RO3

Long Term Investing with Dynamic Hedging using a combination of Stocks and Options

Gin yui, Tsang

RO3

Supervised by

Dr David Rossiter

Submitted in partial fulfilment

of the requirements for COMP4981H

in the

Department of Computer Science and Engineering

The Hong Kong University of Science and Technology

2020-2021

Date of submission: 29th January 2021

Abstract

The Dynamic Hedging (DH) strategy proposed in this thesis is a strategy that can improve return per unit risk. DH strategy is a combination of three independent strategies that can profit in different market condition. To verify the DH strategy's effectiveness, we backtested the system on the SPDR S&P 500 Trust ETF (SPY) from December 2013 to May 2020. Our test result shows that DH strategy outperformed SPY in annual return, Sharpe ratio and Calmar ratio. Our research also includes a practical approach to implement an equity-options backtesting engine in Python.

Keywords:

Investment, quantitative trading, risk parity, diversification, options

Table of Contents

List of Figures

List of Tables

List of Algorithms

1. Introduction

1.1. Overview

Since the 2008 Financial Crisis, central banks have distorted the financial markets through interest rate reduction and quantitative easing (QE) intervention [1] [2]. During these 12 years, the US, China, and Japan alone have injected at least 37 trillion US dollars into the global economy [3], creating increased monetary inflation. The situation has intensified since the outbreak of the coronavirus pandemic. Central banks in major economies (Table 21) started following the Modern Monetary Theory (MMT) to coordinate fiscal and monetary policies to support the fragmented economies [4]. Zero-interest rates, QE, together with MMT, increased the global supply of money and credit, which has flooded into various asset classes such as global equities and precious metals, raising the prices of these assets [5]. The effect of monetary inflation is increased volatility across asset classes, even in conventional hedging assets such as gold and inflation-linked bonds [1] [6] .

Rising volatility increases the risks of non-speculative long-term investors. The most common strategy to hedge against the risk of downward price movement would be reducing the position's exposure by selling the assets. However, such an approach would also reduce potential returns. Another strategy, which has been heavily researched by the academic, is diversification. Through investing in multiple asset classes with low-correlation returns, investors can create balanced portfolios with stable returns [7] [8].

Incorporation of options-based strategies with equity is an alternative approach to portfolio management. Investors can alter their portfolios' exposure by opening various option positions without liquidating their equity positions [9]. However, the high leverage and complexity of options pricing often misguide amateur investors to use it for speculation, posing additional risks to investors [10].

This study investigated a dynamic hedging strategy (DH) involving a combination of stocks and options to deliver sustainable and stable returns for long-term investors. It is hoped that this paper will contribute to the academic community that studies quantitative investing. The DH strategy is designed to help long-term investors minimize losses during bear markets and provide a return that can outperform conventional benchmarks.

The design of our DH strategy is described in the Methodology section.

1.2. Objectives

This study's main goal was to develop a sustainable strategy that allows investors to invest in the equity market without severe drawdown by using options to hedge against risks.

The following objectives were defined to accomplish this goal.

- Gather and polish stocks and options data for backtesting purposes.
    - Adjust stock prices relative to dividend payments.
    - Reconcile options prices of multiple exchanges by using the mean value.
    - Segregate stock time series data into 1-hour intervals for analysis.
- Develop an engine with the following features
    - Calculate the mark-to-market net value of the testing account.
    - Simulate the buying and selling of securities in the past.
    - Provide flexibility to implement multiple strategies.
    - Complete the simulation.
- Evaluate the DH strategy performance relative to the following indicators.
    - Annual cumulative returns
    - Annual volatility
    - Sharpe ratio
    - Calmar ratio
    - Max drawdown
    - Visual comparison with selected benchmarks

1.3. Literature survey

To effectively explore the landscape of investment techniques, quantitative investment, and options trading, we performed a survey to address these areas.

1.3.1. Portfolio management theories

1.3.1.1. Risk parity investing

Risk parity investing, also known as balanced-beta investing, was brought to the world's attention by Bridgewater Associates after they successfully navigated the 2008 financial crisis with more than 40% positive gains [8]. Risk parity investing is about isolating the environment risks by investing in multiple assets that counteract each other (Figure 1). The returns from a risk parity mix are from collecting the risk premium of assets. The mix usually contains equities, commodities, corporate credit, inflation-linked bonds, nominal bonds, and emerging market credit [11].

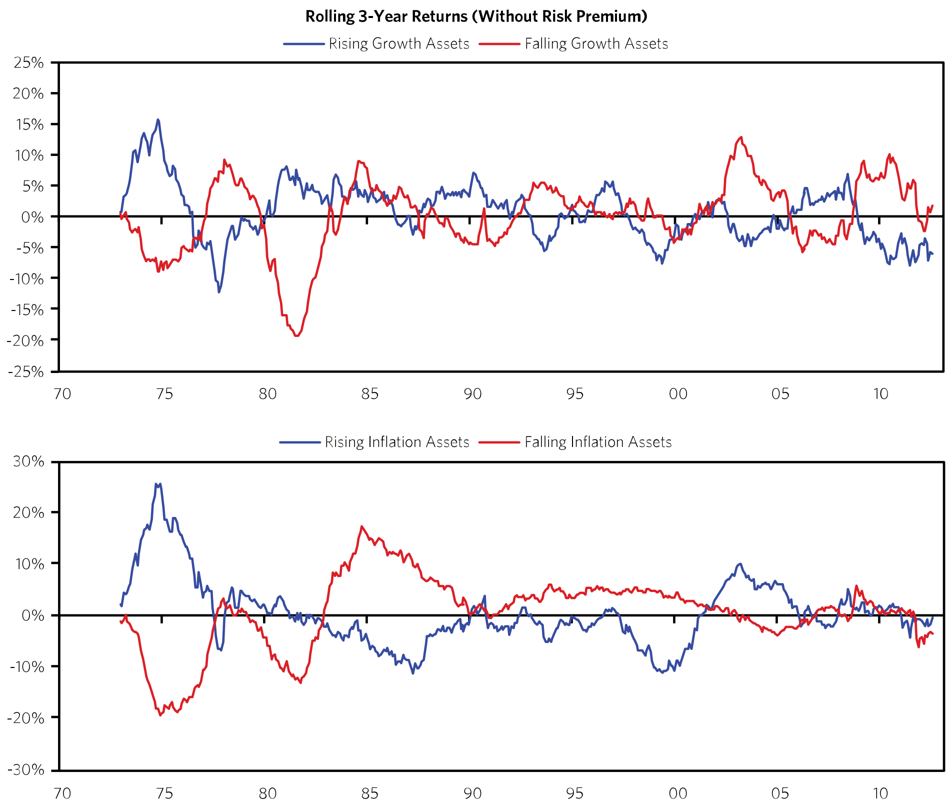

Figure 1 Counter asset allocation Bridgewater Associates (2011)

1.3.1.2. Mean-variance theory

Mean-variance theory, or Modern portfolio theory (MPT), is one of the most influential frameworks for creating a portfolio of assets to maximize expected return for a certain amount of risk. The MPT approach is essentially the extension of diversification. In 1952, Harry Markowitz published a paper in which he quantified variance as risk and explained that one should not evaluate on asset's risk and return independently. [12] In this study, we adopted Harry Markowitz.'s understanding of risk and diversification to construct our DH strategy.

1.3.2. Well-known quantitative investment strategies

1.3.2.1. Momentum strategy for equities

Momentum is a market phenomenon in which stocks that have moved up strongly in the recent past are likely to continue moving upward in the near future. Although there are many momentum strategy variations, the basic approach is to capture market momentum by quantifying the momentum of individual stocks and investing in those exhibiting the highest degree of momentum. Academics and practitioners have confirmed that momentum strategies are valid approaches to investing in the equity market [13].

1.3.2.2. Trend-following strategy for futures

Trend following is a common rule-based strategy in the commodity trading advisor (CTA) industry. It is a systematical approach to identify and trade the trends in commodity markets. This strategy is usually applied in different futures products without any change in the parameters [13]. Such an approach reduces the risk of overfitting.

1.3.3. Option-based strategies relative to long equity

The research done by M.L. Hemler and T.W. Miller analyzed four trivial strategies that combined option positions with long equity positions. They concluded that the covered call, protective put, and collar strategies could reduce the average standard deviation while the covered combination strategy yielded a higher return [9]. The mathematical notations and brief descriptions of the strategies are listed as follows.

Variables	Descriptions
C(t)	Call option at time t
P(t)	Put option at time t
S(t)	Price of the underlying asset at time t
$\boldsymbol{D(t)}$	Value at time t of dividends paid and reinvested over the interval from t − 1 to t

Table 1 Option-based strategies relative to long equity variables for analysis

Covered Call: Long stock plus short call

$$\frac{S(t) + D(t) - S(t-1) - \big(C(t) - C(t-1)\big)}{S(t-1) - C(t-1)}$$

Protective Put: Long stock plus long put

$$\frac{S(t) + D(t) - S(t-1) - \big(P(t) - P(t-1)\big)}{S(t-1) + P(t-1)}$$

Collar: Long stock plus short call plus long put

$$\frac{S(t) + D(t) - S(t-1) - \big(C(t) - C(t-1)\big) + (P(t) - P(t-1))}{S(t-1) - C(t-1) + P(t-1)}$$

Covered Combination: Long stock plus short call plus short put

$$\frac{S(t) + D(t) - S(t-1) - \big(C(t) - C(t-1)\big) - (P(t) - P(t-1))}{S(t-1) - C(t-1) - P(t-1)}$$

Our study followed the same approach of trading options and stocks simultaneously. Similar to the approach of [9], we defined our strategy's value and return functions mathematically before the implementation.

1.3.4. Data collection

1.3.4.1. Yahoo! Finance

Yahoo! Finance provides free historical quotes for stocks and ETFs. They also provide an easy-to-use interface for users to browse and download the data. However, Yahoo! Finance cannot provide historical data for options. Also, their free stocks and ETFs data is only quoted daily, which could not fulfil the hourly quotes' data requirement in this study.

1.3.4.2. The Chicago Board Options Exchange

The CBOE is the largest US options exchange, having the most significant annual options trading volume. They provide historical option pricing data from all their affiliated exchanges at any time interval. The benefit of using CBOE data is its high data reliability and accuracy, which is essential for constructing a realistic simulation. Our research utilized CBOE as the primary data provider for options quotes.

1.3.4.3. TD Ameritrade

TD Ameritrade is a renowned online broker providing brokerage services of stocks, futures, ETFs, and options for retail investors. They provide APIs for their clients to access historical stock data. However, they can only provide real-time options quotes instead of historical options data. Therefore, we only used TD Ameritrade as a reference for commission and a source for daily stock quotes.

1.3.5. Backtesting engine

1.3.5.1. Zipline by Quantopian

The Zipline package is one of the most mature backtesting engines available for public use. It provides high scalability, rich functionality, and native integration in Python. However, it could not handle options data, so it was not suitable.

1.3.5.2. Backtrader

Backtrader is another mature Python backtesting engine. Although it allows options backtesting as open, high, low, and close (OHLC) time series, it cannot handle multiple expiration dates, prices, and directions. Given the complexity of DH strategy, Backtrader was also not suitable for our testing purposes.

1.3.5.3. Options backtesting engine

There are some free options backtesting engines available online for non-commercial purposes, such as Optopsy, Lamdaclass, and Turning Trader. However, the built quality and functionality of these engines are substandard as most of these engines were built by amateurs. Furthermore, the online community for option backtesting is immature due to the inaccessibility of free historical options data. Moreover, the functionality requirement of this study extends beyond the capability of these engines. Thus, we built our own proprietary testing engine for the DH strategy.

1.3.5.4. Amibroker

Amibroker is a commercial market analysis software that supports rigid backtesting functionality. It is one of the fastest backtesting software available in the market. This study will use Amibroker as a benchmark for comparing the performance of our engine.

2. Methodology

2.1. Design

2.1.1. Engine design

2.1.1.1. Data flow pipeline

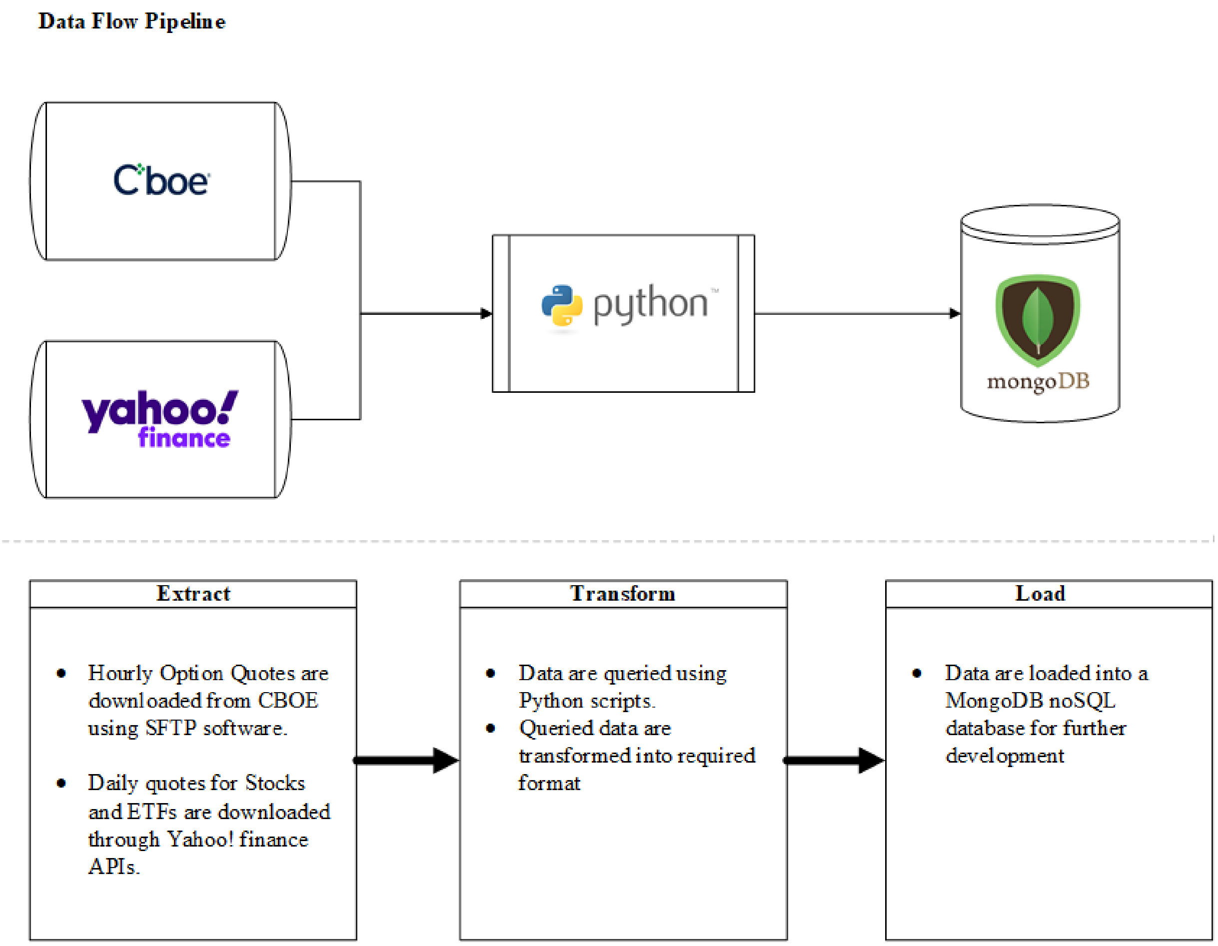

Figure 2 Data flow pipeline

We designed a data flow pipeline for querying hourly-quoted option data from CBOE and daily-quoted stock data from Yahoo! Finance. The data flow pipeline follows the ETL (Extract, Transform, and Load) protocol. The reason for using a NoSQL database to store these data is that it performs better at data assessment when dealing with a large volume of non-structured data than relational databases [14].

2.1.1.2. System architecture

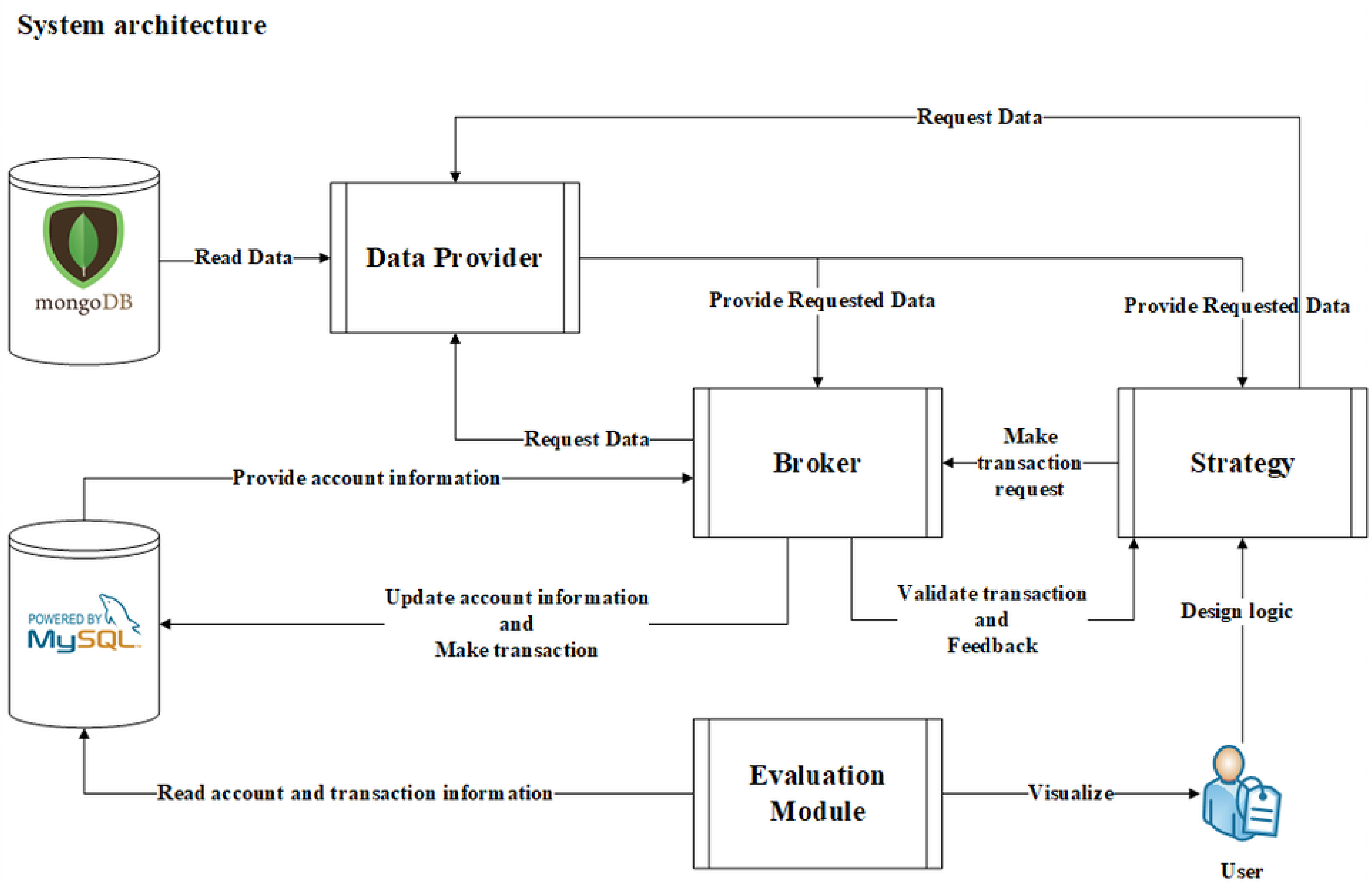

Figure 3 System architecture

Figure 3 shows the relationships between different classes in the engine used in this study.

- **Data Provider module**

The Data Provider module provides requested data from the Broker module and the Strategy module by querying the MongoDB database. It is capable of providing historical hourly-quoted option and stock data on demand. It can also formulate complicated option combinations, such as vertical spreads and back ratios. Moreover, the data provider module can calculate simple technical indicators, like the simple moving average, exponential moving average, and internal bar strength.

- **Broker module**

The Broker module is essential for facilitating the backtesting process. It creates and manages virtual accounts for simulating the changes in different account entries through the testing period.

The Broker module is modelled on TD Ameritrade's actual trading account. It simulates an account by tracking the account's cash balance, margin balance, short balance, long stock balance, short stock balance, long option balance, short option balance, buying powers, maintenance requirements, margin requirements, net liquidity and total commissions and fees. During a simulation, the broker module automatically conducts mark-to-market reconciliation to update the various account entries at the end of a simulated trading day.

The Broker module also handles transactional requests from the Strategy module, such as opening an option position or closing a stock position. It validates the transactions by checking the account entries of the virtual account. For example, it will reject transaction request if the virtual account does not have enough buying power to open a long position.

- **Strategy module**

The Strategy module enables the user to program his or her strategies. The user should specify the operation of the program based on a specified timeframe by manipulating functions provided by the Data Provider module and the Broker module. The user should handle invalid transaction request inside this module.

- **Evaluation module**

The Evaluation module visualizes the performance of the strategy to the user. It can show cumulated returns graphically and present key evaluation statistics. Benchmarking with a selected performance indicator is also available. Figure 4 shows an example of a sample strategy tested with Nvidia (NVDA). We can evaluate a strategy's performances based on annual return metrics, max drawdown, annual volatility, Sharpe ratio, Calmar ratio, Omega ratio, and downside risk. Tail ratio, alpha, and beta.

	gtsangtrading_20201101_1643	NVDA	SPY
Annual Return	59.18%	59.96%	9.10%
Max Drawdown	-32.33%	-57.02%	-19.72%
Annual Volatility	0.34650824752697346	0.4390453463619779	0.1329380556064296
Sharpe Ratio	1.499348151290368	1.286923407783064	0.722400734702952
Calmar Ratio	1.8301007487766117	1.0516347565149367	0.4613801012824536
Omega Ratio	1.6406866556780357	1.3005221521438683	1.1403277365443514
Downside Risk	0.15871134871469714	0.27833959891941656	0.09706838291702383
Tail Ratio	1.3561567438888047	1.1039706257099209	0.9218457878200648
Alpha	0.6247777946004232	0.5266176167083911	0.0
Beta	0.3508914769094779	1.4745510474900199	0.999999999999999

<Figure size 1440x720 with 0 Axes>

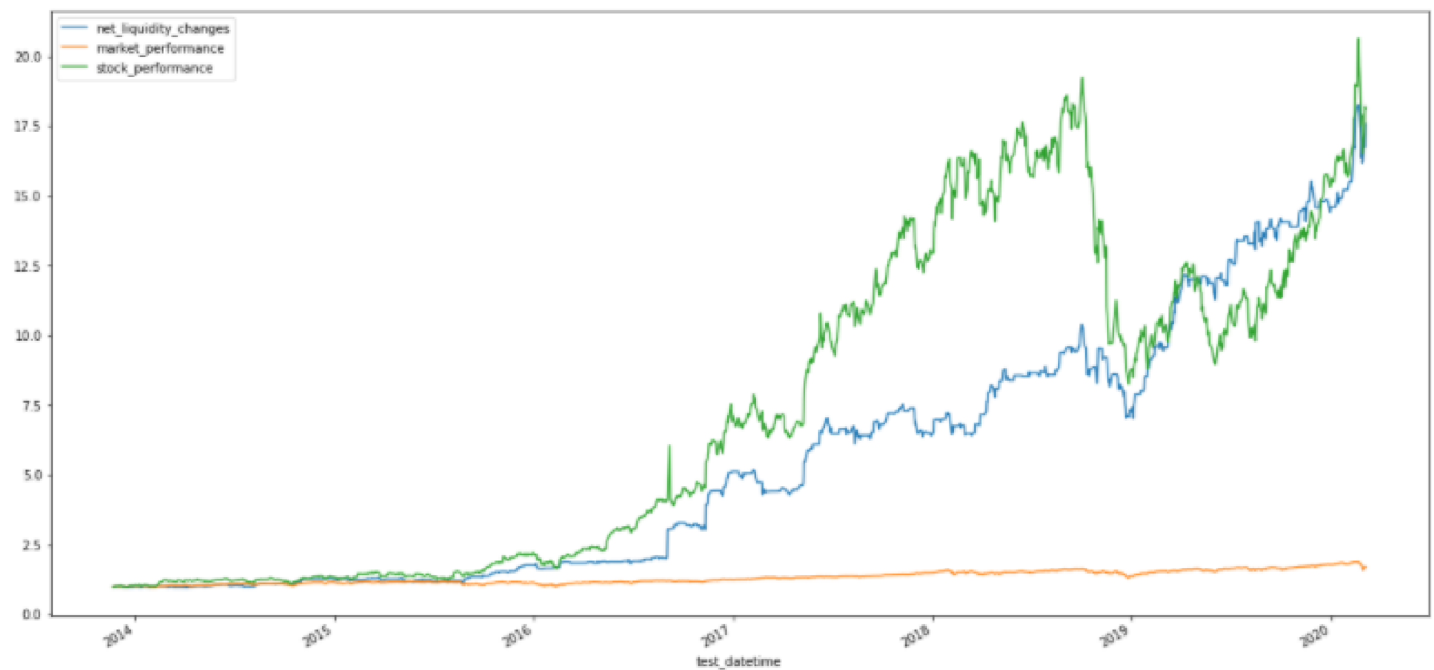

Figure 4 Example of Performance visualization.

2.1.1.3. Database design

- **SQL database**

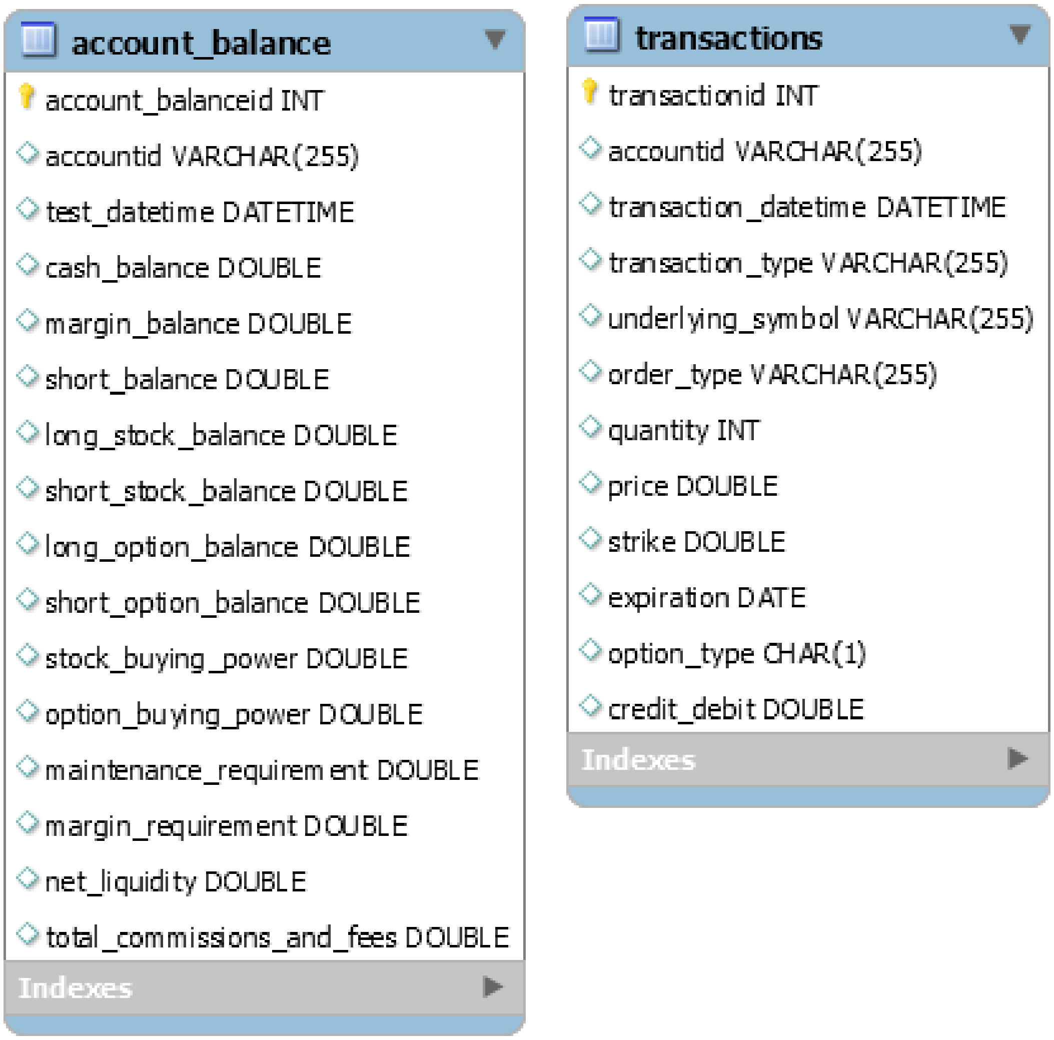

Figure 5 MySQL Database schema

Figure 5 shows the database schema of the MySQL database used in this study. The Broker module accesses account balance and transactions tables. The evaluation module mainly interacts with the account balance table.

- **NoSQL database**

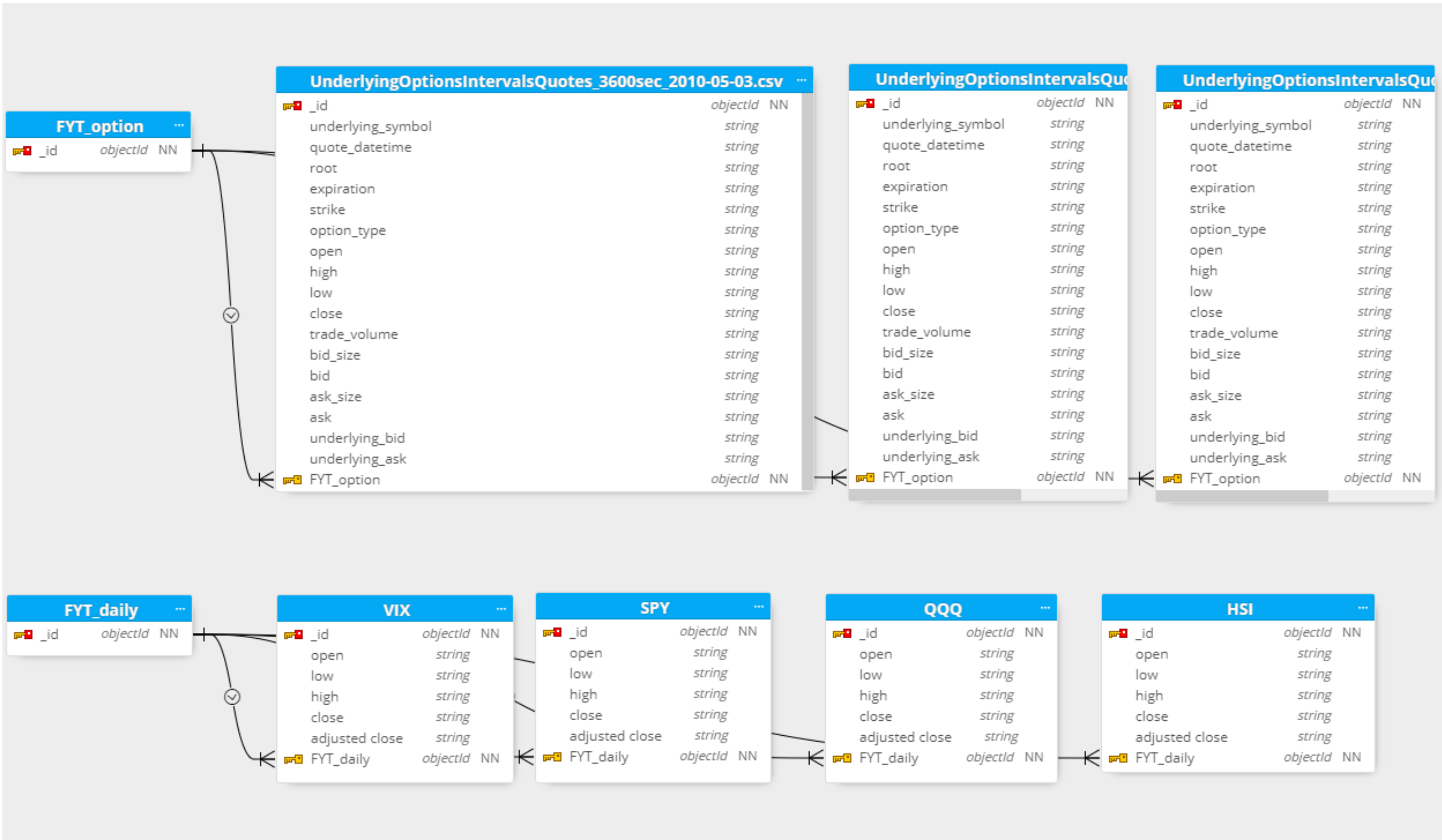

Figure 6 Simplified NoSQL database design

Figure 6 shows a simplified version of the MongoDB NoSQL database. FYT_Option contains the hourly-quoted option data while FYT_daily contains the daily-quoted stock data. Each file under FYT_Option represents one day of all options activities. In contrast, each file under FYT_daily represents ten years of the stock daily quotes.

2.1.2. DH strategy design

2.1.2.1. Overview

Our strategy is intended to capture the fundamental truth of price movements; prices can either go up, down or sideways. The DH strategy is composed of three components to tackle the three situations independently.

#	Components	Descriptions
1	Long Position	A position that gains in value when the underlying asset goes up. E.g. Shares of stock, Bullish options combination
2	Hedge (Short-biased)	A position that gains in value exponentially when the underlying asset goes down. E.g., Long Put option, Put back ratio (short put option plus two long put options)
3	Finance (market-neutral)	A position that gains in value when the underlying asset goes sideways. E.g., Calendar spread, Iron condor (short call spread plus short put spread)

Table 2 Dynamic Hedging components breakdown

The Long Position allows investors to gain in the capital when the asset goes up. The Hedge provides protection to the downside in bear markets. The Finance component provides a way for investors to profit when the market goes sideways. The purpose of this strategy is to diversify the portfolio's exposure to reduce downside risk and improve profitability.

As there are three pieces to our DH strategy, we formulated each part's value functions individually and then combined them. For the mathematical notation, we follow the conventions in Hemler and Miller's study [9], and the book of Jun Nie and Feng Wen [15] with additional parameters representing the expiration and strike price.

For the analysis to follow, the following variables are defined:

Variables	Descriptions
k	Strike price
e	Expiration date
t	Time
$C(k,e,t)$	Call option of strike k, expiration e, at time t
$P(k,e,t)$	Put option of strike k, expiration e, at time t
$S(t)$	Price of the underlying asset at time t, dividend-adjusted
$\boldsymbol{n}(\boldsymbol{t})$	Number of shares at time t
o(t)	Number of contracts used at time t
$\boldsymbol{Pos}(\boldsymbol{t})$	Aggregated position value at time t

Table 3 Variables for analysis

We have tested multiple strategies of different nature.

Code	Strategy Nature	Strategy name	Descriptions
LS-1	Long-Biased	Buy and hold	Long stock throughout the test
LS-2	Long-Biased	Revert back to mean	Long stock when the stock is oversold
LO-1	Long-Biased	Long Call options + Revert back to mean	Long call options when the stock is oversold
SO-1	Short-biased	Long Put options + Revert back to mean	Short put options when the stock is overbought
SO-3	Short-biased	Tail Risk put	Long 5% OTM put
NO-2	Market-neutral	Short Straddle	Short Call + Short Put + 15% OTM put
NO-2b	Market-neutral	Short Straddle with volatility filter	Short Straddle when VIX < 15
NO-2c	Market-neutral	Short Straddle with shorter DTE	Short straddle weekly.
NO-3	Market-neutral	Short strangle	Short 5% OTM put and call
C-1	Combined	Combined strategy	LS-2 + SO-1 + NO-3
C-2	Combined	Combined strategy	LO-1 + SO-1 + NO-3

Table 4 Strategies tested in this study

2.1.2.2. Strategy LS-1: Buy and hold

Strategy LS-1 is a traditional buy and hold strategy; we buy the selected stock and hold it until the end of the testing period.

- **Value function**

The value functions of the components at time t are as follows.

$$n(t) \times S(t)$$

- **Position Management**

We will invest 100% in the long position.

- **Algorithm**

LS-1 Algorithm	Trade logic at time t
if t == 0 then	
OPEN long stock	

Algorithm 1 Strategy LS-1

2.1.2.3. Strategy LS-2: Revert back to mean

Strategy LS-2 follows a technical indicator to determine the timing for entry. If we receive an oversold signal, we will take a long position.

- **Value function**

The value functions of the components at time t are as follows.

$$n(t) \times S(t)$$

- **Technical indicator**

We used the internal bar strength (IBS) to signal our entry and exit. The equation for calculating IBS at time t is as follow [16].

$$IBS(t) = \frac{Close(t) - Low(t)}{High(t) - Low(t)}$$

- **Position Management**

We invest 100% in a long position.

- **Algorithm**

LS-2 Algorithm	Trade logic at time t
if IBS(t-1) < 0.2 then	
OPEN long Stock	
if IBS(t) > 0.8 then	
CLOSE long Stock	

Algorithm 2 Strategy LS-2

2.1.2.4. Strategy LO-1: Long call options

Strategy LO-1 is derived from Strategy LS-2. We simply replace the stock with options.

- **Value function**

The value functions of the components at time t are as follows.

$$o(t) \times C(k,e,t)$$

- **Position Management**

We invest 20% of the account value in a long option position. The reason we do not invest 100% in an option position is that options pricing is hugely volatile.

- **Algorithm**

LO-1 Algorithm	Trade logic at time t

if IBS(t-1) < 0.2 then

  OPEN long call option

if IBS(t) > 0.8 then

  CLOSE long call option

Algorithm 3 Strategy LO-1

2.1.2.5. Strategy SO-1: Long put options

Strategy SO-1 will open a long put options position if the underlying asset is overbought.

- **Value function**

The value functions of the components at time t are as follows.

$$o(t) \times P(k,e,t)$$

- **Technical indicator**

In addition to the IBS indicator, we used Relative Strength Index (RSI) to signal our entry and exit points, The equation for calculating RSI at time t is as follows.

$$RSI = 100 - \frac{100}{1 + RS}$$

where

$$RS = \frac{Average\ of\ Upward\ Price\ Change}{Average\ of\ Downware\ Price\ Change}$$

- **Position Management**

We experimented with different allocation of capital for this strategy. Details are explained in the testing section.

- **Algorithm**

SO-1 Algorithm	Trade logic at time t

if IBS(t-1) > 0.8 and RSI(2,t) > 90 then

  OPEN long put option

if IBS(t) < 0.2 then

  CLOSE long put option

Algorithm 4 Strategy SO-1

2.1.2.6. Strategy SO-3: Tail-risk strategy

Strategy SO-3 opens a monthly-expired long put options position that is 5% OTM and hold until it expires. This strategy is inspired by Meb Faber [16].

- **Value function**

The value functions of the components at time t are as follows.

$$o(t) \times P(k,e,t)$$

- **Position Management**

10% of the net liquidity will be allocated for purchasing the put every month.

- **Algorithm**

SO-1 Algorithm	Trade logic at time t

if t == the expiration of the current put **then**

  OPEN new put

Algorithm 5 Strategy SO-3

2.1.2.7. Strategy NO-2: Short straddle

Strategy NO-2 open short straddle positions by selling ATM call, and ATM put option every month. To protect against downside losses, we purchase an additional put that is 15% OTM. This strategy is created by Joshua Coval and Tyler Shumway in 2000 [17].

- **Value function**

The value functions of the components at time t are as follows.

$$o(t) \times (P\left(k_a , e_j, t\right) + C\left(k_b , e_j, t\right)) - P\left(k_c , e_j, t\right)$$

$where$

$$k_b \approx S(t) \approx k_a > k_c$$

This trade should be a net credit trade.

- **Position Management**

Condition for opening new position: We open a new position one day before the previous position expire.

- **Algorithm**

NO-2 Algorithm	Trade logic at time t

if t + 1 == the expiration of the current straddle **then**

CLOSE old straddle

OPEN new straddle

end if

Algorithm 6 Strategy NO-2

2.1.2.8. Strategy NO-2b: Short straddle with volatility filter

Strategy NO-2b open short straddle positions by selling ATM call, and ATM put option every month. To protect against downside losses, we purchase an additional put that is 15% OTM. This strategy only takes a position when the volatility is below 20.

- **Value function**

The value functions of the components at time t are as follows.

$$o(t) \times (P(k_a , e_j, t) + C(k_b , e_j, t)) - P(k_c , e_j, t)$$

$where$

$$k_b \approx S(t) \approx k_a > k_c$$

This trade should be a net credit trade.

- **Position Management**

Condition for opening new position: We open a new position one day before the previous position expire.

- **Algorithm**

NO-2b Algorithm	Trade logic at time t

if t + 1 == the expiration of the current straddle **and** VIX(t) < 20 **then**

CLOSE old straddle

OPEN new straddle

end if

Algorithm 7 Strategy NO-2b

2.1.2.9. Strategy NO-2c: Short straddle with shorter DTE

Strategy NO-2c open short straddle positions by selling ATM call, and ATM put option every month. To protect against downside losses, we purchase an additional put that is 15% OTM. This strategy takes a position that is seven days before expiration.

- **Value function**

The value functions of the components at time t are as follows.

$$o(t) \times (P(k_a , e_j, t) + C(k_b , e_j, t)) - P(k_c , e_j, t)$$

$where$

$$k_b \approx S(t) \approx k_a > k_c$$

This trade should be a net credit trade.

- **Position Management**

Condition for opening new position: We will open a new position one day before the previous position expire.

- **Algorithm**

The algorithm will be the same as that of Algorithm 6 Strategy NO-2 with 7 days to expiration instead of 30 days.

2.1.2.10. Strategy NO-3: Short strangle

Strategy NO-3 is a short strangle strategy which shorts OTM calls and OTM puts every month.

- **Value function**

The value functions of the components at time t are as follows.

$$o(t) \times (P(k_a , e_j, t) + C(k_b , e_j, t))$$

where

$$k_b \approx S(t) * 105\%$$

and

$$k_a \approx S(t) * 95\%$$

This trade should be a net credit trade.

- **Position Management**

Condition for opening new position: We will open a new position one day before the previous position expire.

- **Algorithm**

NO-3 Algorithm	Trade logic at time t

if t + 1 == the expiration of the current strangle **then**

CLOSE old strangle

OPEN new strangle

end if

Algorithm 8 Strategy NO-3

2.1.2.11. Strategy CO-1: Combined strategy 1

Strategy CO-1 is a combined strategy with LS-2, SO-1, and NO-3. The allocation of capital in each strategy is as follows.

Strategy	**Weight**
LS-1	90%
SO-1	5%
NO-3	2%
Cash	3%

Table 5 CO-1 allocation

2.1.2.12. Strategy CO-2: Combined strategy 2

Strategy CO-2 is a combined strategy with LO-1, SO-1, and NO-3. The allocation of capital in each strategy is as follows.

Strategy	**Weight**
LO-1	20%
SO-1	5%
NO-3	2%
Cash	73%

Table 6 CO-2 allocation

2.1.2.13. Return function

We derive the return function at time t from the aggregated value function by taking the arithmetic difference between interval t and t-1.

Aggregated return

$$R(t) = \frac{Pos(t) - Pos(t-1)}{Pos(t-1)}$$

2.1.2.14. Stock selection universe

The underlying asset used for this study is SPY because it can satisfy the following requirements.

- The asset is publicly traded in one or more regulated exchanges
- The asset provides weekly, monthly, and quarterly expired options.
- The asset is highly liquid for both the options and the stock.
- The asset has a high daily trading volume.

2.1.2.15. Commissions

Commission for the stock position is zero, and the commission for the option is 0.5 USD per contract.

2.2. Implementation

We have achieved a significant milestone of creating a fully functional backtesting engine to carry out further tests. We have developed the Data flow pipeline as designed with data loaded into the internal NoSQL database. In terms of the backtesting engine, the four main modules of Data Provider, Broker, Strategy and Evaluation has been fully implemented and debugged. The implementation of the SQL database also works smoothly with the engine.

The greatest challenge in this project would be the handling of the anomaly of option data. Since we need to combine option quotes from multiple exchanges, we ran into data inconsistency. For example, the price quoted by different exchanges on the same security can be drastically different. We solved these problems by debugging the engine line by line during runtime with Visual Studio Code to fix all the anomalies. It is also the reason why the implementation of the backtesting engine consumed the most amount of time.

The engine is built with the following tools.

Programming languages	▪ Python ▪ SQL ▪ MongoDB
Development kits	▪ Anaconda ▪ Visual Studio Python debugger
IDE	▪ Jupyter Notebook ▪ Visual Studio Code ▪ MySQL workbench ▪ MongoDB Compass Community
libraries	▪ Numpy ▪ Pandas ▪ Matlab plot

Table 7 Development tools list

2.3. Testing

This study consisted of two major components, namely the development of a backtesting engine and the development of a consistent trading strategy. Software testing protocols were adopted for testing the engine, whereas trading strategies were evaluated based on some key financial metrics.

2.3.1. Software testing

Unit Testing was executed throughout the development process of the backtesting engine to ensure the integrity of the modules. Several rounds of integration testing were conducted to ensure that all the modules can function smoothly with each other. Meanwhile, various types of testing were conducted to test the SQL and NoSQL databases. The detailed testing results can be found in Appendix D: Engine testing results and survey.

The testing scope is listed below in Table 8.

In scope	Data Provider, Broker, Strategy and Evaluation modules
Out of Scope	Performance Test
Items not Tested	Invalid data format from external sources

Table 8 Testing Scope of the backtesting engine

2.3.2. Strategy testing

When we designed our test cases for the above strategies, we followed the principle of generalization, i.e., we attempted to choose parameters based on common sense [13]. We also chose not to improve the performance of our strategies by parameter optimization. We aim to provide tests that are intuitive and understandable to illustrate the effectiveness or ineffectiveness of the strategy in the most generic situation. Our approach helped us to mitigate the risk of overfitting and preserve the predictive values of our strategy.

We conducted all the tests for the testing period of 11/21/2013 to 5/27/2020, a total of 1637 effective trading days. During this period, the market experienced different market conditions. Between 2015 and 2016, the market went sideways with no significant trend in both directions. From the beginning of 2016 to 2018, the market was bullish with low volatility. Since 2018 until the end of the testing period, the market has been extremely volatile with VIX quoting at over 70. Thus, our testing period provided us with some perspective to examine the effectiveness of our strategies under various market conditions.

The details of the test cases can be found in Appendix E: Strategy testing results and survey.

2.4. Evaluation

2.4.1. Strategy performance evaluation

This study will evaluate the performance of each strategy based on the following common financial metrics: annual return, max drawdown, annual volatility, Sharpe ratio, Calmar ratio, Omega ratio, downside risk. Tail ratio, alpha, and beta. In the figures below, the blue line represents the equity of the strategy, whereas the orange line represents the benchmark.

2.4.1.1. Long-biased strategies

We have tested three long-biased strategies on SPY, namely Strategy LS-1: Buy and hold, Strategy LS-2: Revert back to mean, and Strategy LO-1: Long call options. Since LS-1 is essential just buying the SPY and holding it until the end, we will set LS-1 as the baseline to benchmark the other strategies.

- **LS-2 performance**

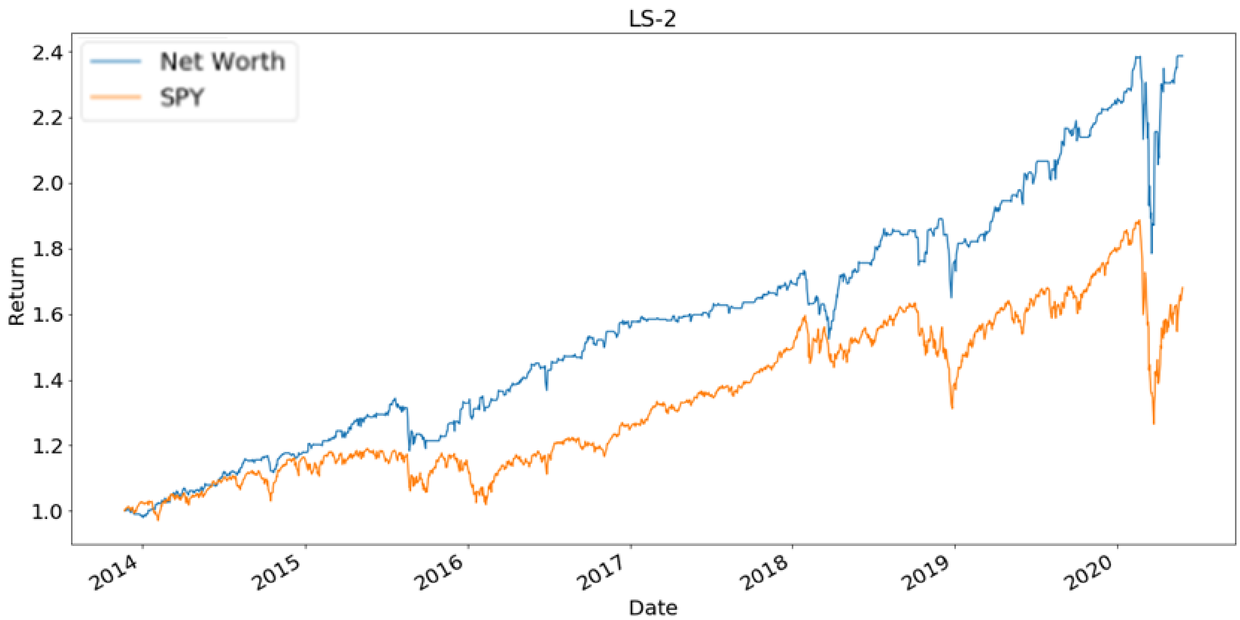

Figure 7 LS-2 Performance

	gtsangtrading_20201114_2324	SPY
Annual Return	14.32%	8.32%
Max Drawdown	-25.14%	-33.00%
Annual Volatility	12.49%	15.16%
Sharpe Ratio	1.135	0.604
Calmar Ratio	0.57	0.252
Omega Ratio	1.376	1.123
Downside Risk	0.086	0.112
Tail Ratio	1.454	0.95
Alpha	0.111	0.0
Beta	0.398	1.0

Table 9 LS-2 Metrics

- **LO-1 performance**

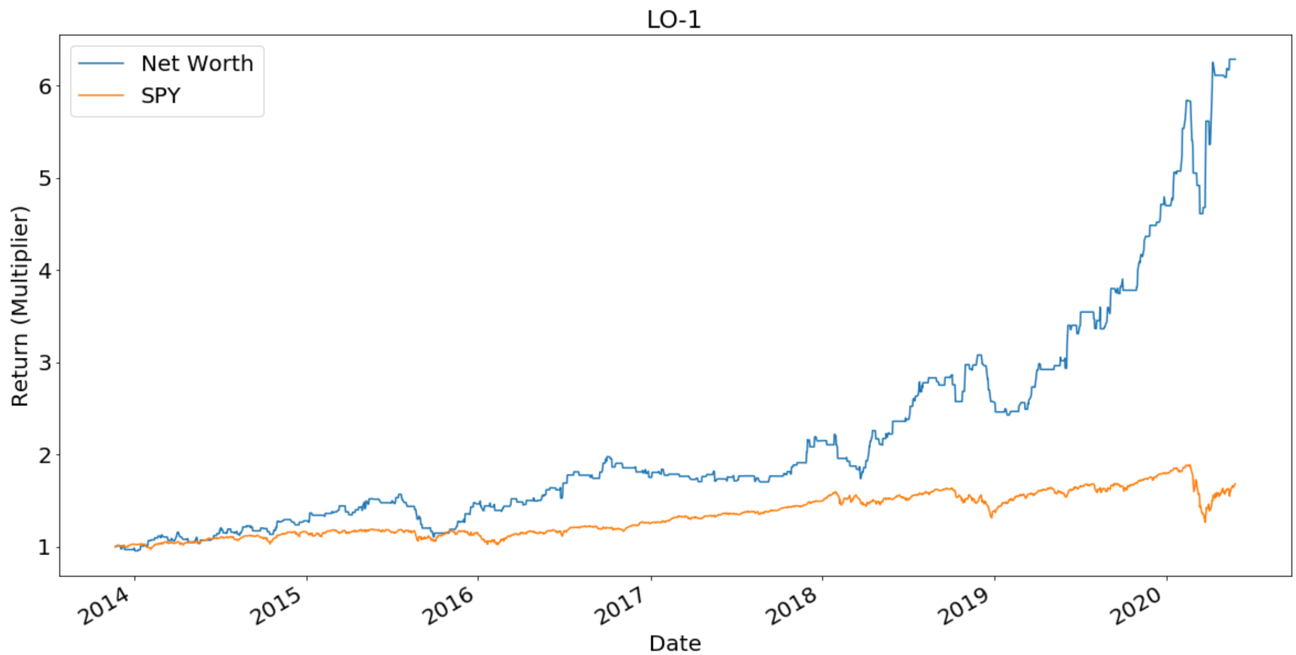

Figure 8 LO-1 Performance

	gtsangtrading_20201115_0121	SPY
Annual Return	32.71%	8.32%
Max Drawdown	-29.56%	-33.00%
Annual Volatility	22.44%	15.16%
Sharpe Ratio	1.374	0.604
Calmar Ratio	1.107	0.252
Omega Ratio	1.517	1.123
Downside Risk	0.14	0.112
Tail Ratio	1.371	0.95
Alpha	0.302	0.0
Beta	0.481	1.0

Table 10 LO-1 Metrics

2.4.1.2. Short-biased strategies

We have tested two short-biased strategies on SPY, namely Strategy SO-1: Long put options and Strategy SO-3: Tail-risk strategy. SO-1 is a better strategy because it has a higher annual return and a better risk-reward ratio.

- **SO-1 performance**

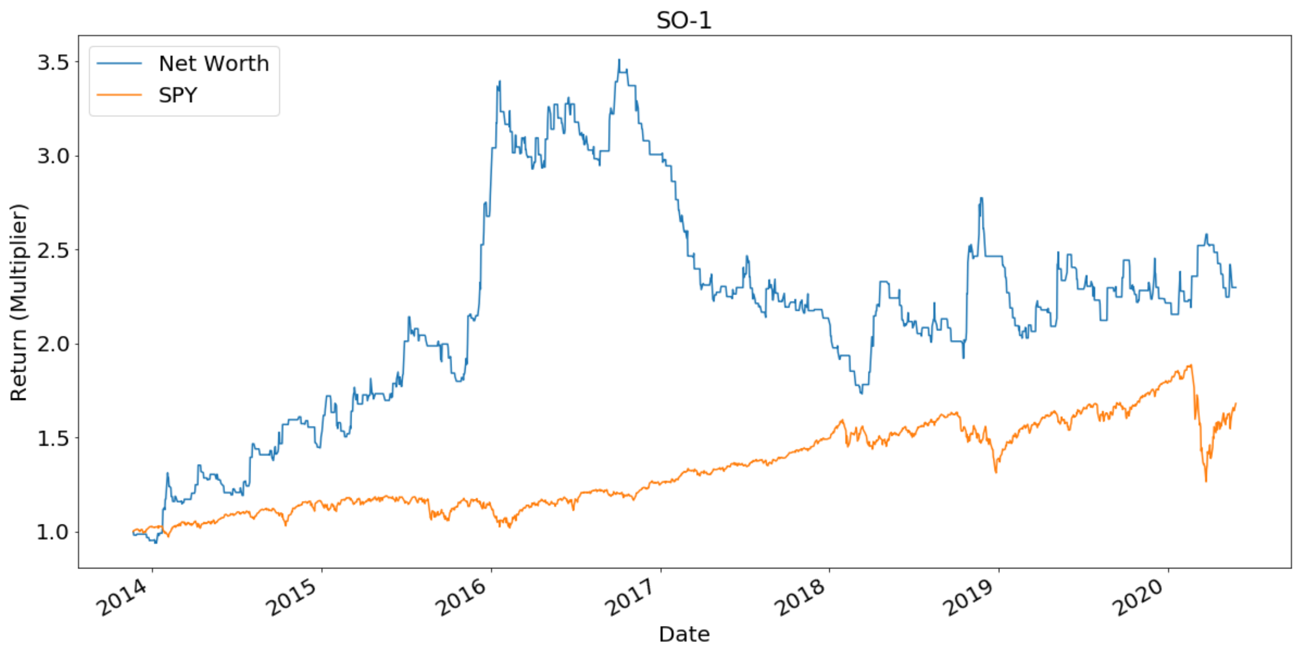

Figure 9 SO-1 Performance

	gtsangtrading_20201115_1447	SPY
Annual Return	13.66%	8.32%
Max Drawdown	-50.67%	-33.00%
Annual Volatility	25.60%	15.16%
Sharpe Ratio	0.626	0.604
Calmar Ratio	0.27	0.252
Omega Ratio	1.199	1.123
Downside Risk	0.143	0.112
Tail Ratio	1.136	0.95
Alpha	0.222	0.0
Beta	-0.439	1.0

Table 11 SO-1 Metrics

- **SO-3 performance**

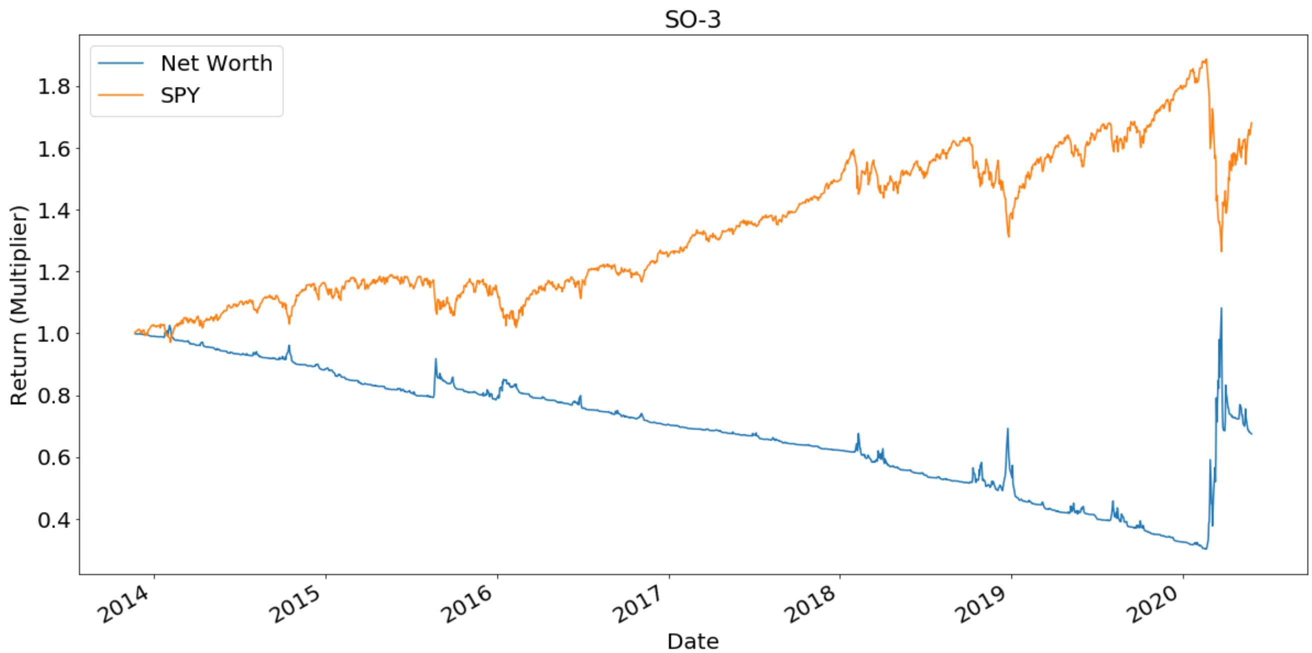

Figure 10 SO-3 Performance

	gtsangtrading_20210103_1830	SPY
Annual Return	-5.88%	8.32%
Max Drawdown	-70.57%	-33.00%
Annual Volatility	36.68%	15.16%
Sharpe Ratio	0.011	0.604
Calmar Ratio	-0.083	0.252
Omega Ratio	1.005	1.123
Downside Risk	0.209	0.112
Tail Ratio	0.846	0.95
Alpha	0.121	0.0
Beta	-1.208	1.0

Table 12 SO-3 Metrics

2.4.1.3. Market neutral strategies

We have tested four neutral strategies on SPY, namely Strategy NO-2: Short straddle, Strategy NO-2b: Short straddle with volatility filter, Strategy NO-2c: Short straddle with shorter DTE, and Strategy NO-3: Short strangle. NO-3 is the best strategy in terms of return.

- **NO-2 performance**

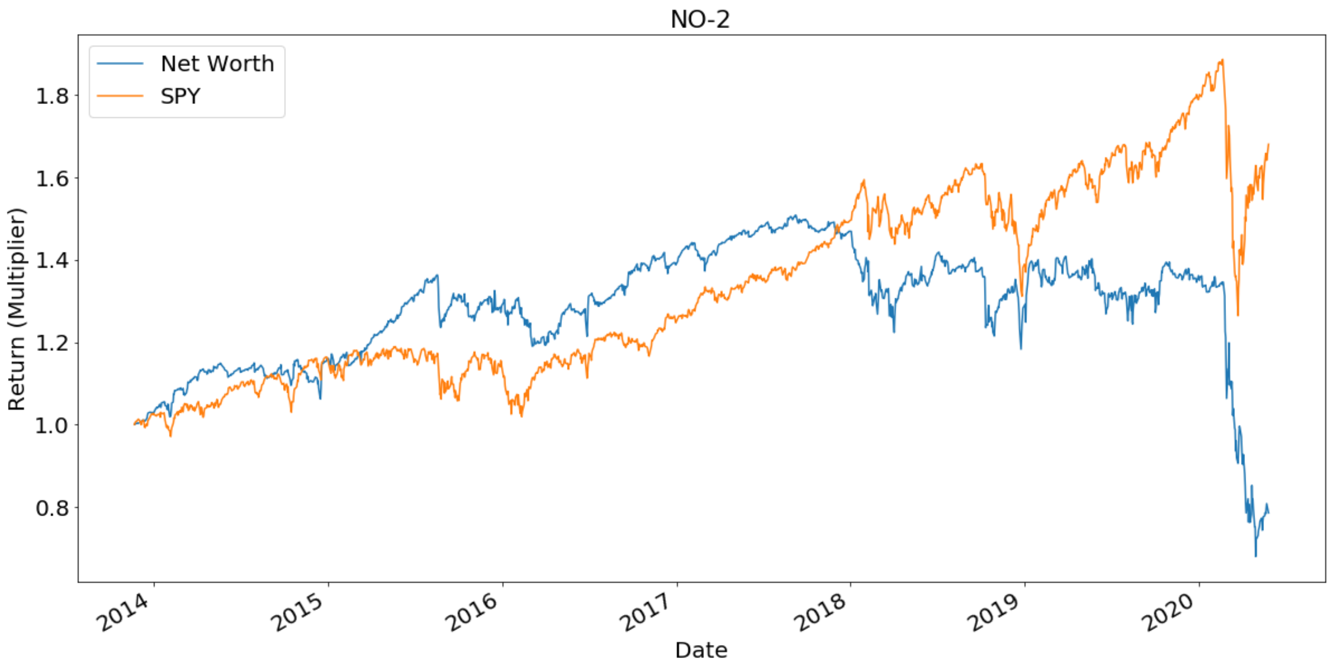

Figure 11 NO-2 Performance

	gtsangtrading_20210102_2202	SPY
Annual Return	-3.65%	8.32%
Max Drawdown	-54.97%	-33.00%
Annual Volatility	17.73%	15.16%
Sharpe Ratio	-0.12	0.604
Calmar Ratio	-0.066	0.252
Omega Ratio	0.972	1.123
Downside Risk	0.138	0.112
Tail Ratio	0.888	0.95
Alpha	-0.037	0.0
Beta	0.177	1.0

Table 13 NO-2 Metrics

- **NO-2b performance**

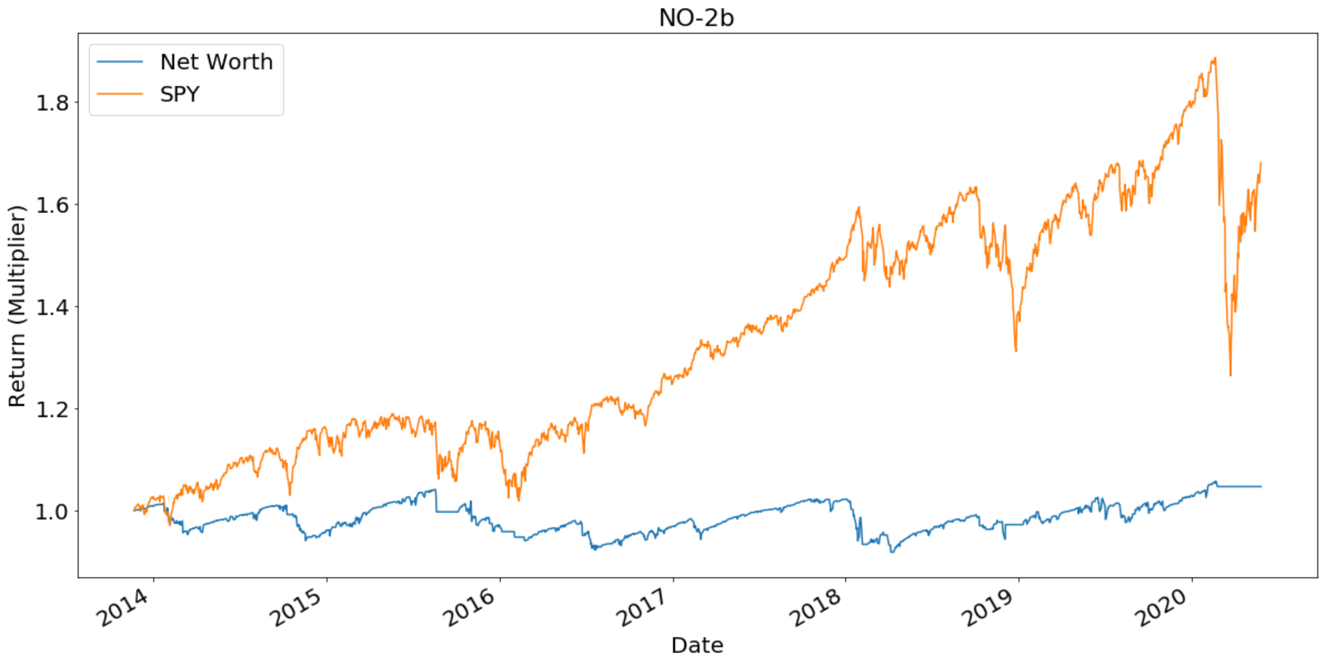

Figure 12 NO-2b Performance

	gtsangtrading_20210103_2015	SPY
Annual Return	0.71%	8.32%
Max Drawdown	-11.77%	-33.00%
Annual Volatility	6.65%	15.16%
Sharpe Ratio	0.141	0.604
Calmar Ratio	0.061	0.252
Omega Ratio	1.036	1.123
Downside Risk	0.054	0.112
Tail Ratio	0.769	0.95
Alpha	0.007	0.0
Beta	0.028	1.0

Table 14 NO-2b Metrics

- **NO-2c performance**

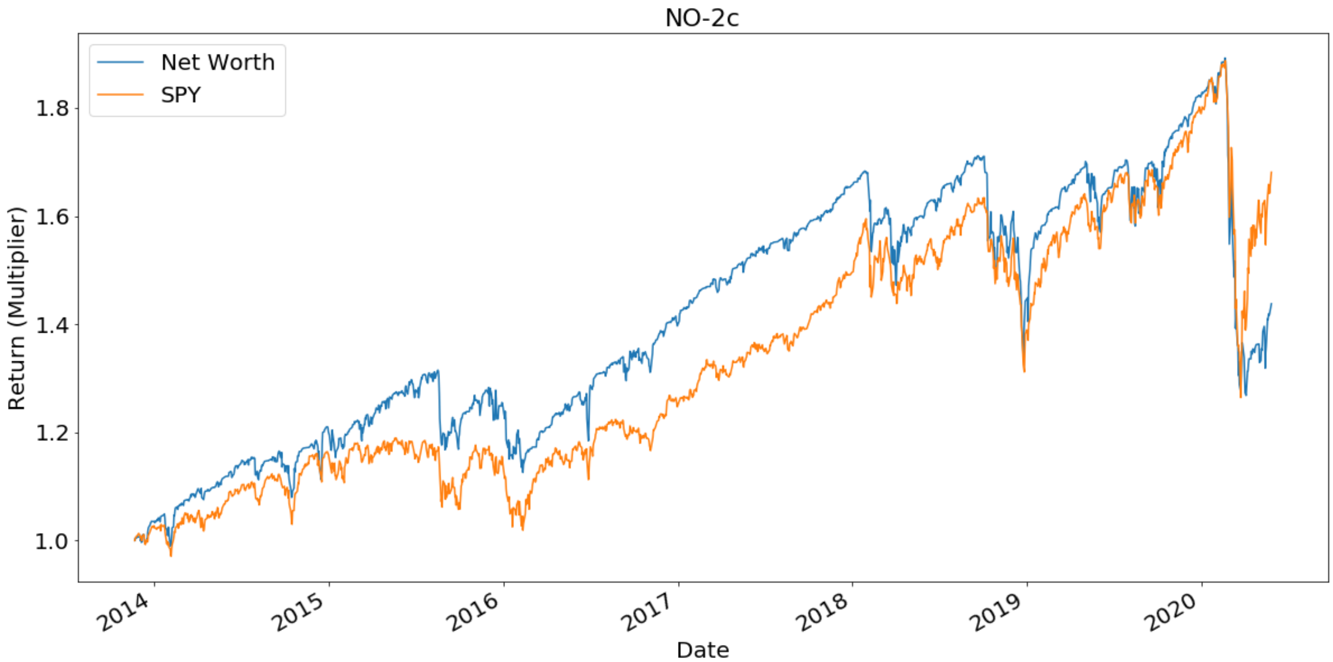

Figure 13 NO-2c Performance

	gtsangtrading_20210103_1802	SPY
Annual Return	5.75%	8.32%
Max Drawdown	-32.97%	-33.00%
Annual Volatility	14.74%	15.16%
Sharpe Ratio	0.454	0.604
Calmar Ratio	0.174	0.252
Omega Ratio	1.107	1.123
Downside Risk	0.113	0.112
Tail Ratio	0.83	0.95
Alpha	0.018	0.0
Beta	0.531	1.0

Table 15 NO-2c Metrics

- **NO-3 performance**

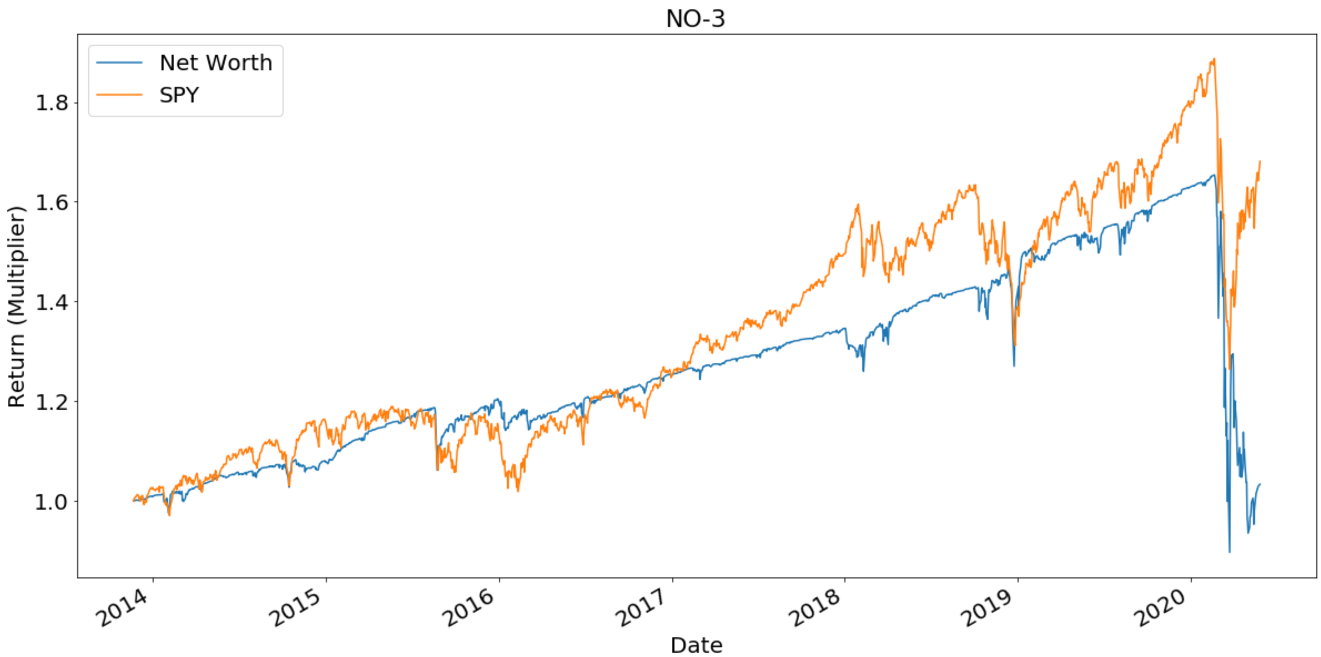

Figure 14 NO-3 Performance

	gtsangtrading_20210103_1907	SPY
Annual Return	0.51%	8.32%
Max Drawdown	-45.75%	-33.00%
Annual Volatility	20.76%	15.16%
Sharpe Ratio	0.128	0.604
Calmar Ratio	0.011	0.252
Omega Ratio	1.054	1.123
Downside Risk	0.148	0.112
Tail Ratio	0.982	0.95
Alpha	-0.017	0.0
Beta	0.48	1.0

Table 16 NO-3 Metrics

2.4.1.4. Combined strategies

We have tested two combined strategies on SPY by combining better performing strategies. The results show an improved annual return and reduced volatility on both systems.

- **CO-1 performance**

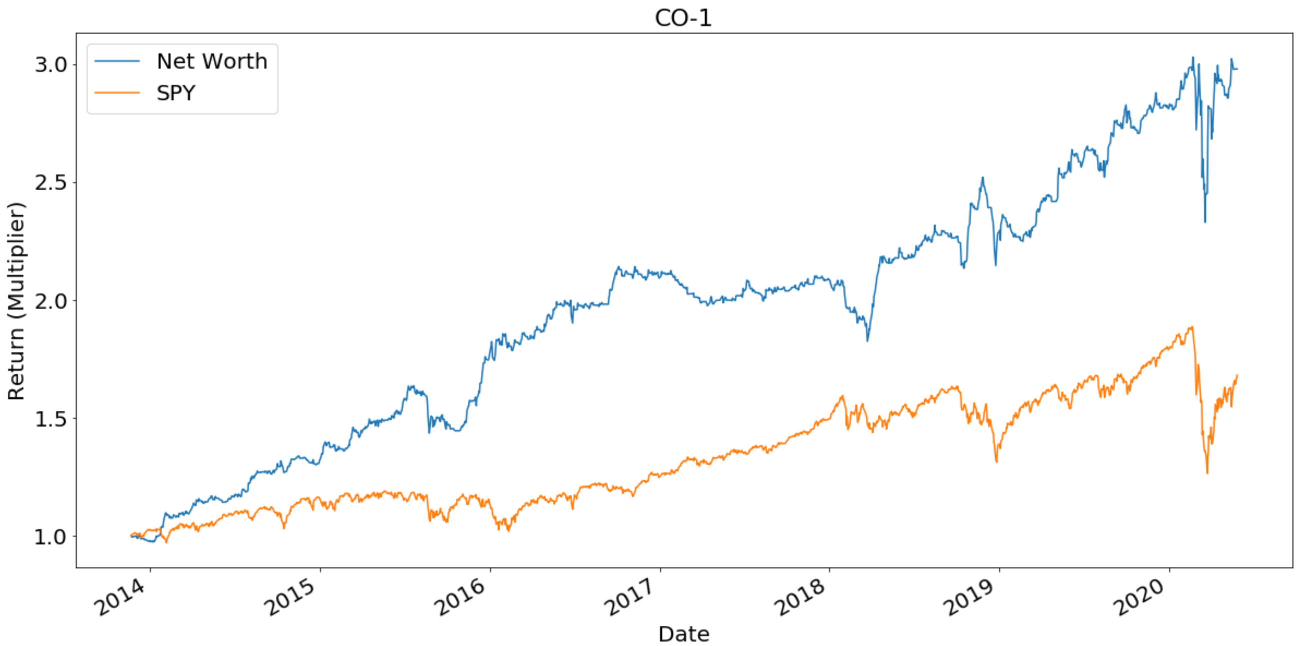

Figure 15 CO-1 Performance

	gtsangtrading_20210107_1520	SPY
Annual Return	18.30%	8.32%
Max Drawdown	-23.13%	-33.00%
Annual Volatility	13.61%	15.16%
Sharpe Ratio	1.304	0.604
Calmar Ratio	0.791	0.252
Omega Ratio	1.347	1.123
Downside Risk	0.09	0.112
Tail Ratio	1.415	0.95
Alpha	0.165	0.0
Beta	0.267	1.0

Table 17 CO-1 Metrics

- **CO-2 performance**

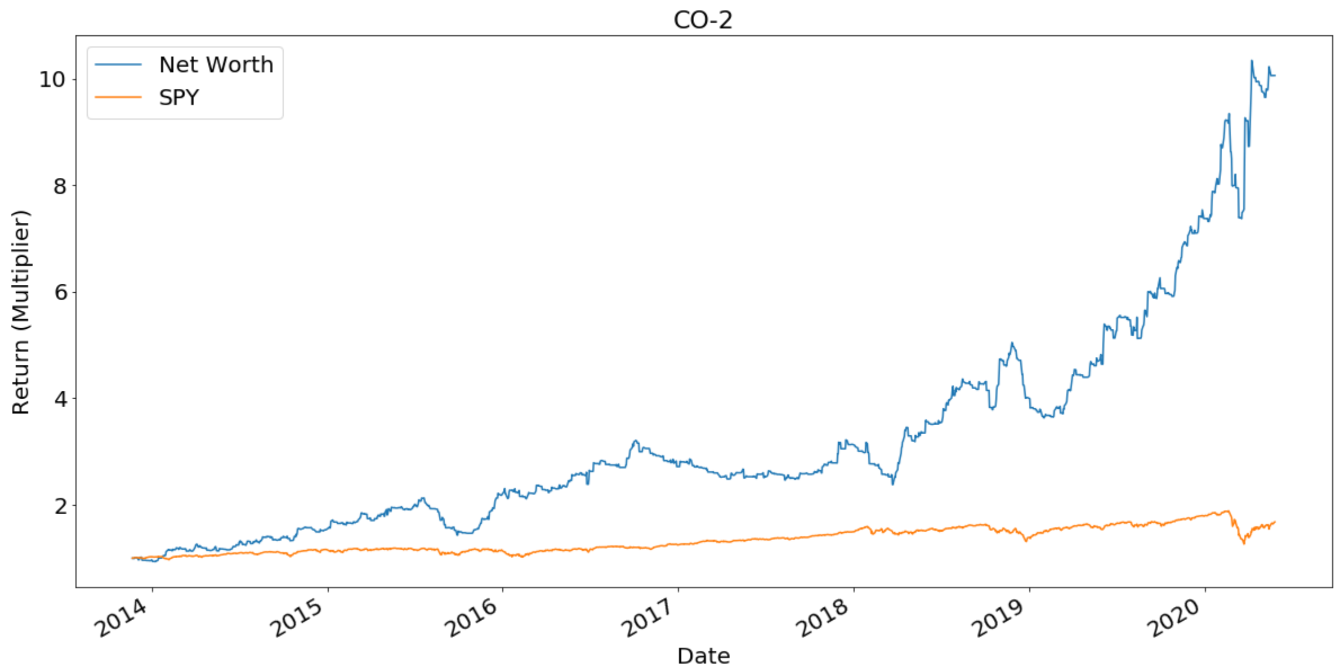

Figure 16 CO-2 Performance

	gtsangtrading_20210107_1547	SPY
Annual Return	42.67%	8.32%
Max Drawdown	-32.74%	-33.00%
Annual Volatility	25.57%	15.16%
Sharpe Ratio	1.519	0.604
Calmar Ratio	1.303	0.252
Omega Ratio	1.447	1.123
Downside Risk	0.158	0.112
Tail Ratio	1.451	0.95
Alpha	0.419	0.0
Beta	0.419	1.0

Table 18 CO-2 Metrics

3. Discussion

3.1. Software comparison

In this section, we compared our backtesting engine with Amibroker, which is a commercial analysis software. The comparison is based on speed, functionality, data source, interface, statistical insight, and usability criteria.

Our engine performed better in terms of functionality and usability as our engine can support equity and options backtesting with standard Python language. We have a long way to go in terms of speed and interface improvement.

Criteria	Our engine	Amibroker
Speed	Slow	At least 3000 times faster than our engine.
Functionality	Supports backtesting equity and options	Only supports backtesting equity data Supports optimization, Monte-Carlo simulation
Data source	Only from CBOE	Supports multiple data sources, including Yahoo Finance, eSignal, IQFeed etc.
Interface	Programming interface with methods to access the engine	Graphical User interface
Statistical insight	Provides 10 standard financial metrics.	Provides standard financial metrics and tools for optimization, Monte-Carlo simulation, and walk-forward analysis.
Usability	Scripting with Python	Scripting with Amibroker Formula Language (AFL)

Table 19 Comparision our engine vs Amibroker

3.2. Strategy discussion

In this study, we tested nine trading systems of different directional bias and chosen the better performing strategy to formulate our combined DH strategy. The combined strategy performed better in terms of annual return and return per unit risk than their component strategies. The following table shows the comparison of financial metrics between the combined DH strategy and the component strategies.

	CO-1	CO-2	LS-2	LO-1	SO-1	NO-3	SPY
Annual return	18.2%	42.67%	14.32%	32.71%	13.67%	0.51%	8.32%
Max drawdown	-22.13%	-32.74%	-25.14%	-29.56%	-50.67%	-45.75%	-33.00%
Annual volatility	13.61%	25.57%	12.493%	22.440%	25.605%	20.76%	15.16%
Sharpe ratio	1.304	1.519	1.135	1.374	0.626	0.128	0.604
Calmar ratio	0.791	1.303	0.57	1.107	0.27	0.011	0.252

Table 20 Strategy comparison

CO-1, which is structured with LS-2, SO-1 and NO-3 produce a better annual return, Sharpe ratio, Calmar ratio, and reduced maximum drawdown than the individual components. On the other hand, CO-2, which is structured with LO-1, SO-1, and NO-3 also produce a better annual return, Sharpe ratio, and Calmar ratio. The improvement of reward per unit risk by combining different strategies is consistent with the theory of risk parity and diversification [7] [8] [11]. We are satisfied with the result produced because it reaffirms the possibility of reducing risk without sacrificing return if we structure our portfolio with diversified strategies. Moreover, both combined DH strategies recovered from the extreme volatility in March 2020, which proves our algorithms' rigidity.

The major challenge for this project is that we only have a limited selection of quantified strategies that can produce positive returns. Besides, some of the systems we chose for the DH strategy seems to lose its competitive edge in the current market regime. For example, NO-3 strategy worked well from 2013 to 2019 until it got destroyed in 2020. Therefore, future research should be focusing on discovering more quantified strategy and applying the model to different asset classes.

3.3. Testing limitations / assumptions

In this section, we discuss some of the limitations and assumptions of our experiments. We will also explain why we should take our backtesting result with a grain of salt.

3.3.1. Overextended bull market

During our testing period, we have been experiencing an overextended bull market with central banks creating monetary inflation to bid up asset prices. The bull market enabled our long-biased strategies to perform exceptionally well. However, we should not expect the situation to continue forever. One possible way to refine this strategy is to test it in different markets with various market conditions.

3.3.2. Testing universe

Due to the limited research resource we have, we were only able to purchase static option data for a few markets. The sample size is too small to call for any statistical advantage with the strategies. However, we believe the current results are promising, which deserves further investigation. The next possible step might be developing our proprietary database by scraping real-time option quotes from free brokerage APIs.

3.3.3. Transaction slippage cost

Our engine does not account for slippage cost, which is the difference between the expected price of a trade and the price at which the trade is executed. All transactions made by this engine is instantaneous no matter the order sizes and the liquidity of the instruments. Since options are derivatives product usually provided by only a few market makers, it is unrealistic to anticipate instant transaction in actual trading. Moreover, we used the midpoint between the bid and ask prices for making option orders. This arrangement might make sense if we are trading a liquid ETF. However, the bid-ask spread for options with extended expiration might be over 1 dollar, which would induce unexpected profit or losses for our system. A much better design would be creating an extra class between the data provider module and the broker module. The broker should send a "transaction request" with an intended price which will only be executed in a later timeframe when the spot price meets the intended price.

3.3.4. Reliance on a technical indicator

In the study, we relied heavily on the IBS indicator. While IBS has strong predictive power in markets with a high tendency to revert to mean, it will malfunction in markets with trending tendency, for example, the energy market [18]. There is also no guarantee that this indicator will function appropriately in the future as more market participant exploit it. We should continue to look for different strategies to take advantage of the various market phenomenon to diversify our bets.

3.3.5. Portfolio optimization

The combined DH strategy described in this thesis has not been optimized because we chose generic parameters for the capital allocation on the component strategies. Thus, there might be a better combination of systems that can produce a better risk to reward ratio. We should try Harry Markowitz's portfolio optimization technique to improve our capital allocation in the future [12].

3.3.6. Overfitting

Since we deliberately chose the better performing strategies to construct the DH strategy, we are exposed to overfitting risk. Likely, some of the chosen strategies will not perform as well as they did in the testing period. Therefore, we should maintain a diversified portfolio of strategies with appropriate capital allocation to mitigate overfitting risk.

4. Conclusion

The DH strategy has proven to be a sustainable strategy that allows investors to invest in the equity market without severe drawdown by using options to hedge against risks. Our DH strategy successfully smoothed the equity curve of individual strategy and produced sustainable, stable, and long-term returns that outperformed SPY ETF. This project also reached the milestone of building a fully functional backtesting engine for equity and equity option. However, our research also carries a lot of assumptions and limitations. Moving forward, we need to focus on improving the speed and functionality of the engine, exploring more quantified strategies, and diversify our model in multiple asset classes. To carry this project forward, we started a new blog www.billerikay.com for sharing these results and trading ideas with more people.

5. References

[1] R. Dalio, Principles for Navigating Big Debt Crisis, Bridgewater Associates, LLP., 2018.

[2] D. Wang, 2020 zhōng guó jīng jì [2020 Chinese Economy], Beijing: zhōng guó yǒu yì chū bǎn gōng sī. , 2020.

[3] Trading Economics, "tradingeconomics.com," 2020. [Online]. Available: https://tradingeconomics.com/united-states/money-supply-m2. [Accessed July 2020].

[4] R. Dalio, "It's Time to Look More Carefully at "Monetary Policy 3 (MP3)" and "Modern Monetary Theory (MMT)"," Bridgewater Associates, LLP., 2019.

[5] R. Dalio, "The Changing Value of Money," in *The Changing World Order*, Bridgewater Associates, 2020, p. Chapter 2 Appendix.

[6] R. C. Rother, "Fiscal Policy and Inflation Volatility," European Central Bank, 2004.

[7] S. Manganelli and A. Popov, "Finance and Diversification," European Central Bank, 2010.

[8] B. Prince, "Risk Parity Is About Balance," Bridgewater Associates LLP., 2011.

[9] M. L. Hemler and T. W. Miller, "The Performance of Options-Based Investment Strategies: Evidence for Individual Stocks During 2003-2013," Mendoza College of Business, Univerisity of Notre Dame, Notre Dame, 2013.

[10] S. K. Choy and . J. Z. Wei, "Option Trading: Information or Speculation," *SSRN Electronic Journal,* March 2009.

[11] Bridgewater Associates , "The all weather story," Bridgewater Associates , 2012.

[12] H. Markowitz, "Portfolio Selection," *The Journal of Finance,* pp. 77-91, 1952.

[13] A. Clenow, Trading Evolved: Anyone Can Build Killer Trading Strateies in Python, Zurich: Equilateral Capital Management GmbH, 2019.

[14] R. Wang and Z. Yang, "SQL vs NoSQL: APerformance Comparison," University of Rochester, 2017.

[15] J. Nie and F. Wen, Decrypt Fund of Hedge Funds, Beijing: Peking University Press, 2018.

[16] M. Faber, "Worried About the Market? It Might Be Time for this Strategy," CAMBRIA, 2017.

[17] J. D. Coval and T. Shumway, "Expected Option Returns," University of Michigan Business School , 2000.

[18] A. S. Pagonidis, "The IBS Effect: Mean Reversion in Equity ETFs," National Association of Active Investment Managers, 2013.

6. Appendix A: Meeting minutes

6.1. Minutes of the 1st meeting

Date	14th September, 2020
Time	2:00 pm
Place	Over Zoom video conference
Present	Erik Tsang, Dr. David
Absent	NA
Recorder	Erik Tsang

6.1.1. Approval of minutes

This is the first formal group meeting, so there were no minutes to approve.

6.1.2. Report on progress

- Completed introduction and methodology of the proposal.
- Completed implementation of the engine.
- Completed implementation of the baseline algorithm.

6.1.3. Discussion items

- Feedback on the proposal
- Acquired approval for early graduation from Prof. David.

6.1.4. Goals for the coming week

- Adjust the proposal according to Prof. David's comments
- Completing the rest of the proposal before 18th September 2020

6.1.5. Meeting adjournment and the next meeting

- Not arranged

6.2. Minutes of the 2nd meeting

Date	9th November, 2020
Time	11:35 am
Place	Over Zoom video conference
Present	Erik Tsang, Dr. David
Absent	NA
Recorder	Erik Tsang

6.2.1. Approval of minutes

No minute approval is required.

6.2.2. Report on progress

- Discussed current progress of completing the back testing engine and some test algorithms
- Show Dr. David the testing results

6.2.3. Discussion items

- Review on progress

6.2.4. Goals for the coming week

- Work in the progress report
- Submit the progress report to Prof. David by 14th November for a brief review

6.2.5. Meeting adjournment and the next meeting

- Final reveal on 16th November before submission.

6.3. Minutes of the 3rd meeting

Date	12th January, 2021
Time	11:30 am
Place	Over Zoom video conference
Present	Erik Tsang, Dr. David
Absent	NA
Recorder	Erik Tsang

6.3.1. Approval of minutes

No minute approval is required.

6.3.2. Report on progress

- Discussed current progress final report and presentation slides

6.3.3. Discussion items

- Review on progress

6.3.4. Goals for the coming week

- Tidy up final report

6.3.5. Submit the final report to Prof. David by 26th January 2021.

6.3.6. Meeting adjournment and the next meeting

- This is the final meeting.

7. Appendix B: Glossary for financial terminology

#	Name	Abbr.	Description
1	Option		Options are financial derivatives based on the value of underlying securities such as stocks. An options contract offers the buyer the opportunity to buy or sell—depending on the type of contract they hold—the underlying asset.
2	Call Option		Call options allow the holder to buy the asset at a stated price within a specific timeframe.
3	Put Option		Put options allow the holder to sell the asset at a stated price within a specific timeframe.
4	Premium		An option premium is a price paid by the buyer to the seller for an option contract
5	Strike Price		A strike price is a set price at which a derivative contract can be bought or sold when it is exercised
6	Intrinsic value		Intrinsic value is the difference between the current price of an asset and the strike price of the option
7	At the Money	ATM	ATM means the options contract with a strike price that is identical to the underlying market price
8	Out of the Money	OTM	OTM means the option contract possesses no intrinsic value
9	In the Money	ITM	ITM means the option contract possesses intrinsic value
10	Long		Long option means being the buyer of the option contract, disregard the directional bias (call/put).
11	Short		The short option means being the selling of the option contract, disregard the directional bias.
12	Option Spread		An option spread is created by the purchase and sale of options of the same class on the same underlying stock but with different strike prices and/or expiration dates.
13	Call spread		A call spread is created by shorting a call option while longing another call option at a different strike price.
14	Put Spread		A put spread is created by shorting a put option while longing another put option at a different strike price.
15	Iron Condor		An Iron Condor is created by selling an equal portion of call spreads and put spreads, taking a credit.
16	Put Back Ratio		A Put Back Ratio is created by selling the ATM Put option and buying OTM put option; the ratio is 1:2.
17	Chicago Board Options Exchange	CBOE	CBOE is the largest US options exchange.

18	Dynamic Hedging Strategy	DH.	This strategy is the focus of this project.
19	Cumulative return		The cumulative return is the total change in the investment price over a set time—an aggregate return, not an annualized one
20	Annual return		The annual return is the return that an investment provides over a period of time, expressed as a time-weighted annual percentage.
21	Max drawdown		maximum observed loss from a peak to a trough of a portfolio, before a new peak is attained.
22	Sharpe Ratio		The ratio is the average return earned in excess of the risk-free rate per unit of volatility or total risk.
23	Calmar Ratio		The Calmar ratio is a measure of risk-adjusted returns for investment funds
24	Omega Ratio		The Omega ratio is a risk-return performance measure of an investment asset, portfolio, or strategy
25	Tail Ratio		Ratio between the 95th and (absolute) 5th percentile of the daily returns distribution.
26	Annual Volatility		Daily volatility times the square root of 252.
27	Alpha		often considered the active return on an investment, gauges the performance of an investment against a market index
28	Beta		Beta measures the volatility of an investment. It is an indication of its relative risk.
29	Downside Risk		Downside risk is the financial risk associated with losses. That is, it is the risk of the actual return being below the expected return, or the uncertainty about the magnitude of that difference.

8. Appendix C: Monetary policies in different countries.

Country	Central Bank	Country Date #	Date	Size	Type of Asset Purchase
Developed Markets					
U.S.	Federal Reserve	1	3/16/2020	700 billion USD	Sovereign, MBS
U.S.	Federal Reserve	2	3/23/2020	Unlimited	Sovereign, MBS, Corporate Bonds
U.K.	Bank of England	1	3/19/2020	200 billion GBP	Sovereign, Corporate Bonds
Europe	European Central Bank	1	3/18/2020	750 billion EUR	Sovereign
Japan	Bank of Japan	1	4/26/2020	Unlimited JGBs, 20 trillion yen in corporates	Sovereign, Corporate Bonds
Canada	Bank of Canada	1	3/27/2020	3.5 billion CAD per week	Sovereign
Australia	Reserve Bank of Australia	1	3/19/2020	Unlimited	Sovereign
New Zealand	Reserve Bank of New Zealand	1	3/23/2020	30 billion NZD	Sovereign
Sweden	Riksbank	1	3/16/2020	300 billion SEK	Sovereign
Emerging Markets					
Israel	Bank of Israel	1	3/23/2020	50 billion ILS	Sovereign
Korea	Bank of Korea	1	3/25/2020	Unlimited repos for 3 months	Repos
Colombia	Banco de la República	1	3/24/2020	12 trillion COP	Sovereign
South Africa	South Africa Reserve Bank	1	3/25/2020	Unspecified amount	Sovereign
Poland	Narodowy Bank Polski	1	3/17/2020	Unspecified amount	Sovereign
Poland	Narodowy Bank Polski	2	4/8/2020	Unspecified amount	Sovereign, State-Guaranteed Bonds
Romania	Banca Națională a României	1	3/20/2020	Unspecified amount	Repos, Local Government Bonds
Hungary	Magyar Nemzeti Bank	1	3/24/2020	Considering resuming its mortgage bond asset purchases	Sovereign, MBS
Hungary	Magyar Nemzeti Bank	2	4/28/2020	1 trillion HUF in govt and 300 billion HUF in mortgage bonds	Sovereign, MBS
Croatia	Hrvatska narodna banka	1	3/13/2020	Unspecified amount	Sovereign
Phillipines	Bangko Sentral ng Pilipinas	1	3/24/2020	300 billion PHP	Sovereign
Mexico	Banco de Mexico	1	4/21/2020	100 billion MXN	Sovereign, Corporate Bonds
Turkey	Central Bank of the Republic of Turkey	1	3/31/2020	Unspecified amount	Sovereign
India	Reserve Bank of India	1	3/20/2020	400 billion INR	Sovereign
Indonesia	Bank Indonesia	1	4/1/2020	Unspecified amount	Sovereign

Table 21 Key COVID-19 Quantitative Easing Announcement. from National Bureau of Economic Research (2020)

9. Appendix D: Engine testing results and survey

Test Cases for Data Provider Module

Test Case ID	TC-DP-01
Test Case Summary	Normal Flow
Test Procedures	1. User requests SPY stock data 2. User requests for SPY option data 3. User requests for SPY credit spread
Expected Output	Data Provider return correct data
Actual Output	Pass
Last Tested	15th November 2020

Test Cases for Broker Module

Test Case ID	TC-BK-01
Test Case Summary	Normal Flow
Test Procedures	1. User request to make stock transaction 2. User request to make option transaction 3. User request to make stock transaction with no cash 4. User request to make option transaction with no cash
Expected Output	1. Success 2. Success 3. Fail 4. Fail
Actual Output	Pass
Last Tested	15th November 2020

Test Cases for Strategy Module

Test Case ID	TC-SG-01
Test Case Summary	Normal Flow
Test Procedures	1. Try Strategy LS-2
Expected Output	Backtest strategy properly
Actual Output	Pass
Last Tested	15th November 2020

Test Cases for Evaluation Module

Test Case ID	TC-EV-01
Test Case Summary	Normal Flow
Test Procedures	1. Load accountid gtsangtrading_20201114_2324
Expected Output	Display visualization and metrics properly

Actual Output	Pass
Last Tested	15th November 2020

Test Cases for Integration Test

Test Case ID	TC-IN-01
Test Case Summary	Normal Flow
Test Procedures	1. Perform LS-2 2. Analyze performance
Expected Output	Performance metrics displayed properly
Actual Output	Pass
Last Tested	15th November 2020

10. Appendix E: Strategy testing results and survey

LS-2 Testing

Code	Parameter description
LS-2-TC-1	Underlying asset: SPY
	Testing period: "11/21/2013 10:30" - "5/27/2020 10:30"
	Initial Capital: 10000 usd
	Account id: gtsangtrading_20201114_2324

LO-1 Testing

Code	Parameter description
LO-1-TC-1	Underlying asset: SPY
	Testing period: "11/21/2013 10:30" - "5/27/2020 10:30"
	Initial Capital: 10000 usd
	Account id: gtsangtrading_20201115_0121
	DTE : 90
LO-1-TC-2	Underlying asset: SPY
	Testing period: "11/21/2013 10:30" - "5/27/2020 10:30"
	Initial Capital: 10000 usd
	Account id:
	DTE : 30

SO-1 Testing

Code	Parameter description
SO-1-TC-1	Underlying asset: SPY
	Testing period: "11/21/2013 10:30" - "5/27/2020 10:30"
	Initial Capital: 10000 usd
	Account id: gtsangtrading_20201115_1447
	DTE: 90
	Capital allocation: 5%
SO-1-TC-2	Underlying asset: SPY
	Testing period: "11/21/2013 10:30" - "5/27/2020 10:30"
	Initial Capital: 10000 usd
	Account id: gtsangtrading_20201115_1448
	DTE: 30
	Capital allocation: 5%

SO-1-TC-3	Underlying asset: SPY
	Testing period: "11/21/2013 10:30" - "5/27/2020 10:30"
	Initial Capital: 10000 usd
	Account id: gtsangtrading_20201115_1449
	DTE: 9
	Capital allocation: 5%
SO-1-TC-4	Underlying asset: SPY
	Testing period: "11/21/2013 10:30" - "5/27/2020 10:30"
	Initial Capital: 10000 usd
	Account id: gtsangtrading_20201115_1450
	DTE: 90
	Capital allocation: 100%

SO-3 Testing

Code	**Parameter description**
SO-3-TC-1	Underlying asset: SPY
	Testing period: "11/21/2013 10:30" - "5/27/2020 10:30"
	Initial Capital: 10000 usd
	Account id: gtsangtrading_20210103_1830
	DTE : 30

NO-2 Testing

Code	**Parameter description**
NO-2-TC-1	Underlying asset: SPY
	Testing period: "11/21/2013 10:30" - "5/27/2020 10:30"
	Initial Capital: 10000 usd
	Account id: gtsangtrading_20210102_2202
	DTE : 30

NO-2b Testing

Code	**Parameter description**
NO-2b -TC-1	Underlying asset: SPY
	Testing period: "11/21/2013 10:30" - "5/27/2020 10:30"
	Initial Capital: 10000 usd
	Account id: gtsangtrading_20210103_2015
	DTE : 30

NO-2c Testing

Code	**Parameter description**
NO-2c-TC-1	Underlying asset: SPY
	Testing period: "11/21/2013 10:30" - "5/27/2020 10:30"

	Initial Capital: 10000 usd
	Account id: gtsangtrading_20210103_1802
	DTE : 9

NO-3 Testing

Code	**Parameter description**
NO-3-TC-1	Underlying asset: SPY
	Testing period: "11/21/2013 10:30" - "5/27/2020 10:30"
	Initial Capital: 10000 usd
	Account id: gtsangtrading_20210103_1907
	DTE : 90

CO-1 Testing

Code	**Parameter description**
CO-1-TC-1	Underlying asset: SPY
	Testing period: "11/21/2013 10:30" - "5/27/2020 10:30"
	Initial Capital: 100000 usd
	Account id: gtsangtrading_20210107_1520

CO-3 Testing

Code	**Parameter description**
CO-2-TC-1	Underlying asset: SPY
	Testing period: "11/21/2013 10:30" - "5/27/2020 10:30"
	Initial Capital: 100000 usd
	Account id: gtsangtrading_20210107_1547

11. Appendix F : Project planning

11.1. GANTT chart

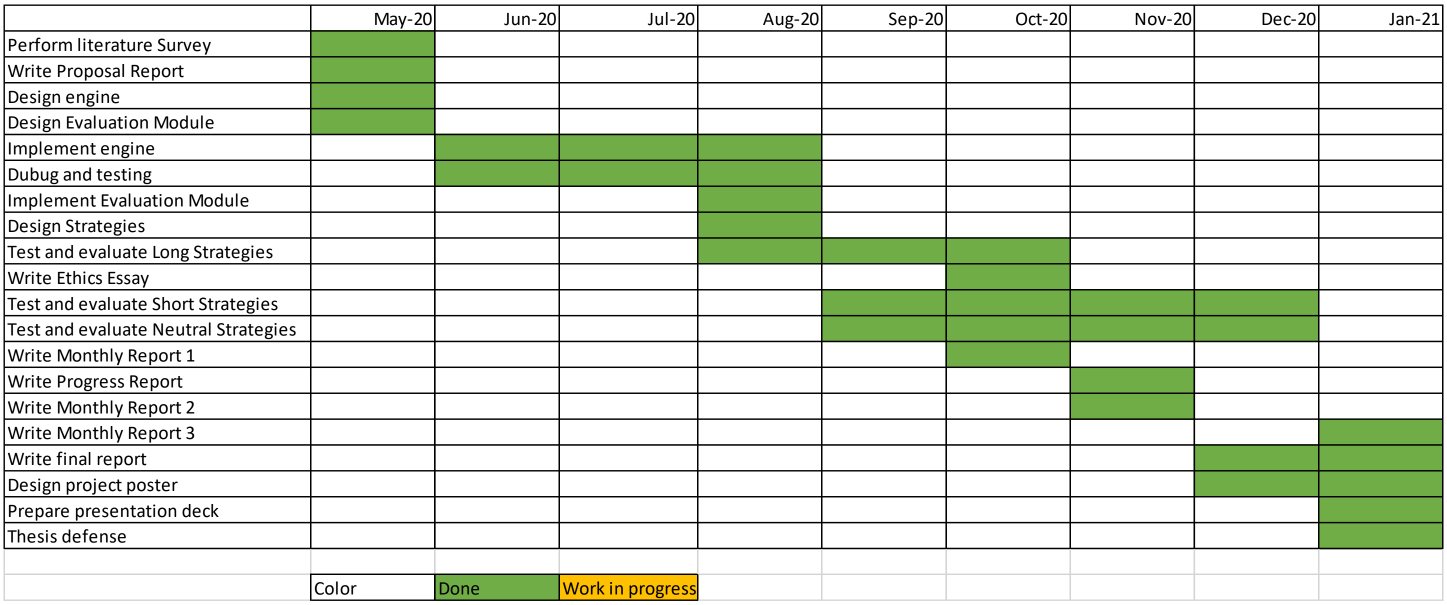

Figure 17 GANTT Chart

11.2. Division of work

Mr Tsang Gin Yui will be fully responsible for everything involved with this project.

12. Appendix G: Hardware and software requirements

12.1. Hardware requirements

- Laptop with Windows 10 installed

12.2. Software requirements

- Windows 10
- Anaconda
- Jyputer Notebook
- Visual Studio Code for debugging
- MySQL
- MongoDB