Phase 2 Documentation

Algo-trading Project

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I. Pre-Holiday Effect Strategy

The Pre-Holiday Effect strategy considers the calendar or specifically the holiday effect anomaly in the equities market. It would seem that there is a possibility for stock markets to rise on the days prior to a holiday. Market returns before holidays are often more than the average returns during normal trading days, by up to more than 10 times.

Fundamentally, it is sensible to comprehend that there are higher chances for market participants to have a feel good effect prior to a holiday, resulting in positive market movement. This positive sentiment could form a strategy for profitable trades.

Fundamental Reason

The basis for this strategy is behavioural. Perhaps short-sellers close their short positions prior to holidays (short sellers are vulnerable to higher losses, ie: unlimited downside as prices can go up on an unlimited basis, compared to going long where downside risk is deemed to be limited to the bought price of the security). On a behavioural basis, the feel good factor around holidays may perhaps result in optimism which corresponds to positive movements in prices.

Investigation on the impact of number of entry days prior to holiday

The SPDR S&P 500 exchange traded fund (ETF) was chosen for this strategy as it is the largest ETF in the world. The value of one share of the ETF is worth approximately 1/10 of the cash S&P 500's current level.

To understand what a good number of days would be to enter the transaction prior to a holiday, an investigation was done where different days were compared. For this investigation, a period of 1, 2, 3 and 4 days prior to the holiday was chosen. It was deemed that any period longer than that would dilute the impact of the pre-holiday factor with other influences coming into effect such as earning results, macro factors, technical indicators, etc.

Backtest Periods

Time Frame	Start Date	End Date
Frame 1	2016, 1, 1	2020, 12, 31
Frame 2	2011, 1, 1	2015, 12, 31
Frame 3	2006, 1, 1	2010, 12, 31
Frame 4	2001, 1, 1	2005, 12 ,31
11 years	2010, 1, 1	2020, 12 ,31

Observations and Results

The tables below summarise the results obtained using QuantConnect by varying the days prior to the holidays between one to four days:

Time Frame	Sharpe Ratio	Average Win	Average Loss	Win Rate	Compounding Annual Return	Drawdown	Net Profit	Alpha	Beta	Annual Std. Dev.
Frame 1	0.32	0.63%	-0.61%	67%	1.14%	4.60%	5.82%	0.011	-0.009	0.031
Frame 2	0.187	0.70%	-0.69%	58%	0.46%	3.10%	2.32%	0.004	0.002	0.021
Frame 3	0.282	1.13%	-1.08%	60%	1.19%	4.30%	6.07%	0.011	-0.008	0.037
Frame 4	0.993	1.26%	-0.64%	73%	3.88%	3.20%	20.97%	0.032	-0.001	0.033
Average	0.4455	0.93%	-0.76%	64.50%	1.66%	3.80%	8.79%	0.0145	-0.004	0.0305

Table 1: Pre-Holiday Effect - 1 day

Time Frame	Sharpe Ratio	Average Win	Average Loss	Win Rate	Compounding Annual Return	Drawdown	Net Profit	Alpha	Beta	Annual Std. Dev.
Frame 1	0.514	0.69%	-0.75%	66%	2.32%	6.00%	12.15%	0.021	-0.01	0.038
Frame 2	0.143	0.77%	-0.55%	47%	0.48%	5.00%	2.40%	0.004	0.002	0.031
Frame 3	0.27	1.30%	-0.99%	52%	1.88%	7.50%	9.75%	0.019	-0.037	0.065
Frame 4	0.583	1.15%	-1.03%	61%	3.25%	7.10%	17.33%	0.028	-0.007	0.048
Average	0.3775	0.98%	-0.83%	56.50%	1.98%	6.40%	10.41%	0.018	-0.013	0.0455

Table 2: Pre-Holiday Effect - 2 days [1]

Time Frame	Sharpe Ratio	Avg Win	Avg Loss	Win Rate	Compounding Annual Return	Drawdown	Net Profit	Alpha	Beta	Annual Std. Dev.
Frame 1	0.283	0.85%	-0.83%	56%	1.52%	11.70%	7.86%	0.015	-0.013	0.048
Frame 2	0.739	0.96%	-0.78%	65%	3.85%	4.70%	20.79%	0.034	-0.01	0.044
Frame 3	0.129	1.96%	-1.45%	46%	0.86%	11.60%	4.39%	0.012	-0.037	0.079
Frame 4	0.357	1.33%	-1.44%	60%	2.23%	13.70%	11.66%	0.02	-0.01	0.056
Average	0.377	1.28%	-1.13%	56.75%	2.12%	10.43%	11.18%	0.02025	-0.0175	0.0568

Table 3: Pre-Holiday Effect - 3 days

Time Frame	Sharpe Ratio	Avg Win	Avg Loss	Win Rate	Compounding Annual Return	Drawdown	Net Profit	Alpha	Beta	Annual Std. Dev.
Frame 1	0.218	0.98%	-1.42%	64%	1.30%	15.00%	6.66%	0.014	-0.01	0.056
Frame 2	0.695	1.17%	-1.00%	63%	4.04%	7.90%	21.89%	0.035	-0.008	0.049
Frame 3	0.068	1.75%	-1.32%	44%	0.26%	19.20%	1.31%	0.008	-0.036	0.088
Frame 4	0.192	1.65%	-1.77%	56%	1.22%	18.40%	6.24%	0.012	-0.002	0.062
Average	0.29325	1.39%	-1.38%	56.75%	1.70%	15.13%	9.03%	0.01725	-0.014	0.0638

Table 4: Pre-Holiday Effect - 4 days

[1] Detail of backtest result for 2 Days Pre-Holiday : Frame 1, Frame 2, Frame 3, Frame 4

It is observed that:

- Over the four periods investigated, on an overall average basis, all four scenarios of varying days showed a higher absolute magnitude of Average Win % compared to Average Loss %. Further, the Win Rate % is higher than the Loss Rate % across all four scenarios (ie: Average Win Rate > 50%, while Average Loss Rate < 50%).
- In terms of compounded annual returns, using a strategy of initiating the transaction 2 and 3 days prior to a holiday is superior compared to 1 and 4 days. Compounding annual returns ranged from 0.48% to 3.25% for 2 days and 0.86% to 3.85% for 3 days. Meanwhile, the simple average over the four distinct periods were at 1.98% and 2.12% respectively for 2 and 3 days, higher compared to 1.66% and 1.70% for 1 and 4 days respectively.
- In terms of drawdowns, initiating the transaction 1 and 2 days prior to a holiday is superior compared to 3 and 4 days. Drawdown ranged between 3.10% and 4.60% for 1 day and 5.00% and 7.50% for 2 days. Meanwhile, the simple average over the four distinct periods were at 3.80% and 6.40% respectively for 1 and 2 days, lower compared to 10.43% and 15.13% for 3 and 4 days respectively.
- In terms of measuring for risk, and using Annual Standard Deviation to represent this, it was found that initiating the transaction 1 and 2 days prior to a holiday is superior compared to 3 and 4 days. Annual Standard Deviation ranged between 2.1% and 3.7% for 1 day and 3.1% and 6.5% for 2 days. Meanwhile, the simple average over the four distinct periods were at 3.05% and 4.55% respectively for 1 and 2 days, lower compared to 5.68% and 6.38% for 3 and 4 days respectively.

Recommendation, Conclusion and Future Work

Based on the results that Average Win % is higher compared to Average Loss % and that the Win Rate % is higher than the Loss Rate % across all four scenarios, this affirms that the pre-holiday effect results in positive outcomes. Thus, is it viable for this strategy to be considered in the portfolio.

In terms of determining the number of entry days prior to holiday, using 2 days showed a better upper half result for both returns (ie: compounded annual returns) and risk (ie: lower Annual Standard Deviation and also Drawdowns). Thus, for this strategy of pre-holiday effect, 2 days prior to the holiday is chosen.

It is envisaged that the effect of the pre-holiday market would be applicable to other equity markets as well. This is a possible future work consideration to investigate its performance to other stock market indices starting with deep and liquid markets such as Japan, Germany, United Kingdom and Hong Kong.

References

Pre-Holiday Effect, from

https://quantpedia.com/strategies/pre-holiday-effect/

Fundamental reason, from

https://www.quantconnect.com/tutorials/strategy-library/pre-holiday-effect

SPDR S&P 500 Trust ETF, from

https://en.wikipedia.org/wiki/SPDR_S%26P_500_Trust_ETF

II. Fama French 5 Factors for Equity

Introduction & Method

The Fama French five-factor model[2], improved from the Fama French three-factor model, is one of the most classic models (Fama and French, 2015).

The Fama French five-factor model was proposed in 2014 and is adapted from the Fama French three-factor model (Fama and French, 2015). It builds upon the dividend discount model which states that the value of stocks today is dependent upon future dividends. Fama and French add two factors; investment and profitability, to the dividend discount model to better capture the relationship between risk and return. The model is as follows:

$R=\alpha+\beta_m MKT+\beta_s SMB+\beta_h HML+\beta_r RMW+\beta_c CMA$ R=α+βmMKT+βsSMB+βhHML+βrRMW+βcCMA

Where:

- MKT is the excess return of the market. It is the return on the value-weighted market portfolio.
- SMB is the return on a diversified portfolio of small-cap stocks minus the return on a diversified portfolio of big-cap stocks.
- HML is the difference between the returns on diversified portfolios of stocks with high and low Book-to-Market ratios.
- RMW is the difference between the returns on diversified portfolios of stocks with robust (high and steady) and weak (low) profitability.
- CMA is the difference between the returns on diversified portfolios of the stocks of low and high investment firms, which we call conservative and aggressive. Here, low/high investment means reinvestment ratio is low/high.

QuantConnect Strategy Thought Process[3]

1) List stocks which have fundamental data and share price above certain prices.
2) Rank the list of stocks based on the following fundamental data which has been weighted:
   a. Book Value
   b. Total Equity,
   c. Operating profit margin
   d. Return on total asset growth
   e. Total asset growth
3) Buy those stocks which are the highest rank while sell the stocks with the lowest rank based on the number of predetermined quantities for buy and sell.
4) Liquidate stocks which hit stop loss before the monthly rebalancing.
5) During monthly rebalancing:
   a. Liquidate those shares which hit the profit target of % of share price
   b. Liquidate those shares which are not in the buy/sell rank
   c. Buy or sell new stocks which are in the highest and lowest rank
   d. Keep holding existing stocks which are in the latest buy/sell rank that has yet to hit profit/loss

[2] Fama, E.F., & French, K.F. (2015). *A five-factor asset pricing model*. Journal of Financial Economics Volume 116, Issue 1, April 2015, Pages 1-22. https://www.sciencedirect.com/science/article/abs/pii/S0304405X14002323

[3] More information from QuantConnect's strategy library : Fama French Five Factors

Backtest Periods

Time Frame	Start Date	End Date
Frame 1	2016, 1, 1	2020, 12, 31
Frame 2	2011, 1, 1	2015, 12, 31
Frame 3	2006, 1, 1	2010, 12, 31
Frame 4	2001, 1, 1	2005, 12 ,31
11 years	2010, 1, 1	2020, 12 ,31

Optimization of Main Parameters

To avoid overfitting, only Frame 1 is used for optimization via individual parameter optimization and thereafter optimized all the selected parameters.

Parameters	Default	Individually Optimized	Optimized as a Whole
Data Normalization[4]	None (factoring splits and dividends)	Raw (No modifications to the asset price at all. Dividends are paid in cash; splits are applied directly to your portfolio quantity)	TotalReturn (Return of the investment adding the dividend sum to the initial asset price)
Coarse Selection	200 and share price > $5	>$20	>$25
Weight of Fundamental Data	BookValuePerShare – 1 TotalEquity – 1 OperationMargin – 1 ROE – 1 Total Asset Growth – 1	BookValuePerShare – 1 TotalEquity –1 OperationMargin – 1 ROE – 1 Total Asset Growth – 2	BookValuePerShare – 2 TotalEquity – 1 OperationMargin – 1 ROE – 1 Total Asset Growth – 2
Position	Buy – 5 Sell – 5 (100/10 = 10% total equity)	Buy – 4 Sell – 3 (100/7 = 14% of total equity per-trade)	Buy – 4 Sell – 2 (100/6 = 16% of total equity per-trade)
Stop Loss	10% (10*10% = 1, 1% risk per trade)	15% (14*15% = 2.1, 2.1% risk per trade)	16% (16*16% = 2.56% risk per trade)
Take Profit	None (profit is made when its not part of the monthly selection)	25%	25%

[4] More information on data normalization in QuantConnect

Results

A. Default Parameters

PSR	0.232%
Unrealized	-$3,880.37
Fees	-$1,252.15
Net Profit	-$7,719.92
Return	-12.85%
Equity	$87,152.57
Holdings	$48,258.06
Volume	$8,001,113.56
Capacity	$1.1M

B. Optimized Parameters

Time Frame	Sharpe Ratio	Avg Win	Avg Loss	Win Rate	Compounding Annual Return	Drawdown	Net Profit	Alpha	Beta	Annual Std. Dev.
Frame 1[5]	0.886	1.85%	-1.12%	48%	17.56%	19.30%	124.71%	0.167	-0.039	0.182
Frame 2[6]	0.467	1.40%	-1.16%	51%%	7.58%	25.90%	44.14%	0.08	-0.037	0.163
Frame 3[7]	0.581	1.55%	-1.08%	48%	9.26%	35.50%	55.74%	0.089	-0.033	0.152
Frame 4[8]	0.269	1.37%	-1.24%	50.00%	3.90%	39.90%	21.07%	0.049	0.047	0.185
11 years[9]	1.025	1.65%	-1.14%	53.00%	19.38%	28.70%	602.61%	0.176	-0.019	0.169

[5] Details of backtest result for Frame 1
[6] Details of backtest result for Frame 2
[7] Details of backtest result for Frame 3
[8] Details of backtest result for Frame 4
[9] Details of backtest result for 11 years

C. Comparison against SPY Results

Time Frame	Start Date	End Date	Fully Optimised Returns	SPY Benchmark
Frame 1	2016, 1, 1	2020, 12, 31	124.71%	99%
Frame 2	2011, 1, 1	2015, 12, 31	44.14%	74.2%
Frame 3	2006, 1, 1	2010, 12, 31	55.74%	10.26%
Frame 4	2001, 1, 1	2005, 12 ,31	21.07%	1.1%
11 years	2010, 1, 1	2020, 12 ,31	602.61%	271.99%

Conclusion

Based on all the results from the backtest, this strategy return is higher than SPY benchmark. Note of caution as this is based on the historical results which may not be representative of the future performance.

References for Individual Parameter Optimization

A. Data Normalization

* Using Raw (price as raw, dividends paid as cash and quantity adjusted on splits)

PSR	0.219%
Unrealized	-$3,881.12
Fees	-$1,247.12
Net Profit	-$6,123.20
Return	-13.27%
Equity	$86,725.14
Holdings	$48,279.52
Volume	$7,961,061.36
Capacity	$1.1M

B. Coarse Selection – optimal results is using share price > $20

* Using top 200 which has the following share prices

Share Price	Returns
$10 (default)	-7.25%
$15	1.23%
$20	***12.23%***
$25	9.34%

C. 5 Factor Weightage – optimal results is using scenario 5

Fundamentals	Return	BookValue	TotalEquity	OpMargin	ROE	TAgrowth
Default	-12.85%	1	1	1	1	1
Scenario 1	-19.10%	2	1	1	1	1
Scenario 2	-18.77%	1	2	1	1	1
Scenario 3	-17.60%	1	1	2	1	1
Scenario 4	-25.89%	1	1	1	2	1
Scenario 5	***-0.31%***	***1***	***1***	***1***	***1***	***2***

Scenario 6	-3.43%	1	1	2	1	2
Scenario 7	-21.87%	2	1	2	1	1

D. Positioning – optimal results is using scenario 3

No. of Holdings	Buy	Sell	Return
Default	5	5	-12.85%
Scenario 1	6	4	-15.50%
Scenario 2	5	4	-21.41%
Scenario 3	***4***	***3***	***-15.28%***
Scenario 4	4	4	-25.78%

E. Stop Loss – optimal results is using 15%

Stop Loss	Return
Default – 10%	-12.85%
5%	-11.34%
8%	4.64%
12%	-2.62%
14%	6.8%
15%	***7.24%***
20%	-9.96%

F. Take Profit – optimal results is using 25%

Take Profit	Return
Default – none	-12.85%
15%	-12.85%
20%	-12.85%
25%	***-12.82%***
30%	-12.85%
23%	-12.85%

III. MPT ETF Allocation Strategy (SPY, QQQ, TLT, GLD)

Introduction & Methodology

This is a Classical Asset Allocation (CAA) with mean-variance optimization (MVO) obtained from QuantConnect[10]. It is based on the work of Keller et al. (2015) in Momentum and Markowitz: A Golden Combination[11].

Using broad range of asset compositions as proposed by Keller and Butler (2014)[12] with a short lookback period (maximum of 12 months), compute the optimal allocation on the Efficient Frontier (EF) with a given target volatility (TV) of 10% for offensive model and 5% for defensive model. We imposed limits (max weights) on all risky assets to enforce greater ex-post diversification. E.g. with a universal cap of 25% or 50% for all assets, the portfolio should contain at least resp. four or two assets (i.e. with non-zero weights). No short-sale constraint (long-only) positions and portfolio is rebalanced on a monthly basis.

QuantConnect Strategy Thought Process

1) List ETFs by type and highest capitalization (to ensure liquidity and have diversification)
2) Each month we estimate the optimal mix of asset weights based on the prior 252 trading days (computed based on optimization of either returns given target volatility or Sharpe Ratio) and use that mix for next month (monthly rebalancing). To enforce greater diversification, we impose limits with maximum weights of 25% for each security.
3) As this is a long hold strategy with monthly rebalancing, stop loss and take profit are not required.

Backtest Periods

Time Frame	Start Date	End Date
Frame 1	2016, 1, 1	2020, 12, 31
Frame 2	2011, 1, 1	2015, 12, 31
Frame 3	2006, 1, 1	2010, 12, 31
Frame 4	2001, 1, 1	2005, 12 ,31
11 years	2010, 1, 1	2020, 12 ,31

[10] More details on the Classical Asset Allocation strategy

[11] Keller, W.J., Butler, A., and Kipnis, I. (2015). *Momentum and Markowitz: A Golden Combination.* Available at SSRN: https://ssrn.com/abstract=2606884 or http://dx.doi.org/10.2139/ssrn.2606884

[12] Keller, W.J., and Butler, A. (2014). *A Century of Generalized Momentum; From Flexible Asset Allocations (FAA) to Elastic Asset Allocation (EAA).* Available at SSRN: https://ssrn.com/abstract=2543979 or http://dx.doi.org/10.2139/ssrn.2543979

Optimization of Main Parameters

Backtest for individual parameter optimization is only done on Frame 1 to avoid overfitting of strategy. It is thereafter optimized for all time frames with the selected parameters. No changes are made to the rolling period and to the security limit to ensure consistency with the model and diversification.

Parameters	Default	Individually Optimized	Optimized as a Whole
Data Normalization[13]	None (factoring splits and dividends)	TotalReturn (Return of the investment adding the dividend sum to the initial asset price)	TotalReturn (Return of the investment adding the dividend sum to the initial asset price)
ETF Universe	8 selected securities	Those + SPY with > % returns	4 securities including SPY
Rolling Period	252	252	252
Volatility	5%	5%	5%
Security Cap	25%	25%	25%
Stop Loss	None	None	None

Results

A. Default Parameters

PSR	23.997%
Unrealized	$20,692.65
Fees	-$228.67
Net Profit	$54,205.01
Return	74.68%
Equity	$174,681.11
Holdings	$174,403.83
Volume	$2,075,929.16
Capacity	$69K

B. Optimized Parameters

Time Frame	Sharpe Ratio	Avg Win	Avg Loss	Win Rate	Compounding Annual Return	Drawdown	Net Profit	Alpha	Beta	Annual Std. Dev.
Frame 1[14]	1.345	1.82%	0.00%	98%	22.75%	27.70%	179.02%	0.213	-0.118	0.146
Frame 2[15]	0.707	1.24%	-0.47%	70%	8.88%	11.20%	53.08%	0.084	-0.38	0.112
Frame 3[16]	0.216	1.48%	-7.52%	84%	2.76%%	50.00%	14.59%	0.046	-0.067	0.2
Frame 4[17]	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA

[13] More information on data normalization in QuantConnect

[14] Details of backtest result for Frame 1

[15] Details of backtest result for Frame 2

[16] Details of backtest result for Frame 3

[17] Backtest result for Frame 4 returns error and not possible for GLD and TLT as both instruments are only available in 2004/2005.

11 years[18]	1.208	1.85%	-0.63%	74.00%	17.77%	28.00%	505.19%	0.163	-0.092	0.127

C. Comparison against SPY Results

Time Frame	Start Date	End Date	Fully Optimised Returns	SPY Benchmark
Frame 1	2016, 1, 1	2020, 12, 31	179.02%	99%
Frame 2	2011, 1, 1	2015, 12, 31	53%	74.20%
Frame 3	2006, 1, 1	2010, 12, 31	15%	10.26%
Frame 4	2001, 1, 1	2005, 12 ,31	NA	1.10%
11 years	2010, 1, 1	2020, 12 ,31	505.19%	271.99%

Conclusion

Based on the overall optimized backtest results, this strategy outperforms SPY on Frame 1, 3 and 11 years but underperforms against SPY in Frame 2. Since there is a limit on the holdings with max of 25% per security at only 5% volatility, both returns and risks have been capped.

Note of caution that this is based on historical results and may not be representative of future performances.

References for Individual Parameter Optimization

A. Data Normalization

* Using Raw (price as raw, dividends paid as cash and quantity adjusted on splits)

PSR	26.968%
Unrealized	$18,925.98
Fees	-$229.10
Net Profit	$56,943.23
Return	75.65%
Equity	$175,652.92
Holdings	$216,972.21
Volume	$2,487,355.63
Capacity	$4.5K

B. ETF Universe

* Building a portfolio of SPY and combination of other ETFs based on the market capitalization and the compounding annual returns of Time Frame 1 for each ETFs

❖ Equity ETF – Selecting ETFs with compounding annual returns above 130%

Symbol	ETF Name	Index	Inception Date (M/D/YYYY)	Market Cap ($)	Returns / SPY (%)
SPY	***SPDR S&P 500 ETF***	***S&P 500 Index***	***01/22/1993***	***361,860,096,000***	***99***
IVV	iShares Core S&P 500 Index Fund	S&P 500 Index	05/15/2000	279,363,590,000	103.75

[18] Details for backtest result for 11 years

	ETF				
VTI	***Vanguard Total Stock Market ETF***	***CRSP US Total Market Index***	***05/24/2001***	***236,066,197,032***	***139.96***
VOO	Vanguard S&P 500 ETF	S&P 500 Index	09/07/2010	217,653,670,032	125.95
QQQ	***Invesco QQQ ETF***	***NASDAQ-100 Index***	***03/10/1999***	***161,001,391,000***	***131.27***
MLPY	Morgan Stanley Cushing MLP High Income Index ETN	Cushing MLP High Income Index	03/16/2011	154,244,599,680	-1.4
VEA	Vanguard FTSE Developed Markets ETF	FTSE Developed All Cap ex US Index	07/20/2007	97,192,786,058	50.79
IEFA	iShares Core MSCI EAFE ETF	MSCI EAFE Investable Market Index	10/18/2012	92,340,072,000	47.95
VWO	Vanguard FTSE Emerging Markets ETF	FTSE Emerging Markets All Cap China A Inclusion Index	03/04/2005	80,206,883,520	105.34
IEMG	iShares Core MSCI Emerging Markets ETF	MSCI Emerging Markets Investable Market Index	10/18/2012	80,056,716,000	86.49
VTV	Vanguard Value ETF	CRSP US Large Cap Value Index	01/26/2004	76,075,924,580	61.29
VUG	Vanguard Growth ETF	CRSP US Large Cap Growth Index	01/26/2004	73,569,994,501	100.23
IJR	iShares Core S&P Small-Cap ETF	S&P Smallcap 600 Index	05/22/2000	69,924,645,000	105.19
IWM	iShares Russell 2000 ETF	Russell 2000 Index	05/22/2000	68,339,376,000	105.26
IWF	iShares Russell 1000 Growth ETF	Russell 1000 Growth Index	05/22/2000	66,992,964,000	105.09
IJH	iShares Core S&P Mid-Cap ETF	S&P MidCap 400 Index	05/22/2000	65,025,811,500	85.16
VIG	Vanguard Dividend Appreciation ETF	NASDAQ US Dividend Achievers Select Index	04/21/2006	58,502,232,973	119.13
ITOT	iShares Core S&P Total U.S. Stock Market ETF	S&P Total Market Index	01/20/2004	38,613,020,000	104.45
USMV	***iShares MSCI USA Minimum Volatility ETF***	***MSCI USA Minimum Volatility (USD) Index***	***10/18/2011***	***28,941,522,000***	***132.84***
IXUS	iShares Core MSCI Total International Stock ETF	MSCI ACWI ex USA IMI Index	10/18/2012	28,223,604,000	55.54
SDY	SPDR S&P Dividend ETF	S&P High Yield Dividend Aristocrats Index	11/8/2005	21,104,978,000	82.85
SCHP	Schwab U.S. TIPS ETF	Bloomberg Barclays U.S. Treasury Inflation Protected Securities (TIPS) Index	08/05/2010	17,215,016,000	103.11

- Bond ETF - Selecting ETFs with compounding annual returns above 130%

Symbol	ETF Name	Index	Inception Date (M/D/YYYY)	Market Cap ($)	Returns / SPY (%)
AGG	iShares Core U.S. Aggregate Bond ETF	Bloomberg Barclays US Aggregate Bond Index	09/22/2003	86,879,205,000	111.01
BND	Vanguard Total Bond Market ETF	Bloomberg Barclays U.S. Aggregate Float Adjusted Index	4/3/2007	71,459,839,983	108.17
VCIT	Vanguard Intermediate-Term	Bloomberg Barclays U.S. 5-10 Year	11/19/2009	43,034,655,694	99.57

	Corporate Bond ETF	Corporate Bond Index			
LQD	***iShares iBoxx $ Investment Grade Corporate Bond ETF***	***Markit iBoxx $ Liquid Investment Grade Index***	***07/22/2002***	***41,239,303,000***	***130.17***
BNDX	Vanguard Total International Bond ETF	Bloomberg Barclays Global Aggregate ex-USD Float Adjusted RIC Capped Index Hedged	05/31/2013	39,770,642,029	92.88
VCSH	Vanguard Short-Term Corporate Bond ETF	Bloomberg Barclays U.S. 1-5 Year Corporate Bond Index	11/19/2009	38,059,861,688	92.71
VYM	Vanguard High Dividend Yield ETF	FTSE High Dividend Yield Index	11/10/2006	36,742,440,963	52.98
BSV	Vanguard Short-Term Bond ETF	Barclays Capital U.S. 1-5 Year Government/Credit Float Adjusted Index	4/3/2007	32,071,877,483	110.92
TIP	iShares TIPS Bond Fund ETF	Barclays U.S. Treasury Inflation Protected Securities (TIPS) Index (Series-L)	12/04/2003	26,993,591,000	124.19
MBB	iShares MBS Bonds ETF	Bloomberg Barclays US Mortgage Backed Securities Index	03/13/2007	25,781,268,000	82.1
IGSB	iShares Short-Term Corporate Bond ETF	ICE BofAML 1-5 Year US Corporate Index	1/5/2007	25,333,672,000	93.12
HYG	iShares iBoxx High Yield Corporate Bond ETF	Markit iBoxx $ Liquid High Yield Index	4/4/2007	21,542,178,000	80.12
SHY	Barclays 1-3 Year Treasury Bond ETF	ICE U.S. Treasury 1-3 Year Index	07/22/2002	19,468,882,000	92.29
SHV	iShares Short Treasury Bond ETF	ICE U.S. Treasury Short Bond Index	1/5/2007	14,940,952,000	64.06
IEF	Ishares 7-10 Year Treasury Bond ETF	ICE U.S. Treasury 7-10 Year Index	07/22/2002	13,784,488,000	113.28
TLT	***iShares 20+ Year Treasury Bond ETF***	***ICE U.S. Treasury 20+ Year Index***	***07/22/2002***	***12,259,020,000***	***131.87***

❖ Commodity ETFs - Selecting ETFs with compounding annual returns above 100%

Symbol	**ETF Name**	**Index**	**Inception Date (M/D/YYYY)**	**Market Cap ($)**	**Returns / SPY (%)**
GLD	***SPDR Gold Shares ETF***	***NA - Physically owns a precious metal***	***11/18/2004***	***58,565,690,000***	***124.93***
IAU	***iShares COMEX Gold Trust ETF***	***NA - Physically owns a precious metal***	***01/21/2005***	***28,556,403,000***	***119.86***
SLV	iShares Silver Trust ETF	NA - Physically owns a precious metal	04/21/2006	15,259,296,000	90.7

❖ Portfolio Mix (Default Volatility at 5%).

It is noted that portfolios with *more* than 2 asset classes of ETFs (Equity, Bonds and/or Commodity) tend to give higher returns compared to portfolios with only 2 asset classes of ETFs. The top three portfolios with highest returns are further tested against different volatility levels.

Portfolio Mix	Equity ETFs	Bond ETFs	Commodity ETFs	Returns
Original	SPY, EFA, EEM, JPXN, VGT	TLT, IEF	-	75.65%
1	SPY, VTI, QQQ, USMV	LQD, TLT,	GLD, IAU	136.57%
2	***SPY, VTI, QQQ***	***LQD,TLT***	***GLD, IAU***	***206.90%***
3	SPY, VTI, USMV, QQQ	LQD, TLT	-	112.67%
4	SPY, QQQ	LQD, TLT	GLD	145.33%
5	SPY, QQQ	LQD	GLD, IAU	129.11%
6	SPY, VTI	TLT	GLD	134.61%
7	SPY, USMV	TLT	GLD	92.98%
8	***SPY, QQQ***	***TLT***	***GLD***	***179.02%***
9	***SPY, QQQ***	***LQD***	***GLD***	***177.81%***
10	SPY, QQQ	TLT	IAU	137.47%

❖ Volatility Level

It is noted that higher volatility does not result in higher return. Based on the selected portfolio mixes, the top 3 highest returns are from the ones with the lowest volatility (5%).

Portfolio Mix	Equity ETFs	Bond ETFs	Commodity ETFs	Returns for 5% volatility	Returns for 7% volatility	Returns for 10% volatility	Returns for 15% volatility
2	SPY, VTI, QQQ	LQD, TLT	GLD, IAU	***206.90%***	122.53%	154.36%	188.23%
8	SPY, QQQ	TLT	GLD	***179.02%***	139.84%	165.46%	176.20%
9	SPY, QQQ	LQD	GLD	***177.81%***	160.86%	159.09%	144.35%

❖ Comparison at Multiple Time Frames (Default Volatility at 5%).

It is noted that portfolio mix 8 is the most suitable over the long term with 505% return.

Time Frame	Portfolio Mix 2 Returns[19]	Portfolio Mix 8 Returns[20]	Portfolio Mix 9 Returns[21]
Frame 1	206.9%	***179.02%***	177.81%
Frame 2	13.36%	***53.08%***	50.88%
Frame 3	21.74%	***14.59%***	19.61%
Frame 4	NA	***NA***	NA
11 years	330.07%	505.19%	435.19%

[19] Details for backtest result for Portfolio Mix 2 - Frame 1, Frame 2, Frame 3, Frame 11 years
[20] Details for backtest result for Portfolio Mix 8 - Frame 1, Frame 2, Frame 3, Frame 11 years
[21] Details for backtest result for Portfolio Mix 9 - Frame 1, Frame 2, Frame 3, Frame 11 years

IV. Carry Trade Strategy with Currencies (Forex)

Introduction

Carry trade is a common strategy in forex which aims to sell low-interest rate currencies and buy into high-interest rate currencies rather. It seeks to capture the spread between the currency rates. It is as if you borrow money from a country with a low interest rate, in order to invest in another country that offers a higher interest rate.

Concept

Nine currency pairs (available on Quandl) are selected and the custom data are imported using AddData(type, symbol, resolution, timeZone, fillDataForward).

```
from QuantConnect.Python import PythonQuandl
class QuandlRate(PythonQuandl):
    def __init__(self):
    self.ValueColumnName = 'Value'
```

The nine currency pairs are as follow:

- USD/EUR
- USD/ZAR
- USD/AUD
- USD/JPY
- USD/TRY
- USD/INR
- USD/CNY
- USD/MXN
- USD/CAD

The forex symbols are then sorted by the value of interest rate. The algorithm goes *long* on currency pairs with *high interest rate* and *short* on currency pairs with *low interest rate.* This strategy is rebalanced on a monthly basis.

Backtest Periods

Time Frame	Start Date	End Date
Frame 1	2016, 1, 1	2020, 12, 31
Frame 2	2011, 1, 1	2015, 12, 31
Frame 3	2006, 1, 1	2010, 12, 31
Frame 4	2001, 1, 1	2005, 12 ,31

Results and Observations

The backtest results reflected promising win rates for the majority of the four time frames, even with one financial crisis that occured in one of the years.

Time Frame	Sharpe Ratio	Avg Win	Avg Loss	Win Rate	Compounding Annual Return	Drawdown	Net Profit	Alpha	Beta	Annual Std. Dev.
Frame 1[22]	0.908	0.12%	-0.01%	84%	7.27%	8.90%	42.08%	-0.052	-0.005	0.057
Frame 2[23]	0.234	-0.09%	-0.08%	52%	1.68%	14.60%	8.53%	0.013	0.006	0.056
Frame 3[24]	0.206	0.13%	-0.10%	69%	2.12%	12.30%	11.09%	0.019	-0.011	0.092
Frame 4[25]	0.111	0.05%	0.00%	100.00%	0.47%	9.10%	2.37%	0.004	0.002	0.035

Key observations with regards to the performance of the strategy:

➢ In Frame 1, the win rate has improved tremendously from previous 5 years hitting 84% of total 117 trades put through. The average loss is very minimal at 0.01% negative while the win rate has increased to 12% from previous.

➢ In Frame 2, the win rate is lower but above the 50% cut off percentage. The average win is still higher than the average loss.

➢ In Frame 3, the average win is still higher than the average loss, and with an above average win rate of 69% in total 105 trades is good by standards.

➢ In Frame 4, there is a 100% win rate reflected in all the 44 trades in that time frame. Although the average win is minimal, the effectiveness is 100%.

Conclusion

The returns of this carry trade strategy has been consistently good over the years. It is believed that there is a low correlation between the returns of a carry trade strategy with forex and the returns of traditional asset classes such as equities and bonds. In the modern portfolio theory, a carry trade strategy is a proven profitable way of diversifying a portfolio. However, investors must pay attention to the correlation of the carry trade strategy with the global financial environment and the exchange rate stability.

[22] Details of backtest result for Frame 1
[23] Details of backtest result for Frame 2
[24] Details of backtest result for Frame 3
[25] Details of backtest result for Frame 4

V. Asset Class Momentum with ETFs Strategy

Introduction and Methodology

The strategy is adapted from Mebane Faber's work[26]. It is based on a rotational momentum system that compares the performance of different asset classes and picks only the best-performing assets from the investment universe into the portfolio. It finds its entry points using the momentum effect[27].

The investment universe consists of 15 ETFs from 5 different asset classes. The invested portfolio consists of n ETFs that have the strongest n-month momentum. Momentum is defined as the rate of change in price movements on a daily basis and measured using the momentum indicator MOM(symbol, period) from QuantConnect's LEAN. Each ETF is weighted equally with the portfolio being held for one month period and then rebalanced every month.

The strategy is backtested for the below parameters.

1) **Momentum Period**
   This initial strategy looks back on the 12-month momentum to determine an entry. With the rise of technology in recent years, trading has become easily accessible with even lower brokerage fees. News and information that influences the market movement are easily disseminated with speed compared to years back. Hence, the strategy will be tested on shorter lookback periods of 3-month momentum and 6-month momentum to explore the possibility or effect of capturing an impending momentum earlier.
2) **Portfolio Allocation**
   This initial strategy constructs a portfolio of only 3 ETFs. To explore the benefit of diversifying with lesser weightage in each ETFs, the strategy will be subsequently tested on a portfolio allocation with more ETFs (i.e., 5 ETFs) after establishing the optimum momentum period.

Identifying Asset Classes

- Equities
- Bonds
- REITS
- Foreign Stocks
- Commodities

Deciding on Representative ETFs

The below 15 ETFs are chosen based on the market capitalization of the ETFs.

- Equities (US S&P 500) : SPY, VOO, IVV
- Bonds (Total Bond Market): AGG, BND, BNDX
- REITS : VNQ (North America), VNQI (Global excluding US), REET (Global)
- Foreign Stocks (Foreign Large Cap) : VEA IEFA EFA
- Commodities (Broad Diversified) : DBC, PDBC, GSG

[26] Faber, M. (2007). *A Quantitative Approach to Tactical Asset Allocation.* The Journal of Wealth Management, Spring 2007. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=962461
[27] More information on Asset Class Momentum strategy in Quantpedia and QuantConnect

Backtest Periods

Time Frame	Start Date	End Date
Frame 1	2016, 1, 1	2020, 12, 31
Frame 2	2011, 1, 1	2015, 12, 31
Frame 3	2006, 1, 1	2010, 12, 31
Frame 4	2001, 1, 1	2005, 12 ,31
20 years	2001, 1, 1	2020, 12 ,31

Results

A. Momentum Period Parameter (Based on portfolio of 3 ETFs)

Time Frame	Sharpe Ratio	Avg Win	Avg Loss	Win Rate	Compounding Annual Return	Drawdown	Alpha	Beta	Annual Std. Dev.	Compounding Annual Return (SPY Benchmark)
Frame 1	0.583	2.52%	-2.29%	62%	12.60%	43.3%	0.162	-0.222	0.225	14.74%
Frame 2	0.715	5.94%	-1.87%	71%	11.54%	20.2%	0.111	-0.046	0.148	11.74%
Frame 3	0.159	4.61%	-8.19%	58%	1.31%	52.7%	0.034	-0.032	0.209	1.97%
Frame 4	0.991	47.08%	-1.73%	25%	12.47%	12.2%	0.108	-0.009	0.109	0.22%
20 years	0.534	6.94%	-3.38%	63%	10.00%	52.5%	0.108	-0.081	0.190	N/A

Table 1: Portfolio of 3 ETFs for 12-month momentum period - Default [28]

Time Frame	Sharpe Ratio	Avg Win	Avg Loss	Win Rate	Compounding Annual Return	Drawdown	Alpha	Beta	Annual Std. Dev.	Compounding Annual Return (SPY Benchmark)
Frame 1	0.667	1.37%	-1.94%	83%	9.27%	23.6%	0.086	-0.014	0.126	14.74%
Frame 2	0.639	2.44%	-1.86%	67%	9.27%	26.2%	0.086	-0.003	0.134	11.74%
Frame 3	0.791	4.65%	-3.28%	60%	14.58%	29.7%	0.136	-0.033	0.171	1.97%
Frame 4	0.576	4.35%	-1.48%	40%	6.37%	17.1%	0.058	-0.023	0.100	0.22%
20 years	0.683	3.12%	-2.23%	66%	10.46%	31.0%	0.098	-0.021	0.141	N/A

Table 2: Portfolio of 3 ETFs for 3-month momentum period [29]

Time Frame	Sharpe Ratio	Avg Win	Avg Loss	Win Rate	Compounding Annual Return	Drawdown	Alpha	Beta	Annual Std. Dev.	Compounding Annual Return (SPY Benchmark)
Frame 1	0.639	3.88%	-2.45%	73%	12.32%	37.7%	0.141	-0.153	0.188	14.74%
Frame 2	0.854	4.29%	-1.72%	80%	12.61%	18.5%	0.113	-0.005	0.131	11.74%
Frame 3	0.873	30.95%	-1.34%	74%	20.86%	40.7%	0.203	-0.068	0.229	1.97%
Frame 4	0.847	8.04%	-1.81%	62%	11.40%	15.8%	0.101	-0.017	0.119	0.22%
20 years	0.769	5.21%	-1.97%	74%	14.48%	40.7%	0.140	-0.067	0.176	N/A

[28] Details of backtest result for portfolio of 3 ETFs 12-month momentum: Frame 1, Frame 2, Frame 3, Frame 4, 20 years
[29] Details of backtest result for portfolio of 3 ETFs 3-month momentum: Frame 1, Frame 2, Frame 3, Frame 4, 20 years

Table 3: Portfolio of 3 ETFs with 6-month momentum period [30]

B. Portfolio Allocation Parameter (Based on 6-month momentum period)

Time Frame	Sharpe Ratio	Avg Win	Avg Loss	Win Rate	Compounding Annual Return	Drawdown	Alpha	Beta	Annual Std. Dev.	Compounding Annual Return (SPY Benchmark)
Frame 1	0.741	2.74%	-1.73%	64%	14.20%	38.2%	0.	-0.114	0.181	14.74%
Frame 2	0.704	5.99%	-1.91%	50%	12.61%	22.0%	0.12	-0.011	0.168	11.74%
Frame 3	0.66	4.13%	-1.98%	55%	12.93%	34.1%	0.128	-0.054	0.19	1.97%
Frame 4	0.821	4.40%	-1.17%	58%	5.68%	7.5%	0.049	-0.008	0.059	0.22%
20 years	0.627	3.84%	-1.81%	58%	10.13%	38.30%	0.099	-0.049	0.152	10.13%

Table 4: Portfolio of 5 ETFs for 6-month momentum period [31]

Observations and Conclusion

Based on the backtest results, it is observed that the initial strategy to construct a 3 ETFs portfolio with 12-month momentum period performs at a wide varying degree for the different time frames with significant drawdowns. While the portfolio with 3-month momentum period has a lower volatility and drawdown consistently over the 4 time frames, it is compensated with mediocre win-loss rate and a lacklustre average wins compared to the average losses. The portfolio with 6-month momentum period appears to be more well-rounded particularly with a decent average wins compared to its average losses and has a slightly more consistent win-loss rate over the different time frames.

Time Frame 3 is of a particular interest considering the 2008 market crash happened during that period and it would be a great test on the performance of the strategy during market crashes. Among all the different momentum periods backtested, it is well observed that a shorter momentum period allows a better capture of the movements in the market and to act on it at a better speed compared to a 12-month momentum period. The 6-month momentum period returns the most favourable result despite the increase in volatility at Time Frame 3.

The backtest result of diversifying and increasing the portfolio allocation from 3 ETFs to 5 ETFs with the momentum period held constant at 6-month does not seem to yield a significantly better result. Hence, the parameter is not further explored.
It should also be noted that all the ETFs have different inception dates and might not be present at the earlier time frames. For better understanding and objectivity, the details of the ETFs that are present at the different time frames are as follows.

Time Frame	Symbol	ETF Name	Asset Class	Inception Year
Frame 1	SPY	SPDR S&P 500 ETF	S&P 500 Index	1993
	IVV	iShares Core S&P 500 Index Fund ETF	S&P 500 Index	2000
	EFA	iShares MSCI EAFE ETF	Foreign Large Cap	2001

[30] Details of backtest result for portfolio of 3 ETFs 6-month momentum : Frame 1, Frame 2, Frame 3, Frame 4, 20 years
[31] Details of backtest result for portfolio of 6 ETFs 6-month momentum : Frame 1, Frame 2, Frame 3, Frame 4, 20 years

	BND	Vanguard Total Bond Market Index Fund ETF	Total Bond Market	2003
	VNQ	Vanguard Real Estate Index Fund ETF	REIT - North America	2004
Frame 2	GSG	iShares S&P GSCI Commodity-Indexed	Commodity - Broad Diversified	2006
	AGG	iShares Core US Aggregate Bond ETF	Total Bond Market	2007
	VEA	Vanguard Developed Markets Index Fund ETF	Foreign Large Cap	2007
	DBC	PowerShares DB Com Indx Trckng Fund	Commodity - Broad Diversified	2007
	VOO	Vanguard 500 Index Fund ETF	S&P 500 Index	2010
	VNQI	Vanguard Global ex-US Real Estate Index Fd ETF	REIT - Excl. America	2010
Frame 3	IEFA	iShares Core MSCI EAFE ETF	Foreign Large Cap	2012
	BNDX	Vanguard Total International Bond Index Fund ETF	Total Bond Market	2013
	REET	iShares Global REIT ETF	REIT - Global	2014
	PDBC	Invesco Optimum Yld Dvsfd Cmd Str No K-1 ETF	Commodity - Broad Diversified	2014

Generally, an ETF is a great instrument for a portfolio to gain exposure in different asset classes with great liquidity while limiting the unsystematic risk that is industry-specific or company-specific. The rotational momentum system has shown a decent compounding annual return in comparison to the SPY benchmark in a consistent manner over the different time frames.

Nevertheless, since the backtests are performed on historical data, more forward-looking factors are recommended to be taken into consideration. This is especially so at the current time with the rise of multiple alternative investments that are gaining momentum and have great growth potential in the future. Depending on factors such as individual trading and investing preference, risk appetite, time horizon, etc., the suitability of this strategy varies and the strategy should be tweaked accordingly.

VI. MA Crossover, Risk Premia & Momentum Strategy for Forex

Sourcing for correlated currency pairs is a strong tool that you can use to help you understand the markets better and develop high-probability trading strategies. You can also manage risk and diversify trading instruments effectively, especially if you monitor correlation coefficients regularly and always be alerted to news or information on market changes and the shifting of currency relationships.

In QuantConnect, it offers forex trading through two popular brokerages: FXCM and OANDA. QuantConnect hosts 13 currency pairs from April 2007 to present (provided by FXCM[32]), and 71 currency pairs from April 2004 to present (provided by OANDA[33]). However, it was noted that there may be slightly different prices depending on your choice on brokerages that you are trading on.

Identify Currency Pairs That Are Highly Correlated

The below tables show the correlation of currency pairs that were calculated over a period of one month and one year[34].

Currency Pairs	EUR/USD	GBP/USD	USD/CHF	USD/JPY	EUR/JPY	USD/CAD	AUD/USD	EUR/CHF	AUD/NZD	USD/SGD
EUR/USD	1	0.69	-0.95	-0.74	0.36	-0.54	0.89	-0.08	-0.66	-0.61
GBP/USD	0.69	1	-0.56	-0.36	0.46	-0.58	0.88	0.23	-0.75	-0.41
USD/CHF	-0.95	-0.56	1	0.71	-0.33	0.53	-0.83	0.4	0.59	0.64
USD/JPY	-0.74	-0.36	0.71	1	0.36	0.14	-0.6	0.1	0.47	0.16
EUR/JPY	0.36	0.46	-0.33	0.36	1	-0.56	0.4	0.01	-0.27	-0.62
USD/CAD	-0.54	-0.58	0.53	0.14	-0.56	1	-0.68	0.11	0.27	0.43
AUD/USD	0.89	0.88	-0.83	-0.6	0.4	-0.68	1	-0.02	-0.72	-0.47
EUR/CHF	-0.08	0.23	0.4	0.1	0.01	0.11	-0.02	1	-0.07	0.24
AUD/NZD	-0.66	-0.75	0.59	0.47	-0.27	0.27	-0.72	-0.07	1	0.19
USD/SGD	-0.61	-0.41	0.64	0.16	-0.62	0.43	-0.47	0.24	0.19	1

Table 1: Correlation of currency pairs (one-month period)

Examples of strong positive correlations		Examples of strong negative correlations	
EUR/USD and AUD/USD	+0.93	EUR/USD and USD/CHF	-0.96
GBP/USD and AUD/USD	+0.92	GBP/USD and USD/CAD	-0.96
EUR/JPY and AUD/USD	+0.91	EUR/JYP and USD/CAD	-0.92
EUR/JPY and EUR/CHF	+0.92	USD/CAD and AUD/USD	-0.96
USD/CAD and USD/SGD	+0.95	EUR/USD and USD/SGD	-0.96

Table 2: Examples of highly correlated currency pairs (one-year period)

[32] List of currency pairs provided by FXCM:
https://www.quantconnect.com/docs/data-library/forex#Forex-FXCM-Brokerage-Forex-Data
[33] List of currency pairs provided by OANDA:
https://www.quantconnect.com/docs/data-library/forex#Forex-OANDA-Brokerage-Forex-Data
[34] Correlation of currency pairs (one month and one year period) retrieved as of 11 April 2021:
https://za.investing.com/tools/correlation-calculator

Decide on Currency Pairs

Based on the observation of the correlation coefficients on a monthly and yearly time frames and the popularity of the currency pairs traded in OANDA[35], the following six currency pairs had been identified to make a trade.

- EUR/USD
- GBP/USD
- USD/CHF
- AUD/USD
- USD/CAD
- USD/JPY

Manage Risk

For currency pairs (with strong positive correlations), separating lengthy and high positions within separate pairs may increase your profits. However, if a wrong forecast had been made, it could also maximise losses.

For currency pairs (with strong negative correlations), possessing lengthy and high positions on both the pairs will cancel each other out since these pairs proceed in opposite directions.

Therefore, most traders usually hold positions on correlated pairs for expansion, while preserving the same general direction (either upwards or downwards) to protect themselves from risk even if a pair proceeds against them. Yet, they benefit from the other pair if it ever happens.

Confirmation of Strategy

There are many indicators in the markets that can be applied to test and confirm your trading strategy. Some of the popular forex trading strategies[36] include: Moving Average (MA), Relative Strength Index (RSI), Bollinger Bands, etc. However, indicators are subjective and adding indicators do not necessarily guarantee higher returns. You may test different indicators in QuantConnect to develop your own strategy that works best for you.

The following strategies were explored in this report for forex trading.

A. Moving Average Crossover[37]

Moving Average Crossover strategy uses 2 Moving Averages: fast MA and slow MA. In this report, MA was applied to some currency pairs that were identified earlier (*see section on "Decide on Currency Pairs"*) by using a 5 period Simple Moving Average, SMA(5) for the fast MA and a 40 period Simple Moving Average, SMA(40) for the slow MA.

A *bullish* crossover occurs when the fast MA (SMA(5)) crosses *above* the slow MA(SMA(40), while a *bearish* crossover occurs when the fast MA (SMA(5)) crosses *below* the slow MA(SMA(40).

The performance of this strategy is sensitive to the choice of currency pairs and other parameters such as the period used for the fast and slow MA, length of historical data used for backtesting, change of resolution (daily, hour, minute, second or tick).

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[35] Popular forex pairs traded in OANDA retrieved as of 11 April 2021: https://www.oanda.com/sg-en/trading/cfds/forex/
[36] Examples of some recommended forex indicators: https://www.fxcm.com/markets/insights/c/forex/forex-indicators/
[37] More information on the strategy, Moving Average Crossover: https://www1.oanda.com/forex-trading/learn/trading-tools-strategies/moving-averages

B. Risk Premia[38]

This strategy enters long-short positions in the forex market based on signals from a skewness indicator. It was suggested that there is a positive linear relationship between the Sharpe ratio of risk premia strategies and their negative skewness.

The implementation of the strategy goes *long* for a forex pair when the skewness indicator is *lower* than a minimum threshold (-0.6) and *short* the pair when the indicator *exceeds* a maximum threshold (0.6).

The performance of this strategy is sensitive to the choice of currency pairs and other parameters such as adjustment of the thresholds for entering long and short positions (0.6, -0.6), length of historical data used for backtesting.

C. Momentum Strategy[39]

This trend following strategy exploits short-term momentum in the non-linear trend (low frequency) component of the forex market and uses the MA rule to measure this momentum.

The performance of this strategy is sensitive to the choice of currency pairs and other parameters such as choice of lag parameters in MA rules and length of historical data used for backtesting.

Backtest Periods

Time Frame	Start Date	End Date
Frame 1	2016, 1, 1	2020, 12, 31
Frame 2	2011, 1, 1	2015, 12, 31
Frame 3	2006, 1, 1	2010, 12, 31
Frame 4	2001, 1, 1	2005, 12 ,31
11 year	2010, 1, 1	2020, 12 ,31

Table 3: Time frame for backtesting

Results and Observations

When using QuantConnect to perform backtesting of historical data, it is recommended to use past 5 years or more for better confirmation of your strategy. However, it was observed that there are some gaps in the results when we run some backtest period in QuantConnect. This was because some of the years/periods were not available[40] in QuantConnect (i.e. date started for AUDNZD: 02 May 2004, EURUSD: 05 May 2002).

QuantConnect supports Python coding. Therefore, paying attention to the indentation and spacing in the block of codes is important to avoid any indentation error in Python. In one scenario that we had encountered, it only retrieved the result of the last currency pair, despite that there are more currency pairs used for backtesting (due to indentation error).

[38] More information on the strategy, Risk Premia in Forex Markets:
https://www.quantconnect.com/tutorials/strategy-library/risk-premia-in-forex-markets

[39] More information on the strategy, Momentum Strategy Based on the Low Frequency Component of Forex Market:
https://www.quantconnect.com/tutorials/strategy-library/the-momentum-strategy-based-on-the-low-frequency-component-of-forex-market

[40] Refer to QuantConnect Data Explorer for available Forex and its display range:
https://www.quantconnect.com/data/tree/forex

It was also observed that depending on the choice of currency pairs, having more currency pairs retrieved better results (i.e. higher Sharpe ratio, higher win rate) and returns. Moreover, having more currency pairs also helps to diversify and minimise risk. However, there could be more issues to resolve (i.e. coding error) if many currency pairs were used for backtesting in QuantConnect. Therefore, in this report, six currency pairs were used as an example.

The performances of the strategies are very sensitive to many factors such as the choice of currency pairs, change of parameters, etc. It can be quite time-consuming to conduct many rounds of trials to test different parameters, so as to optimise the performances of these strategies.

Time Frame	Sharpe Ratio	Avg Win	Avg Loss	Win Rate	Compounding Annual Return	Drawdown	Net Profit	Alpha	Beta	Annual Std. Dev.
Frame 1	0.173	0.24%	-0.13%	0%	0.39%	3.80%	2.00%	0.003	0.006	0.019
Frame 2	-0.049	0.30%	-0.20%	38%	-0.16%	4.90%	-1.00%	0	-0.007	0.021
Frame 3	0.516	0.40%	-0.24%	45%	1.85%	4.80%	10.00%	0.015	-0.002	0.03
Frame 4	-0.113	0.34%	-0.22%	39%	-0.29%	5.10%	-1.00%	-0.002	0.003	0.02

Table 5: Performance of selected currency pairs (2001 to 2020) using MA Crossover[41]

Time Frame	Sharpe Ratio	Avg Win	Avg Loss	Win Rate	Compounding Annual Return	Drawdown	Net Profit	Alpha	Beta	Annual Std. Dev.
Frame 1	-0.135	0.44%	-0.57%	0%	-1.15%	19.10%	-6.00%	-0.01	0.017	0.057
Frame 2	-0.117	0.54%	-0.51%	47%	-1.06%	15.40%	-5.00%	-0.014	0.061	0.058
Frame 3	-0.657	0.70%	-0.86%	50%	-7.39%	31.90%	-32.00%	-0.058	0.04	0.086
Frame 4	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

Table 6: Performance of selected currency pairs (2001 to 2020) using Risk Premia[42]

Time Frame	Sharpe Ratio	Avg Win	Avg Loss	Win Rate	Compounding Annual Return	Drawdown	Net Profit	Alpha	Beta	Annual Std. Dev.
Frame 1	0.121	4.02%	-4.39%	58%	0.78%	20.70%	4.00%	0.007	0.026	0.059
Frame 2	-0.214	0.00%	-3.54%	0%	-2.72%	23.70%	-13.00%	-0.016	0.022	0.075
Frame 3	-0.288	5.41%	-4.30%	29%	-4.13%	28.90%	-19.00%	-0.025	-0.008	0.087
Frame 4	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

Table 7: Performance of selected currency pairs (2001 - 2020) using Momentum Strategy (EURUSD)[43]

Recommendation and Conclusion

Currency correlations is a powerful tool that you can consider developing high-probability trading strategies. You will also be guided in risk management, if you diversify currency pairs effectively and monitor their correlation coefficients regularly (i.e., daily, weekly, monthly, or yearly timeframes).

Moreover, you must be aware that currency correlations are shifting continuously over time mainly due to economic and political factors.

Therefore, it is imperative to stay updated on news or information on market changes that affect the shifting of currency relationships. It is also recommended to check for currency correlations that are

[41] Details of backtest results for MA Crossover: Frame 1, Frame 2, Frame 3 and Frame 4
[42] Details of backtest results for Risk Premia Frame 1, Frame 2 and Frame 3
[43] Details of backtest results for Momentum Strategy Frame 1, Frame 2 and Frame 3

long-term to obtain deeper insights; and apply some indicators to test which trading strategy works best for you.

The methods of trading forex that are outlined within this report are just ideas. You should trade forex in a way that suits your own individual style, needs, goals and risk appetite.

References

Currency pair correlations - forex trading. (2021, February 02). Retrieved April 11, 2021, from https://www.actionforex.com/articles/forex-trading/357495-currency-pair-correlations-forex-trading/

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Shor, R., & Team, F. (2019, July 12). Forex indicators. Retrieved April 11, 2021, from https://www.fxcm.com/markets/insights/c/forex/forex-indicators/

VII. Market/Bond Rotation Strategy (Macro Conditions)

Intuitively, it might be possible to generate excess returns via cleverly timed entries and exits in and out of the equity market. This algo may be a first step toward developing a strategy that derives optimal moves in and out of the market on the basis of early indicators of equity market downturns.

Introduction & Thesis

Resources and industrial products are early in the value chain and market value drops in corresponding firms are early indicators of growth worries that ultimately affect other sectors and the broader market.

Equity market value growth benefits substantially from cheap debt, such that increases in bond yields (i.e., drops in bond prices) should be an early indicator of a slowdown in growth. The general benchmark for the board market to be SPY ETF (SPDR S&P 500 trust), thus, the selected alternative investments should have low/ negative correlation coefficient to SPY in order to benefit from the slowdown in growth.

Based on the theory of business cycle (Yield Curve and Credit/Debt Cycle)[44][45], it will be prudent to get out of the equity market and rotate capital into the bonds, commodities and inverse etf to capitalise and hedge during bear market conditions.

Tracking Market Environment : Sources

➢ **Metals:** The DBB ETF (Invesco DB Base Metals Fund) provides the signal. DBB tracks the prices of three key industrial metals:aluminum, copper and zinc.

➢ **Natural Resources:** The IGE ETF (iShares North American Natural Resources) seeks to track the investment results of an index composed of North American equities in the natural resources sector.

➢ **Cost of Debt:**

1. The SHY ETF (iShares 1-3 Year Treasury Bond) provides the signal. SHY tracks short-term US Treasury debt (1-3 years).
2. The TLT ETF (iShares 20+ Year Treasury Bond ETF) seeks to track the investment results of an index composed of U.S. Treasury bonds with remaining maturities greater than twenty years.

Changes in these bond ETFs signifies the debt's 'risk-free' interest yield should be indicative of changes in firms' cost of debt which is based on the risk-free rate (risk-free rate + risk premium).

➢ **USD:** The UUP ETF (Invesco DB US Dollar Index Bullish Fund) seeks to track changes, whether positive or negative, in the level of the Deutsche Bank Long USD Currency Portfolio Index - Excess ReturnTM (DB Long USD Currency Portfolio Index ER or Index) plus the interest income

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44 Estrella, Arturo; Mishkin, Frederic S. (1998). "Predicting U.S. Recessions: Financial Variables as Leading Indicators" (PDF). *Review of Economics and Statistics*. **80**: 45–61. doi:10.1162/003465398557320. S2CID 11641969.

45 Drautzburg, Thorsten. "Why Are Recessions So Hard to Predict? Random Shocks and Business Cycles." Economic Insights 4, no. 1 (2019): 1-8.

from the Fund's holdings of primarily US Treasury securities and money market income less the Fund's expenses.

- **Silver:** The SLV ETF (iShares Silver Trust) seeks to reflect generally the performance of the price of silver.
- **Gold:** The GLD ETF (SPDR Gold Trust) tracks the gold spot price, less expenses and liabilities, using gold bars held in London vaults.
- **Disambiguate GPLD/SLVA pair via inflation expectations:** The RINF ETF (ProShares Inflation Expectations) tracks an index with long exposure to US TIPS and short exposure to US Treasurys of equal maturity, gaining when yields on Treasuries increase relative to those on TIPS.
- **Utilities:** The XLU ETF (Industrial Select Sector SPDR Fund) provides the signal. XLI tracks the broad US utilities sector.
- **Industrials:** The XLI ETF (Industrial Select Sector SPDR Fund) provides the signal. XLI tracks the broad US industrial sector.
- **Safe haven currency (CHF):** The FXF ETF (Invesco CurrencyShares Swiss Franc Trust) offers exposure to the Swiss franc relative to the U.S. dollar, increasing in value when the franc strengthens and declining when the dollar appreciates. This fund could be appropriate for investors seeking to hedge exchange rate exposure or bet against the greenback.
- **Risk currency (AUD):** The FXA ETF (Invesco CurrencyShares Australian Dollar Trust) offers exposure to the Australian dollar relative to the U.S. dollar, increasing in value when the Aussie dollar strengthens and declining when the American dollar appreciates. This fund could be appropriate for investors seeking to hedge exchange rate exposure or bet against the greenback. For investors seeking exposure to the AUD/USD exchange rate
- **Inverse ETF:** DOF ETF (ProShares Short Dow30) provides inverse exposure to the price-weighted Dow Jones Industrial Average, which includes 30 of the largest US companies.

	DBB	SHY	TLT	UUP	GLD	SLV	RINF	XLU	XLI	FXF	FXA	DOG
SPY	0.88	-0.26	-0.18	-0.28	0.55	0.11	0.58	0.94	0.90	0.20	0.00	0.93

Table 1: Correlation coefficient

Universe

The parameters to screen for quality companies based on fundamental values:
- EVToEBITDA >0
- BasicAverageShares (3-Month) >0
- BasicAverageShares (3-Month) x Price > 2B
- EPS >0
- Price > 5

This allows the algorithm to set its universe to filter out unprofitable companies and small cap and penny stocks. Furthermore, the algorithm will seek stocks with the highest momentum by ranking via dollar-volume.

“In the Market”

The resolution chosen in the algorithm is hourly. This is to allow quicker reaction to the market condition. The parameters are paired as such:

- GLD-SLV
- XLI-XLU
- FXF-FXA

These pairing offers a ratio to signal whether the market condition is favourable to stay invested in the equity market or bond/inverse ETF. The confluence factors:

- DDB
- IGE
- SHY
- UUP
- RINF

The algorithm will seek to find a significance of 1% out of an observation rolling period of 252-day. If the extreme condition is true, it will increase the likelihood of the algorithm to produce an “out the market” signal. This is to re-assess/disambiguate double-edged signals provided by the paired signals.

When the signal provides a positive indication to stay “in the market”, the algorithm will look to invest in the top 50 stocks set in the filtered universe. The weight distribution of each stock weighted in favour of the stock with the highest momentum.

The rebalancing portfolio will take place once a month to monitor the performance of the stocks. This is to remove noise in the market and reduce fees due to frequent transactions.

“Out the Market”

Conversely, when the signal provides a positive indication to stay “out the market”, the algorithm will liquidate all stocks holding and rotate capital to bonds, gold and inverse ETF. In order to prevent the algorithm from switching in and out the market frequently due to false signals, a wait out period is introduced to reduce the market noise. The wait out period will allow the portfolio to stay out of the equity market with a minimum of 15-day once “out the market” signal is triggered. The algorithm will only check after the wait out period whether the market conditions allow the portfolio to invest in the equity market.

The bonds, gold and inverse ETF are as follows:

- TLT
- SHY
- GLD
- UUP
- DOG

The weight distributions are equal to provide a balanced exposure during bear market conditions.

Parameter Optimisation

To avoid overfitting, a base of 15-day wait out is chosen because the fastest correction is in 2018 when S&P500 found rebounded after 15 days[46]. An improvement to the algorithm performance will be an introduction of a dynamic wait out period based on the volatility of the market. Higher standard deviation will increase the wait out period to protect the portfolio from getting in the equity market too soon; the converse is held true.

Backtest Periods

Time Frame	Start Date	End Date
Frame 1	2016, 1, 1	2020, 12, 31
Frame 2	2011, 1, 1	2015, 12, 31

Results & Improvement Opportunities

Time Frame	Sharpe Ratio	Avg. Win	Avg. Loss	Win Rate	Compounding Annual Return	Drawdown	Net Profit	Alpha	Beta	Annual Std. Dev.
Frame 1[47]	1.221	1.08%	-0.54%	52%	22.73%	19.30%	178.78%	0.179	0.143	0.163
Frame 2 [48]	1.197	0.76%	0.49%	56%	15.90%	15.30%	109.25%	0.128	0.076	0.114
11 years [49]	1.250	0.91%	0.51%	56%	20.66%	18.40%	690.22%	0.161	0.141	0.143

Time Frame	Market/ Bond Rotation	SPY Benchmark
Frame 1	178.78%	99%
Frame 2	109.25 %	74.2%
11 years	690.22 %	271.99%

Table 1: Net Profit of Market/Bond Rotation Strategy against SPY benchmark

[46] Williams, S. (2018). *How Long Do Stock Market Corrections Last?* The Motley Fool. https://www.fool.com/investing/2018/04/11/how-long-do-stock-market-corrections-last.aspx
[47] Details of backtest result for Frame 1
[48] Details of backtest result for Frame 2
[49] Details of backtest result for 11 years

Based on all the results from the backtest, this strategy return is higher than SPY benchmark. However, there are some pitfall to this algorithm:

➢ From 2017-2019, the algorithm mostly stayed out of the equity market in preparation of a correction that only came in 2020. During that period, the equity market continued to grind higher and the bond market underperformed. Hence, the algorithm underperformed the SPY benchmark during that period.
➢ The algorithm was unable to backtest further in the past as some ETF was not available.

Here are some proposed improvement to enhance the performance of the algorithm:

➢ Different ETFs/ways to measure prices of resources (e.g., additional key resources such as oil), industrial goods (e.g., a stronger focus on industrial capital goods), and bonds (e.g., corporate bonds instead of government bonds)
➢ Additional aspects—other than resources, industrial goods, and bond yields—that could provide early indicators of equity downturns
➢ Improvement of settings (e.g., waiting period, %-points indicating 'substantial' drops)
➢ Code improvements (errors/unintended outcomes, efficiency)

VII. Subreddit Sentiment

Many have heard of the subreddit "wallstreetbets." It is one of Reddit's most popular hubs for retail traders to share their ideas or positions. Its popularity skyrocketed and hit mainstream media due the short squeeze of GME in early 2021.

This algorithm scrapes the subreddits looking for posts related to the stocks: SPCE, LULU, TLRY, and CLOV (these stocks tend to be a popular conversation in the retail investor space). Then it conducts a sentiment analysis of the comments in the identified post and stores the values in a data frame.

The algorithm may contradict Odd Lot Theory[50], which states that the small investor is usually wrong. But today, retail investor participation in the market is at an all-time high, and there are plenty of simple stock analysis tools to help small investors make informed decisions. If the general sentiment from retail investors is up, then they could be purchasing the underlying equity.

The Reddit Sentiment trading indicator uses Natural language processing (NLP) and VADER (Valence Aware Dictionary and sEntiment Reasoner)[51] to set up a rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in news articles and social media. This allows the algorithm to build a collection of most talked about stocks in the subreddit forum.

Universe

There is no integration between Reddit API and QuantConnect, hence a python script is required to obtain the most talked about stocks in the subreddit forum[52]. The python script will need to run regularly to update the list of stocks the algorithm will be tracking.

The algorithm also takes a collection of the top 10 mentioned stocks, titles,texts and timestamp. These data were exported into a csv and imported into dropbox. This is because the URL does not change when a new file is overwritten with the same name. This allows the algorithm to work without changing the code.

Strategy

The algorithm will collect words indicating the sentiment, and score the positive or negative side of the news for each stock. The sum of the sentiment score is calculated for each stock and then used as a proxy for the direction and weight of the insights.

The algorithm will take a long position in the when the sentiment is generally positive and short position when the sentiment is generally negative

Backtest Periods

Time Frame	Start Date	End Date
Frame 1	2016, 1, 1	2020, 12, 31

[50] Scott, G. (2021). *Odd Lot Theory Definition*. Investopedia. https://www.investopedia.com/terms/o/oddlottheory.asp
[51] Hutto, C.J. & Gilbert, E.E. (2014). *VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text*. Eighth International Conference on Weblogs and Social Media (ICWSM-14). Ann Arbor, MI, June 2014. https://github.com/cjhutto/vaderSentiment
[52] More details of the Python script here.

Results & Improvement Opportunities

Time Frame	Sharpe Ratio	Avg. Win	Avg. Loss	Win Rate	Compounding Annual Return	Drawdown	Net Profit	Alpha	Beta	Annual Std. Dev.
Frame 1[53]	0.31	0.70%	-0.57%	53%	3.92%	20.80%	21.25%	0.046	-0.034	0.133

Time Frame	News Sentiment	SPY Benchmark
Frame 1	21.25%	99%

Table 1: Net Profit of Subreddit Sentiment Strategy against SPY benchmark

Based on all the results from the backtest, this strategy return is significantly lower than SPY benchmark. Here are the possible reason:

- ➢ As the list of popular stocks are dynamically changing, the backtest of the fixed set of stocks is not an accurate representation of the historical performance.
- ➢ There is no filter for predatory wallstreetbets submissions[54].
- ➢ Only searches for mentions of ticker names but not company names.

Here are some proposed improvement to enhance the performance of the algorithm:

- ➢ An automated list that dynamically changes the universe.
- ➢ An idea to prime the algorithm for live trading is to use a neural network. It will create a prediction for the next set of sentiment scores and use those predictions to manage risk.

[53] Details of backtest result for Frame 1
[54] More details at Reddit

IX. News Sentiment with NLP & VADER via Tiingo API

The news sentiment trading indicator uses natural language processing (NLP) and VADER (Valence Aware Dictionary and sEntiment Reasoner)[55] to set up a rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in news articles and social media.

The objective is to measure the market participants' sentiment towards the market and trade in the direction of the overall market trend.

QuantConnect provides a 3rd party API integration (Tiingo) to obtain news and events.

Universe

The algorithm takes a collection of the highest volume stocks from cyclical sectors such as Technology, Consumer Cyclical, Financial Services and Basic Materials. These sectors are chosen due to the nature of strong reaction to external factors such as news and events.

The algorithm will then seek stocks with the highest momentum by ranking via dollar-volume.

Strategy

The resolution chosen in the algorithm is hourly. This is to allow quicker reaction to the news and events.

The algorithm will collect words indicating the sentiment, and score the positive or negative side of the news for each stock. The sum of the sentiment score is calculated for each stock and then used as a proxy for the direction and weight of the insights. The algorithm will take a long position in the top 10 assets by sentiment ranking. The algorithm emits 10 insights per day.

Backtest Periods

Time Frame	Start Date	End Date
Frame 1	2016, 1, 1	2020, 12, 31

[55] Hutto, C.J. & Gilbert, E.E. (2014). *VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text*. Eighth International Conference on Weblogs and Social Media (ICWSM-14). Ann Arbor, MI, June 2014. https://github.com/cjhutto/vaderSentiment

Results & Improvement Opportunities

Time Frame	Sharpe Ratio	Avg. Win	Avg. Loss	Win Rate	Compounding Annual Return	Drawdown	Net Profit	Alpha	Beta	Annual Std. Dev.
Frame 1[56]	1.144	0.79%	-0.68%	60%	25.95%	20.60%	217.38%	0.123	0.571	0.166

Time Frame	News Sentiment	SPY Benchmark
Frame 1	217.38%	99%

Table 1: Net Profit of News Sentiment Strategy against SPY benchmark

Based on all the results from the backtest, this strategy return is higher than SPY benchmark. However, there are some pitfall to this algorithm:

➢ One of the limitations with this model is that the words used are not exhaustive and more could be added to better categorize positive and negative sentiment. The sample size, accuracy of describing a trend of an asset, and the scoring scale determine the trade signal and algorithm's performance. Generally speaking, the larger the sample size,the more precise the scoring scale is, and the more accurately the signal. If we polish the description words sample pool, the result should reflect this more refined.

➢ The algorithm was unable to backtest further in the past because there is insufficient data provided by Tiingo API. A possible solution is to seek another source to supplement the data required.

Here are some proposed improvement to enhance the performance of the algorithm:

➢ Currently, the scoring system is based on a predefined dictionary provided by VADER. NLP machine learning can improve the ability to adapt and learn to improve the scoring system.

[56] Backtest results link not available for free account as the total orders exceeds 10,000

Portfolio Management using Modern Portfolio Theory (MPT)

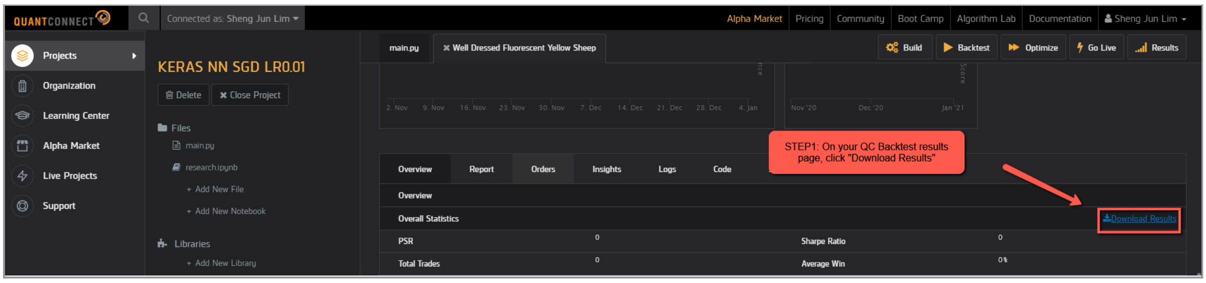
Evaluation of Strategies

Following the backtest of the various strategies, the results of the strategies will need to be analysed and compared to be able to arrive at a decision on which strategies should be used, and the resource amount to be allocated to each strategy within the trader/investor's portfolio. For this purpose, the Modern Portfolio Theory (MPT) framework is utilised.

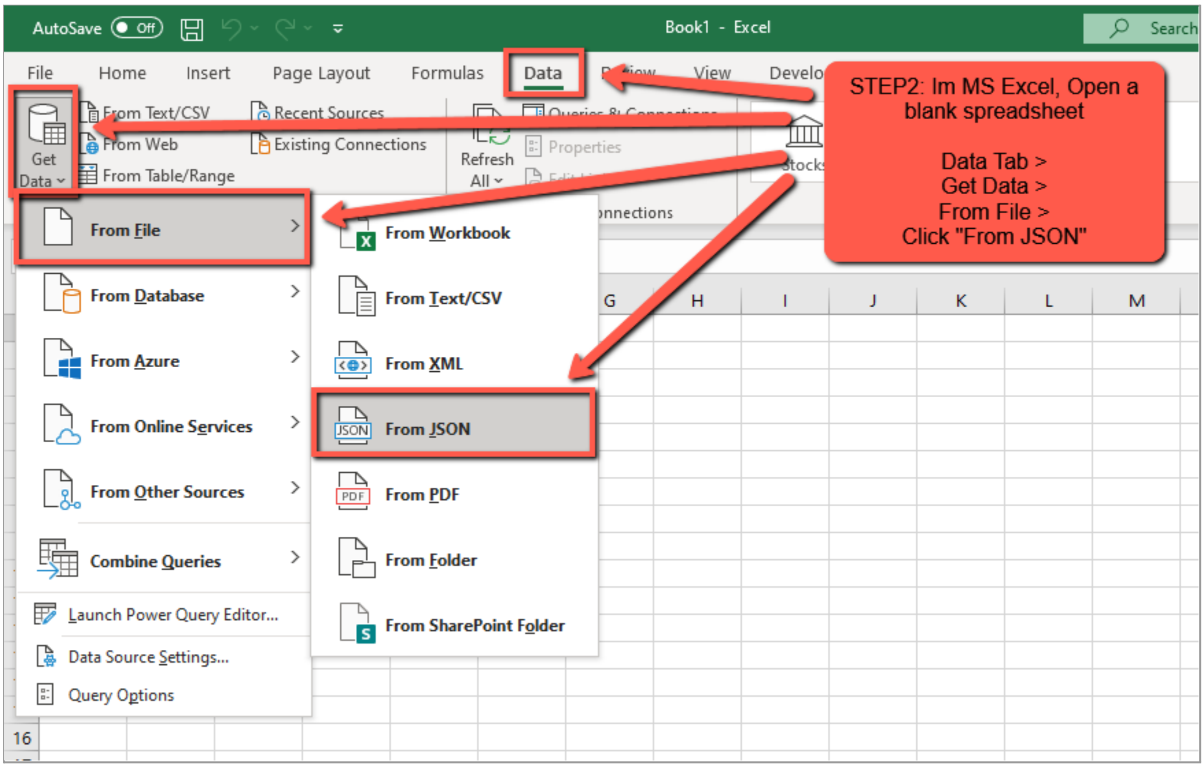
A. Extraction of Strategy Backtest Data

Prior to any analysis, the strategy backtest data (equity) must be extracted from the backtest data generated in QuantConnect. The data extraction is repeated for all strategies under consideration. The following steps outline the method of data extraction utilized.

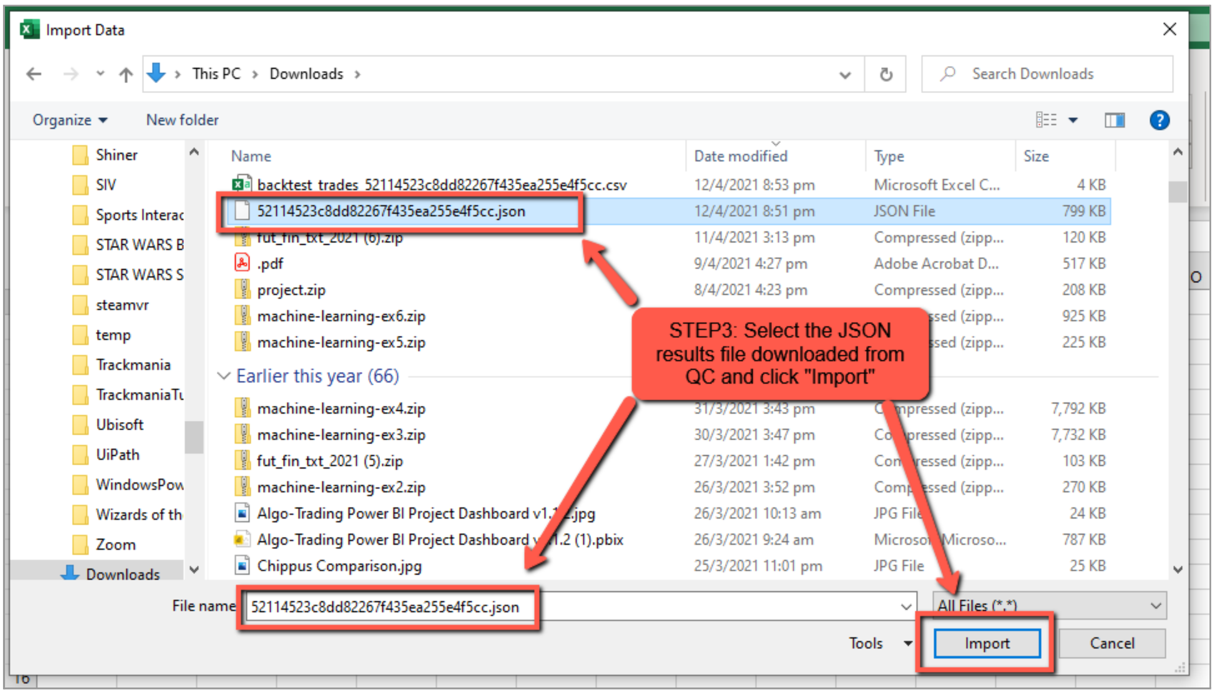
Step 1: Downloading the QuantConnect backtest results JSON file
From within the relevant QuantConnect backtest results page, click "Download Results" to download the backtest results JSON file to the computer.



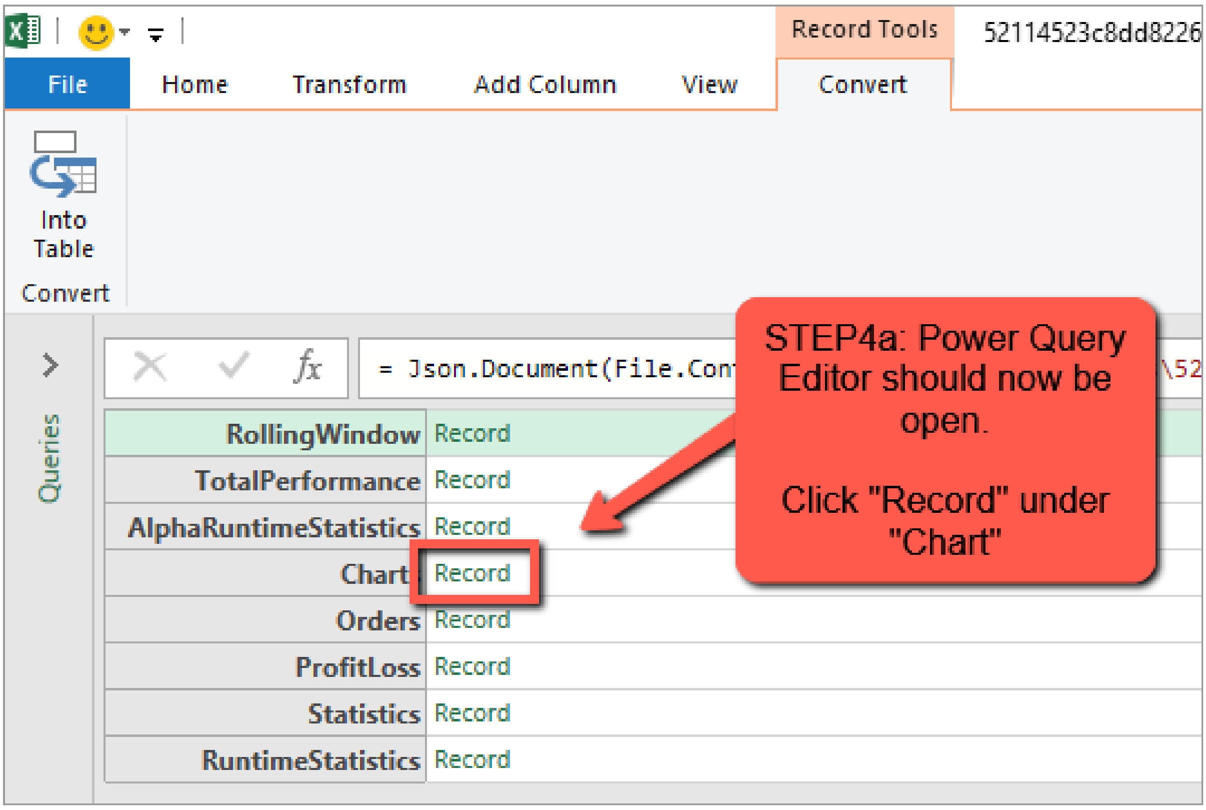
Step 2: Opening the backtest JSON file with Microsoft Excel
Open a new Microsoft Excel spreadsheet, within the "Data" tab, click "Get Data" > "From File" > "from JSON".

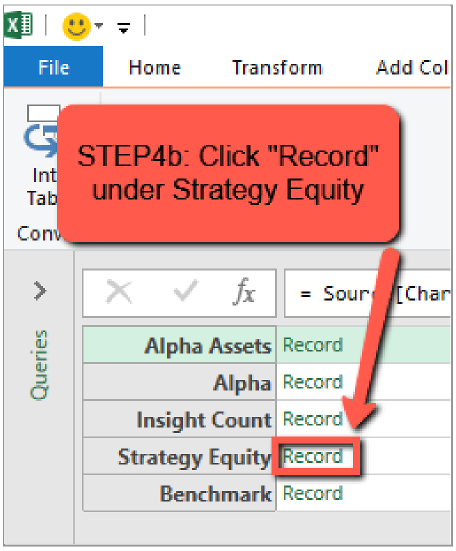


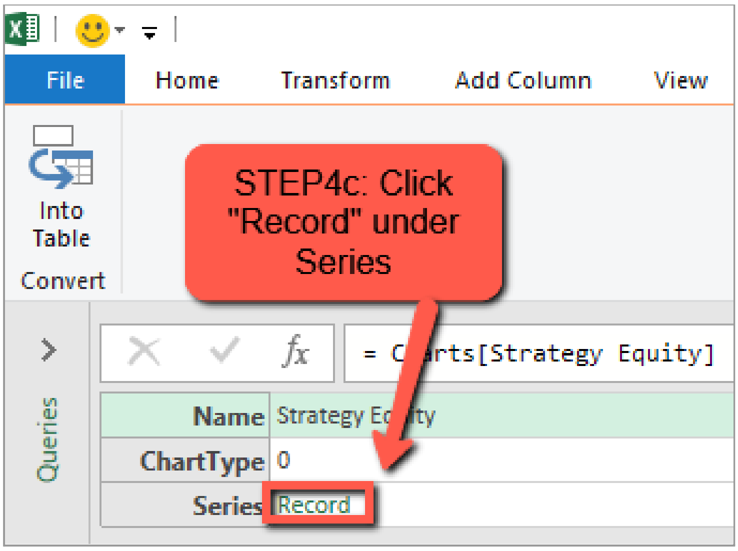
Step 3: Importing the downloaded backtest results JSON file
Select the JSON file to be processed and click "Import".

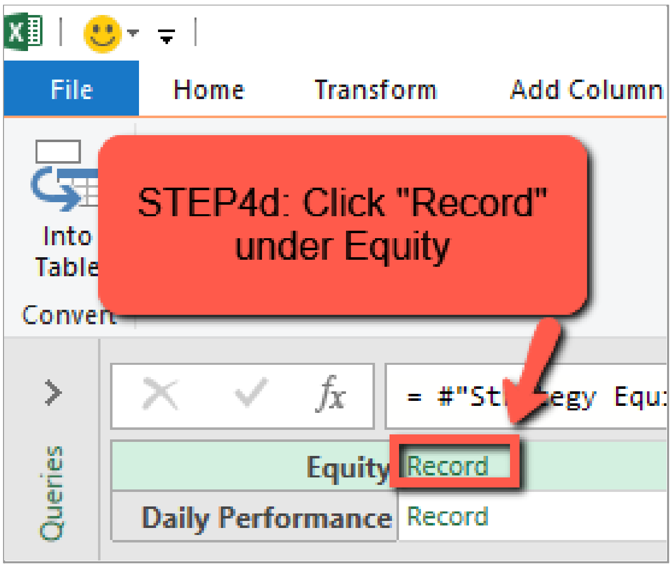


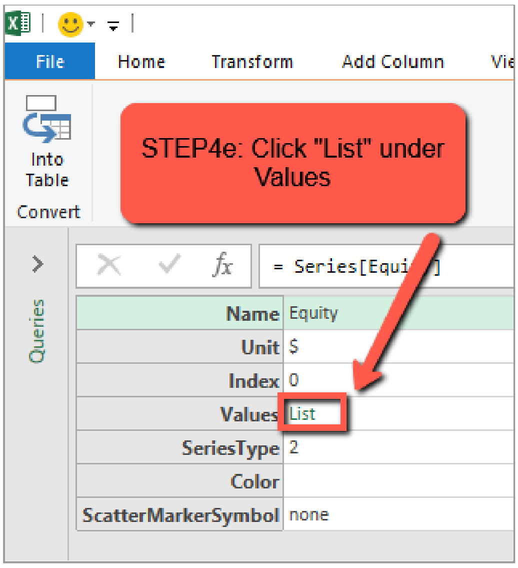
Step 4: Expanding the JSON records to access the strategy's equity data
Following import of the JSON file, the records will now be accessible within Excel's Power Query Editor. The diagrams below detail the order of expansion of the relevant records.





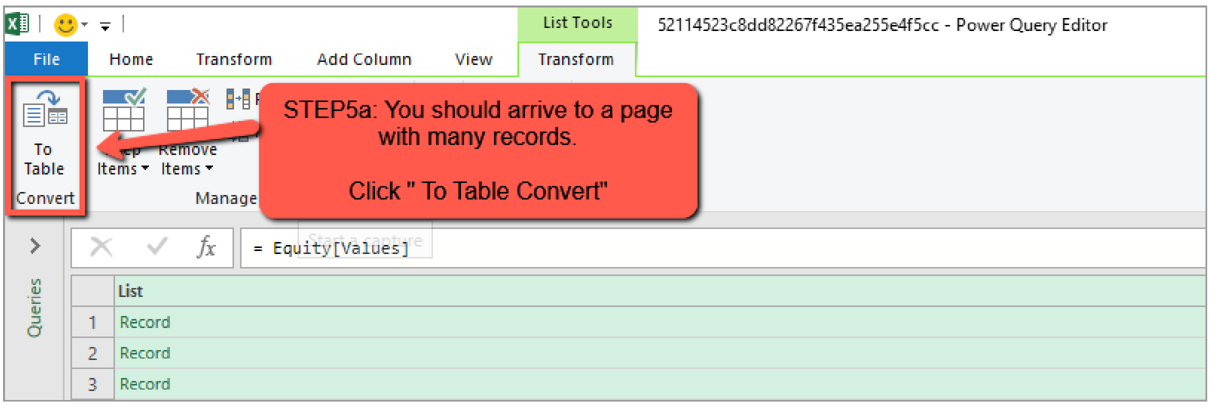


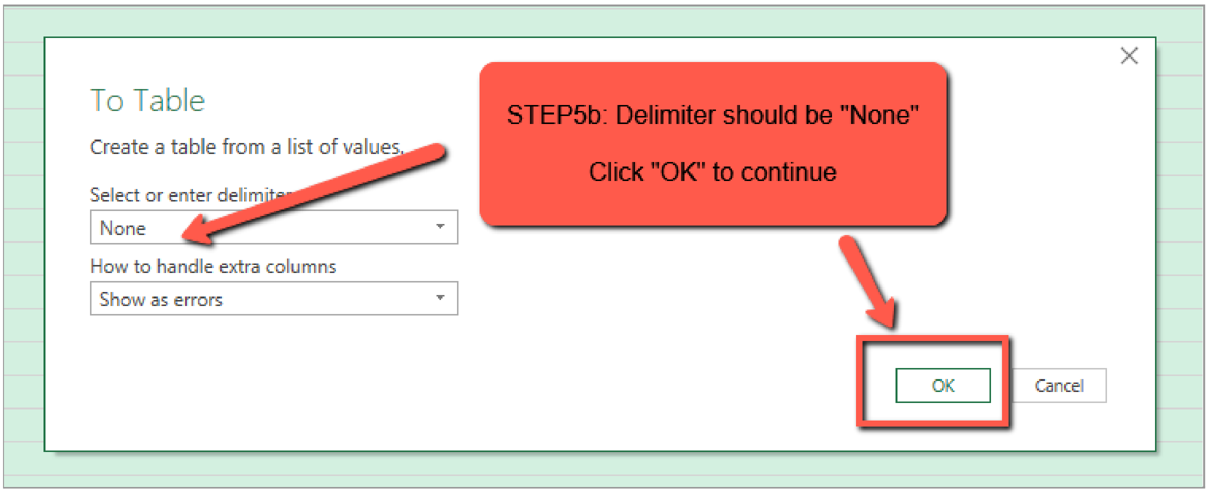


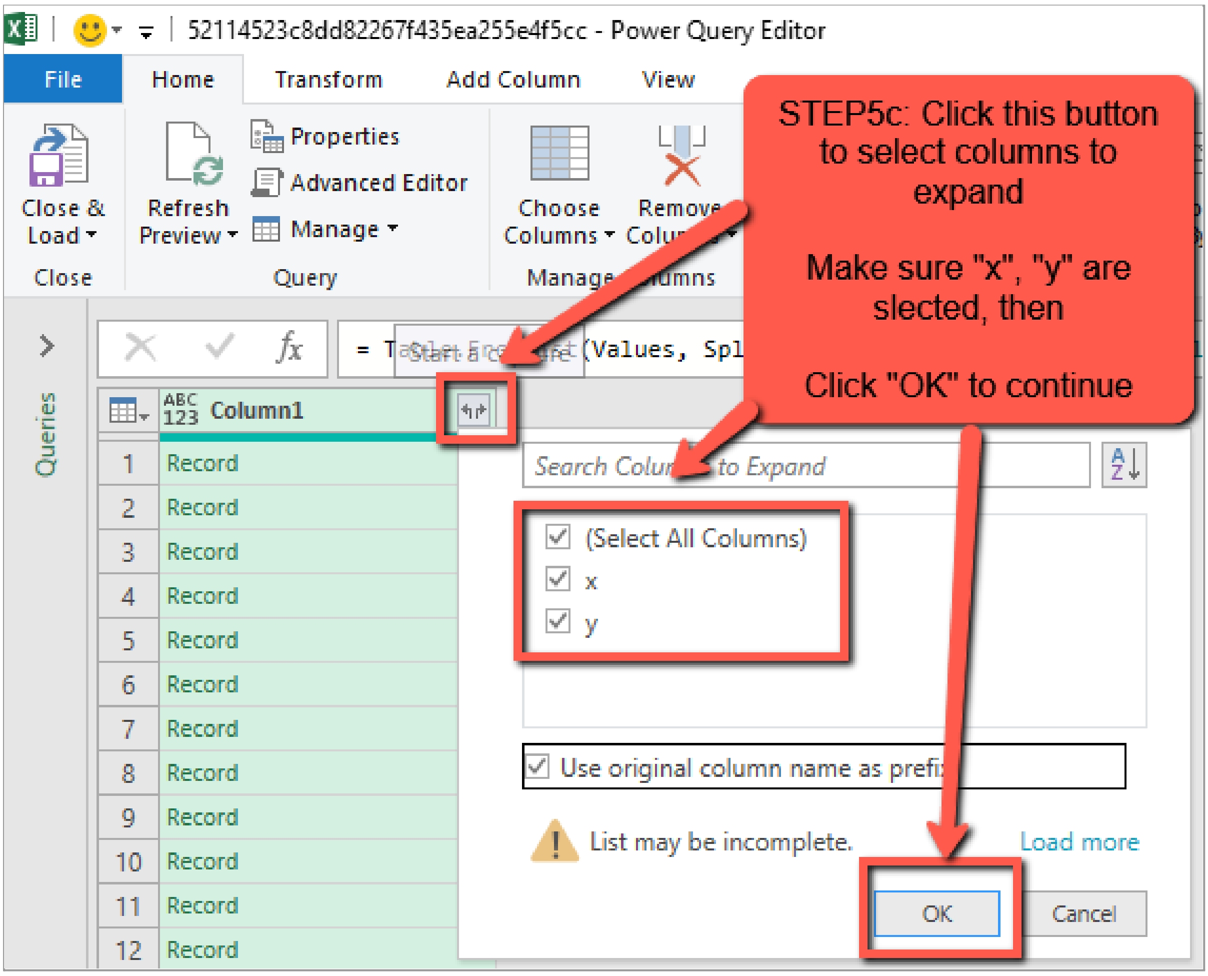


Step 5: Expansion of equity data fields

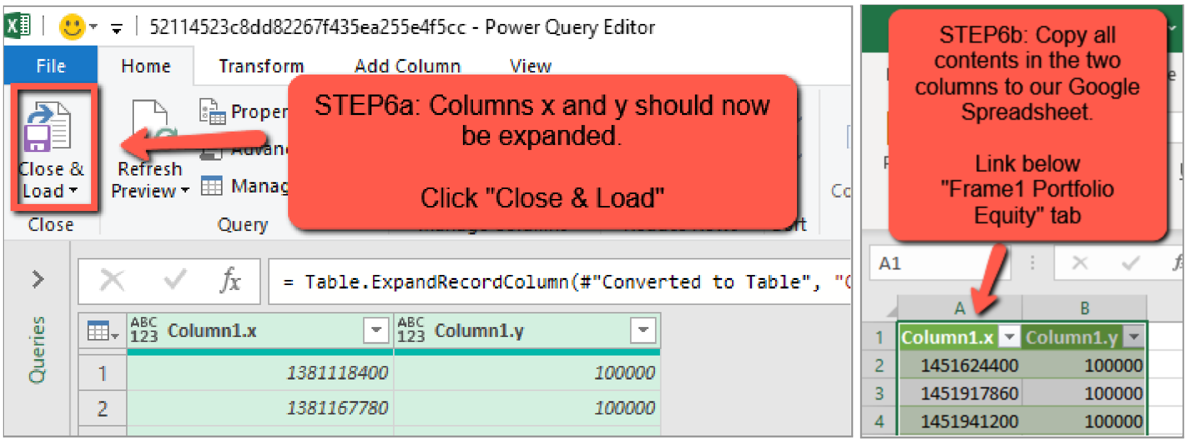
Following Step 4, the properly expanded record is almost ready to be converted into a table. The diagrams below detail the expansion of the equity data fields.




To Table
Create a table from a list of values.
Select or enter delimiter
None
How to handle extra columns
Show as errors
STEP5b: Delimiter should be "None"
Click "OK" to continue
OK
Cancel


52114523c8dd82267f435ea255e4f5cc - Power Query Editor
File
Home
Transform
Add Column
View
Close & Load
Refresh Preview
Properties
Advanced Editor
Manage
Choose Columns
Close
Query
STEP5c: Click this button to select columns to expand
Make sure "x", "y" are slected, then
Click "OK" to continue
Queries
Column1
Record
Search Columns to Expand
(Select All Columns)
x
y
Use original column name as prefix
List may be incomplete.
Load more
OK
Cancel

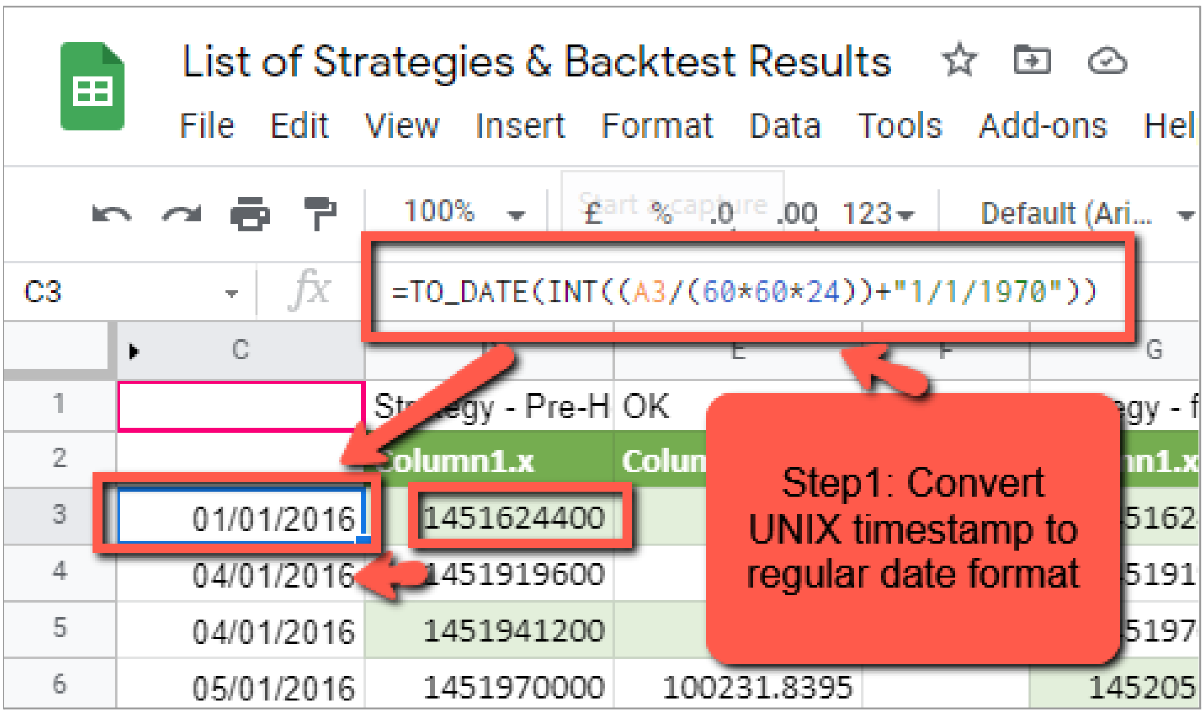
Step 6: Conversion of the equity data into a table and copying it to a Google Sheets spreadsheet
The diagrams below outline the conversion of the records into tabular form that can finally be used for analysis. For ease of analysis, the table is copied into a Google Drive spreadsheet that can be accessed by the MPT Python script for analysis.



B. Preparation of Strategy Equity Data for Modern Portfolio Theory Framework

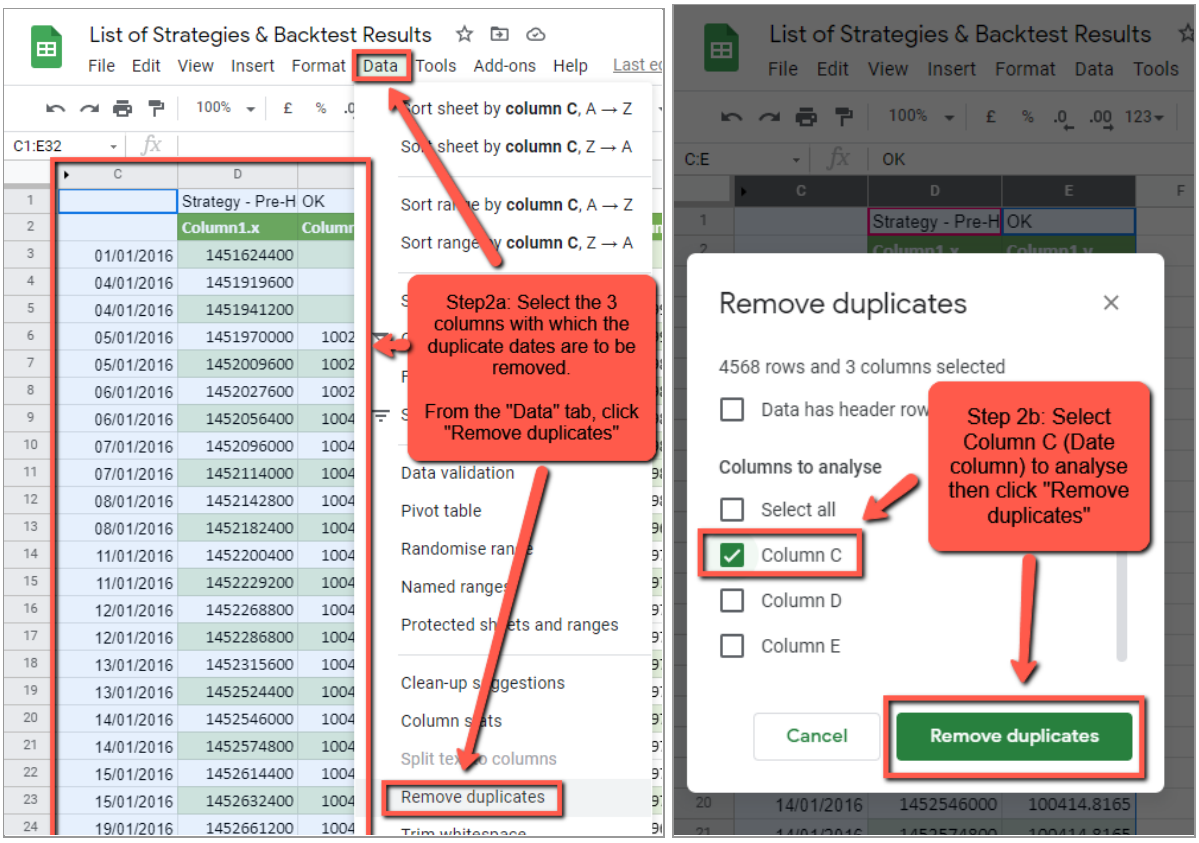
Comparing the performance(equity) between different strategies required the preparation of data to fit a common time-series. Most of the strategies backtested followed a 5-day trading week, however, some had more than 5 trading days a week. It was opted to down-sample the equity results of strategies with more than 5 trading days to fit 5 trading days a week.

Step 1: Conversion of UNIX timestamp to regular date
The QuantConnect results file stores date-time information as a UNIX timestamp. For purposes of subsequent analysis in the MPT framework, we convert the timestamp into regular date format and omit time information. The diagram below shows the spreadsheet formula used to convert the UNIX timestamp to a regular date format.



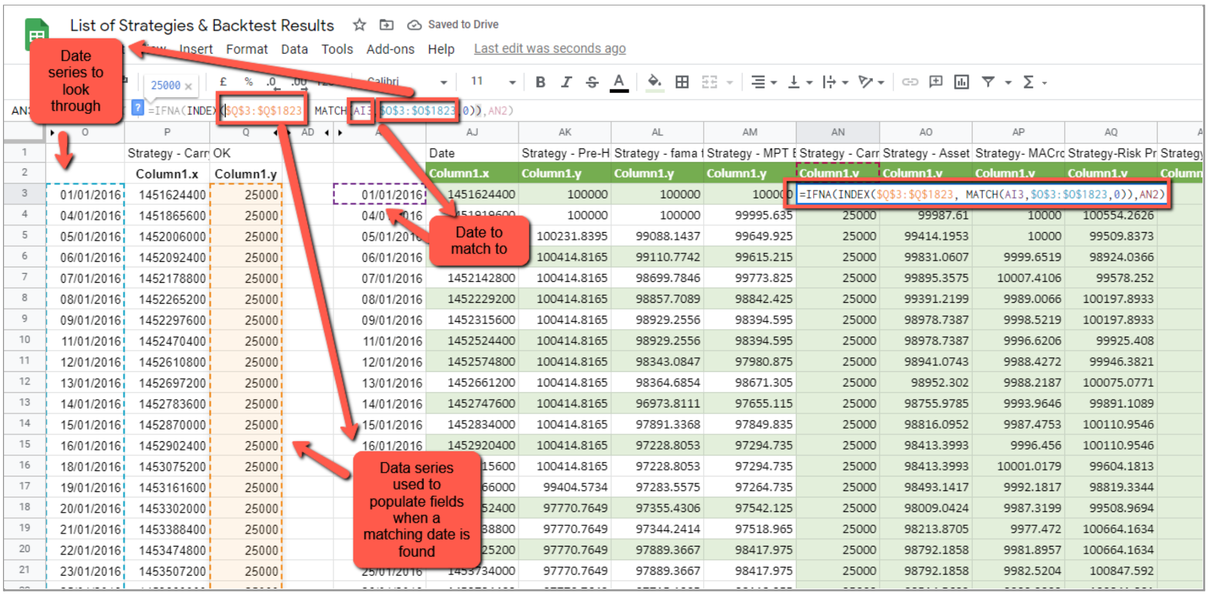
Step 2: Removing Duplicate Rows

Following Step 1, entries with duplicate dates will now be present in the table. These entries will need to be removed. The following diagrams outline the method to remove duplicate date rows from the data.



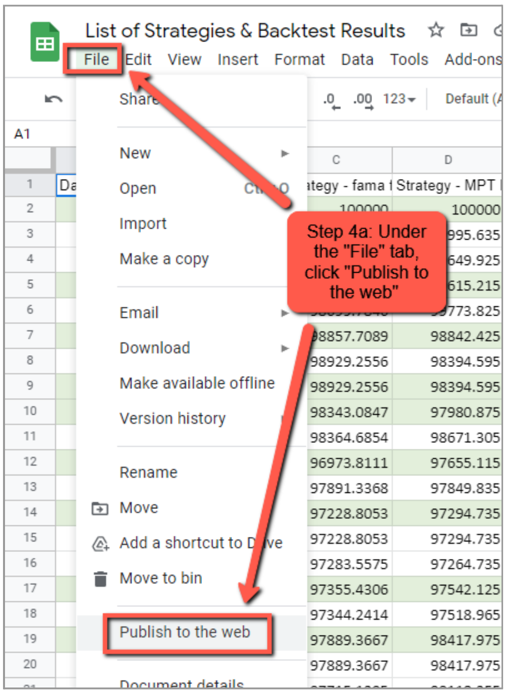
Step 3: Down-sampling data series with more than 5 trading days per week

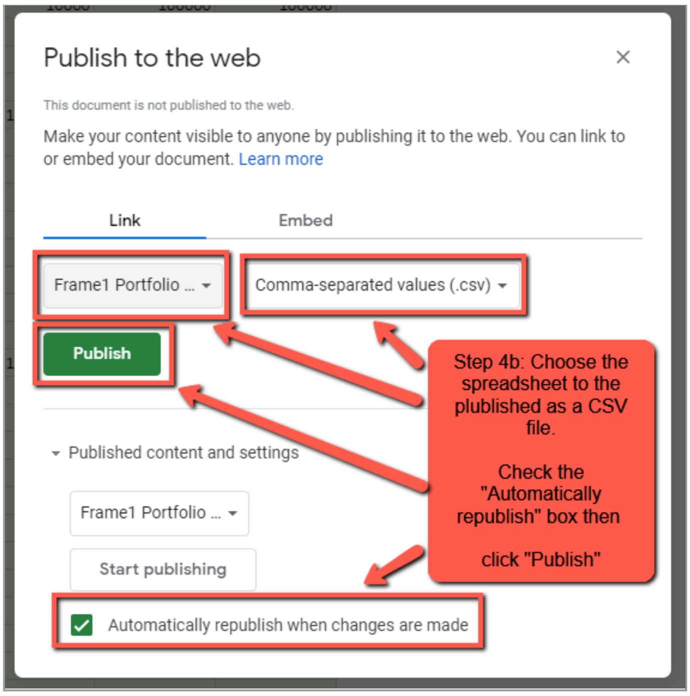
For equity data series that have more than 5 trading days per week, we use the INDEX and MATCH functions to match dates and equity data to a 5-day trading week. The diagram below shows the formula used to perform this operation.

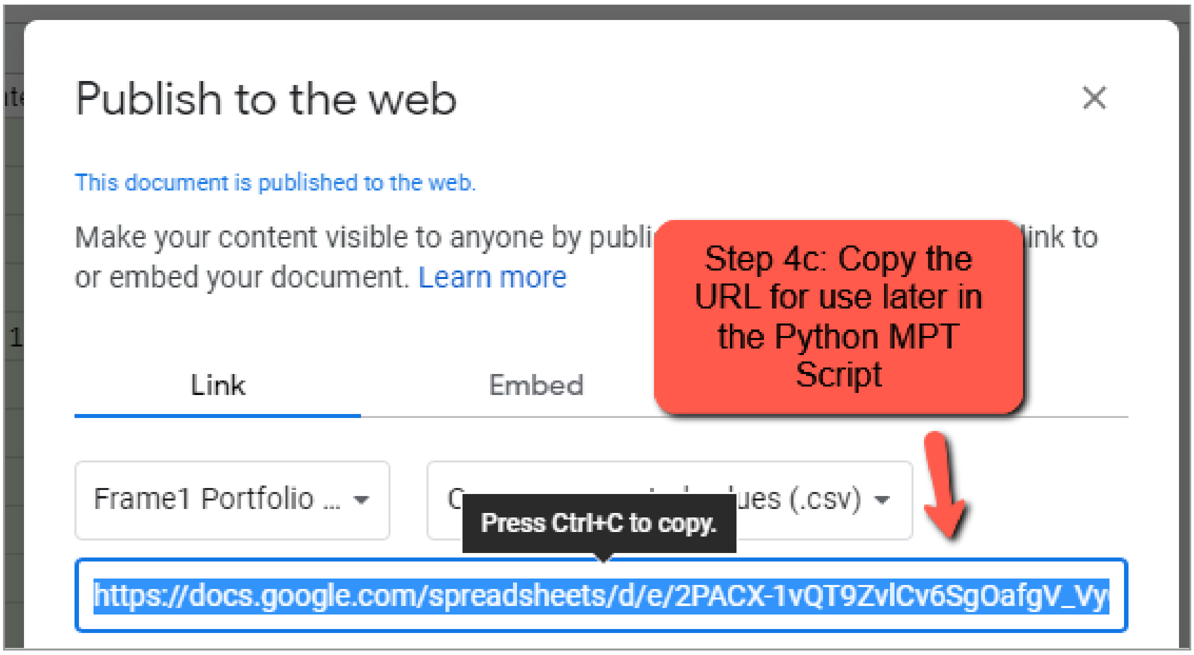


Step 4: Publishing of Spreadsheet data for access by MPT Python Script

Once all strategies have been processed to fit a common time-series, the data can be published to allow access by the MPT Python Script. The diagrams below outline the steps to accomplish this.

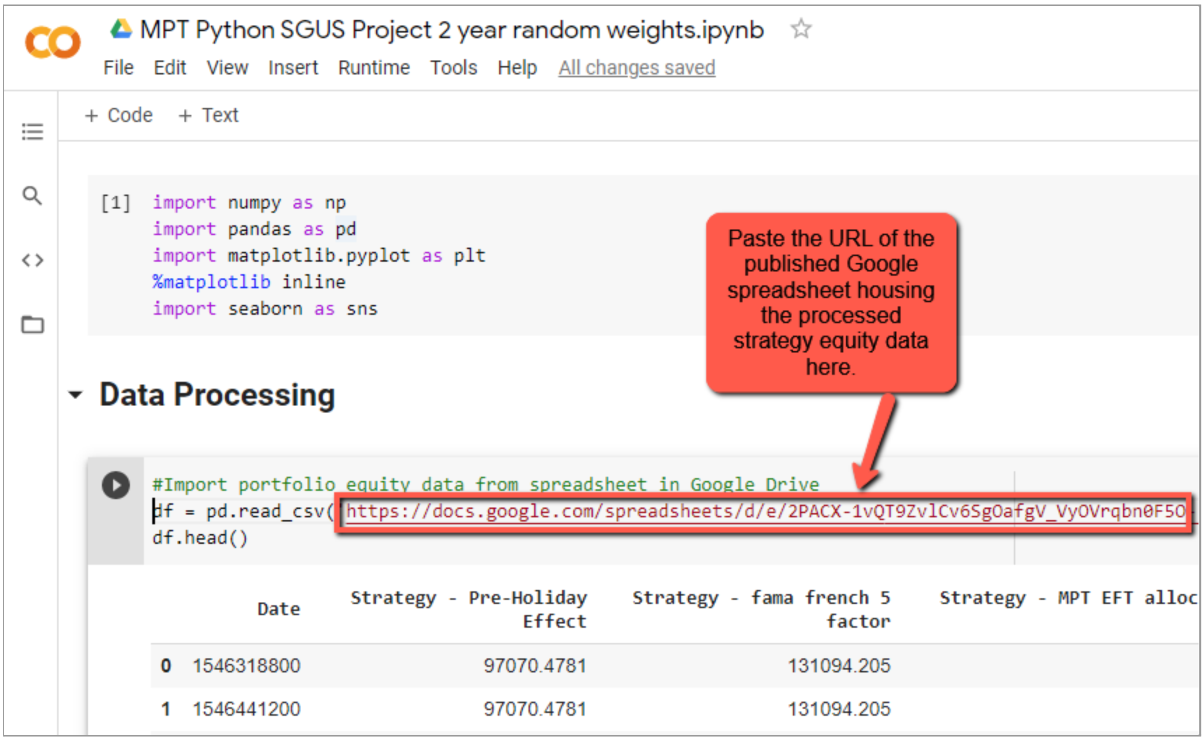






Modern Portfolio Theory (MPT) Framework Analysis

The processed strategy equity data can now be processed within the MPT Google Colab Notebook. After we paste the URL of the published Google spreadsheet containing the processed strategy equity data into the Python Script (shown below), all the notebook cells can be run to produce analysis using the MPT framework.



Step 1: Analysing Strategy Correlation

The MPT script produces a correlation matrix using the Seaborn library. Strategies with a high correlation should be noted and considered for exclusion. Having multiple strategies with high correlation may expose the portfolio to greater risks and drawdown should market conditions go against the strategies.

From the correlation matrix shown in Figure 1, it is observed that 2 pairs of strategies have a high correlation (above 0.5). The highly correlated strategy pairs are:

1) Asset Class Momentum (ETFs) - MPT EFT allocation (SPY, QQQ, TLT, GLD) - correlation 0.72
2) Asset Class Momentum (ETFs) - Tiingo News NLP - correlation 0.53

The exclusion of 1 or 2 of these strategies from the overall portfolio should be considered after further analysis of the risks & returns of these strategies.

```python
[7]  #Correlation matrix
     corr_matrix = df.pct_change().apply(lambda x: np.log(1+x)).corr()
```

```python
[8]  plt.figure(figsize=(12,7))
     corr_matrix_plot = sns.heatmap(corr_matrix, vmin=-1, vmax=1, annot=True)
```

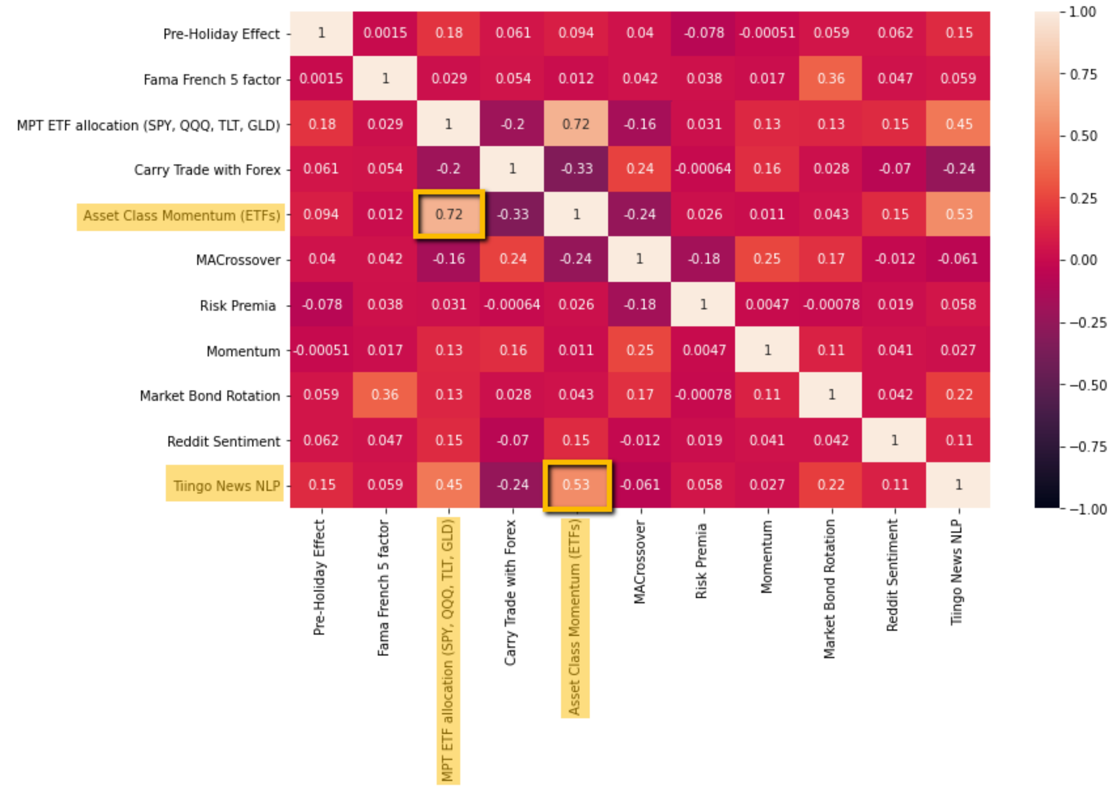


Figure 1: Strategy Correlation Matrix

Step 2: Analysing Returns vs Risk

Figure 2 below shows the Returns vs Risk of the strategies under comparison. The return values are the mean yearly returns calculated over a 2 year backtest period. The volatility figures(annual standard deviation) which represents the riskiness of the strategy are derived from the daily standard deviation figures of individual strategies' daily equity figures.

```
# Creating a table for visualising returns and volatility of assets/strategies
assets = pd.concat([ind_er, ann_sd], axis=1)
assets.columns = ['Returns', 'Volatility']
assets
```

	Returns	Volatility
Pre-Holiday Effect	0.120012	0.036998
Fama French 5 factor	0.426970	0.229962
MPT ETF allocation (SPY, QQQ, TLT, GLD)	0.325569	0.201672
Carry Trade with Forex	0.085539	0.050871
Asset Class Momentum (ETFs)	-0.042183	0.205385
MACrossover	0.035480	0.019159
Risk Premia	0.073794	0.058815
Momentum	0.147510	0.058204
Market Bond Rotation	1.178451	0.217444
Reddit Sentiment	0.185401	0.125153
Tiingo News NLP	0.567022	0.196713

Figure 2: Returns & Volatility Comparison

The annualized volatility of the S&P of 0.177 over the last 5-year period was chosen as the benchmark for classifying strategies into high-risk(volatility >0.177) and low-risk(volatility <0.177).

The strategies highlighted in yellow were shown to have a high correlation(higher than 0.5). It was observed that over the last 2 years, the Asset Class Momentum (ETFs) strategy was not profitable and should be omitted from the final portfolio.

Omitting the Asset Class Momentum (ETFs) strategy from the portfolio eliminated strategy pairs with a high correlation. The remaining strategies shall be included in the overall portfolio.

Step 3: Plotting the Efficient Frontier & Obtaining Portfolio Weights for the Portfolio incorporating High-risk and Low-risk Strategies

Following the decision to omit the Asset Class Momentum (ETFs) from the final portofolio, the MPT script is re-runned to obtain the portfolio weights using the Markowitz Efficient Frontier.

The MPT script assigns a user configurable number of permutations of random weights to the different strategies and plots the corresponding return & volatility figures to create the Efficient Frontier plot. The number of permutations was set at 100000 for the analysis.

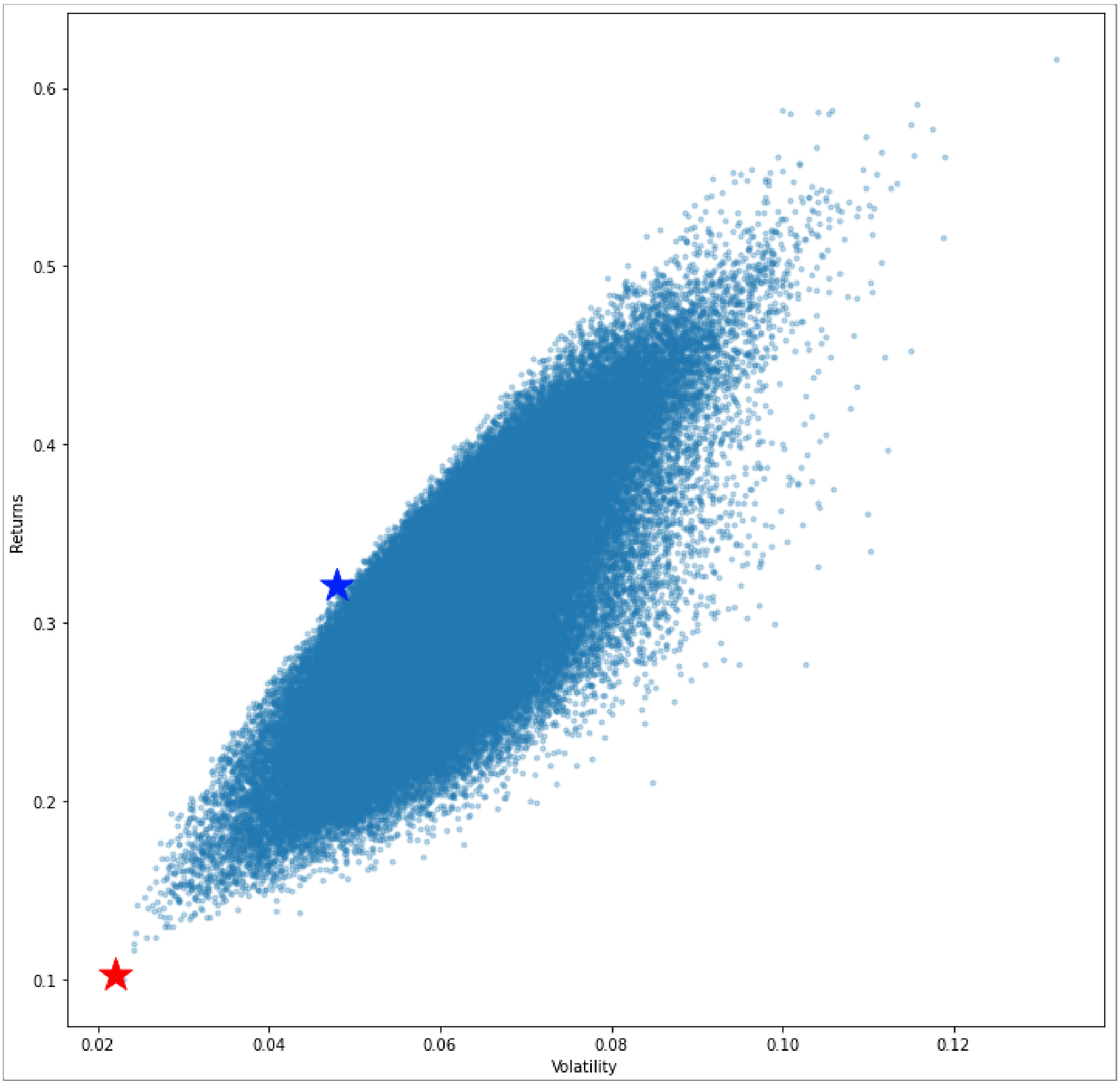


Figure 3a: Efficient Frontier for the Portfolio Incorporating high-risk & low-risk strategies

Figure 3a shows the Efficient Frontier Plot. The red star represents the point of portfolio allocation with the lowest volatility while the blue star represents the point of portfolio allocation with the highest Sharpe Ratio.

	Returns	Volatility
Pre-Holiday Effect	0.120012	0.036998
Fama French 5 factor	0.426970	0.229962
MPT ETF allocation (SPY, QQQ, TLT, GLD)	0.325569	0.201672
Carry Trade with Forex	0.085539	0.050871
MACrossover	0.035480	0.019159
Risk Premia	0.073794	0.058815
Momentum	0.147510	0.058204
Market Bond Rotation	1.178451	0.217444
Reddit Sentiment	0.185401	0.125153
Tiingo News NLP	0.567022	0.196713

Figure 3b: Returns & Volatility of Strategies for the Portfolio Incorporating high-risk & low-risk strategies

```
#Getting parameter/weights of the point with minimum volatility
min_vol_port = portfolios.iloc[portfolios['Volatility'].idxmin()]
# idxmin() gives us the minimum value in the column specified.
min_vol_port
```

```
Returns                                          0.102699
Volatility                                       0.021967
Pre-Holiday Effect weight                        0.203089
Fama French 5 factor weight                      0.015064
MPT ETF allocation (SPY, QQQ, TLT, GLD) weight   0.027895
Carry Trade with Forex weight                    0.092707
MACrossover weight                               0.266673
Risk Premia  weight                              0.230906
Momentum weight                                  0.093418
Market Bond Rotation weight                      0.000830
Reddit Sentiment weight                          0.067445
Tiingo News NLP weight                           0.001973
Name: 27880, dtype: float64
```

Figure 3c: Returns, Volatility & Strategy Weights for the Portfolio Incorporating high-risk & low-risk strategies (Lowest Risk)

```
# Finding the optimal portfolio (i.e. Highest Sharpe Ratio)

# risk factor(risk-free rate)
rf = 0.0161  #1.61% Average return of Singapore Savings Bonds over 10 years https://www.mas.gov.sg/bo

optimal_risky_port = portfolios.iloc[((portfolios['Returns']-rf)/portfolios['Volatility']).idxmax()]
optimal_risky_port
```

```
Returns                                         0.320604
Volatility                                      0.047891
Pre-Holiday Effect weight                       0.207079
Fama French 5 factor weight                     0.004470
MPT ETF allocation (SPY, QQQ, TLT, GLD) weight  0.020180
Carry Trade with Forex weight                   0.180610
MACrossover weight                              0.064733
Risk Premia  weight                             0.120258
Momentum weight                                 0.139403
Market Bond Rotation weight                     0.172059
Reddit Sentiment weight                         0.037709
Tiingo News NLP weight                          0.053499
Name: 19502, dtype: float64
```

Figure 3d: Returns, Volatility & Strategy Weights for the Portfolio Incorporating high-risk & low-risk strategies (Highest Sharpe Ratio)

The risk-free return rate used to calculate the Sharpe Ratios is 1.61%. This value is the average return of the Singapore Savings Bonds over 10 years.

Step 4: Plotting the Efficient Frontier & Obtaining Portfolio Weights for the Portfolio Incorporating Low-risk Strategies

Similar to Step 3, the MPT script is re-runned to obtain the portfolio weights for the Portfolio incorporating only low-risk strategies (volatility < 0.177).

Figure 4a shows the Efficient Frontier Plot. The red star represents the point of portfolio allocation with the lowest volatility while the blue star represents the point of portfolio allocation with the highest Sharpe Ratio.

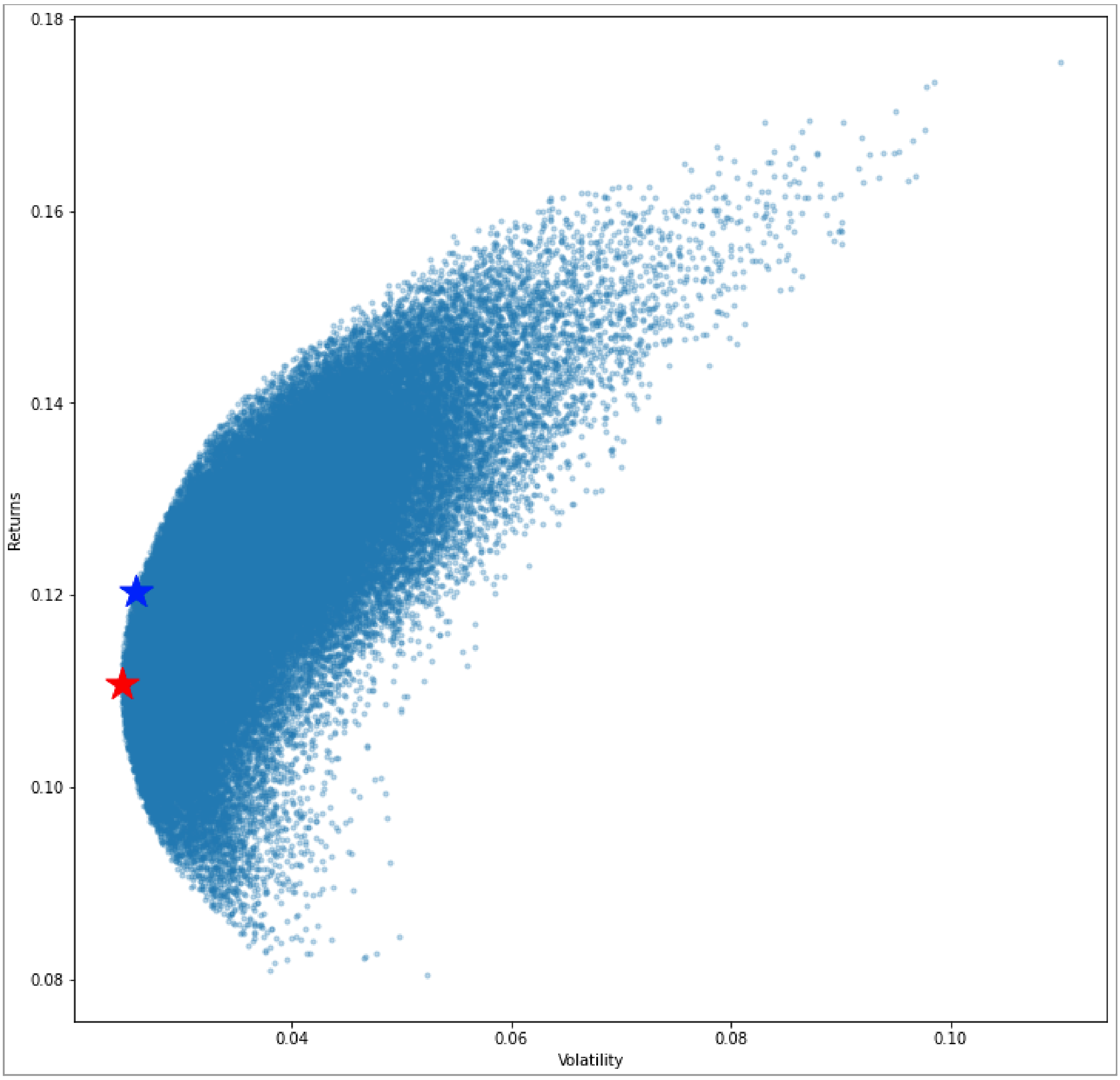


Figure 4a: Efficient Frontier for the Portfolio Incorporating only low-risk strategies

	Returns	Volatility
Pre-Holiday Effect	0.120012	0.036998
Carry Trade with Forex	0.085539	0.050871
Risk Premia	0.073794	0.058815
Momentum	0.147510	0.058204
Reddit Sentiment	0.185401	0.125153

Figure 4b: Returns & Volatility of Strategies for the Portfolio Incorporating only low-risk strategies

```
#Getting parameter/weights of the point with minimum volatility
min_vol_port = portfolios.iloc[portfolios['Volatility'].idxmin()]
# idxmin() gives us the minimum value in the column specified.
min_vol_port
```

```
Returns                          0.110787
Volatility                       0.024545
Pre-Holiday Effect weight        0.423380
Carry Trade with Forex weight    0.210414
Risk Premia  weight              0.176291
Momentum weight                  0.164745
Reddit Sentiment weight          0.025171
Name: 17948, dtype: float64
```

Figure 4c: Returns, Volatility & Strategy Weights for the Portfolio Incorporating only low-risk strategies (Lowest Risk)

```
# Finding the optimal portfolio (i.e. Highest Sharpe Ratio)

# risk factor(risk-free rate)
rf = 0.0161  #1.61% Average return of Singapore Savings Bonds over 10 years https://www.mas.gov.sg/b

optimal_risky_port = portfolios.iloc[((portfolios['Returns']-rf)/portfolios['Volatility']).idxmax()]
optimal_risky_port
```

```
Returns                          0.120382
Volatility                       0.025777
Pre-Holiday Effect weight        0.469496
Carry Trade with Forex weight    0.137043
Risk Premia  weight              0.110352
Momentum weight                  0.219509
Reddit Sentiment weight          0.063600
Name: 8033, dtype: float64
```

Figure 4d: Returns, Volatility & Strategy Weights for the Portfolio Incorporating only low-risk strategies (Highest Sharpe Ratio)

The risk-free return rate used to calculate the Sharpe Ratios is 1.61%. This value is the average return of the Singapore Savings Bonds over 10 years.

Step 5: Plotting the Efficient Frontier & Obtaining Portfolio Weights for the Portfolio Incorporating High-risk Strategies

The MPT script is re-runned to obtain the portfolio weights for the Portfolio incorporating only high-risk strategies (volatility > 0.177).

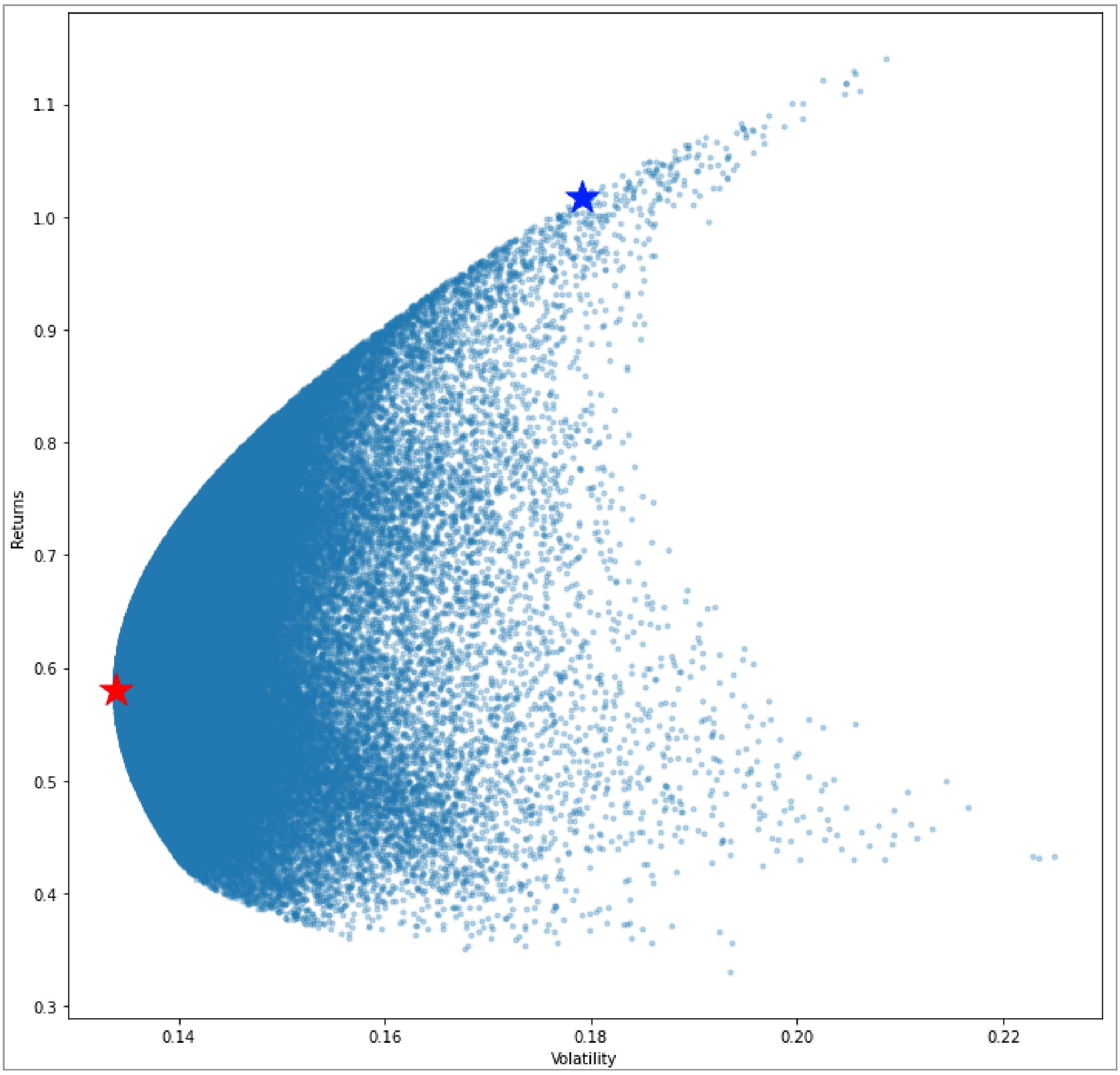


Figure 5a: Efficient Frontier for the Portfolio Incorporating only high-risk strategies

Figure 5a shows the Efficient Frontier Plot. The red star represents the point of portfolio allocation with the lowest volatility while the blue star represents the point of portfolio allocation with the highest Sharpe Ratio.

	Returns	Volatility
Fama French 5 factor	0.426970	0.229962
MPT ETF allocation (SPY, QQQ, TLT, GLD)	0.325569	0.201672
Market Bond Rotation	1.178451	0.217444
Tiingo News NLP	0.567022	0.196713

Figure 5b: Returns & Volatility of Strategies for the Portfolio Incorporating only high-risk strategies

```
#Getting parameter/weights of the point with minimum volatility
min_vol_port = portfolios.iloc[portfolios['Volatility'].idxmin()]
# idxmin() gives us the minimum value in the column specified.
min_vol_port
```

```
Returns                                         0.580181
Volatility                                      0.133867
Fama French 5 factor weight                     0.250886
MPT ETF allocation (SPY, QQQ, TLT, GLD) weight  0.290691
Market Bond Rotation weight                     0.193783
Tiingo News NLP weight                          0.264641
Name: 40448, dtype: float64
```

Figure 5c: Returns, Volatility & Strategy Weights for the Portfolio Incorporating only high-risk strategies (Lowest Risk)

```
# Finding the optimal portfolio (i.e. Highest Sharpe Ratio)

# risk factor(risk-free rate)
rf = 0.0161  #1.61% Average return of Singapore Savings Bonds over 10 years https://www.mas.gov.sg/bo

optimal_risky_port = portfolios.iloc[((portfolios['Returns']-rf)/portfolios['Volatility']).idxmax()]
optimal_risky_port
```

```
Returns                                         1.017960
Volatility                                      0.179061
Fama French 5 factor weight                     0.002179
MPT ETF allocation (SPY, QQQ, TLT, GLD) weight  0.010629
Market Bond Rotation weight                     0.742211
Tiingo News NLP weight                          0.244981
Name: 31617, dtype: float64
```

Figure 5d: Returns, Volatility & Strategy Weights for the Portfolio Incorporating only high-risk strategies (Highest Sharpe Ratio)

The risk-free return rate used to calculate the Sharpe Ratios is 1.61%. This value is the average return of the Singapore Savings Bonds over 10 years.

Recommendations & Conclusion

The table below summarizes the returns and volatility of the different portfolio types.

Portfolio Type	Annual Returns	Volatility	Sharpe Ratio
High & Low Risk (Lowest Volatility)	0.107	0.0220	4.68
High & Low Risk (Highest Sharpe Ratio)	0.321	0.0479	6.69
Low Risk (Lowest Volatility)	0.111	0.0245	4.51
Low Risk (Highest Sharpe Ratio)	0.12	0.0258	4.67
High Risk (Lowest Volatility)	0.58	0.1339	4.33
High Risk (Highest Sharpe Ratio)	1.018	0.1791	5.69

Table 1: Comparison of Portfolio Allocations using MPT Efficient Frontier

It is interesting to note that the values of both low-risk portfolios and the High & Low Risk (Lowest Volatility) portfolio are very similar. On further inspection, the individual weights vary across the three cases.

The High & Low Risk (Highest Sharpe Ratio) portfolio offers an annual return at least 20% higher than the 3 previously mentioned portfolios for a corresponding increase in volatility of about 0.02. This substantial improvement in returns for a small increase in volatility offers an enticing proposition and should be thoroughly considered for implementation.

The high-risk portfolios offer very substantial annual returns of 58.0% & 101.8% at a substantially increased risk of 0.1339 and 0.1791. These portfolios may be suitable for investors with a big risk appetite looking for the potential of large returns.

Although some of the portfolios look very promising, it is important to note that past performance is not a guarantee of future returns. Frequent performance monitoring, review and re-assessment of the portfolio allocation should be conducted for whichever portfolio allocation is chosen to be implemented.