Department of Economics and Finance
香港城市大學
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EF4328: Asset Management - C01

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Team Galaxy

Final Project Report

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1. Introduction and Background

1.1 Security Screening

In November 2022, the Conference of Parties of the UNFCCC (COP27) was held in the Arab Republic of Egypt. More than 35,000 participants, including 100 Heads of State and Government Officials took part in the event, discussing climate action on the different sectors around the world. One of the representative outputs from COP27 was that the "Loss and Damage Fund" was established, further promising the global effort to "fight for climate justice and climate ambition" through "not crossing the line of taking our planet over the 1.5 degree temperature limit" (United Nations, 2022).

Tailwinds from COP27 could lead to the continuing momentum of ESG investment. In alignment with the market's interests, ESG-related equities and ETFs will be considered as the portfolio's asset class components. The reason for excluding credit from the portfolio is because 2023's ESG debt supply is not expected to match 2021's record of $1.8 trillion. This could have resulted from poor investment sentiments on the fixed income markets due to interest rate hikes and high level of energy costs (Bloomberg L.P., 2022). In terms of ETFs, they were included in the portfolio for their advantages including diversification of investment choices/ risk, index performance tracking, and transparency. (BlackRock, 2022). Accordingly, the relevant securities will be screened through various internal categories on the Bloomberg Terminal, utilizing a top-down investment approach.

First of all, equities were screened through the Equity Screening function {EQS <GO>} (Figure 1). As the portfolio's theme will be ESG, the components of the Bloomberg ESG Data Index were considered. Although there are numerous ESG indices in the market from different index providers such as MSCI and S&P Global, there were limitations in accessing the index components free of charge, which was the reason why the component-revealing index was specifically targeted. For a higher level of transparency and liquidity, stocks listed in the United States was one of the screening criterias as well. Among the 3,836 stocks matching the criterias, the top stocks with the highest Annualized Total Return for the 5 Years were considered for the portfolio (Figure 2). 4 stocks were selected after excluding securities with limited data on price.

For the ETF screening, the Exchange Traded Funds function {ETF <GO>} was used (Figure 3). Similar to screening equities, ESG indicators and US exchanges were considered, narrowing down the candidates to 178 ETFs. 4 ETFs with the highest Annualized Total Return for the 5 Years were selected, excluding the ones without sufficient price data.

Ultimately, the 8 securities selected for the portfolio (4 equities and 4 ETFs) are listed in the following chart. For seamless report writing, the securities will be represented by their corresponding "Bloomberg Tickers" throughout the report, in which further strategies and performance measurements will be explored.

Security	Bloomberg Ticker	Asset Class
Enphase Energy Inc (U.S.)	ENPH US Equity	Equity
Celsius Holdings Inc (U.S.)	CELH US Equity	Equity
K92 Mining Inc (Canada)	KNT CN Equity	Equity
Xenon Pharmaceuticals Inc (U.S.)	XENE US Equity	Equity
First Trust NASDAQ Clean Edge Green Energy Index Fund (U.S.)	QCLN US Equity	ETF
iShares Global Clean Energy ETF (U.S.)	ICLN US Equity	ETF
VanEck Low Carbon Energy ETF (U.S.)	SMOG US Equity	ETF
Invesco WinderHill Clean Energy ETF (U.S.)	PBW US Equity	ETF

1.2 Strategy Selection

To a certain extent, all human beings are subject to cognitive bias, meaning that their perception of the world might deviate from norm and rationality. A direct reflection of cognitive bias can be seen in financial markets, where prices overreact due to confirmation bias, and underreact due to lack of perfect information or contrarian market participants. To capitalize on this psychological bias, this report has adopted a reversal strategy covering the

entire investment horizon. Using daily historical prices for each individual security, the strategy prompts the long-only portfolio to rebalance by entering a long position for the qualifying securities if their open price at time T + 1 is lower than open price at time T. Amongst the securities with long position, if their open price at time T + 1 is higher than open price at time T, their long positions will then be closed.

As mentioned by leading financial economist Lasse Heje Pedersen, statistical arbitrage traders frequently make bets on price reversals (Pederson, 2019). Simple reversal strategy involves buying stocks with the lowest returns over the past days and short those with the highest returns, while sophisticated strategies seek to estimate returns in light of security's characteristics. As an extension of what was taught in the lecture, this report aimed to explore the daily reversal strategy in portfolio management, and to evaluate its performance over time.

Other than reversal strategy, this report also explored a statistical approach for asset allocation. By adjusting the weights for all securities using R programming, monthly return of the portfolio will be maximized every month under the portfolio optimization strategy. For details, security transactions are recorded as well by computing the executed number of shares for every period.

In addition, the report has also adopted a moving average (MA) crossover strategy for comparison. Due to its simplicity in smoothing out market noise, the MA crossover rule has been one of the most popular trend-following strategies favored by practitioners. Previous studies exploring the MA strategy have also yielded convincing results, especially with long signals (Brock, 1992). To further explore this technical indicator, the report explored MA crossover strategy by using a five-day simple moving average (SMA) and fifty-day (SMA). If five-day SMA crosses above fifty-day SMA, long positions will be entered for all qualifying securities, whereas if five-day SMA goes below fifty SMA then all qualifying securities with previous long positions will be closed.

1.3 Data Collection

For the portfolio's 8 securities, the price data were extracted from Yahoo Finance, except for KNT. The price data here refers to the daily opening price for 5 years, from 24th November 2017 to 18th November 2017. Although KNT is listed in the United States, it is headquartered in Canada, meaning the prices are displayed in CND in Yahoo Finance for the security. For alignment with the rest of the securities, the USD price data of KNT was extracted from the Bloomberg Terminal.

Apart from the 8 securities, data on the treasury bill and benchmark index were collected as well. To be more specific, daily opening price data for 5 years on the 1-month treasury bill (DGS1MO), is provided by FRED (St. Louis Fed's economic database) and integrated into R. The relevant data will be used in terms of the risk-free rate for the performance measurement of strategies. Moreover, daily opening price data of MSCI World ESG Leaders Index (GSIN Index). GSIN was selected among the various ESG-tracking indices, as it provides more than 5 years of opening price data on the Bloomberg Terminal. This will be used for comparison with the performance of the strategies on the 8 securities.

2. Empirical Analysis

2.1 Reversal Strategy

2.1.1 Enter-exit Trading Rule

For reversal strategy, at each time period, we consider whether to enter a long position or exit a long position, instead of considering the balancing of the whole portfolio. An R function named reversal(st) is used to generate the portfolio given the daily open price of the 8 equities/ETFs:

a) reversal(st) takes st (an equity/ETF ticker) as the input. The function then reads the daily open price data of st. The transaction cost is set as 1%;
b) At the initial stage, \$125,000=\$1M/8 is assigned to 8 equities/ETFs as their initial budget. All trade on the single asset will be afforded within its own budget, instead of all capital of the portfolio;
c) The trading size of each trade is fixed for each stock (denoted as t.size). It equals to floor(\$125,000/highest price of the stock);

d) For day t, if the open price on day t+1 is lower than its open price, whether the cash is enough for an order of entering a long position will be considered. If the cash satisfies the requirement, then an order is executed at open price on day t+1 to enter a long position of t.size shares. Cash in hand is deducted by t.size * open price on day t+1 * (1+transaction cost). Number of shares owned is added by t.size;

e) For day t, if its open price is higher than the execution price of any previous enter orders, and the entered long positions have not been exited yet, the order with the earliest execution time will be exited at open price on day t (First-In-First-Out). Number of shares owned is deducted by t.size. Cash in hand is added by t.size * open price on day t * (1-transaction cost);

f) For day t, e) is considered before d) since it is expected to make more cash for potential enter orders on day t.

After looping all tickers into reversal(st), we combine all trade records to a single data frame called all.trade. A sample screenshot of all.trade is given below:

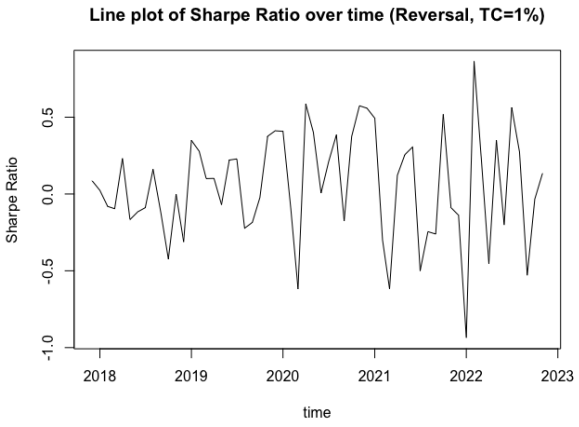
	stock	order.num	position	Date	open.price	execution.price	size	num.shares	cash	status
2	ENPH	1	Enter	2017-11-24	2.85	2.72	391	391	123925.8448	exited
3	ENPH	2	Exit	2017-11-28	2.72	3.01	-391	0	125090.9857	to.exit
4	ENPH	3	Enter	2017-11-29	3.1	2.89	391	391	123949.6958	exited
5	ENPH	4	Enter	2017-11-30	2.89	2.88	391	782	122812.355	exited
6	ENPH	5	Exit	2017-12-04	2.89	2.94	-391	391	123950.3996	to.exit
7	ENPH	6	Enter	2017-12-04	2.94	2.65	391	782	122903.8881	exited
8	ENPH	7	Exit	2017-12-06	2.65	2.73	-391	391	123960.6438	to.exit
9	ENPH	8	Enter	2017-12-06	2.73	2.72	391	782	122886.4886	exited
10	ENPH	9	Exit	2017-12-08	2.72	2.84	-391	391	123985.8242	to.exit
11	ENPH	10	Enter	2017-12-08	2.84	2.78	391	782	122887.9744	exited
12	ENPH	11	Enter	2017-12-11	2.78	2.71	391	1173	121817.7683	exited
13	ENPH	12	Enter	2017-12-12	2.71	2.7	391	1564	120751.5113	exited
14	ENPH	13	Enter	2017-12-13	2.7	2.68	391	1955	119693.1525	exited
15	ENPH	14	Exit	2017-12-15	2.68	2.7	-391	1564	120738.2955	to.exit
16	ENPH	15	Exit	2017-12-18	2.78	2.82	-391	1173	121829.8893	to.exit
17	ENPH	16	Enter	2017-12-18	2.82	2.56	391	1564	120818.9197	exited
18	ENPH	17	Enter	2017-12-19	2.56	2.47	391	1955	119843.492	exited
19	ENPH	18	Exit	2017-12-21	2.47	2.5	-391	1564	120811.217	to.exit
20	ENPH	19	Exit	2017-12-22	2.56	2.6	-391	1173	121817.651	to.exit
21	ENPH	20	Enter	2017-12-22	2.6	2.43	391	1564	120858.0197	exited

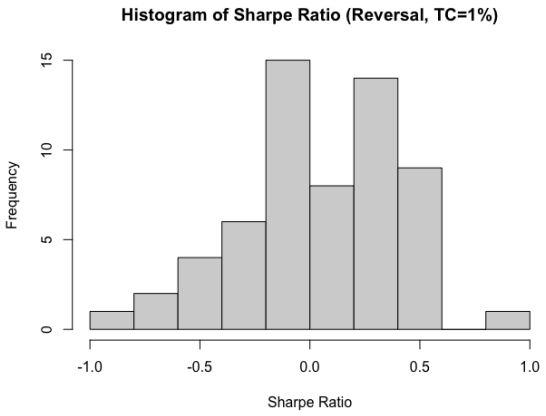
2.1.2 Performance Measurement

Transaction cost	Total value of the portfolio	Cumulative return	Mean of monthly excess return
1%	$1,335,542.7	33.55%	1.66%

The asset weight within the portfolio at the end of each month = (number of entered shares of the stock at the month end) * (asset price at the month end)/total value of the portfolio at month end. The weighted monthly expected return of the portfolio is sum of (weight of asset * monthly asset excess return). The mean of weighted monthly expected return is 1.66%.

Sharpe Ratio over time & Frequency of Sharpe Ratio





(a) Compare the cumulative return with the benchmark return

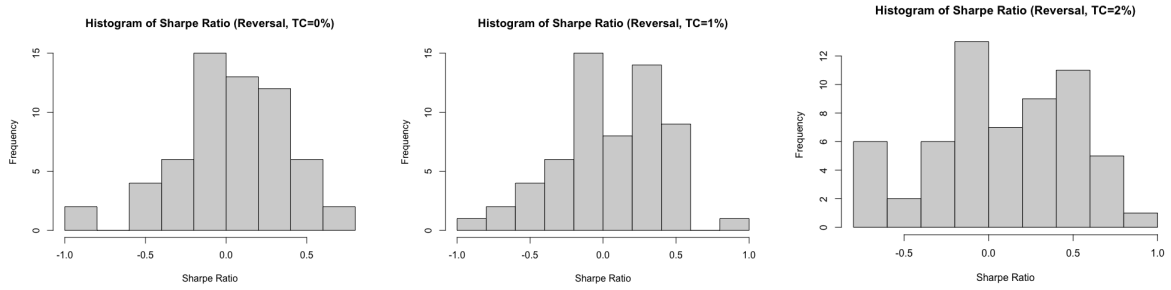
The total value of the portfolio at the end of the trading period is $1,335,542.7, which has a 33.55% 5-year cumulative return. The benchmark return is 30.75%. Therefore, the portfolio outperforms the benchmark.

(b) Compare the portfolio performance under different transaction costs

	Total transaction number	Mean of weighted monthly excess return	Total value of the portfolio	Cumulative return
No transaction cost	4749	1.192203%.	$3,177,830	217.783%

Transaction cost = 1%	3838	1.66%.	$1,335,542.7	33.55%
Transaction cost = 2%	3011	1.485537%	$715,235.8	-28.4764%

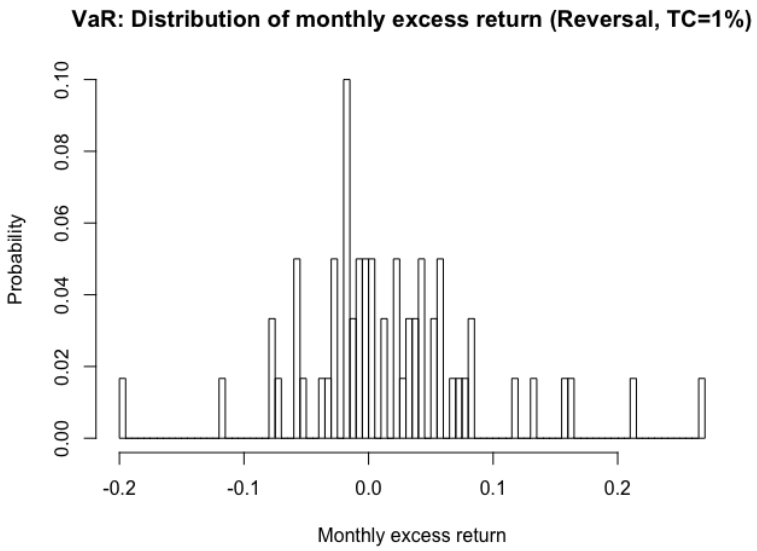
Total number of trade decreases when transaction cost increases, indicating that higher transaction cost leads to a lower trading frequency. With a lower transaction cost, the trade is more frequent. Higher transaction costs also cause a severe loss in total value of portfolio and cumulative return. Increase of 1% in transaction cost can lead to a huge decrease in cumulative return. When transaction cost = 0, the portfolio has a cumulative return of 217.783%. Meanwhile, when transaction cost = 2%, the portfolio suffers from a loss of -28.4764%.



The distribution of Sharpe Ratio changes with transaction cost. When transaction cost =0%, most of the Sharpe Ratio are in the range of [-0.2, 0.5]. Most of the monthly Sharpe Ratios are positive. When transaction cost =1%, most of the transaction costs are still in the range of [-0.2, 0.5]. However, there are less monthly Sharpe Ratio in the range of [0, 0.2]. When transaction cost = 2%, there are more monthly Sharpe Ratios falling into the negative range, especially the bin of lower boundary. There is a higher frequency for negative Sharpe Ratio.

2.1.3 Risk Management

Below is the plot of VaR for the strategy (transaction cost = 1%). There is a 95% possibility that the excess return will be higher than -10% in each month.



2.2 Portfolio Rebalancing

2.2.1 Rebalancing Rule

For portfolio rebalancing strategy, we look at a wide range of dynamic portfolio optimization issues with complicated models of return predictability, transaction costs, trading constraints, and risk concerns. In general, determining an ideal strategy is virtually always difficult. To optimize the portfolio, we suggest a convex optimization and provide an entirely statistical computing approach. An R package named CVXR is used to process the optimization model.

a) Rebalancing frequency is monthly-base starting from January 2018 to November 2022, generally we rebalance 59 times in total within 5 years.
b) Set the optimization problem (objective) is to rebalance the position to get the highest expected return based on month i-1.
c) Set the constraint: sum of weights <=0.9 to leave 10% cash in hand each time for liquidity requirements; weight for a single stock <=0.3 for diversify purpose; all weights >=0 means no short selling. We did not consider sharpe ratio into the problem since variance is not a convex function.
d) After solving the optimization problem, we can get optimal weights, optimal excess return and variance for each portfolio, which are stored in the table all.trade.
e) Assume the initial budget to start is 1,000,000 dollars with 10% cash. The budget for month i is 0.9*(initial budget * portfolio excess return for month i-1) + 0.1*1M.

f) Knowing the price of each stock at each rebalancing date, the shares needed to long for each stock equals budget /[price*(1+transaction cost)], which stored in the table opt.share (sample below)

g) Due to the feature of convex optimization, the final result could not be sharp positive integers. We consider small numbers around 0 (such as -1, -2) as 0.

h) If the prices for all the 8 stocks decrease during month i, the optimizer may decide not to long anything during this period and choose to liquidate all the assets, resulting in all 0s in the row (e.g., on 2018-12-03). When the price jumps back, the position will be adjusted accordingly.

Below is the formulation of the convex optimization problem:

For month t,

Decision Variables: $w_i, i = 1, 2, ..., 8$ (percentage weighting on each asset among total budget)

Objective Function:

Maximize weighted expected excess return: $\sum_{i=1}^{8} w_i * (return_i - r_f)$

subject to: $\sum_{i=1}^{8} w_i \leq 90\%$ (Always leave at least 10% cash in hand)

$w_i \leq 30\%$ (Invest at most 30% on a single asset for diversification)

$w_i \leq 0$ (Weight on each asset is always non-negative)

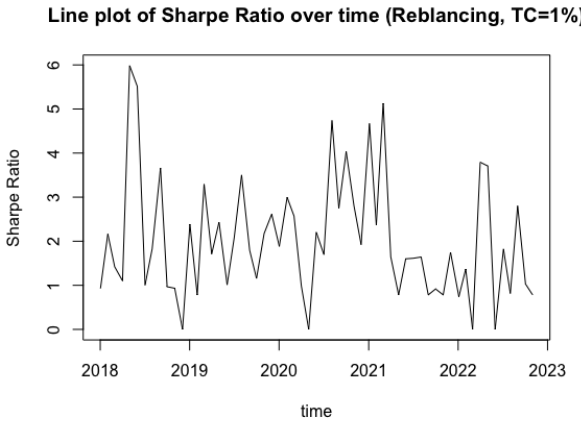
We solve the convex optimization problem at each month.The optimal solution is the vector of weighting on 8 assets that generates the highest weighted expected excess return at that month.

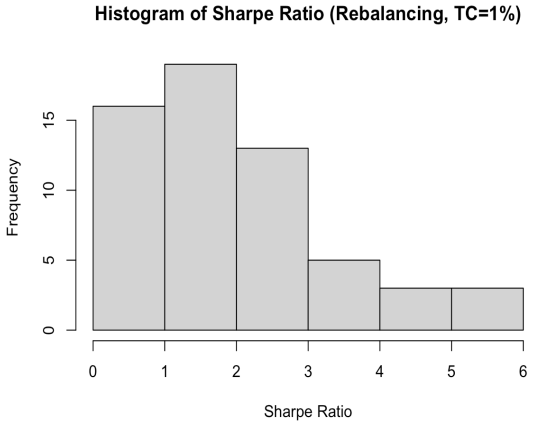
	ENPH	CELH	XENE	QCLN	ICLN	SMOG	PBW	KNT	Date
1	0	0	0	0	0	0	0	0	2018-01-02
2	0	83915	12968	-1	-1	-1	-2	47846	2018-02-01
3	0	73815	13882	29541	-1	0	0	-1	2018-03-01
4	67387	-1	15558	-1	-1	-1	-1	67386	2018-04-02
5	55155	0	15284	0	0	0	0	55155	2018-05-01
6	0	57683	16126	0	0	0	0	70543	2018-06-01
7	76418	0	0	40298	0	0	523419	0	2018-07-03
8	75150	0	16165	0	0	0	0	75150	2018-08-01
9	-1	0	15312	0	5201	12130	-1	0	2018-09-04
10	0	27563	18260	42531	0	0	-3	0	2018-10-01
11	70617	0	0	0	0	0	0	70617	2018-11-01
12	0	0	0	0	0	0	0	0	2018-12-03
13	85214	-1	0	-1	5367	13749	-1	0	2019-01-02
14	0	0	0	0	0	0	0	66149	2019-02-01
15	85765	0	14573	0	0	0	0	85765	2019-03-01

2.2.2 Performance Measurement

Transaction cost	Total value of the portfolio	Cumulative return	Mean of monthly excess return
1%	$4,004,148	300.41%	15.61%

Sharpe Ratio over time & Frequency of Sharpe Ratio





(a) Compare the cumulative return with the benchmark return

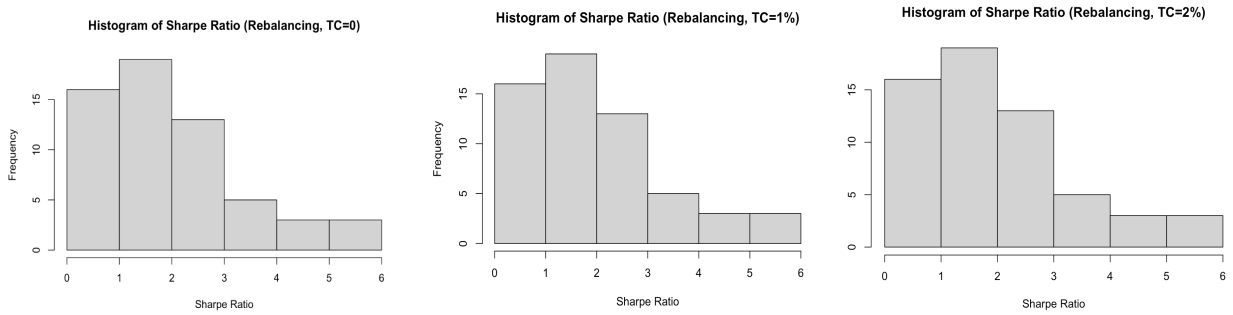
The total value of the portfolio at the end of the trading period is $4,004,148, which has a 300.41% 5-year cumulative return. The benchmark return is 30.75%. Therefore, the portfolio performs well above the benchmark.

(b) Compare the portfolio performance under different transaction costs

Transaction cost	Total transaction number	Mean of weighted monthly excess return	Total value of the portfolio	Cumulative return
0	60	15.61%	$4,044,145	304.41%
1%	60	15.61%	$4,004,148	300.41%
2%	60	15.61%	$3,964,880	296.49%

As we are implementing the purely statistical optimization model while only considering the optimal weight for each asset rather than other factors, the transaction number, monthly excess return and sharpe ratio look unchanged under different transaction costs. However, if we use our cash pool to pay the transaction cost, that is another story and the optimal weights should be affected.

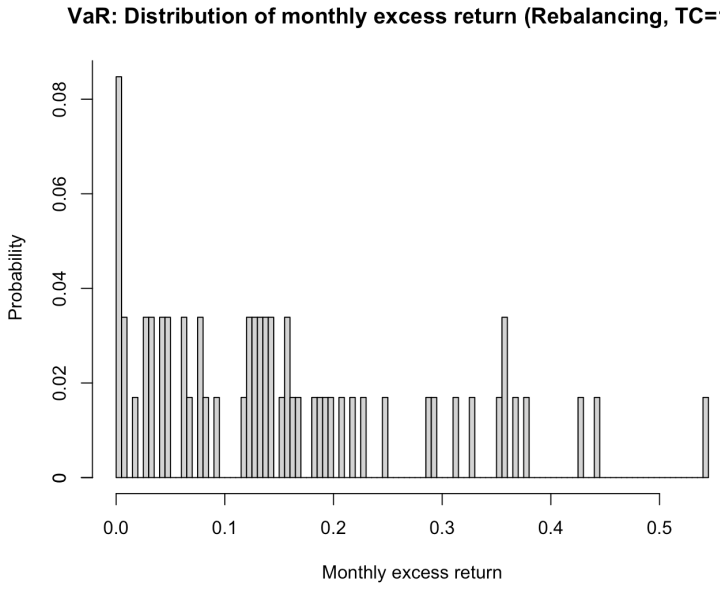
Monthly Sharpe Ratio over time:



Since we use a convex optimization model, the optimized return and variation are calculated automatically and the figures are fixed no matter what percentage the transaction cost is. The histograms for each scenario are exactly the same.

2.2.3 Risk Management

The VaR for the rebalancing strategy (transaction cost = 1%) is shown below. There is a 95% possibility that the excess return will be higher than 0% in each month.



2.3 Moving Average Strategy

2.3.1 Enter-exit Trading Rule

For each of the eight assets, we determined when to enter a new trade and when to exit the trade, rather than looking at the entire portfolio and defining how it is balanced. Therefore, broadly speaking, it is a kind of Enter-exit trading rule.

After using the same method to obtain the daily open price of the eight assets during the past five years, we first defined a function ind_SMA.trade() to simulate the simple moving average trading on the specified equity/ETF:

a) We used the SMA() function to calculate the 5-day and 50-day moving average of the daily open prices.
b) We assigned $125,000=$1M/8 to each equity/ETF so initial cash is $125000 and the initial number of shares we own is 0.
c) Execution price for this trade is the open price on the next trading day, and execution date is the next trading day.
d) If the 5-day moving average crosses above the 50-day moving average and we have free cash, we enter long and the trading size is calculated using floor(cash/(execution price*(1+transaction cost))), which means we buy as many shares of this asset as we can using the cash on hand.
e) If the 5-day moving average crosses below the 50-day moving average, we exit long and the trading size equals the total number of shares on hand because we sell all the shares.
f) For each trade, we recalculated the remaining cash on hand by subtracting or adding the trading size*execution price*(1+transaction cost), the number of shares on hand, and recorded the transaction with predefined variables, including trading date, order number, position , execution price, trading size, number of shares, and cash on hand.

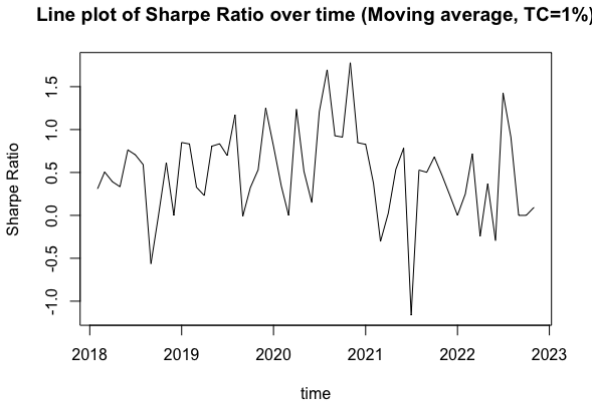
Next, we applied the ind_SMA.trade() function to record all trades for each asset and merged the trades on eight assets in the dataframe all.trade. A sample screenshot of all.trade is shown below.

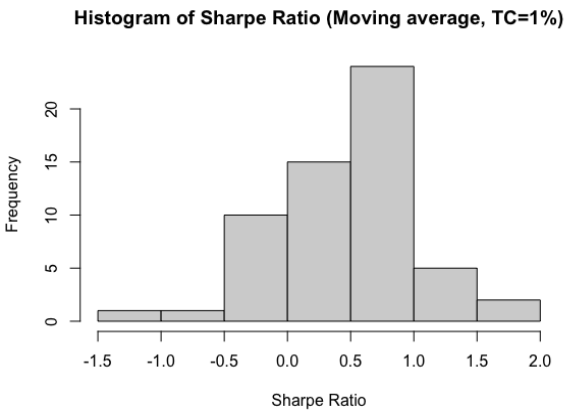
	Date	stock	order.num	position	execution.price	size	num.shares	cash
2	2018-02-14	ENPH	1	Enter	2.83	43732	43732	0.824399999997695
3	2018-07-31	ENPH	2	Exit	5.8	43732	0	251109.9684
4	2018-10-05	ENPH	3	Enter	4.64	53582	53582	3.28360000002431
5	2018-10-09	ENPH	4	Exit	4.63	53582	0	245607.097
6	2018-10-19	ENPH	5	Enter	4.88	49831	49831	0.064200000022538
7	2018-10-26	ENPH	6	Exit	4.3	49831	0	212130.6312
8	2018-11-06	ENPH	7	Enter	5.44	38608	38608	2.83599999998114
9	2018-12-27	ENPH	8	Exit	4.87	38608	0	186143.5864
10	2019-01-11	ENPH	9	Enter	5.6	32910	32910	4.62639999997918
11	2019-09-12	ENPH	10	Exit	25.129999	32910	0	818762.6108191
12	2019-12-04	ENPH	11	Enter	23.93	33876	33876	3.40401910012588
13	2020-03-17	ENPH	12	Exit	28.07	33876	0	941393.7308191
14	2020-04-30	ENPH	13	Enter	47.509998	19618	19618	22.07864746009
15	2020-06-19	ENPH	14	Exit	46.810001	19618	0	909157.49226928
16	2020-07-13	ENPH	15	Enter	56.25	16002	16002	43.8672692800174
17	2021-02-24	ENPH	16	Exit	170.660004	16002	0	2703636.2374372
18	2021-04-28	ENPH	17	Enter	150.360001	17803	17803	8.54865616885945
19	2021-05-03	ENPH	18	Exit	140.389999	17803	0	2474378.0693312
20	2021-06-16	ENPH	19	Enter	144.009995	17011	17011	126.504136748146
21	2021-08-20	ENPH	20	Exit	162.729996	17011	0	2740644.46647319

2.3.2 Performance Measurement

(Transaction cost = 1%)	Total value of the portfolio	Cumulative return	Mean of weighted monthly excess return
	$6,282,367	528.24%	10.35%

Sharpe Ratio over time & Frequency of Sharpe Ratio





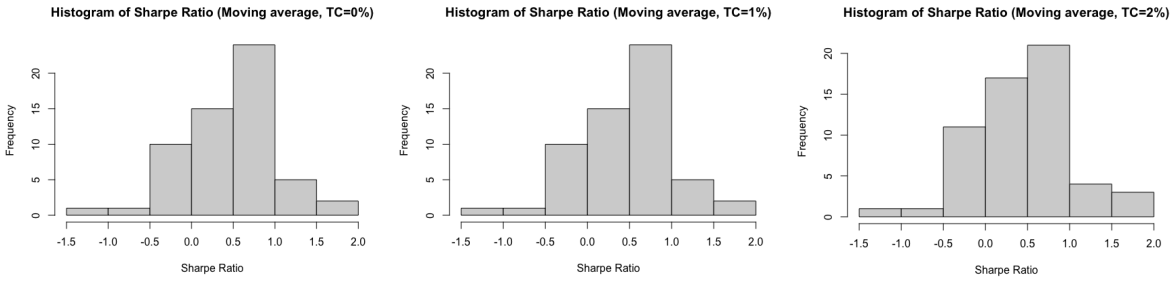
(a) Compare the cumulative return with the benchmark return

The total value of the portfolio at the end of the trading period is $6,282,367, which has a 528.24% 5-year cumulative return. The benchmark return is 30.75%. Therefore, the portfolio performs well above the benchmark.

(b) Compare the portfolio performance under different transaction costs

	Total transaction number	Mean of weighted monthly excess return	Total value of the portfolio	Cumulative return
No transaction cost	365	10.24%	$8,767,226	776.72%
Transaction cost = 1%	362	10.35%	$6,282,367	528.24%
Transaction cost = 2%	361	10.45%	$4,548,476	354.85%

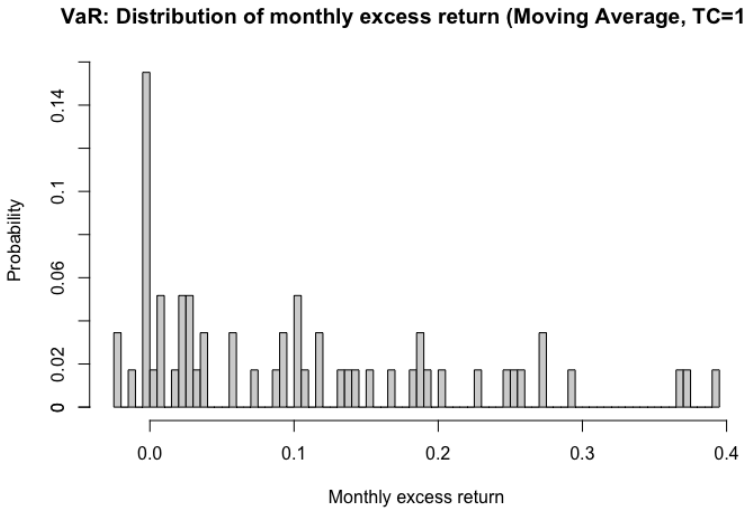
Monthly Sharpe Ratio over time:



The total transaction number, mean of weighted monthly excess return and histograms of Sharpe Ratio ratio are fairly similar under different transaction costs, which is partly because for the moving average strategy, we adjust the trading size for each transaction according to the transaction cost. For the total value of the portfolio and cumulative return, it is obvious that transaction cost has a huge impact on the trading outcome. The total portfolio value and cumulative return increase a lot when transaction cost decreases every 1%. The total value of the portfolio when there is no transaction cost ($8,767,226) is almost two times of the total value of the portfolio when the transaction cost is set to be 2% ($4,548,476); the cumulative return when there is no transaction cost (776.72%) is more than twice as much as the cumulative return when the transaction cost is set to be 2% (354.85%).

2.3.3 Risk Management

The VaR for the moving average strategy (transaction cost = 1%) is shown below. There is a 95% possibility that the excess return will be higher than 0% in each month.

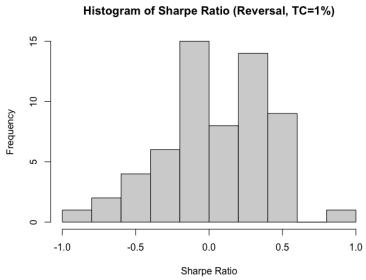


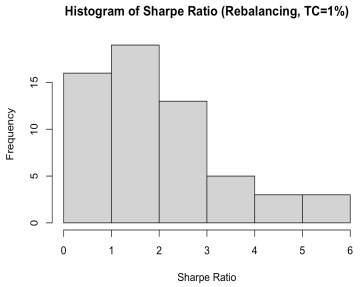
3. Conclusion and Discussion

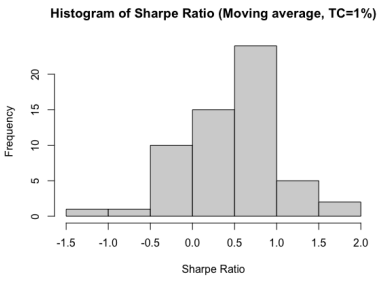
The results of the three strategies are as follows:

(Transaction cost = 1%)	Reversal Strategy	Portfolio Rebalancing	Moving Average Strategy
Mean of weighted monthly excess return	1.66%	15.61%	10.35%
Total value of the portfolio	$1,335,542.7	$4,004,148	$6,282,367
Cumulative return	33.55%	300.41%	528.24%

Monthly Sharpe Ratio over time:







Accordingly, it can be conceived from the results that the Moving Average Strategy has been the most profitable one for the ESG portfolio, among the three strategies. The reason for this could be because of its effectiveness for separating out random variations by smoothing price data and forming trend lines. Nevertheless, as moving averages with lengths of 10, 20, 50, 100, and 200 are common for the Moving Average Strategy, these lengths can be applied to any time frame depending on the trading time horizon. Therefore, the five-day and fifty-day may not be the "best" periods to generate the largest Sharpe Ratio, and thus there is still room for improvement in the portfolio performance.

Although the Reversal Strategy and the Portfolio Rebalancing Strategy have recorded a lower profit, the two strategies could have performed better if there were ways to overcome the limitations of the current portfolio. In terms of the Reversal Strategy, the trading size may be set to be flexible to allow more liquidity and fully exploit the profit opportunities. Also, compared to other strategies, the trading frequency is much higher, which incurs a significant transaction cost. Moreover, for the Portfolio Rebalancing, current trading frequency is much lower than other strategies and many other factors such as transaction cost could be included into convex optimization. The perceived results and limitations from backtesting will enable the strategies to be maximized for the ESG investment.

Appendix

Figure 1. Bloomberg Terminal - {Equity Screening <GO>}

Figure 2. Bloomberg Terminal - {Watchlist Analytics <GO>}

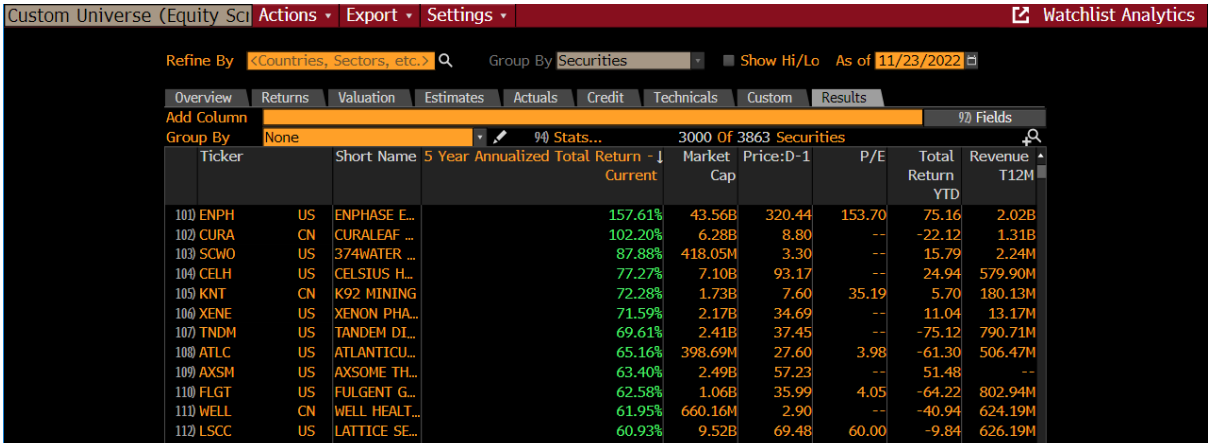


Figure 3. Bloomberg Terminal - {Exchange Traded Funds: New Search {GO}

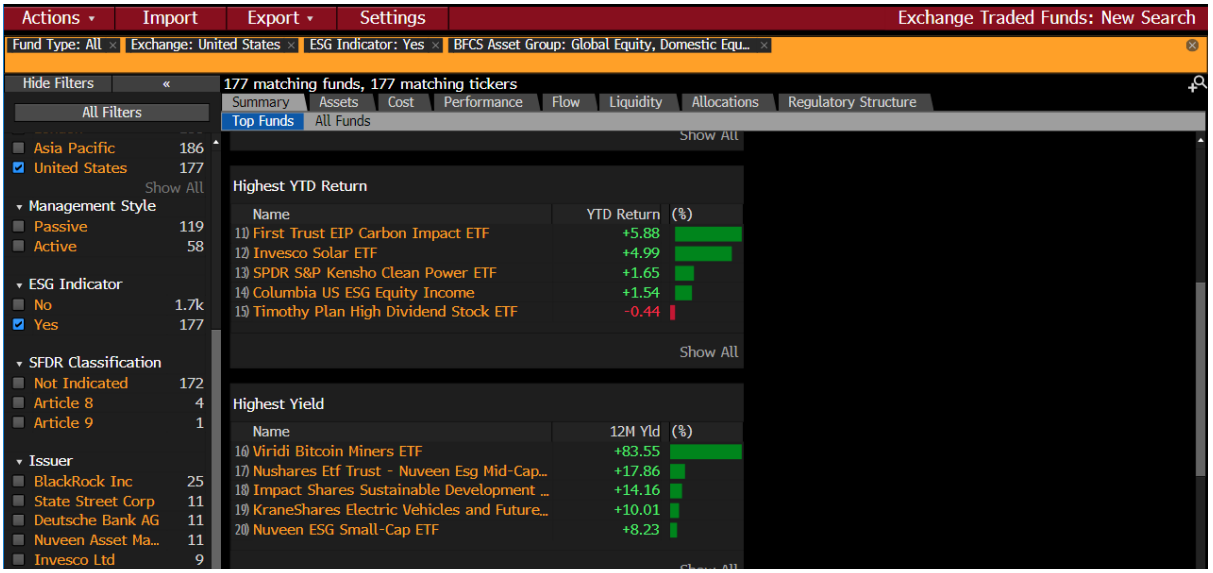


Figure 4. Bloomberg Terminal - {Exchange Traded Funds: New Search {GO}

References

BlackRock. (2022). *ETFs explained - advantages of etfs: Blackrock Hong Kong*. Retrieved December 12, 2022, from https://www.blackrock.com/hk/en/ishares/education/advantages-of-etfs

Bloomberg L.P. (2022, December 5). *November 2022: Global ESG Monthly.* Bloomberg Intelligence. Retrieved December 12, 2022, from Bloomberg Terminal.

Brock, W., Lakonishok, J., & LeBaron, B. (1992). Simple Technical Trading Rules and the Stochastic Properties of Stock Returns. *The Journal of Finance*, *47*(5), 1731–1764. https://doi.org/10.2307/2328994

Pedersen, L. H. (2019). *Efficiently inefficient: How smart money invests and market prices are determined*. Princeton University Press.

United Nations. (2022). *COP27: Delivering for people and the planet*. United Nations. Retrieved December 12, 2022, from https://www.un.org/en/climatechange/cop27