Automated device for long-term investment portfolio

6CCS3PRJ Final Year Individual Project

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Abstract

Algorithmic trading refers to the use of computer programs to automate the trading process and execute it with little or no human intervention. This project focus on building a long-only algorithm trading strategy using both financial ratios and technical indicators to pick a long-term, low turnover rate portfolio. Its performance is then being compared to three other famous value algorithm strategies to analyse the return, risk and strength of the algorithm.

The developed algorithm and three other algorithms were developed on Quantopian platform and using many of its open-source libraries and datasets to test and analyse the past performance of the algorithm.

Originality Avowal

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Quang Dung Nguyen

22nd April 2019

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Abbreviations

FA Fundamental Analysis.

ROIC Return on Invested Capital.

ROA Return on Assets.

ROE Return on Equity.

ROI Return on Investment.

PE Price to Earnings.

PB Price to Book

PEG Price to Earnings / Earnings Growth.

SR Sharpe Ratio.

DY Dividend Yield.

EY Earnings Yield (by Magic Formula not PE).

AM Acquirer’s Multiples.

EBIT Earnings before interest and tax.

EV Enterprise Value.

S&P 500 Standard & Poor Index 500.

Chapter 1

Introduction

1.1. Background and Motivation

Since 90s, advancement in computational technology has made collection of data more affordable and more accessible. As a highly profitable business, there has been several techniques that extracted historical data to predict the stock market movement and direction. Even with the randomness contributed by the nature of human and many other unknown factors, there has been many examples proving that it is possible to profit from the stock market using computational resources derived from mathematical and statistical method. The success of quantitative hedge funds such as Renaissance Technologies, Citadel Investment Group, or Goldman Sachs Asset Management (GSAM) in 2000s have led to a flock of computer scientists and mathematicians to Wall Street, using popular technical methods such as statistical arbitrage or mean reversion to make billions by exploiting the inefficiencies in the market .

Figure 1.1 shows the increasing volume of trades executed by algorithm in US equities market. Algorithmic Trading volume have been gradually increased to 85% in 2012.It is also estimated that fundamental and discretionary trader only accounts for 10% of trading volume stock, estimated by Marko Kolanovic, global head of quantitative and derivatives research at JP Morgan [1]. Moving to automated trading is also embraced by Goldman Sachs, according to President David Solomon. There were only 3 equity traders left at Goldman's equity trading desk, compared to 500 traders just 15 -20 years ago [2]. However, some best quantitative funds estimated that the transaction cost can be accounted for 20% - 50% of their returns [3]. Moreover, the recent event of 2010 Flash Crash when Dow Jones Industry Average plunged around 9% within 5 minutes- the second largest intraday point drop in the history, has raised concern about short-term volatility and unease about the market' stability when most trades are made by machines.

The trend towards more automation in the financial market while active fundamental stock pickers have become more scarce have inspired me to create a value fundamental algorithm to utilise this trend. The algorithm will benefit with a low-trading frequency (once per month or once per year), which will significantly decrease the portfolio turnover rate and transaction cost comparted to high frequency trading. Furthermore, weekly rebalance versus high-frequent orders in seconds or nanoseconds, this algorithm will not affect the market as much as other high-frequent algorithm

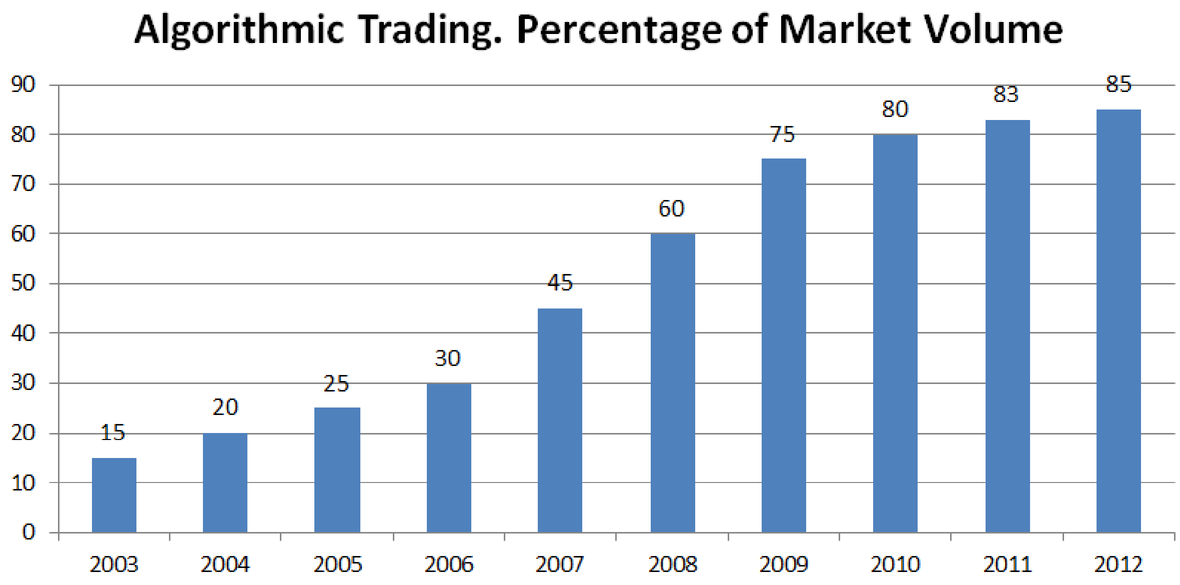

Figure 1.1. Algorithmic Trading. Percentage of market volume. Source: Morton Glantz, Robert Kissell [4].

1.2. Objectives

The main objective of this paper is to contribute to the development of value long-only algorithm trade, which can be executed live on the stock market. The project aim is to create an algorithm on Quantopian platform, utilizing different financial ratios and momentum indicators. Another objective of the project is to use the created algorithm to test against other famous algorithm (Magic Formula, Acquirer’s Multiple and the Piotroski F-Score Algorithm). The algorithm Acquirer’s Multiple is built upon the Acquirer’s algorithm by BlackCat [5] while the Piotroski F-Score algorithm is developed by Guy Fleury [6]- both are members of Quantopian platform.

1.3. Report Structure

Chapter 2 outlines the introduction background overview of various related topics and existing works that have created the theoretical perspective for the project, followed by Chapter 3 which outlines the requirements of the system

In Chapter 4 outlines the general design of algorithm and the implementation of the algorithm

In Chapter 5, an analysis and evaluation of the algorithm will be carried out. Furthermore, there will analysis of its performance relative to other value algorithm

In final Chapter 6, conclusions and future work is further discussed along with potential improvements of the algorithm

Chapter 2

Background

2.1. Fundamental Analysis (FA)

Fundamental analysis is used to calculate the intrinsic value (or true value) of a company to determine whether it is undervalued or overvalued. Fundamental analysis collects data from a company's previous financial statement and its financial ratios to help investors to predict the future growth of the company. Investors doing fundamental analysis can also consider other qualitative factors (e.g. management of the company) and external factors (e.g. macroeconomic indicators such as interest rate, GDP, industry recent outlook).

Fundamental analysis has been made famous Benjamin Graham and Warren Buffett through their value investment strategy.

2.1.1 Financial Ratio

- **EY (Earnings Yield) – Joel Greenblatt Magic formula** [11]: is NOT the universal earnings yield ratio (Price to Earnings Ratio). It can show how much a business earn in comparison to its purchasing price. A high operating income is preferred, as it shows that the company generates more profit with the purchasing value of the company.

$$Earnings\ Yield = \frac{Operating\ Income(EBIT)}{Enterprise\ Value(Market\ Value + Debt)}$$

- **AM (Acquirer's Multiples) – in Tobias Carlisle Acquirer's Multiple:** [16]. Essentially the opposite of earnings ratios. It can only show how much a buyer of a company has to pay to acquire the business. A company with lower Acquirer's Multiples is more attractive to private equity funds, as it is cheaper to buy the whole company, especially when compared to its same industry peer. As value investor, a low Acquirer's Multiple is also preferred.

$$Acquirer's\ Multiple = \frac{Enterprise\ Value(EV)}{Earnings\ Before\ Interest\ and\ Tax\ (EBIT)}$$

- **ROIC (Return on Invested Capital Ratio):** shows how well the company make use of its invested capital. ROIC can provide investors the overview performance of a company's management performance as how effective the management generate income from capital its management allocated. It gives a broader perspective than Return on Equity as this also includes debts, which show how well management doing to both shareholders and bond holders (or debt issuers)

$$Return\ on\ Capital(ROC) = \frac{(NetOperatingProfit - AdjustedTaxes)}{Invested\ Capital(Debt + Equity)}$$

- **ROA (Return on Assets):** is an indicator to show how well the management is at creating profit using company's assets.

$$Return\ on\ Assets(ROA) = \frac{Net\ Income}{Average\ Total\ Assets(Assets\ on\ balance\ sheets)}$$

- **ROE (Return on Equity):** Another indicator to show how well the management is at generating profit by allocating a company's equity efficiently. It should how well the management doing to return to shareholders.

$$Return\ on\ Equity(ROE) = \frac{Net\ Income}{Average\ ShareHolders'Equity(Assets - Liabilities)}$$

- **DR (Debt ratio):** is used to measure the extend that a company finances its operation through debt. The higher the ratio, the more leveraged the company, implying greater financial risk of not being able to pay debt.

$$Debt\ Ratio(DR) = \frac{Total\ Debt}{Total\ Assets}$$

- **PE (Price/Earnings Ratio):** shows how many times a stock is traded per each dollar of its EPS. For most value investors, a low PE value is preferable, as it indicates the number of years required to return the investment. However, a high PE is not necessary negative, as it may indicate more expected growth of the company. Some quants prefer the reverse E/P(Earning/Price) ratio as this ratio is more reliable when EPS turns negative.

$$PE = \frac{Stock\ Price}{Earnings\ Per\ Share(EPS)}$$

- **PEG (price to earnings growth ratio):** is an extension of PE ratio, as it takes into account the growth rate of a stock's earnings. Using PEG ratio, investors can decide whether or not the stock is undervalued or overvalued. In general, a PEG ratio greater than 1 means the stock is overpriced, while a PEG that smaller than 1 means the stock is undervalued, relative to its growth

$$PEG = \frac{Price\ to\ Earning\ Ratio(PE\ Ratio)}{Earnings\ growth\ rate}$$

- **P/B (Price to book value):** indicates how much investors pay for the net assets of the company. It shows the correlation the market price of the company to the balance sheet's value of the company. It can indicate whether a stock is undervalued or overvalued, when compared to same sectors' stock ratios.

$$P/B = \frac{Market\ Price\ Per\ Share}{Book\ Value\ Per\ Share}$$

- **DY (Dividend Yield):** indicates how much investors receive company's annual dividend compared to its share price. A dividend normally seen as an annual return to investor's pocket, and a high dividend is normally desirable, even though it is not always the case. A high dividend yield can imply that the stock's price is either falling too fast or the company management can't find appropriate resources to invest in. However, income investors still prefer a high dividend yield, if they choose stocks over bonds

$$Dividend\ Yield = \frac{Annual\ Dividend\ Received}{Share\ Price}$$

- **SR (Sharpe Ratio):** or normally known as risk-adjusted return ratio, is used to understand the return of an investment compared to its risk.

$$Sharpe\ Ratio = \frac{Return\ of\ the\ portfolio - Risk\ Free\ Return}{Standard\ Deviation\ of\ the\ portfolio\ excess\ return}$$

  Risk Free Return normally uses 3-month US Treasury Bonds, as the short-term bonds faces nearly zero risk as it is backed by the US Government.

- **CAPE (S&P Shiller P/E):** cyclically adjusted price-to-earnings ratio (Shiller P/E or CAPE) is normally used to decide whether a stock market is overpriced or underpriced. It utilizes the average of ten years of earnings adjusted to inflation, and hence considers the cycle of the economy onto the price of the stock.

2.2. Technical Analysis (TA)

- **Trend:** Stock price rarely move in a straight line. Instead, price tends to move to create highs and lows in a given time period. In technical analysis, trend is the overall direction of these highs and lows. There are three main way of trends: up, down or sideways. An uptrend is made up of ascending, higher highs and higher lows while a downtrend is made of descending, lower highs and lower lows [7]. A trend can exist for weeks, months or years, normally characterised by higher highs or lower lows, but it doesn't have to be. For example, the market can go sideway for a week but in 12-month moving average the market still in uptrend [8].

- **Momentum:** is also a technical analysis and different to trend trading. Trend can be seen as overall theme while momentum can be seen as a current state of the market. For example, if the market trend recently is going up but lack momentum (recent poor earnings report, gloom economic outlook, etc.), the market can go sideway because there is no momentum, but the 12-month trend is still uptrend [8]. Some common way of calculating momentum if the short-term moving average or price cross the longer-term moving average or price (e.g. the price of 30-day moving average cross 100-day moving average)

- **Volatility:** Volatility shows the fluctuation level around prices' mean in stocks. It can be used to evaluate risk and drawdown of a stock individually or of a whole portfolio. Common volatility indicators are standard deviation, max drawdown or Bollinger Band. It can also be used alongside return to calculate the risk- adjusted return, as known as Sharpe Ratio. According to Modern Portfolio Theory (MPT), volatility creates more risk that is associated with the increasing degree of dispersion of return of stocks around the average [9].

2.3. Review of any relevant literature

Value Investing have been around for many years, mostly known and made famous by investors such as Benjamin Graham through his books "Security Analysis" in 1934 and "The Intelligent

Investor” in 1949. It is further being popularized by one of his most successful students Warren Buffett through his extraordinary success with his holding company, Berkshire Hathaway. Both Benjamin Graham and Warren Buffett looks for companies with a high intrinsic value compared to its market price(“Cheapness”) and a large “margin of safety” (the company is highly undervalued that it protects investor from potential risk if his/her calculations is not totally correct) to invest in.

Fama and French ’s three factor model [10] developed in 1992, as additional to the CAPM (capital asset pricing model) also considers more value perspective into stocks, using book-to-market value as the indicating performance, as it beat the market until 1992. Investing has evolved over the last decades since the publication of the Intelligent Investor and Warren Buffett is now more interested in investing in Quality Stock rather than stock that is only cheap with his saying” it is better to buy a wonderful company at a fair price than a fair company at a wonderful price”. Quality is then marked attractive investment field, with leading industry thinkers such as Joel Greenblatt with his “Little Book that Beats the Market” [11] has encourage many investors to include its company’s management allocation efficiency to consideration (measure by return on invested capital or ROIC). The Magic Formula performance from 1988-2004, before the book was published can be seen in Figure 2.1.

Many institutional investors such as Blackrock, is now promoting its customers to integrating earnings quality into its investment strategies [12]. Piotroski’s F Score [13] developed on 2000 by Professor Joseph Piotroski, which used nine criteria to determine the strength of a firm’s financial position by analyzing its financial statement. Its performance has been largely outperformed the market since 2000 till 2016, as since in Figure 2.2. There are many other researches to compare the results of these value algorithms such as Novy - Marx in his “The other side of value: The gross profitability premium [14]. He also shows that a quality gross-profit-to-assets indicator, has as much power in predicting the return of assets as book-to-market- price ratio [15]. Another related ratio, published on his book the “Acquirer’s Multiple” in 2014, Tobias E. Carlisle propose an acquirer’s multiple by to define the price a buyer must pay to acquire a company [16]. It shows the undervalue of company, especially compared to its same industry peers. Carlisle also argue that it has largely outperformed the market since 1999, as see in Figure 2.3. The screen generated a total return of 6765%, or a compound growth rate of 25% per year from 1999-2017[18].

Magic Formula Returns			
Year	Magic Formula	Market Average*	S&P 500
1988	27.1%	24.8%	16.6%
1989	44.6%	18.0%	31.7%
1990	1.7%	-16.1%	-3.1%
1991	70.6%	45.6%	30.5%
1992	32.4%	11.4%	7.6%
1993	17.2%	15.9%	10.1%
1994	22.0%	-4.5%	1.3%
1995	34.0%	29.1%	37.6%
1996	17.3%	14.9%	23.0%
1997	40.4%	16.8%	33.4%
1998	25.5%	-2.0%	28.6%
1999	53.0%	36.1%	21.0%
2000	7.9%	-16.8%	-9.1%
2001	69.6%	11.5%	-11.9%
2002	-4.0%	-24.2%	-22.1%
2003	79.9%	68.8%	28.7%
2004	19.3%	17.8%	10.9%
Average	33%	15%	14%

Figure 2.1. The performance of Magic Formula from 1988-2004. Source: The Little Book That Still Beats the Market [11].

Statistics

	Total Return	Annualized Return	Max Drawdown	Risk Statistics (MONTHLY Period) Sharpe	Sortino	StdDev	CorrelBench	R-Squared	Beta	Alpha
Screen	335.21%	9.51%	-58.28%	0.54	0.71	17.47%	0.90	0.80	0.98	5.83%
iShares Russell 3000 ETF	91.12%	4.08%	-55.77%	0.24	0.32	15.96%	-	-	-	-

DOWNLOAD

Figure 2.2. The performance of Piotroski's Score from 2000-2016. Source: Collin Moshman [17]

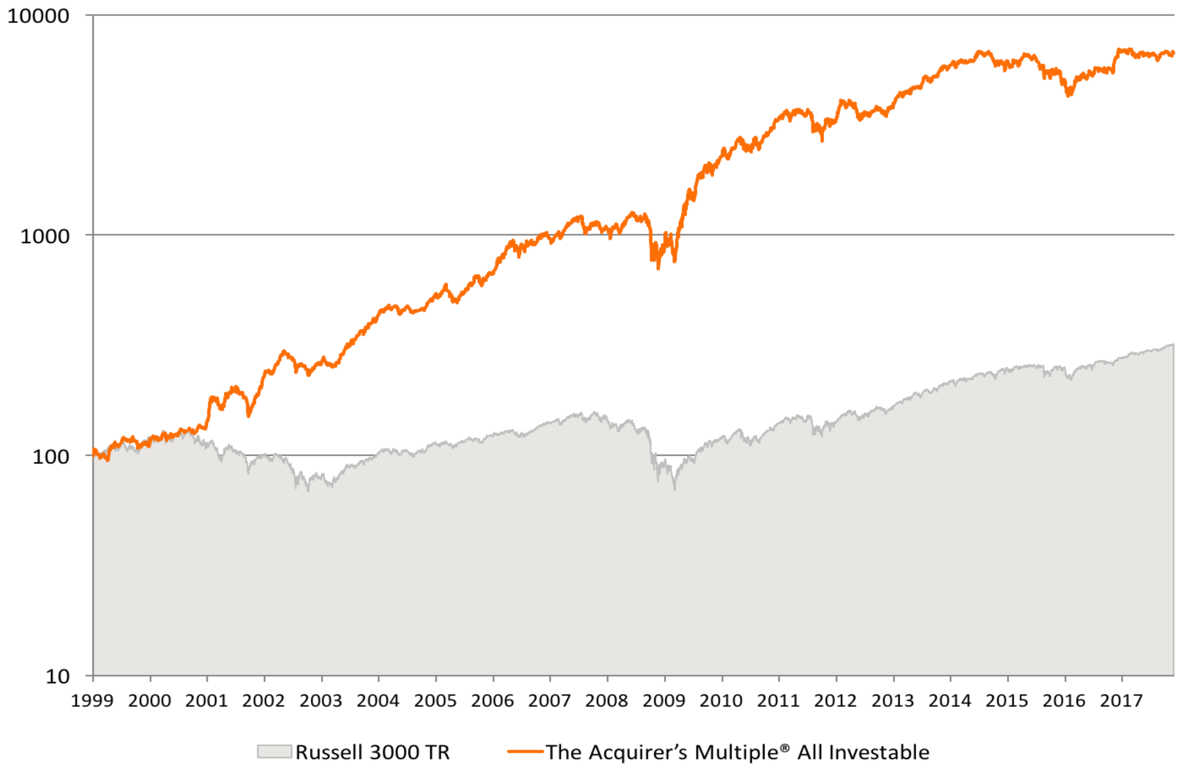

Figure 2.3. Performance of Acquirer's Multiple from 1999 to 2017. Source: Johnny Hopkins [18]

Chapter 3

Requirements

The project main aim is to create an automated algorithm on Quantopian platform, utilizing different financial ratios and momentum indicators to create a stock portfolio. The other aim of the paper is to compare the created algorithm to other famous quality algorithms in terms of many evaluation metrics, all developed on Quantopian. There are number of software and hardware specifications required in order to execute the algorithm and test the result. Firstly, the algorithm will be run on the Quantopian platform, so the user will need to have a Quantopian account. If user doesn't have a Quantopian account, user can't perform the algorithm, as the algorithm utilises many of Quantopian native libraries as well as its built-in data sources. Secondly, as Quantopian is an online platform, users may use a web browser to access it, and a reliable internet connection is also recommended, in order not to interrupt the backtest results. Thirdly, the backtest is only shown in paper-trading environment, not in real-world trading environment. In order to execute real-life trading, users need to install zipline-live [19] to execute the algorithm in real market. Note that past performance is no indicators of the future performance.

Chapter 4

Design and Implementation

4.1. General Design of the Algorithm

The algorithm uses the general flow of the program introduced in Rishi Narang's book "Inside the Blackbox" [20], as seen in Figure 4.1.

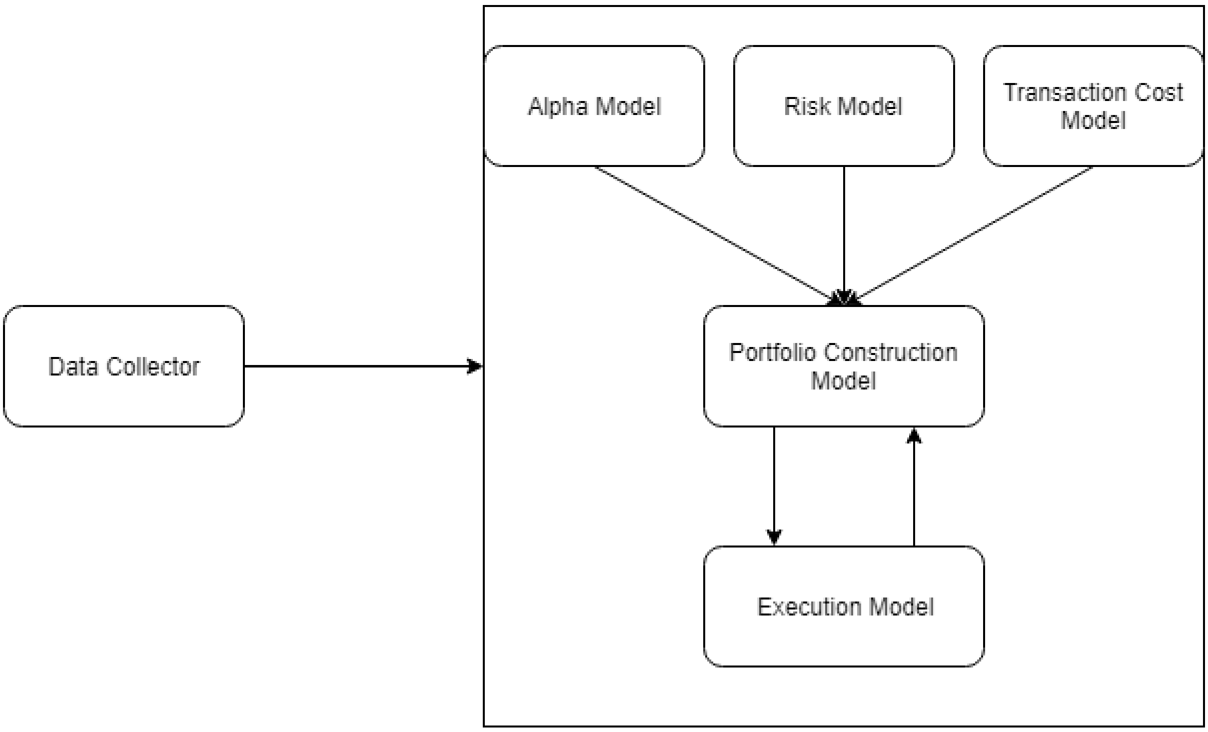

Figure 4.1. The flow of the typical trading program. Source: Inside the black box: A Simple Guide to quantitative and high-frequency trading [20]

Using the above model (figure 4.1) our model will consist of a data- collector, Alpha Model, Risk Model, Transaction Cost Model, Portfolio Construction Model and Execution Model. The alpha will produce targeted buying positions while the Risk model will set constraints within the model. The

Data Collector will collect fundamental data from Morningstar package, as well as the closing price of the stock for the last 30 day to calculate the volatility of the stock. The transaction cost model will estimate the set the transaction of the model. In portfolio construction model, receiving inputs from Alpha and Risk model and Transaction cost model, will produce an equal-weighted portfolio. The execution model, with inputs from the portfolio, will execute orders at the given scheduled time of the function

4.1.1. Data Collector

The data will be collected from Quantopian's built-in database by calling from its database. It is then passed to different class for each data types to get the output for the specific stock. The Data Collector will collect:

- US Equity closing price in the last 30 days to be used in calculating stock's Momentum and stock's volatility
- Fundamental Data: Price to Book ratio (PB), Price to Earnings Ratio (PE), Dividend Yields (DY), Return on Assets (ROA), Return on Equity (ROE), Return on Invested Capital(ROIC) and Earnings Yield(EY) of a company.

After calling the data, it will pass inside the model to be used by the alpha and risk model. The flow can be seen in Figure 4.3.

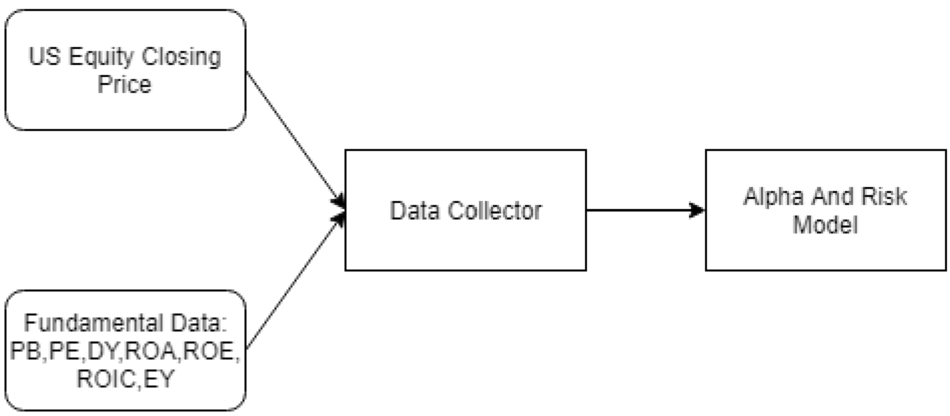

Figure 4.3. The Flow of Data in Data Collector model

4.1.2 Alpha Model

Alpha model is used to create a buying list of stocks. Inspired by both value investing and quality strategy, the aim of the alpha is to find a list of 25 stocks with Cheap Valuation but Good Management team while showing a good momentum and low volatility (low risk). It is a Factor-Based Strategy, and, while all other factors are weighed equally, I weighted the Return on Invested Capital twice the size of normal factor because I believe the quality of its management is very important. The weight is set as below:

- Return on Invested Capital * 2
- Price to Earnings, Price to Book, Dividend Yield, Return on Equity, Return on Asset, Earnings Yield *1

The Maths function of the ranking weight is

Weight = PE_rank * 1 + PB_rank * 1 + DY_rank * 1+ ROE_rank * 1 + ROA_rank *1 + EY_rank * 1 + ROIC_rank *2

Where:

- PE_rank and PB_rank are ranks of Price to Earnings and Price to Books Ratio, the lower the ratio the better (cheap company). PE_rank and PB_rank is ranked from lowest to highest
- DY_rank is rank of dividend yield, the higher the ratio the better (good income from dividend). DY_rank is ranked from highest to lowest
- ROE_rank, ROA_Rank, ROIC are ranks of return on equity, return on assets, return on invested capital. The higher the ratio, the better (good company management and quality company)
- EY_rank is the rank of Earnings Yields by Joel Greenblatt, the higher the ratio the better (cheap companies).

-The flow of the alpha model is as followed. After receiving the data from Data Collector, the alpha model will do two things.

- Firstly, it will define the trading universe of the Alpha Model. The initial trading universe consists of the biggest 2000 stocks by market cap and each stock needs to be defined in a sector. After that the universe is being filtered by momentum and volatility. Momentum of the stock in last month (30 days) must be greater than 1 while the volatility of the stock in the last 15 days must be in the lowest 600 volatile stock. As the portfolio is executed every month, I believe this will avoid us to trade a bad momentum stock and stock that recently suffer major price change.
- Secondly, the stock will then be ranked by all imported fundamental indicators as listed in Data Collector: Price to Earnings, Price to Book, Dividend Yield, Return on Equity, Return on Equity, Earnings Yield and Return on Invested Capital. The sum of all ranking will then be calculated, and the list of top 25 stocks will be added into the buy list. The flow of the alpha model can be seen in figure 4.4.

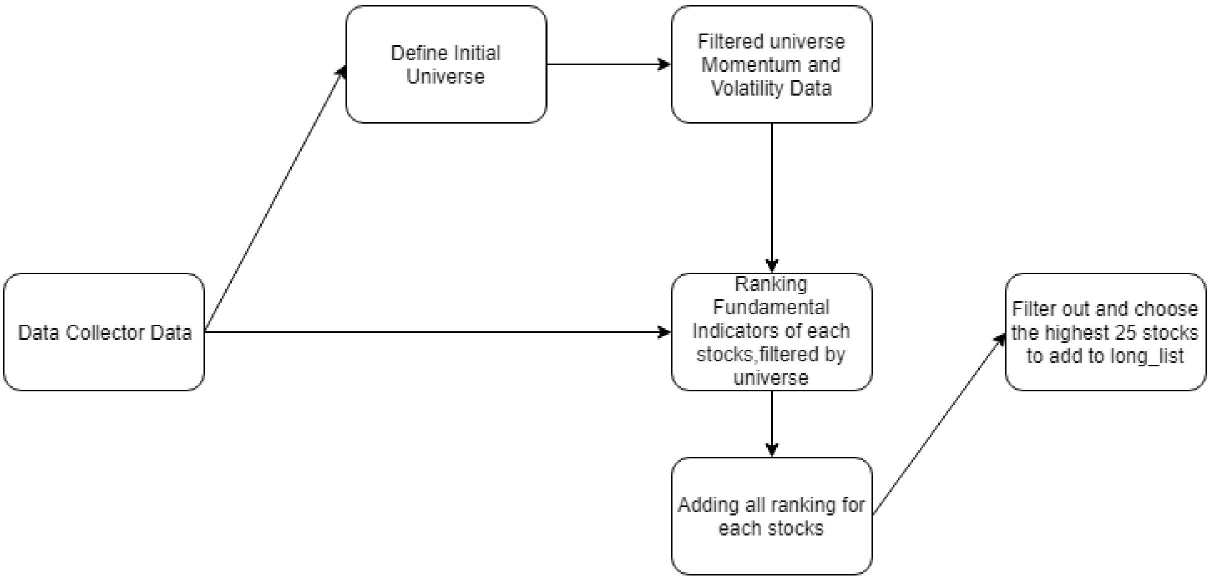

Figure 4.4. The Flow of Execution in Alpha Model

4.1.3. Risk Model and Transaction Cost Model

Both risk and transaction cost model defined constraints of the portfolio. The risk model will limit the size of any particular positions to less than 4% of the portfolio to make sure the portfolio doesn't have any leverage (borrow money to trade).

The transaction cost model will define the commissions cost and slippage of the portfolio. Commissions are fees paid to brokers for the service of connecting us to other market participants. Commissions and fees are fixed, normally at rate of 0.05 per share, with the minimum cost of 1$ per transaction [20]. Slippage: is the change in price between when a trader decides to trade and when the trade was actually executed in the exchange. As the market always constantly moves and time pass, there will be a difference between when the decision was made and when the trade is actually executed. The more accurate the estimate of slippage, the better cost-estimate will be [20].

4.1.4. Portfolio Construction Model

Portfolio Construction Model will receive inputs from alpha model, risk model and transaction cost model to construct a desired portfolio. It is there to make sure the portfolio balance between risk, reward and the transaction cost of doing the strategy [20]. The output of the portfolio construction model is a desired portfolio. The desired portfolio will be equal-weight between 25 desired stocks- which mean a weight of 4% for each position. The inputs and output of the portfolio construction model can be seen in figure 4.5.

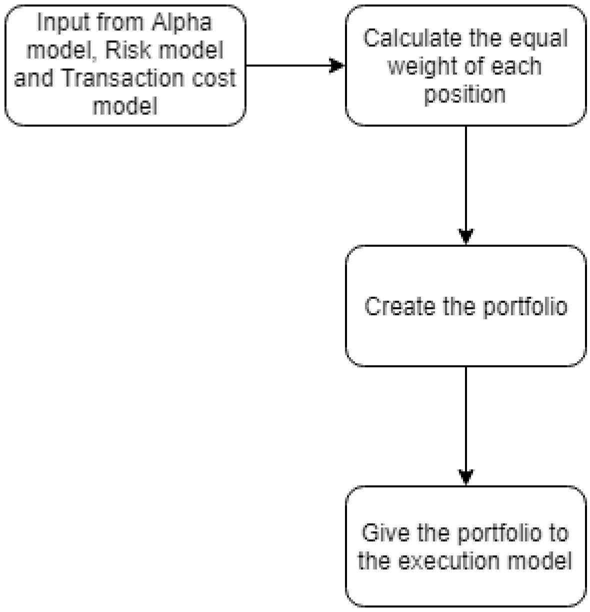

Figure 4.5. The input and output of the portfolio construction model

4.1.5. Execution Model

Execution Model is used to implement the wanted portfolio with input from Portfolio Construction Model by either buying or selling securities. Its working flow are as below:

- If the stock is in the desired portfolio of the Portfolio Construction model and the buying order can be filled in the market, the execution model will buy the stock.
- If the stock is no longer in the desired portfolio of the Portfolio Construction model and the selling order can be filled, it will sell the stock.
- Otherwise, the portfolio will stay the same.
- The execution model will be rerun again the next week to see if it can buy and sell the stock.

The flow of execution model is seen in figure 4.6.

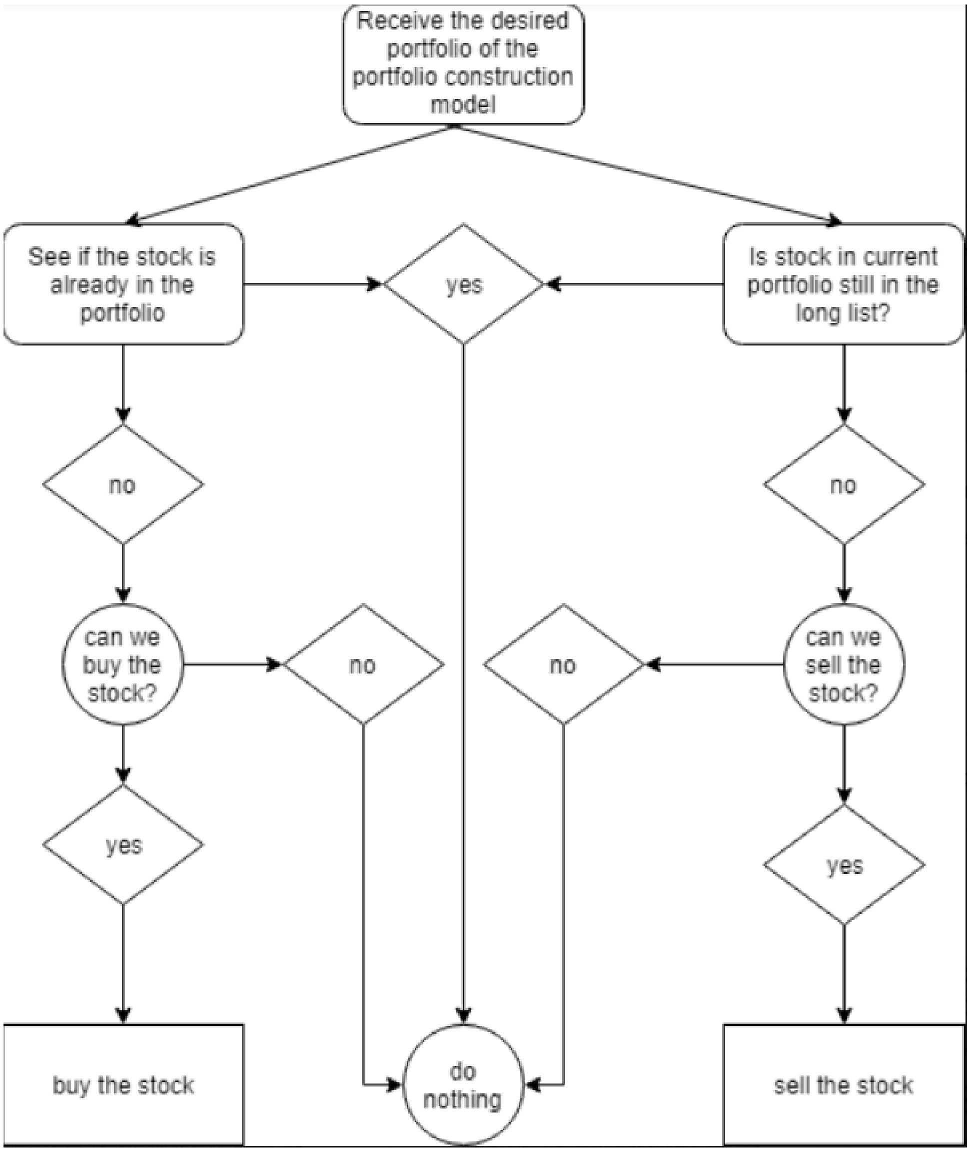

Figure 4.6 The process of the execution model

4.2. Implementation of the Algorithm

The developed algorithms, as well as other developed algorithms, were implemented using Quantopian platform. Some description of the backtest of the algorithm will be discussed, along with any challenges faced in implementing these algorithms.

4.2.1. Implementation challenges and some results

One of the most difficult decisions, due to a variety of available financial ratios and indicators, was to choose which indicators to use. At first, the result of the algorithm was really depressing, trailing the market (S&P 500), even though I use many indicators that proved to work in the past such as **EY (Earnings Yield)** or **ROIC (**Return on Invested Capital**)-** two components in the Magic Formula**.** Many people state that once the useful and predictive metrics was published, it will lose its power, as state by Jim O'Shaughnessy on his book" What work on Wall Street" [21]. He stated that since the publication of Eugene Fama and Ken French three-factor model published originally in the June 1992[22], the ratio have underperformed the market in many periods. The same seems to happen to the Magic Formula I implemented in the backtest and using the same strategy, so I have to implement a different approach and combining more factors into the model. Below are the different results at different stage of implementing the algorithms. In figure 4.7 is the initial result when using only Magic Formula indicators, the algorithm works well till the book was published (2006) and it has trailing the market even since. Figure 4.8 is my algorithm performance during the same time period.

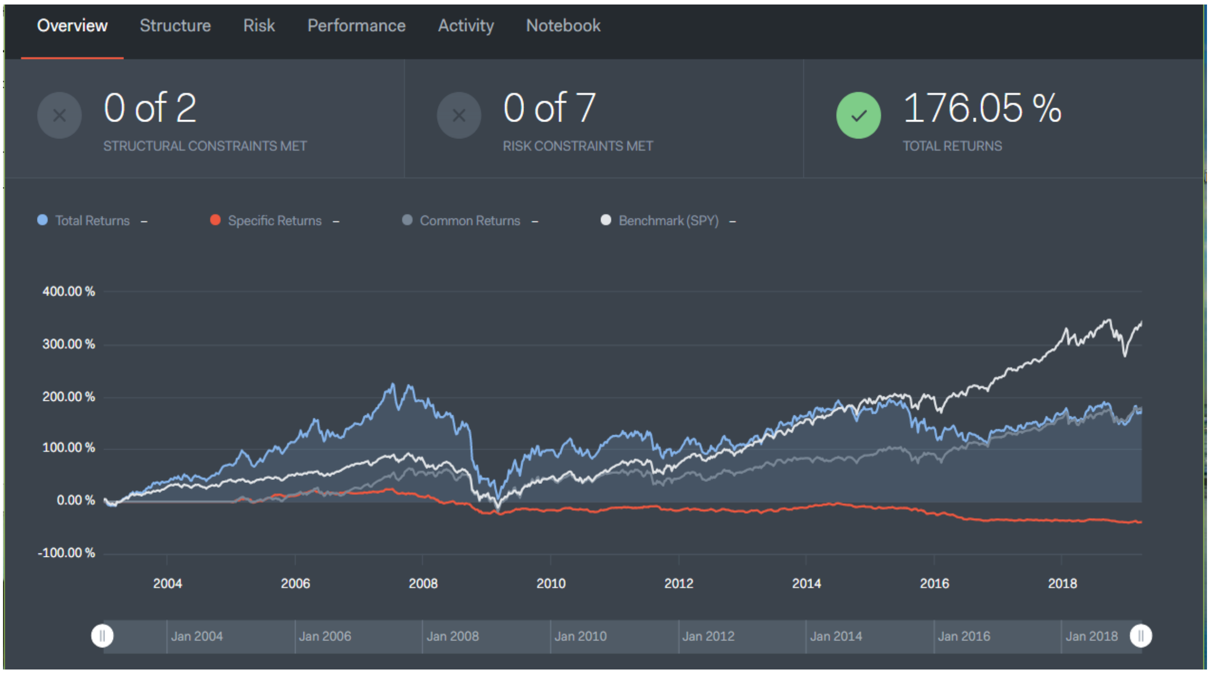

Figure 4.7. Initial Results, when only apply 2 factors of the magic formula, rebalance yearly.

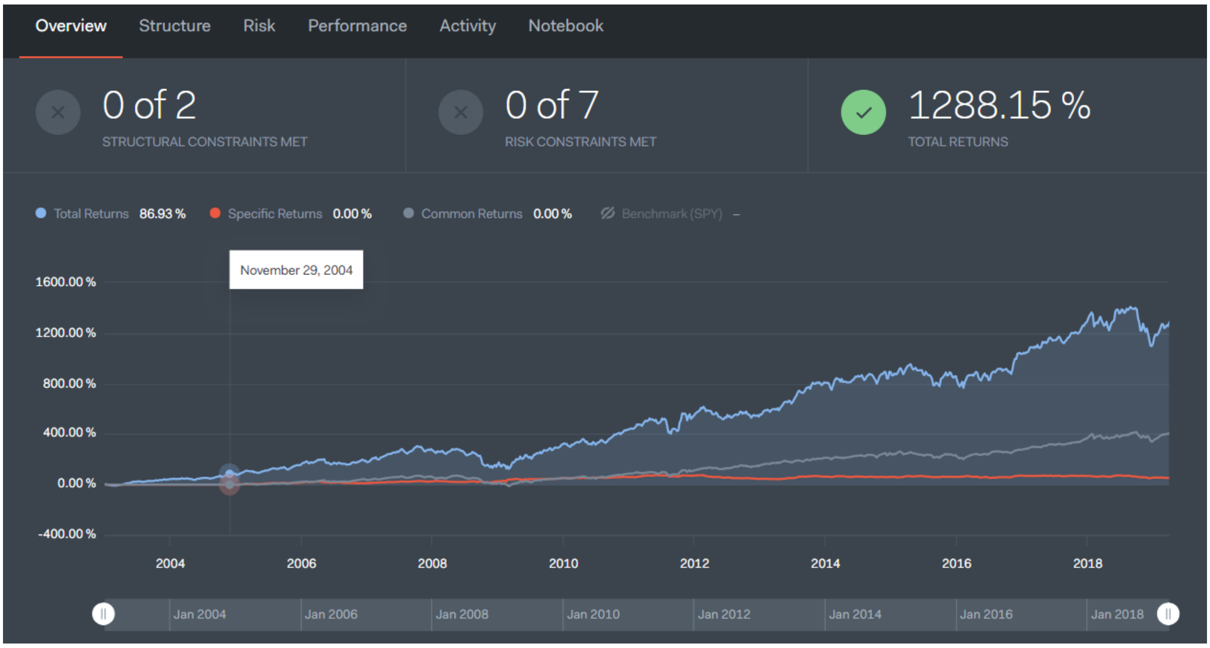

Figure 4.8. Later Results

4.2.2. Early Testing of the algorithm

At the early stage of the algorithm, the idea is developed only on using Notebook of Quantopian(an Ipython notebook designed for Quantopian) . Once the trading algorithm has proved to produce a reliable profit, the algorithm will be implemented into Algorithm Section of Quantopian (where you can see not only results of the algorithm during set time period, but you will also record different factors such as leverage or positions of the algorithm as well as comparing the algorithm performance in many crisis to the market(e.g Lehmann Brother bankruptcy, financial crisis). This risk will be analyzed further in Chapter 5: Results and Evaluation.

Chapter 5

Results and Evaluation

5.1. Evaluation Metrics

In order to test the performance of the algorithm, there are many metrics that being used:

- **Cumulative Return:** is the aggregate change in price of the portfolio over a period of time, calculated in percentage.

$$Cumulative\ Return = \frac{End\ Value\ of\ the\ portfolio - Start\ value\ of\ the\ portfolio}{Start\ value\ of\ the\ portfolio}$$

- **Sharpe Ratio** also known as risk-adjusted return ratio, is used to understand the return of an investment compared to its risk.

$$Sharpe\ Ratio = \frac{Return\ of\ the\ portfolio - Risk\ Free\ Return}{Standard\ Deviation\ of\ the\ portfolio\ excess\ return}$$

  Risk Free Return normally uses 3-month US Treasury Bonds, as the short-term bonds faces nearly zero risk as it is backed by the US Government

- **Max Drawdown:** the difference in valuation from a peak to a trough of a portfolio, before a new peak is attained, calculated in percentage. [23]

$$Max\ Drawdown = \frac{(Trough\ Value - Peak\ Value)}{Peak\ Value}$$

- **Gross Leverage:** The ratio of total valuation of assets compared to portfolio's total equity. A high gross leverage normally correlates with higher level of risk.

$$Gross\ Leverage = \frac{Total\ Assets}{Total\ Equity\ (Assets - Debts)}$$

- **Beta:** A beta coefficient is a measure of the volatility, or systematic risk, of an individual stock in comparison to the unsystematic risk of the entire market. If a stock has a beta of 1.0, it indicates that its price activity is strongly correlated with the market. A stock with a beta of 1.0 has systematic risk, but the beta calculation can't detect any unsystematic risk. Adding a stock to a portfolio with a beta of 1.0 doesn't add any risk to the portfolio, but it also doesn't increase the likelihood that the portfolio will provide an excess return. [24]

$$Beta = \frac{Covariance(Return\ of\ Portfolio, Return\ all\ Market)}{Variance\ (Return\ of\ all\ market)}$$

These metrics are used to evaluate different aspects of the portfolio, alongside the performance of S&P 500 index, as well as the algorithm risk during the Lehman brother crash in 2008, the event that triggered the 2008 recession.

All algorithms are tested during the same time-period: from 1st January 2003- 1st April 2019

5.2. The Magic Formula Result

This section will talk about the performance of Magic Formula that I developed based on the Magic Formula by Joel Greenblatt.

- **The Magic Formula Overall Review:** The magic formula consists of two main parts: Earnings Yield and Return on Invested Capital, both of which are weighted equally. The algorithm will calculate both ratios of a company, ranking each company's Ratios in order. The system will then add the ranking of two ratios and choose 25 companies with highest ranking. The algorithm is scheduled to buy at the beginning of January and sell at the beginning of December, to make sure it can sell all the positions before January with an stock's universe of 50 million market cap or more.

The performance of the Magic Formula algorithm is seen as below.

- **First Date Range (1st January 2003- 1st April 2019):**

	Backtest
Annual return	6.5%
Cumulative returns	176.0%
Annual volatility	23.0%
Sharpe ratio	0.39
Calmar ratio	0.09
Stability	0.38
Max drawdown	-69.0%
Omega ratio	1.07
Sortino ratio	0.54
Skew	-0.36
Kurtosis	5.00
Tail ratio	0.95
Daily value at risk	-2.9%
Gross leverage	0.91
Daily turnover	1.3%
Alpha	-0.02
Beta	1.05

Figure 5.2.1. Evaluation Metrics of the Magic Formula

Figure 5.2.2. Magic Formula vs S&P 500

Stress Events	mean	min	max
Lehmann	-0.14%	-5.81%	5.14%

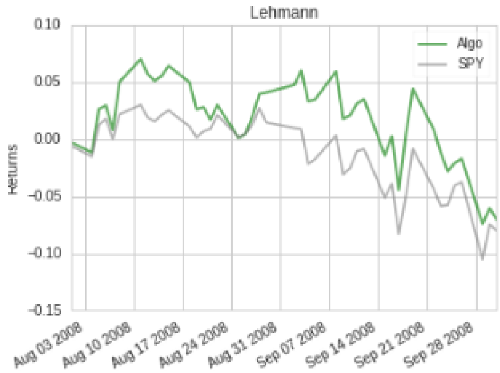

Figure 5.2.3. Magic Formula Performance during Lehman Brother's bankruptcy

- **Evaluation of the Magic Formula:** The magic formula that I developed have underperformed the S&P 500 in the tested time period (176.05% vs 344.03% of S&P 500). As seen in figure 5.2.2, the algorithm outperformed the market from 2003-2008, before the financial crisis of 2008 but can't recover after the financial crisis. Its Sharpe Ratio of 0.39 and max drawdown of -69% shows that the algorithm is limited and not having a great reward for the amount of volatility it faces. This can be explained because the algorithm picks stock with more than 50 million market cap which can increase the risk by picking really cheap but not quality stock. Its beta of 1.05 shows that most of the algorithm's return are correlated to the market performance. During the Lehmann crisis, the algorithm performance is quite similar to that of S&P500 (Figure 5.2.3),even if perform slightly better. The results show that the algorithm have underperformed the market heavily since the publication of the "Little Book that beats the market" in 2005. The algorithm can be improved by instead of holding for 1-year as stated in the book, it should rebalance more often (i.e. monthly or quarterly) and increase the market cap of the stock to improve the quality of the pick (My backtest of minimum market cap of 1 billion increased to 251% as seen in figure 5.2.4).

Start date	2003-01-06
End date	2019-04-01
Total months	194
	Backtest
Annual return	8.1%
Cumulative returns	251.7%

Figure 5.2.4. The return of magic formula If market cap is increased to 1 billion

5.3. The Acquirer’s Multiples and Piotroski’s F-Score overview and result

5.3.1. The Acquirer’s Multiples Result, developed upon code by Black Cat [5]

- **Overall review of the Acquirer’s Multiple algorithm**: The Acquirer’s Multiple is developed by Tobias Carlisle in his book “Acquirer’s Multiples” [25]. It consists of only one financial ratio- Acquirer’s Multiples, which is essentially the opposite of earnings ratios, as he argues that most return is derived from the Acquirer’s Multiples. It can only show how much a buyer of a company has to pay to acquire the business. The algorithm by BlackCat calculate the Trailing-12-month of the Acquirer’s Multiple, and then decrease the universe sensible stock universe (no ETFs, no over-the-counter stocks, etc.). It is then ranked the Acquirer’s Multiples and buy 25 stocks with the lowest Acquirer’s Multiples. The algorithm is set to rebalance once per month.

  The performance of the Acquirer’s Multiple can be seen in figures below.

	Backtest
Annual return	12.7%
Cumulative returns	596.7%
Annual volatility	22.9%
Sharpe ratio	0.64
Calmar ratio	0.23
Stability	0.89
Max drawdown	-55.0%
Omega ratio	1.12
Sortino ratio	0.89
Skew	-0.36
Kurtosis	4.59
Tail ratio	1.00
Daily value at risk	-2.8%
Gross leverage	0.97
Daily turnover	0.7%
Alpha	0.03
Beta	1.09

Figure 5.3.1.1 Evaluations metrics of the Acquirer's Multiples

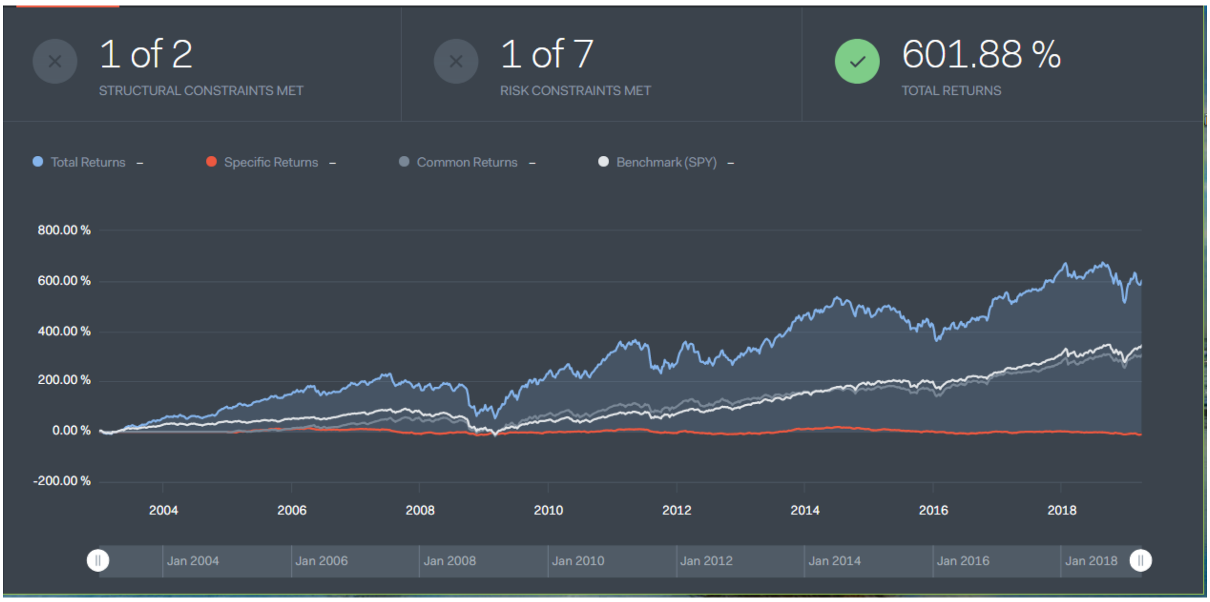

Figure 5.3.1.2. Acquirer's Multiple vs S&P 500

Stress Events	mean	min	max
Lehmann	-0.21%	-6.10%	4.28%

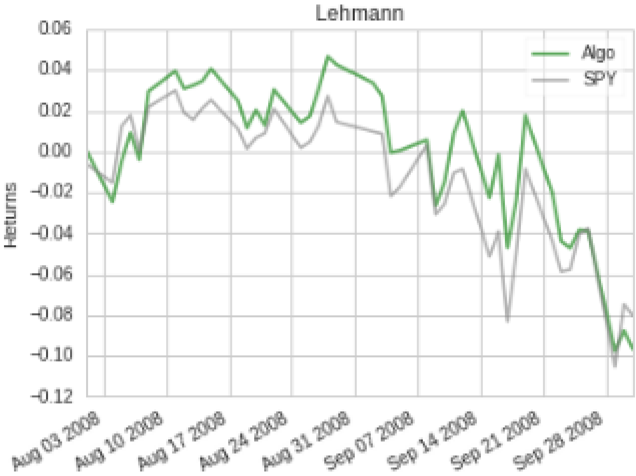

Figure 5.3.1.3 Acquirer's Multiple Performance during Lehman Brother's bankruptcy

- **Evaluation of the Acquirer's Multiple:** The Acquirer's Multiple developed by BlackCat[5] have outperformed the S&P 500in the tested time period (601.88% vs 344.03% of S&P 500). As seen in figure 5.3.1.2, the algorithm outperformed the market since 2003-2008, it can correlate to the performance of the market after 2008-2019. Its Sharpe Ratio of 0.64 and max drawdown of -55% is by no means a great number, but it still shows that the algorithm is better than the Magic Formula. Its beta of 1.09 shows that most of the algorithm's return are correlated to the market performance. During the Lehmann crisis, the algorithm performance is quite similar to that of S&P500 (Figure 5.3.1.3). Both Acquirer's Multiple and Magic Formula has gross leverage less than 1, show that they are both not leveraged portfolio. As the algorithm have been optimised by BlackCat, there is not so much room for a long-only algorithm.

5.3.2. The Piotroski's F- Score Result, developed upon code of Guy Fleury [6]

- **Overall Review of the Piotroski's F-Score Algorithm by Guy Fleury**: The F-Score is developed by Joseph Piotroski in his research "Value investing: The use of historical financial statement information to separate winners from losers" [13]. It consists of 9 different categories to assess the financial strength of a company. There is a score from 0-9, in which the higher the F-score is, the stronger financial position of the company. In this algorithm developed by Guy Fleiry[6], he created 9 categories of the F-Score, and award one point of F-Score for a stock if it matches one category. The algorithm will then rank stocks by its F-Score and short 10 lowest F-score stocks and buy the 10 highest F-score stocks. The algorithm will be run at the end of each month.

  The performance of the Piotroski's score can be seen in figures below.

	Backtest
Annual return	15.7%
Cumulative returns	963.1%
Annual volatility	24.1%
Sharpe ratio	0.73
Calmar ratio	0.29
Stability	0.88
Max drawdown	-54.0%
Omega ratio	1.13
Sortino ratio	1.07
Skew	0.05
Kurtosis	3.89
Tail ratio	1.07
Daily value at risk	-3.0%
Gross leverage	3.39
Daily turnover	1.9%
Alpha	0.15
Beta	0.24

Figure 5.3.2.1 Evaluations metrics of the F-Score Algorithm

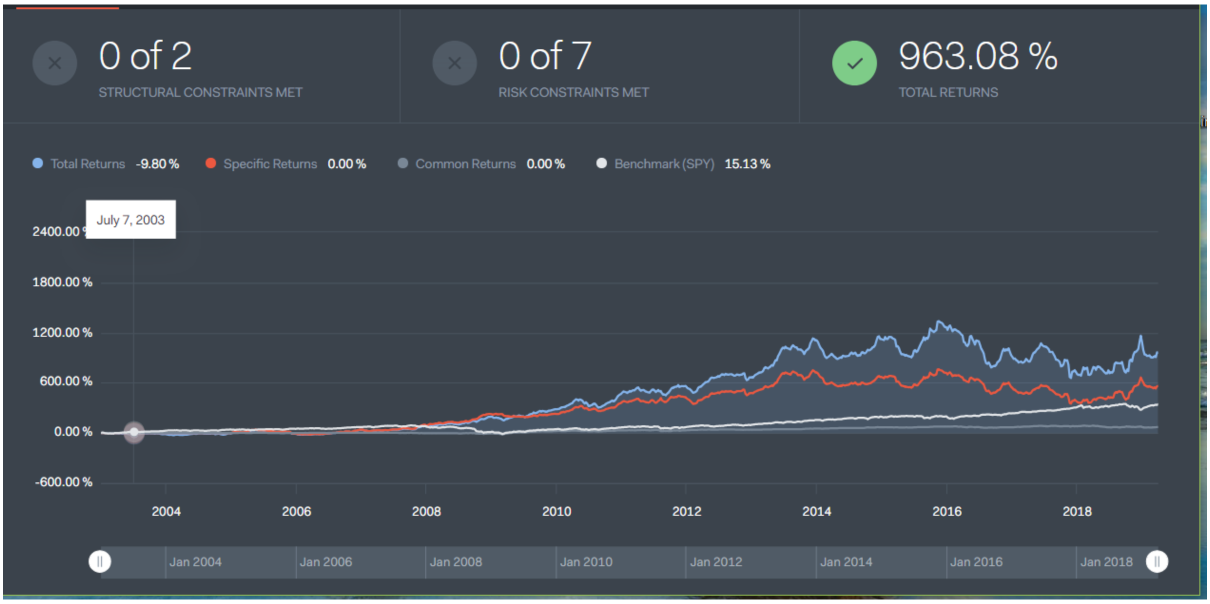

Figure 5.3.2.2. F-Score vs S&P 500

Stress Events	mean	min	max
Lehmann	0.32%	-4.53%	6.61%

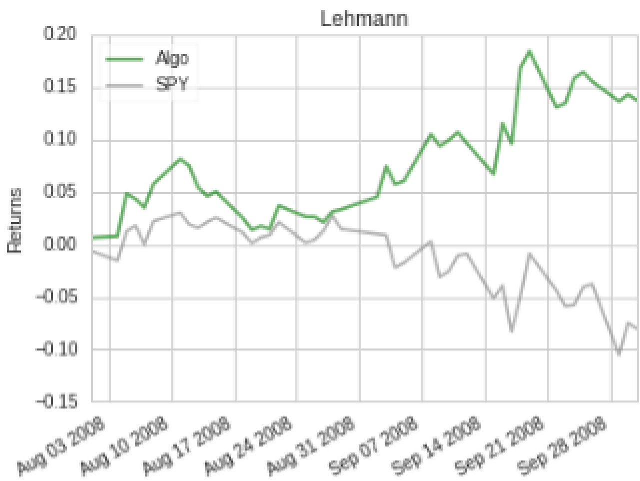

Figure 5.3.2.3 F-Score Performance during Lehman Brother's bankruptcy

- **Evaluation of Piotroski's F-Score Algorithm:** F-Score Algorithm developed by Fleury[6] have outperformed the S&P 500in the tested time period (963.08% vs 344.03% of S&P 500). As seen in figure 5.3.2.2, the algorithm keeps pace with the market since 2003-2008, its performance then outperformed the market significantly after 2008-2019. Its Sharpe Ratio of 0.73 and max drawdown of -54% (figure 5.3.2.1) is relatively similar to Acquirer's Multiple and better than the Magic Formula. Its beta of 0.24 shows that most of the algorithm's return are independent of market performance. During the Lehmann crisis, the algorithm performed much better than the S&P 500 while market declined, the algorithm still provided positive result. The advantage of this F-Score Algorithm is that it can still provide profit even when the market declines. However, its return can be explained by the gross leverage of 3.39(figure 5.3.2.1) and it can be highly risky if the algorithm models doesn't go as well as planned (since 10th November 2015- 27th November 2017, the algorithm went down 53% while the S&P 500 rises steadily). The algorithm can be improved by developing a lower leverage to produce a more stable return, at cost of sacrificing profit.

5.4. My Value Long-only Algorithm Result and comparison to other algorithms

This section will talk about the performance of the long-only value algorithm that I developed, as stated in The Design and Implementation part of the project.

The performance of the algorithm can be seen below:

	Backtest
Annual return	17.5%
Cumulative returns	1267.8%
Annual volatility	22.5%
Sharpe ratio	0.83
Calmar ratio	0.38
Stability	0.96
Max drawdown	-46.4%
Omega ratio	1.16
Sortino ratio	1.18
Skew	-0.24
Kurtosis	5.09
Tail ratio	0.97
Daily value at risk	-2.8%
Gross leverage	1.00
Daily turnover	7.5%
Alpha	0.08
Beta	1.04

Figure 5.4.1. Evaluations metrics of the Value Long-Only algorithm

Figure 5.4.2. Value Long-Only Algorithm results vs S&P 500

Stress Events	mean	min	max
Lehmann	-0.19%	-7.81%	7.22%

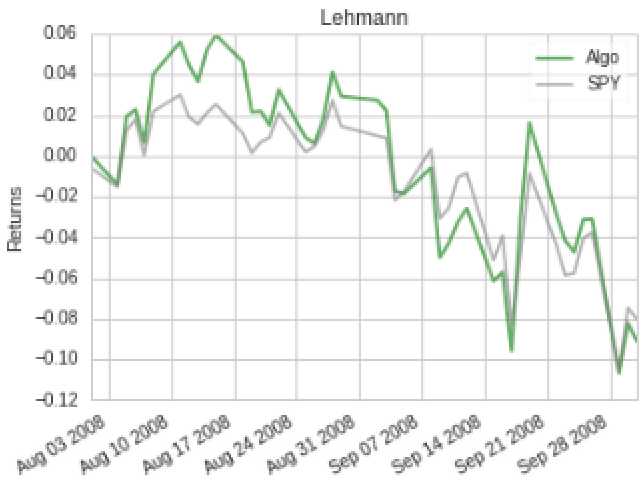

Figure 5.4.3. Value Long-Only Performance During Lehmann Crisis

- **Evaluation of My Value Long-Only Algorithm to other Algorithms:** The algorithm I developed have outperformed the S&P 500 in the tested time period (1288.08% vs 344.03% of S&P 500). As seen in figure 5.4.2, the algorithm outperformed the market slightly from 2003-2008, it keeps outperformed the market since then till 2019. Its Sharpe Ratio of 0.83 and max drawdown of -46.4% (figure 5.4.1) is a bit better than the Acquirer's Multiple and the F-Score Algorithm while much better than the Magic Formula. Its beta of 1.04 shows that most of the algorithm's return correlates to the market performance. During the Lehmann crisis, the algorithm performed relatively the same as the S&P 500(figure 5.4.3). **The advantage** of the Value Long-Only Algorithm is that by combining more than 1 or 2 factors that have been widely known and used by other investors, its 7-factor model have outperformed the market significantly as it can consider more aspects of the business, while not depending on only one factor. Furthermore, with gross leverage of exactly 1 (figure 5.4.1), the algorithm doesn't need to worry too much about paid interest rate while borrowing to invest in real-live trading, compared to other leveraged portfolio (e.g. F-Score Algorithm) .Another advantage of the algorithm is by utilising momentum and volatility sector, it performed just a bit better than average market during the crisis. However, the **main disadvantage** of the algorithm is that its performance depends on the market return, with beta of 1.04(Figure 5.4.1). Its maximum drawdown is also correlated to the financial crisis (46.45% from 10th October 2007 to 9th March ,2009(figure 5.4.4). Another disadvantage is that the starting capital is $100000, so the algorithm is targeted to the relatively rich trader, even though the performance with $10000 capital still outperformed the market.

Worst drawdown periods	Net drawdown in %	Peak date	Valley date	Recovery date	Duration
0	46.45	2007-10-10	2009-03-09	2009-12-21	574
1	24.34	2018-08-31	2018-12-24	NaT	NaN
2	23.31	2011-07-22	2011-08-22	2011-10-24	67
3	19.54	2015-04-23	2016-02-11	2016-11-17	411
4	17.25	2006-05-10	2006-09-11	2007-01-31	191

Figure 5.4.4. Maximum drawdown of the long-only algorithm

Chapter 6

Conclusion and Future Work

6.1. Conclusion

The comparison of different algorithm has shown some promising results by combining different financial ratios and technical indicators. In the long-run, by buying cheap company (through low PB, PE, high earnings yields), quality company (ROIC, ROE, ROA) at a good momentum and low volatility can provide the performance that beats the market. Even though the Magic Formula, Acquirer's Multiples and Piotroski' F-Score have outperformed the market during the past, there needs to be more factors added to weight the actual value of the company. The portfolio also needs to be more active (monthly or quarterly vs yearly), rebalancing more frequently to create a better overall result while not significantly increase the transaction cost of the portfolio.

6.2. Future work

- The algorithm I developed can be traded in real-live using zipline-live library [19]. You can also test real-life paper trading in the Quantopian platform.

- The main disadvantage of the algorithm is its high correlation to the S&P 500. The algorithm can be used alongside other long-short strategy to decrease the systematic risk to the S&P 500 (such that that of Fleury's F-Score) and increase the Sharpe Ratio.

- The portfolio can also be better optimised to decrease the dependencies of different positions in the portfolio.

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