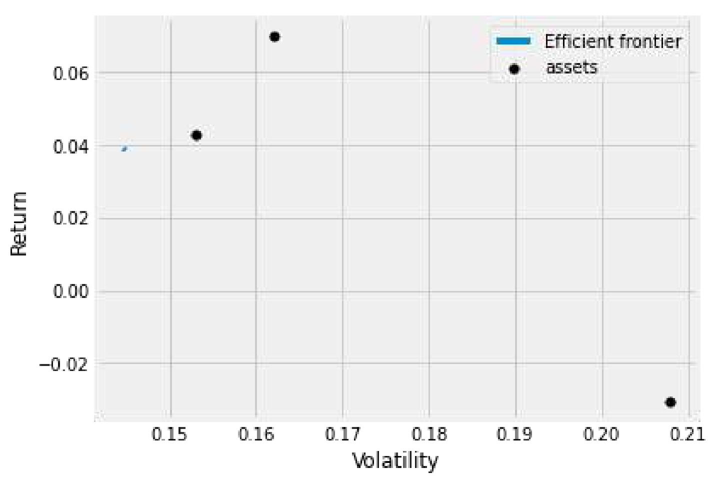


Figure 3: 3 portfolios all combinations with box constraint

The output of the box constraints shows the poorest of the three other methods. Based on table 1, the box constraint has the lowest Expected annual return, Annual volatility, and Sharpe Ratio.

Collect data of all portfolio performance in each type of constraint:

	no_constraint	long_only	weight_constraint
Annual_Return	0.173182	0.133766	0.106981
Annual_Volatility	0.158158	0.134716	0.127704
Sharpe_Ratio	0.953812	0.841062	0.688679

1. We observed that non-constraint portfolios have the highest value in expected annual return, average annual volatilities, and average Sharpe ratio in case of no constraints.

2. In the case of long-only constraints, we observed that portfolios have the highest value in expected annual return, average annual volatilities, and average Sharpe ratio.

3. In the case of weight constraints (minimum weight of 10% and a maximum weight of 40% are imposed), we observed that portfolios have the lowest value in expected annual return, average annual volatilities, and average Sharpe ratio.

Conclusion:

1. Each investor should choose the constraints that best suit their needs (high return or low risk).

2. If we require low risk, we should select weight constraints. And we should consider several sets of weights constraints and show their impact on the optimized portfolio weights. We think that it may be helpful to complete this analysis to get the lowest risk.

3. We may verify that its weights constraints are compatible with its views on volatilities, risk factors, Sharpe ratios.

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