

Louvain School of Management

High-frequency momentum and contrarian strategies on large caps.

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Abstract

Putting ourselves in the shoes of a High Frequency trader, we built 81 contrarian strategies and 81 momentum strategies in order to see which active strategies would give a better performance compared to the Benchmark, here it was the Buy & Hold strategy. We performed our tests only on the large caps using the NASDAQ database with the trading history of forty large caps. After removing the chance effect and performing return analysis, risk adjusted return and risk analysis. We found that in general contrarian strategies were better than momentum strategies and that using trend indicators did not yield very good results. Once we take into account transaction costs, none of the strategies can generate abnormal profits.

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1. Introduction

High frequency trading has become an important component of the financial markets in a very short time. The estimated level of activity directly attributable to HFT activities is difficult to estimate, but it is considered quite large. The main reason for the emergence of HFT is the evolution of the market structure, including decimalization, REG NMS rules and the electronic automation of limit order books. Among the major market participants, there are many different views on the influence of HFT on market quality. Some believe that its impact is positive, others believe that it is negative or even that it has a neutral impact on the markets. This difference of opinion can be explained by the fact that HFTs can operate in very different ways. If they operate as market-makers, they are generally beneficial to the market because they provide liquidity. There is a counter argument to this positive point that since HFT's are not bound by the obligations that other traditional market makers must fulfill, HFT's can cause disruptions in the market by leaving the market of their own will, so HFT's are not reliable in this regard. One could also note as a positive point that HFTs engage in arbitrage strategies which allows for a more efficient price but HFTs also engage in strategies that disrupt the markets which would therefore have a negative effect on it. They are also blamed for the Flash Crash of 2010. The benefits of HFTs are therefore nuanced (Carrion, 2012). Baron et al (2018) found that the benefits of HFTs compared to each other were mostly due to relative latency. Thus, the HFT with the best latency will have a better performance than the others. Speed is therefore important in many strategies, including market making and cross market arbitrage strategies. Carrion (2012) looked at the sources of HFT profitability based on their market timing performance, i.e. the relative performance of moving one's investment based on predictions of future market trends. They looked at HFT trading performance as measured in a Volume Weighted Average Price (VWAP) analysis and found that HFTs have intraday market timing skills, buying when prices are temporarily low and selling when prices are temporarily high. This finding is consistent with the fact that there is economically significant predictability in intraday prices. From this observation, we also wanted to try to exploit this predictive effect to see if it was possible to make a profit using contrarian and momentum strategies and to see if the general market trend is important to be profitable or if the profit only comes from micro movements in the market.

For this purpose, we will develop and test several trading strategies apply in an HFT framework in order to see if it is possible to effectively capture micro price movements in order to make a profit on the NASDAQ thanks to an algorithm we have developed. These various strategies belong to two of the most popular families of strategies, namely the momentum strategy on the one hand and the contrarian strategy on the other hand. To explain these two different strategies simply, let me define what a momentum trader is and what a contrarian trader is. First, a momentum trader uses a momentum strategy when the investor buys an asset that is in an uptrend in the belief that this asset will continue to rise or when he sells an asset that is in a downtrend in the belief that this asset will continue to fall. On the contrary, a contrarian trader uses a contrarian strategy when an investor buys an asset that is in a downtrend in the belief that the trend of this asset will revert and the asset will rise or when he sells an asset that is in an uptrend in the belief that the trend of this asset will revert and the asset will fall.

In order to capture the maximum profits from these two kind of strategies, the timing of entry and exit is very important. Knowing when to enter a position and when to exit a position is in itself a good part of both strategies. The idea is to test a set of factors or combination of factors so as to create buy or sell signals and then combine them to see which strategies outperform the selected benchmark. In addition to these factors, a strategy might work well on some types of companies (depending on the characteristics of the underlying company such as the size, the sector or the market on which it is traded) but not on other types of companies. In this study, we separate companies according to their market capitalization. We will come back to the database in more details in a later section.

We will then analyze the different returns produced by the strategies via three different axes, returns, risk-adjusted returns and risks. We will also continue our analysis with other tools and in particular, tools allowing to correct the data snooping. In the finance and economics literature, data snooping is prevalent. Only a few financial data sets are available for empirical analysis in practice. When researchers use the same data set to assess the significance of different models (technical trading rules) individually, this is also known as data mining. It is difficult to create a meaningful joint test because these individual statistics are generated from the same data set, hence related to one another, especially when the number of models (strategies) being tested is huge (Hsu, Hsu and Kuan, 2010).

It is important to take into account that the conclusions that will come from my thesis come from an analysis on only the NASDAQ, at a certain moment, for certain stocks and which could differ from what happens in other cases

My thesis will be organized in this way. Section two, a brief review of the literature. Section three, a description of the database used. Section four, an explanation of the methodology used to create the strategies and the analysis. Section five, the analysis of the results and section six the conclusion of my work.

2. Literature review

2.1. Definition

Strategies applied using a high-frequency algorithm are typically what high-frequency trading firms (hereafter HFT) do. What lies behind the name HFT has not yet been clearly defined, but if we follow the partial definition given by the Concept release of the U.S. Securities and Exchange Commission (SEC) it is a proprietary firm, i.e., professional traders acting on their own account and generating a large number of transactions on a daily basis, with a number of characteristics. Proprietary firms can be organised in different ways such as a proprietary trading firm, a proprietary trading desk of a multi-service broker-dealer, or a hedge fund for example.

HFTs possess these 5 characteristics. First, they use sophisticated and very fast programs to generate, route and execute orders. Second, they use co-location services and individual data streams offered by exchanges and others. This is to minimise network latencies. Third, they establish and liquidate positions in a very short time (down to a few milliseconds). Fourth, they submit many orders that are cancelled shortly after submission. And fifth, they end the trading day in a position as close to equilibrium as possible in order not to have any large uncovered positions overnight. (SEC, 2014)

It should be noted that for a proprietary firm to be defined as HFT, it is not necessary to have all the different characteristics above. Indeed, this is just a framework trying to define what an HFT is and not a truth set in stone. The SEC itself states that HFTs do not have a fixed definition and can encompass a wide range of strategies in addition to being passive market making (SEC, 2014).

HFT is often referred to as algorithmic trading. Algorithmic trading as defined by Hendershott and Riordan (2009) describes the use of computer algorithms to automatically make trading decision, submit orders and manage those orders after submission. HFT is therefore a type of algorithmic trading but conversely algorithmic trading is not necessarily HFT because by definition HFTs hold their positions over very short time horizons and try to end the day's trading in a neutral position, which is not always the case for algorithmic trading (Brogaard, 2010).

HFT players are important players in the US equity markets. From 2007 to 2012, they accounted for between 35% and 61% of market volume (Tabb, 2012).

2.2. Contrarian and Momentum strategies

If we look a little more closely at momentum and contrarian trading and investing, the literature goes in two main directions to explain these approaches. One axis seeks an explanation from a more rational point of view and the other seeks to find an explanation in behavioural finance. (Galariotis, 2014).

According to Jegadeesh and Titman (1993) the Momentum strategy is based on the underreaction hypothesis, which states that investors do not react sufficiently to new information, which makes it difficult for prices to adjust correctly. Liu, Warner and Zhang (2008) attribute more than half of the performance of momentary strategies to macroeconomic factors such as the growth rate of industrial production.

As for the contrarian strategy, authors such as De Bondt and Thaler (1985) associate this anomaly with the fact that investors have an excessive reaction to new information. Fama and French (1993) and other authors argue that the contrarian strategy can be explained by market risk. The time horizon of the performance of these strategies is quite different. Thus, for contrarian strategies, they seem to perform better over the short-term (week or month) and long-term (3 to 5 years or more). As for momentum strategies, they seem to be more profitable in the medium term (3 to 12 months) (Conrad and Kaul, 1998).

When we talk about HFT, the time horizon is much shorter since transactions occur at the millisecond and these strategies are applied intraday. Despite everything, this observation remains the same, there is still the notion of momentum and contrarianism.

Fung and Lam (2004) working with Hong Kong index futures observed that after a large price adjustment up or down the previous night, a price reversal would mostly take place at the market opening. The price reversal is directly proportional to the price change that occurred overnight (Fung, Mok and Lam, 2000). They also observe that the same thing can happen during the day. (Fung and Lam, 2004). Wang, Peng and Huang (2009) also observe abnormal returns on the Taiwan Stock Exchange when using a contrarian strategy intraday. The strategy is more effective for a holding period of 5 minutes rather than 30 minutes. Verousis and Ap

Gwilym (2011) find that reversals are more frequent for small caps and when the trade size is smaller.

Kang (2005) conducts his study on the New York Stock Exchange and finds that in a day when considering large caps, a stock that has performed well relative to others will continue its momentum movement for an hour and a half. This will be followed by a reversal and therefore a decline in value. On the small cap side, the effect will last all day. As with the contrarian strategy, this effect is more present at the beginning of the day.

This implies that shortly after the opening, markets are not at equilibrium because the impact of what happened during the night is felt at the opening. It should also be noted that at the close this same kind of disruption occurs as some traders close their positions.

In a paper, Brogaard (2010) found that HFTs, in his study, tend to follow price reversal strategies driven by order imbalances

As Galariotis (2014) explains, momentum and contrarian strategies have been studied many times over and the literature generally agrees that asset returns are not as random as the theory of market efficiency would suggest and that predictable patterns can be observed, which allows for profitable contrarian and very profitable momentum strategies.

It is therefore possible to obtain positive income from these strategies but in the context of high frequency trading the windows for entering or not entering the market can be very short given that HFTs receive information sometimes at the millisecond level, which allows them to capture a good number of micro-anomalies during the same day and as I explained above the timing of entry and exit from the market is very important in order to capture these anomalies. In the idea that predictable patterns can be observed in the markets, we will judge as an anomaly the fact that the asset price deviates from a specific variation. This variation will represent the n -th percentile of all observed differences in ticks between two sell orders. This approach considers that past data is a good indicator of what will happen today, which is only true if the market is very stable. In order to still take into account the general trend during the day, we can add some filters. The two filters that will be used in this paper are the Volume Weighted Average Price (VWAP) and the Moving-Average Crossover.

There is not much literature involving Momentum and Contrarian strategies with HFTs. The typical way for an HFT to make a profit is to act as a market maker providing liquidity to other investors and they will earn the bid-ask spread. They are also rewarded on some

exchanges for acting as a market maker. HFTs also make money through statistical arbitrage. For example, if the same two stocks have different prices between two exchanges, they can use their speed to take advantage of this fluctuation, before it disappears, and make a profit. (Bajpai,2022)

Nevertheless, Brogaard (2010) found that HFTs, in his study, tend to follow price reversal strategies driven by order imbalances

2.3. Trend Indicator

2.3.1. VWAP

The VWAP is the ratio of the value traded to total volume traded over a particular time horizon. It is considered one of the best technical indicators because it takes both price and volume (Maurya, Rai and Yadav, 2021). When possible, a trader will try to buy when the price is below the VWAP, as this is the best buy price on average, and sell when the price is above the VWAP, as this is the best sell price on average (Mitchell). The VWAP is used by many traders as an indicator to confirm the market trend so if the price arrives near the VWAP and the trend is upward the market trend is indeed upward and if the price arrives near the VWAP and the trend is downward the market trend will continue to be downward (Maurya, Rai and Yadav, 2021). If we take our case again, a positive or negative anomaly could indicate a trend and if the price is close to the VWAP it would confirm this trend. In the case of a momentum strategy, we will therefore take a long position if the price is above the VWAP and a short position if the price is below the VWAP and vice versa in the case of a contrarian strategy.

2.3.2. Moving-Average Crossover

The Moving-Average Crossover is also a useful trend indicator. First of all, two moving averages have to be calculated. One will be defined as the slow-moving average and the other will be defined as the fast-moving average. The fast-moving average will, due to its construction, put more weight on the most recent data, in contrast to the slow-moving average which is based on older prices. In order to capture the trend, it will be sufficient to compare the two moving averages over time and see which one is superior to the other. If the fast one is higher than the slow one, this means that recent prices are above past prices, which indicates an upward trend. On the contrary, if the fast one is lower than the slow one, this means that past prices are above recent prices, which would indicate a downward trend (Levine, Pedersen and Stamelos, 2018). In the same way as the VWAP, we could therefore use the Moving-Average Crossover to confirm the trend of our anomalies.

3. Data

We will use during this work a database containing the trading history of 120 U.S. stocks conducted in the Nasdaq exchange. This sample was selected by Terrence Hendershott and Ryan Riordan. These exchanges were executed on business days during the premarket, the regular market and the after-hours market at the beginning of January 2008 until the end of December 2009 and from 22/02/2010 to 26/02/2010.

The variables that can be found in the dataset are the date and time when the trade took place as well as the trade volume and the stock price. The exchanges are millisecond timestamped.

The different stocks included in this database can be divided into three categories depending on the market capitalization of each. For the purpose of our work, we will only use the large capitalization category and we will trade exclusively during the regular market. This division is based on the market capitalization at the end of 2009 of the different stocks in the database. If the stocks have a market capitalization of more than \$10 billion, they fall into the large-cap category (Brogaard, 2010). Table X describes, the companies' symbol, the names associated with the ticker of the different stocks in this specific category as well as the market capitalization and on which markets they are listed. The market cap comes from the work of Carion (2012)

Table 1: Sample stocks

Ticker	Stock Name	Listing	Market Cap (billions)
AA	ALCOA INC	NYSE	13.570
AAPL	APPLE INC	NASDAQ	185.548
ADBE	ADOBE SYSTEMS INC	NASDAQ	18.211
AGN	ALLERGAN INC	NYSE	17.763
AMAT	APPLIED MATERIALS INC	NASDAQ	16.442
AMGN	AMGEN INC	NASDAQ	55.438
AMZN	AMAZON.COM INC	NASDAQ	52.715
AXP	AMERICAN EXPRESS CO	NYSE	45.703
BHI	BAKER HUGHES INC	NYSE	14.946
BIIB	BIOGEN IDEC INC	NASDAQ	15.120

BRCM	BROA DCOM CORP	NASDAQ	13.737
CB	CHUBB CORP	NYSE	16.753
CELG	CELGENE CORP	NASDAQ	27.363
CMCSA	COMCAST CORP	NASDAQ	33.884
COST	COSTCO WHOLESALE CORP	NASDAQ	26.850
CSCO	CISCO SYSTEMS INC	NASDAQ	139.305
CTSH	COGNIZANT TECH SOLUTIONS	NASDAQ	14.322
DELL	DELL INC	NASDAQ	25.911
DIS	DISNEY (WALT) CO	NYSE	60.590
DOW	DOW CHEMICAL	NYSE	32.565
EBAY	EBAY INC	NASDAQ	29.903
ESRX	EXPRESS SCRIPTS INC	NASDAQ	26.445
GE	GENERAL ELECTRIC CO	NYSE	171.357
GENZ	GENZYME CORP	NASDAQ	15.221
GILD	GILEAD SCIENCES INC	NASDAQ	42.952
GLW	GORNING INC	NYSE	27.483
GOOG	GOOGLE INC	NASDAQ	128.612
GPS	GAP INC	NYSE	14.835
HON	HONEYWELL INTERNAT. INC	NYSE	30.704
HPQ	HEWLETT-PACKARD CO	NYSE	119.564
INTC	INTEL CORP	NASDAQ	113.408
ISRG	INTUITIVE SURGICAL INC	NASDAQ	13.516
KMB	KIMBERLY-CLARK CORP	NYSE	25.286
KR	KROGER CO	NYSE	14.363
MMM	3M CO	NYSE	57.045
MOS	MOSAIC CO	NYSE	25.993
PFE	PFIZER INC	NYSE	141.635
PG	PROCTER & GAMBLE CO	NYSE	183.803
PNC	PNC FIN.SVCS GROUP INC	NYSE	27.792
SWN	SOUTHWESTERN ENERGY	NYSE	14.726
			Mean : 51.284

Table 2 presents the descriptive analysis on the large caps. The database covers 509 days. During this period there have been 463,893,602 trades for a total of 91,436 million shares and a total of 3,507,380 million dollar volume. On average, each transaction is about 197 shares for a standard deviation of 86. The daily average dollar volume is 6,890 million and the average share volume is 180 million. The 10th percentile gives the daily share volume and dollar volume respectively, 111 million and 3,889 million. For the 90th percentile, we have 264 million and 10,773 million.

Table 2 : Trade summary statistics

Descriptive Statistics	Large Cap sample
Days in Sample	509
Number of Trades	463,893,602
Total Share Volume (millions)	91,436
Total Dollar Volume (millions)	3,507,380
Trade size	
Mean	197
Std Dev	86
Number of Trades/Day	
Mean	911,382
Std Dev	354,488
10 th %ile	565,634
Median	851,448
90 th %ile	1,350,044
Daily Share Volume (millions)	
Mean	180
Std Dev	66
10 th %ile	111
Median	169
90 th %ile	264
Daily Dollar Volume (millions)	
Mean	6,890
Std Dev	2,915
10 th %ile	3,889

Median	6,167
90 th %ile	10,773

We followed the same presentation method as Carrion (2012) to present the different descriptive statistics. Unlike them, we only described what happens in the large caps between 9:35 am and 3:55pm. (regular market hour minus a safety margin that we will discuss in the next section)

4. Methodology

As we have seen in the theoretical part, contrarian and momentum strategies can allow an investor to make a profit and that HFTs can produce a market timing performance. We based ourselves on the work of Duvinage, Mazza and Petitjean (2014) in order to construct our different strategies. In another framework, they had also used percentiles on returns to define an acceptable level of spread before entering or leaving the market in the context of contrarian strategy analysis. Without taking into account the transaction costs, this had produced significant results in some cases. We found that this was a relevant way to approach buy or sell signals in the market for contrarian strategies and we also wanted to test if this could be true for momentum strategies. Here we calculated our percentiles on tick changes.

The basic strategy on which the combinations with other parameters will be applied is the following: if during the day, we observe a rise or fall in price between two successive transactions of the same stock equivalent to a certain percentile, it will be a buy or sell signal. The signal will depend on whether we are testing contrarian or momentum strategies.

The observation of a large drop will be a buy signal for the contrarian strategy because we will expect a price reversal towards its equilibrium level. We will assume that this large drop is due to the overreaction of investors following an event and this led to a movement of the price more important than it should have been, this movement will be corrected thereafter. For the same reasons but in the opposite direction, the observation of a large rise will be a selling signal.

As for the momentum strategy the signals will be reversed, the observation of a large positive price movement will be a buy signal as we expect this movement to continue and conversely the observation of a large decline will be a sell signal. We will assume that investors have not reacted enough to the information they had and that therefore the bullish or bearish movement will continue.

We will use percentile values to define what we mean by a large decline or a large increase. These percentiles will be calculated either on the previous day's data, or on the first ten minutes of the current trading day's data and finally, we will use a moving average on the last five percentiles calculated on the previous day data. We will use three percentile pairs 10th-90th, 5th-95th and 1st-99th.

For example, in the contrarian cases, during the trading day if we observe a price decrease that is smaller than or equal to the previously calculated 5th percentile, we will have a buy signal and at the moment we observe a price increase or a positive return greater than or equal to the 95th percentile we will have a sell signal.

We will implement and test all strategies via the "R Studio" software. Implementing the strategies was a real challenge given the amount of data to process. We had to be very precise and optimize the code as much as possible in order to obtain results in a short time. Some of our optimizations allowed us to reduce the computation time up to three times. To do so, we have limited as much as possible the details and unnecessary steps by adding Boolean and variable. Each time we checked the important blocks in the creation of the strategies either by taking out the maximum of details in order to be able to trace the algorithm and to check the key points, or by simulating data or even by using Excel to see if we would have had the same kind of results. You will find via this link here ([Master Thesis](#)) the different codes used to calculate the historical returns for each strategy. You can also contact me if you have other questions via this address.

4.1. Position

In most cases, we will start our trading day at least five minutes after the opening of the regular market by taking a position in the market (position +1) and we will end the day at most five minutes before the closing of the regular market by closing our position (position 0). We used this five-minute safety margin to avoid the high volatility that is present at the opening and closing due to overnight correction.

Once in the +1 position, when there is a sell signal, we will close our position and then take a short position (-1 position) on the next trade, so there will be a delay of one trade between the appearance of a signal and the change of position. We will perform the opposite procedure in case we are in a -1 position if we observe a buy signal, after closing our position we will take a long position (+1 position). In addition to closing, we will leave the market (position 0) only when we reach a stop loss. We will discuss in more detail these different stop losses in a different section.

In the other case, the time we enter the market will depend on the strategy that is being applied. If it is a strategy where we calculate the tick variation in the first ten minutes of the day, we enter the market at least fifteen minutes after the opening of the regular market. When

using a strategy where we use moving averages, we enter the market at least eighteen minutes after the opening.

The position taken in the market at the opening may also depend on what our trend indicators indicate at the moment we enter in the market. When they are used, for example in the case of a contrarian strategy, if they indicate that the trend is bearish, we will take a long position (position +1) and if they indicate that the trend is bullish, we will take a short position (position -1). It will, of course, be the opposite in the case of a momentum strategy.

Concerning the benchmark to which we will compare our different strategies, we will take a long position (position +1) at least five minutes after the opening of the regular market and close our position (position 0) at most five minutes before the end of the regular market.

In general, we will always be the first and last transaction observed in the database after removing the different time constraints. Moreover, we will not take into account a change of position if it happens due to an outlier. During our work, we will define the level of outliers as any price that deviates by +/- ninety percent from the previous price. All outliers will be ignored.

To summarize, we will only be able to be in the 0, -1 and +1 position for all the strategies developed in our work.

4.2. Signals

As we have seen before, the basic strategy on which other parameters are based is the one based on three pairs of percentiles. We will use the same calculation method for each pair. The only thing that will change is the time horizon, whether it is ten minutes, one day or five days. For instance, if we use the rolling moving average on the 5th-95th percentiles. We will first calculate for each day the 5th-95th percentiles on the tick changes, in other words, we will subtract from each observed price its previous price in order to see the price variation between the different transactions, which will therefore correspond to the tick change. Then, we will eliminate the variations that do not interest us and that could interfere with the calculation of the percentiles. This concerns variations equal to 0 and variations involving outliers. Once filtered, we will calculate the 5th and 95th percentile. If we do this for each day, we will obtain two series of values and in our example, we will perform a moving average on the last five days of these series in order to find two values that we will use as signals for the next day.

In addition, we will use or not two ways to take into account the general trend of the market at the moment we encounter a signal. The idea behind this is to match the general market trend with what our signal is telling us. For example, in the Momentum case, not taking into account a signal given by the high percentile, which we will associate with the beginning of momentum, while the general market trend is bearish.

We will use the VWAP (Volume Weighted Average Price) so in the case of Contrarian/Momentum strategies, we will look at both when we have a buy signal due to the low/high percentile and if the price is below/above the VWAP to validate a buy signal and vice versa for the sell.

As an additional parameter to the signals, we will also use two moving averages, one on a five-minute horizon and the other on a thirteen-minute horizon (Farlay, 2022). If these two moving averages are used in the case of Contrarian/Momentum strategies, we will look to see both if we are below/above the low/high percentile and furthermore if the five-minute moving average is below/above the thirteen-minute moving average if this is the case then there could be a buy signal and vice versa for the sell signal.

4.3. Cash Management

We will consider during the tests that we will have full pockets, by full pocket we mean that we will always be able to take a position even if we have lost money during the previous trading day. We will always be able to return to the market without suffering the consequences of our various losses.

4.4. Costs

Although there is no unanimous answer when it comes to all fees applied to a transaction, we will use 5 bps in our case. This is a value found in the literature. In addition, after a brief discussion with Jonathan A. Broggard, who has a lot of experience with HFTs, he suggested that 5 bps was a reasonable value for my case. He also told me that HFTs work hard to bring down costs (personal communication, April 20, 2022).

4.5. Strategies' combinations

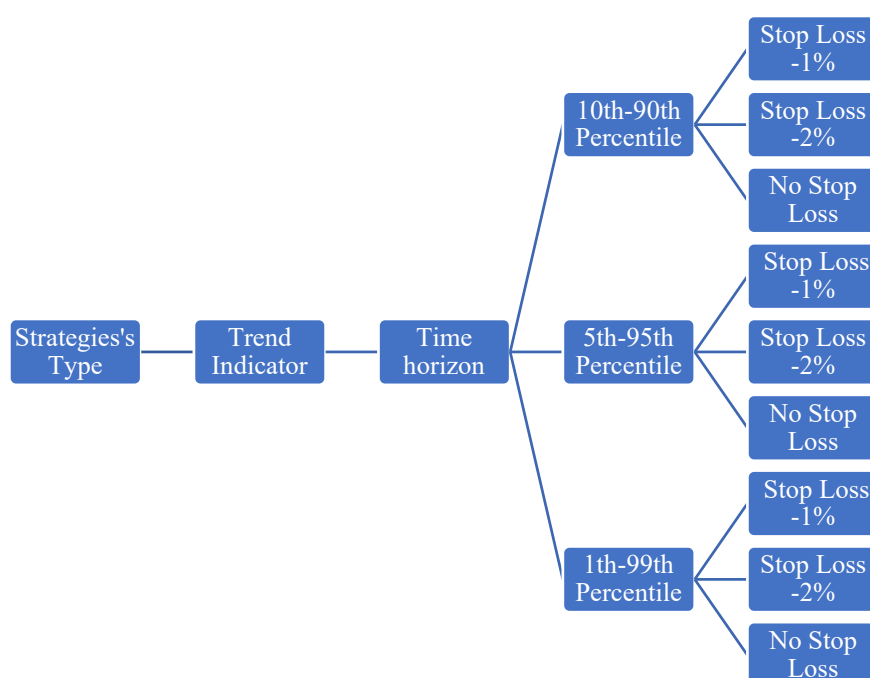
In addition to the different signals, we will set two types of stop loss. One that will end the trading day, this one will be set arbitrarily at -5%. In other words, if during the day we reach a total return smaller than -5%, we will leave our position (position 0) and we will return to the market only the next day. In parallel to this stop loss, we will put or not stop losses controlling the profitability during the duration of a position. These will be set at -1% and -2%, in case

we take a position if we notice that during the day this position gives a return smaller than -1% or -2% we will leave our position (position 0). Once the position is closed, we will wait for the next signal before taking a position again.

We will therefore articulate our strategies according to all the criteria discussed above. We will first choose the type of strategy we want to apply based on whether the price will return to its equilibrium (Contrarian) or whether the price will continue to follow the movement that it currently follows (Momentum). Then, whether or not the market trend will be taken into account and in what way (VWAP and 2 MA). Then, the time horizon to be used to calculate the different percentile pairs (10th-90th, 5th-95th and 1st-99th). We will use three time horizons the first 10 minutes of the day, the day before and a moving average over the last 5 days. Finally, if yes or no we will use a stop loss on the duration of the position taken and the level of this stop loss (-1% and -2%). In any case we will use a stop loss of -5% for the whole day.

You will find below a flow chart showing the various combinations of the tested strategies.

Figure 1 : Strategies' combinations



There will be a total of 162 (2x3x3x3x3) strategies tested. They will be detailed in Appendix

4.6. Analysis

We will therefore run all these strategies + the benchmark on our entire database. We will thus obtain 163 series of daily returns for each large cap. Due to the nature of some strategies, we will not have an equal number of return observations for each of them but we will choose to homogenize this by removing the trading days that are not common between all the different strategies. This will allow us to better compare the different strategies, moreover some methods explicitly require the same number of observations for each case. We will therefore find for each strategy a total of 499 observations, from 2008-01-09 to 2009-12-31.

In order to calculate the daily returns, we will follow the following method. We will look at what we actually gained or lost and we will divide this by the price observed when we entered the market. The total gains or losses will be defined as follows:

$$Total\ Gains\ or\ Lost = \sum_{i=s+1}^e position_{i-1} * (price_i - price_{i-1})$$

With "s" representing the time when we start the trading day and "e" the end of the trading day.

We will have as a daily return measure:

$$R_d = \frac{Total\ Gains\ or\ Lost}{price_s}$$

To analyze all return series, we will use three packages. The first is the "PerformanceAnalytics" package (Peterson et al., 2020), which offers all sorts of econometric functions for performance and risk analysis. The package includes many of the tools proposed by Carl Bacon (2008). This package will be used for all the performance measurement, risk-adjusted performance measurement and risk measurement part

"StepwiseTest" (Hsu and Vincent, 2016) offers a collection of stepwise procedures to conduct multiple hypothesis testing, this package is based on the work of Romano and Wolf (2007) and Hsu, Kuan and Yen (2014).

"PeerPerformance" (Ardia, Boudt and Bouamara, 2021) provides functions to perform peer performance analysis of fund returns as described in a paper by Ardia and Boudt (2018).

These last two packages will be used to consider luck, we will come back to them in more detail in the next section.

We will follow 3 axes, the return analysis, the risk-adjusted return analysis and finally the risk analysis. We will come back in more detail to the functions we will use in the next sections. In the same way as for the implementation of the strategies, we will use the "R Studio" software.

We will first analyze our strategies without taking into account transaction costs and then with them

4.6.1. Performance Measure

4.6.1.1. Annualized return

Some investors are interested in the gross value of the returns they could get if they followed a certain strategy. As a measure of return, we will use the Annualized Return. This will make it easier to compare all the strategies with each other and with our benchmark. To do this, we will use the function "Return.annualized". This default function uses the geometric method because it allows us to take into account the effect of compounding on the returns, i.e., the fact of reinvesting what we have gained or lost during a period on the following period and one of so many in a row, which is the common way of doing things for investors. The use of compound return is therefore considered a more accurate measure of the performance of an investment over time than the average return because the average return does not take into account the history and the compounding effect (Gallant, 2022). The function works as follows, it scales our daily returns to the yearly scale by raising the compounded return to the number of periods in a year and taking the root to the number of total observations. (Peterson and al., 2020) Here, we will use 250 periods (scale) in a year rather than the commonly used 252 periods to better account for the homogenization performed on our 499 observations (n):

$$\bar{R}_a = \sqrt[n]{\prod_{t=1}^n (1 + R_{d,t})^{scale}} - 1$$

4.6.2. Risk-adjusted return measure

When investing, an investor will often seek to maximize the expected return based on the level of risk to which they are exposed. In order to take this into account, we will use the Sharpe Ratio and the Sortino Ratio

4.6.2.1. Sharpe Ratio

In order to measure the risk-adjusted return, Sharpe (1966) developed a ratio directly linking volatility and excess return on an asset or portfolio, the Sharpe Ratio. In the most traditional

case, the standard deviation of excess returns is used as a measure of volatility. We will therefore calculate this ratio using the "SharpeRatio" function (Peterson et al., 2020). Here, we will use a risk-free rate of 0.

$$\text{Sharpe Ratio} = \frac{\overline{(R_d - R_f)}}{\sigma}$$

It is better to have a large Sharpe Ratio because it means that per unit of risk taken, the excess return is large.

Despite the fact that the "traditional" Sharpe Ratio is criticized for taking into account the good risk (positive fluctuation) and that even its creator recommends the use of other indicators (Peterson et al., 2020), we will use it since it is the most widely used way of calculating risk-adjusted returns (Fernando, 2022).

4.6.2.2. Sortino Ratio

Sortino proposes in a paper co-authored with Price (1994) an improvement of the Sharpe Ratio to better take into account skill and excess performance by using the downside deviation as a measure of risk rather than the standard deviation used in the calculation of the Sharpe Ratio. Sortino argues that risk should be measured in terms of not reaching the target, so only values below the target should be used to calculate the risk measure. The target is referred to as the Minimum Acceptable Return or MAR. The MAR will therefore be used as a point of comparison when calculating the Sortino Ratio (Peterson et al., 2020). Here, we will set the MAR to 0.

$$\text{Sortino Ratio} = \frac{\overline{(R_d - MAR)}}{\delta_{MAR}}$$

With δ_{MAR} representing the Downside Deviation from the MAR:

$$\delta_{MAR} = \sqrt{\sum_{t=1}^n \frac{\min [(R_{d,t} - MAR), 0]^2}{n}}$$

All this will be done with the "SortinoRatio" function.

As with the Sharpe Ratio, when comparing different investment strategies, a higher Sortino ratio is preferable to a lower one because it means that the investment yields more return per unit of bad risk taken.

4.6.3. Risk measurement

Risk analysis is also an important component of investment analysis. Here, we will look more precisely at four risk measures which will allow us to have an analysis on different levels regarding the risks. We will look at the Value at Risk, the Expected Shortfall, the Ulcer Index and finally the Maximum Drawdown. Investors prefer to look at the negative variations because it is what impacts them negatively rather than the positive variations. Indeed, if the return is driven upwards thus having a positive variation compared to previously is beneficial. The opposite is not.

4.6.3.1. Value at Risk

Value at Risk (VaR) is a way for an investor to see the worst-case scenarios that could occur at a certain probability level over a specific time horizon. It is widely used and has become a standard in the financial industry to measure downside risk. Here we will use the historical VaR which uses observed returns to simulate the distribution of returns and find the VaR. In our case the Var is calculated as follows:

$$VaR = q_p$$

With q_p , which is the $p\%$ empirical quantile of the negative return series (Peterson et al., 2020). Here, we will use a 95% confidence level.

We will again use "Performance Analytics" and the "VaR" function. The output value will represent in our case the return value separating the distribution of returns into 5% on one side and 95% on the other when looking at the left tail of our distribution. In other words, we will probably have a 5% chance of having a smaller or equal return than the VaR when applying this investment. It is therefore preferable to have a VaR value as large as possible.

Note: we often prefer the modified version of the VaR but this method did not give us results for each strategy because of some "extraordinary" returns.

4.6.3.2. Expected Shortfall

The Expected Shortfall (ES) or expected tail loss (ETL) or the also Conditional Value at risk depends directly on the VaR, it will give the expected loss in the worst-case scenario. It is calculated by taking the average of the possible returns that fall beyond the VaR (Chen , 2020). We will use the "ETL" function with the same parameters as for the VaR.

4.6.3.3. Annualized Standard deviation

In order to assess the risk associated with each strategy, we will also use the annualized standard deviation. This is the most commonly used measure of volatility. It compares the

historical returns with the average returns in order to see the dispersion around the average. When calculating it, it uses the unbiased estimator of the standard deviation and in order to annualize it, the square root of the number of periods in a year is taken. This measure has the disadvantage of taking into account both positive and negative variations around the average, whereas in practice what has a negative impact on an investment are the negative variations

$$Annualized\ Std\ Deviation = \sqrt{scale} * \sqrt{\sigma}$$

4.6.3.4. Ulcer Index

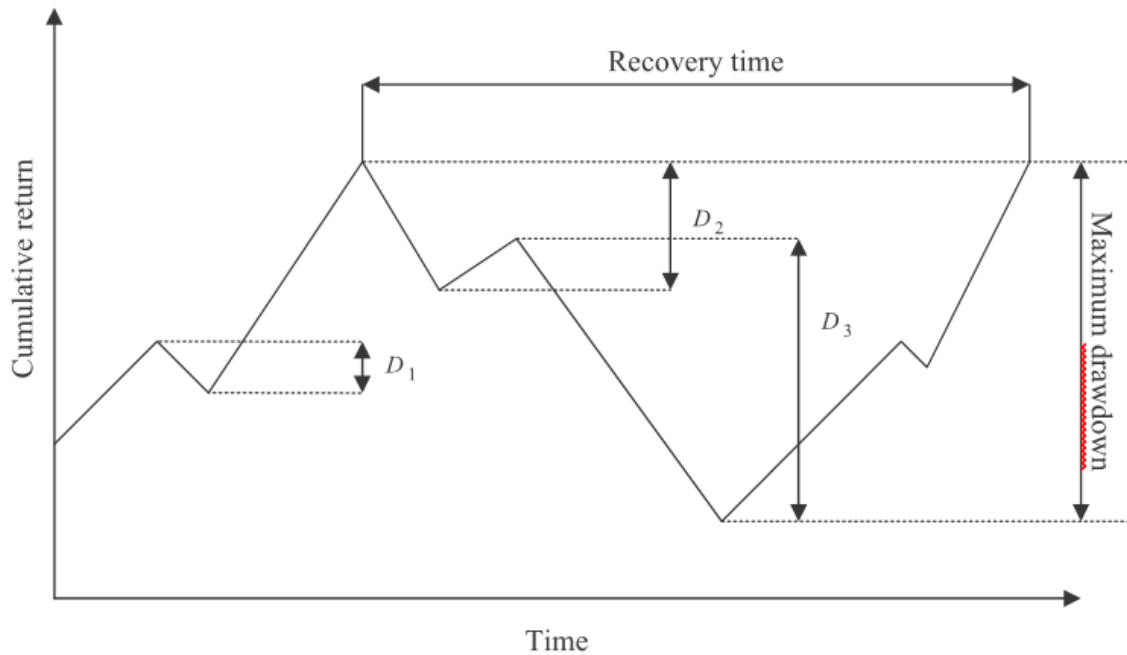
The Ulcer Index was developed by Martin (Martin and McCann, 1987), it takes into account drawdowns and the impact of the duration of drawdowns by selecting the negative returns for each period below the previous peak. The impact of large drawdowns will have a significant impact because they will be squared (Peterson et al., 2020). This is again an indicator measuring downside risk as this is the risk that matters most to a trader. It measures the percentage drawdown a trader could expect from the top over this period. It is therefore preferable to have a small Ulcer Index (Downey, 2021) We will calculate it with the function "UlcerIndex".

$$Ulcer\ Index = \sqrt{\frac{\sum_{i=1}^n D_i^2}{n}}$$

4.6.3.5. Maximum Drawdown

The Maximum Drawdown represents the drawdown relative to the largest observed peak. First you have to calculate the cumulative returns and then see what the maximum value is. As soon as the cumulative returns fall below the maximum cumulative returns, it is a drawdown. Drawdowns are measured as a percentage of this maximum cumulative return from the peak (Peterson et al., 2020).

Figure 2 : Drawdown and Maximum Drawdown (Bacon, 2008)



The Maximum Drawdown will therefore represent the maximum loss observed from the largest peak and it can be used to assess the preservation of capital (Hayes, 2021) even if we made the assumption that we have full pockets it is always important to look at it.

4.6.4. Data Snooping

When we want to see if one model is superior to another and we evaluate many models individually, some will inevitably be superior by simple chance. The observation is the same for other cases of analysis. Indeed, when testing a hypothesis, we have to choose a certain level of confidence and it can happen that sometimes we reject the null hypothesis when it is true (type 1 error).

We will therefore analyze some performance measures by correcting the data snooping in order to obtain more rigorous results and to be able to sort out the different strategies. Indeed, giving weight to a strategy that performs only by chance is not relevant.

4.6.4.1. Stepwise Superior Predictive Ability

To analyze whether the different strategies produce a greater average return than the benchmark by correcting for the chance effect we will use the Stepwise Superior Predictive Ability (Step-SPA) a method proposed by Hsu, Hsu and Kuan (2010) through the "StepwiseTest" package. We chose the step-SPA because it is more powerful (Hsu, Kuan and Yen, 2014) than its predecessor the Stepwise Reality Check (Romano and Wolf, 2005)

considering all the power criteria defined by Romano and Wolf. The algorithm will serve us to be able to compare the average returns for each strategy with the benchmark and see if statically strategy i is better than the benchmark by taking into account luck. We will test the following null hypothesis:

$$H_0: \overline{Strategy_i} - \overline{Benchmark} \leq 0$$

If H_0 is rejected, it means that at a certain level of confidence, the alternative hypothesis will be true and that the tested strategy will statistically offer a higher average return than the benchmark.

The Step-SPA method will compare the critical value found from a resample of our data with the t_stat calculated from our data directly. The critical value corresponds to the value that will be used to reject or not the null hypothesis and it will represent the value that will control the k_FWER (familywise error rate) thus the fact of rejecting at least k true null hypothesis when it is true (type 1 error) at a confidence level α . Here we will set our k to 1 and α to 0.05. If the t_stat is greater than the critical value we will reject the null hypothesis. The method used for the resample and the stationary bootstrap of Politis and Romano (1994). The t_stat for our test will be :

$$t_stat = \sqrt{n} * \frac{\overline{Strategy_i} - \overline{Benchmark}}{\sqrt{sd_i^2 + sd_{benchmark}^2}}$$

The $boot_stat$ needed by the algorithm to find the critical value will be calculated as follows:

$$boot_stat = \sqrt{n} * \frac{(\overline{Strategy_{boot,i}} - \overline{Benchmark_{boot}}) - (\overline{Strategy_i} - \overline{Benchmark})}{\sqrt{sd_i^2 + sd_{benchmark}^2}}$$

As recommended by Hansen (2005) we will use as estimator of the standard deviation of the bootstrap the standard deviation of our data

4.6.4.2. Peer Performance

In addition to the averages, we will analyze the different strategies with the benchmark included ($n + 1$) in order to see what models allow us to obtain an outperformance compared to the others from the point of view of the Sharpe ratio and this after removing the chance effect. Ardia and Boudt (2017) recommend evaluating the peer performance using three peer performance parameters by proposing a non-parametric estimator that controls for the risk of

false discoveries by the approach of Storey (2002). There are thus three ways to evaluate the performance relative to the other peers. Equal-Performance, thus the percentage of strategies that perform as well as the strategy on which the peer performance is realized. Outperformance, i.e., the percentage of strategies that perform worse than the strategy on which the peer performance is realized. Underperformance, i.e., the percentage of strategies that perform better than the strategy on which the peer performance is realized.

In order to find the outperformance ratio (the ratio that will interest us in our analysis), we must first find the estimator of the number of peers that perform equally to the strategy of interest and the estimate of the equal-performance ratio:

$$\widehat{\pi}_i^0 = \frac{\widehat{n}_i^0}{n}$$

With i representing the strategy i on which the peer performance is realized.

With $\widehat{n}_i^0$ defined as the number of estimated p-values exceeding λ_i and then divided by $1 - \lambda_i$. It will also incorporate an additional adjustment to link the extrapolation to the numbers of peers (n) and a correction factor taking into account the bias induced as a result of the truncation. It will be used to estimate the number of peers that perform equivalently with the strategy of interest.

$$\widehat{n}_i^0 = c_i^0 * \min\left\{\frac{\sum_{j \neq i} I\{\widehat{p}_{i-j} \geq \lambda_i\}}{1 - \lambda_i}, n\right\}$$

With $I\{\}$ returning 1 if the inequation is true and 0 otherwise also called indicator function.

With λ_i the value that minimizes the estimated mean squared estimation error of $\widehat{\pi}_i^0$.

$\widehat{p}_{i-j}$ is defined as twice the probability integral transform of minus the absolute value of the studentized test statistics under the null hypothesis. The probability integral transform states that if X is a continuous random variable with a cumulative distribution function F_X then the random variable $Y = F_X(X)$ has a uniform distribution on $[0,1]$. Here, it will be a standard normal cumulative distribution and it will be estimated through bootstrapping (block) on the empirical data. The null hypothesis is that the difference in performance between strategy i and the other strategies j is not equal to 0, i.e., that they not equal.

$$\widehat{p}_{i-j} = 2 * \widehat{F}_{i-j}(-|\widehat{t}_{i-j}|)$$

The estimator of the outperformance ratio will be calculated as follows:

$$\widehat{\pi}_i^+ = \frac{1}{n} * \max\left\{ \sum_{j \neq i} I\{\hat{t}_{i-j} \geq \hat{q}_{i-j}^{\gamma^+}\} - \hat{n}_i^0 * (1 - \gamma^+), 0 \right\} \text{ if } \sum_{j \neq i} I\{\hat{\Delta}_{i-j} \geq 0\} \geq \frac{n}{2}$$

$$\hat{\pi}_i^+ = 1 - \hat{\pi}_i^0 - \hat{\pi}_i^- \text{ otherwise}$$

With $\hat{\Delta}_{i-j}$ as the estimator of the difference in performance between strategy i and strategy j.

With $\hat{q}_{i-j}^{\gamma^+}$, being the γ^+ _quantile of the distribution of $\hat{t}_{i-j}$ under the null hypothesis (critical value). The null hypothesis is in this case that the strategy of interest is underperforming relative to the others.

The term $-\hat{n}_i^0 * (1 - \gamma^+)$ will serve to correct for the presence of false positives (type 1 error) and by choosing a sufficiently small γ^+ , it will avoid false negatives (type 2 error).

The estimator of the underperformance ratio will be calculated as follows:

$$\widehat{\pi}_i^- = \frac{1}{n} * \max\left\{ \sum_{j \neq i} I\{\hat{t}_{i-j} \leq \hat{q}_{i-j}^{\gamma^-}\} - \hat{n}_i^0 * \gamma^-, 0 \right\} \text{ if } \sum_{j \neq i} I\{\hat{\Delta}_{i-j} \geq 0\} < \frac{n}{2}$$

$$\hat{\pi}_i^- = 1 - \hat{\pi}_i^0 - \hat{\pi}_i^+ \text{ otherwise}$$

With $\hat{q}_{i-j}^{\gamma^-}$, being the γ^- _quantile of the distribution of $\hat{t}_{i-j}$ under the null hypothesis (critical value). The null hypothesis in this case is that the strategy of interest is overperforming relative to the others.

The term $-\hat{n}_i^0 * \gamma^-$ will be used to correct for the presence of false positives (type 1 error) and by choosing a large enough γ^- , it will avoid false negatives (type 2 error).

To perform all these steps in our case, we will use the "PeerPerformance" package and the "sharpescreening" function.

Note: In order to get more details about this peer performance method the reader is invited to consult the work of Ardia and Boudt (2017).

5. Analysis and Results

We will therefore carry out these various analyses on all the returns calculated previously on all the large caps for each of the strategies studied and the Benchmark in order to compare them with each other or just to see if the strategies are significantly better than the Benchmark.

For the analysis of the different measures, We decided to focus on the average of the measures on all the large caps in order to better analyze in a global way the performance of the strategies on all the large caps for each measure used in the framework of our analysis and we also looked to see if the strategy was really performing for each large cap to look at how many times the strategy for each stock beats the benchmark so we can see the global performance and see if in a general terms it is working well. We found that theses methods were a good way to facilitate the analysis. You will still find the details of the top ten strategies by stock in the Appendix.

Note : You can find more details on the different analyses for each stocks via the following link : [Master Theisis](#)

Again, to make it easier to understand, we have separated the different strategies into general strategies. We will vary these general strategies according to the time horizon on which we have calculated the different percentiles and according to whether we are in a contrarian or momentum case.

Thus the legend of the graphs will be:

Day_1_C/M represents the use of the last day percentile calculation method in the Contrarian/Momentum case

Min_10_C/M represents the use of the first ten minutes of the day to calculate percentiles in the Contrarian/Momentum case

Day_5_C/M represents using the last five days to calculate percentiles in the Contrarian/Momentum case

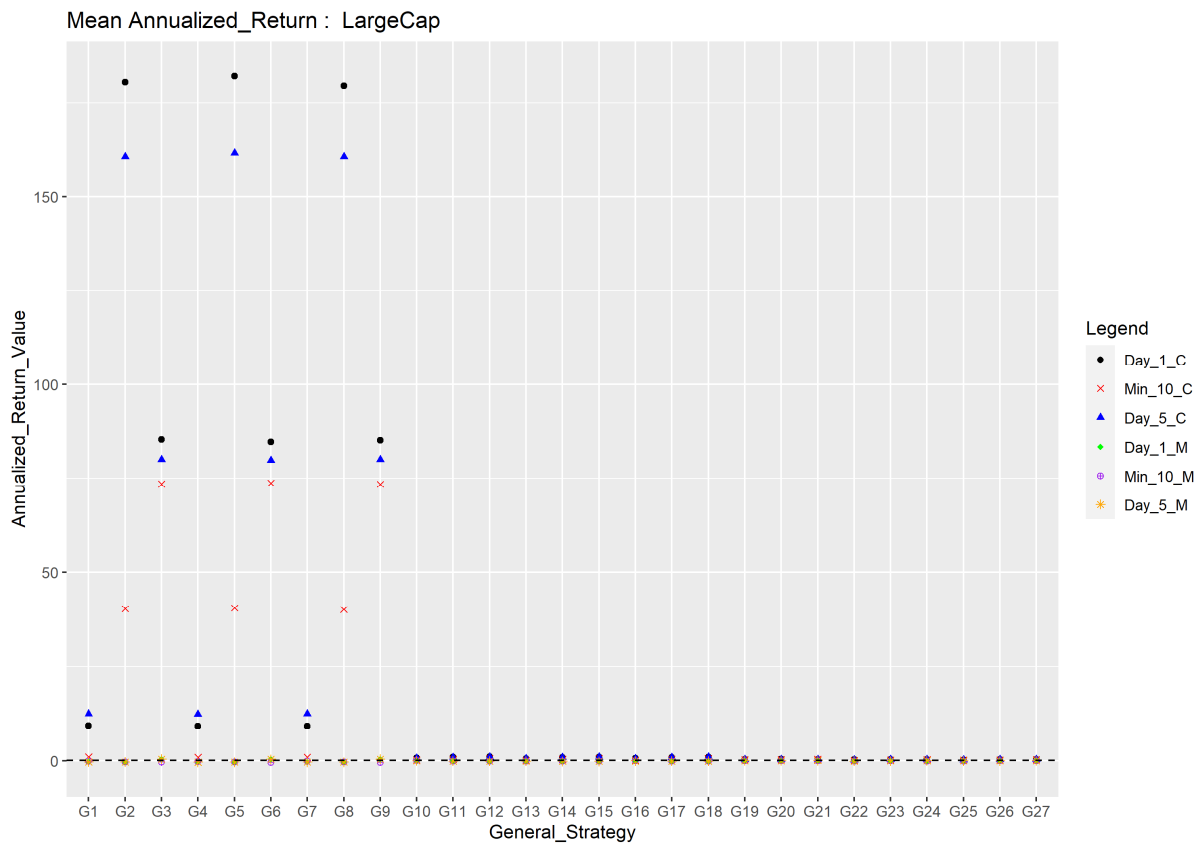
Table 3: General Strategy

Strategy	Combination
G1	Percentile 1-99 NoStopLoss
G2	Percentile 5-95, NoStopLoss
G3	Percentile 10-90, NoStopLoss
G4	Percentile 1-99, StopLoss 1%
G5	Percentile 5-95, StopLoss 1%
G6	Percentile 10-90, StopLoss 1%
G7	Percentile 1-99, StopLoss 2%
G8	Percentile 5-95, StopLoss 2%
G9	Percentile 10-90, StopLoss 2%
G10	Percentile 1-99, NoStopLoss,VWAP
G11	Percentile 5-95, NoStopLoss,VWAP
G12	Percentile 10-90, NoStopLoss,VWAP
G13	Percentile 1-99, StopLoss 1%, VWAP
G14	Percentile 5-95, StopLoss 1%, VWAP
G15	Percentile 10-90, StopLoss 1%, VWAP
G16	Percentile 1-99, StopLoss 2%, VWAP
G17	Percentile 5-95, StopLoss 2%, VWAP
G18	Percentile 10-90, StopLoss 2%, VWAP
G19	Percentile 1-99, NoStopLoss,MA
G20	Percentile 5-95, NoStopLoss,MA
G21	Percentile 10-90, NoStopLoss,MA
G22	Percentile 1-99, StopLoss 1%, MA
G23	Percentile 5-95, StopLoss 1%, MA
G24	Percentile 10-90, StopLoss 1%, MA
G25	Percentile 1-99, StopLoss 2%, MA
G26	Percentile 5-95, StopLoss 2%, MA
G27	Percentile 10-90, StopLoss 2%, MA

5.1. Performance Measure

5.1.1. Annualized Return

Figure 3: Mean Annualized Return



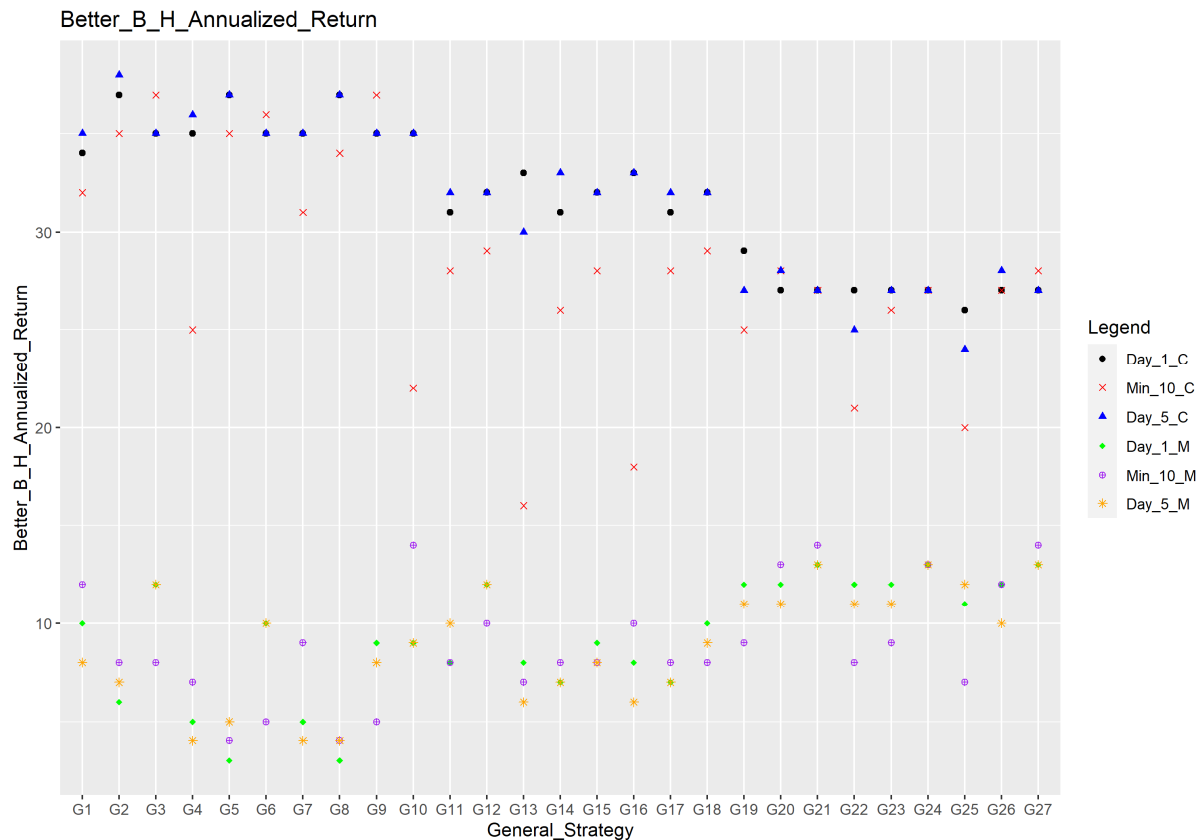
When we take the mean of the annualized returns on all the large caps, we can clearly see that the contrarian strategies using only the 5th-95th percentile perform much better and that the impact of the stop-loss between the trades does not have much impact probably because we will change position very often and therefore, we will rarely reach these different stop-loss. We also observe that when using the 5th-95th percentile, the calculation on the previous day's data is the most optimal and the one on the first ten minutes is far behind. This can be explained by the fact that the first ten minutes of data gives a very different volatility compared to the volatility of the rest of the day, there could be two explanations to that either the fact that we started the day too early that our safety margin of five minutes is not optimal to be sure not to suffer the volatility of the beginning of the day (which could bias our calculations) or that the sample is not large enough and therefore a time interval not large enough. The result is that when using the 5th-95th percentile the variation giving the most optimal variation is the one calculated on the previous day. We also find the same pattern for

the 10th-90th percentile but with much smaller differences in terms of annualized returns when choosing to use one day, ten minutes or five days. This means that the small variations corresponding to the 10th-90th percentile are probably similar whatever the way of calculating them contrary to the variations calculated on the 5th-95th percentile. More generally, momentum strategies and strategies that do not use a trend indicator (VWAP and MA) are not represented in the top performers.

You will find in Appendix 2 for each stock, the ten best performing strategies sorted from best to worst.

If we now compare all the strategies from the point of view of annualized return with the Benchmark.

Figure 4 : Number of times that the strategy beats the Benchmark (Annualized Return)



When comparing all the strategies with the Benchmark, we can observe that most of the contrarian strategies beat the Benchmark more than half of the time.

Among the contrarian strategies, we can see three levels of performance. The strategy not using a trend indicator beats the Benchmark more often than the strategies using the VWAP which themselves beat the Benchmark more often than the strategies using the MA. This trend

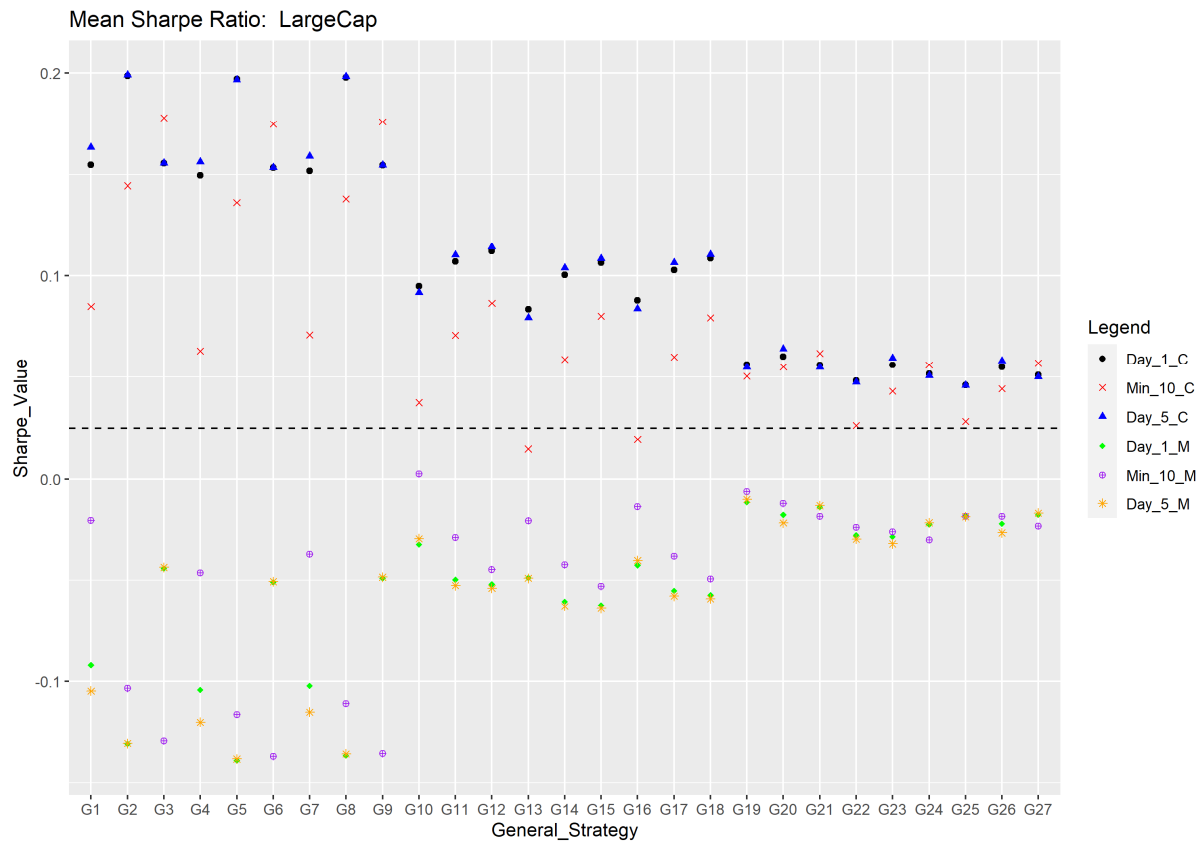
seems to be reversed in the Momentum case. There is only one exception for the contrarian strategies using the 1st-99th percentile calculated on the five days before or the day before where the strategy very often beats the Benchmark even if we have seen that previously it does not give annualized returns as important as those not using the VWAP.

We can therefore assume that during a negative or positive price variation, the price will tend to return to its equilibrium level rather than continuing in the direction of the variation and to place oneself as a contrarian allows to take the best advantage of this effect and to have the highest annualized return. The level of variation that best allows us to take advantage of this return to equilibrium is the variation defined by the 5th-95th percentile on the previous day's data. The 1st-99th percentile likely represents too large a range to take advantage of its variations. We can imagine that in the 1st-99th percentile what happens in the 5th-95th percentile could happen, but we could not take advantage of it because this level of variation does not trigger a signal in the 1st-99th case. As for the 10th-90th percentile, it probably represents too small a gap to take advantage of. Trend indicators limit our ability to take advantage of this return to the equilibrium. Indeed, their application in the strategy requires that to take a signal into account the general trend must match what the signal indicates, this can sometimes block our position in the strategy and therefore prevent the strategy from effectively taking advantage of all the variations.

5.2. Risk-adjusted performance measure

5.2.1. Sharpe Ratio

Figure 5: Mean Sharpe Ratio



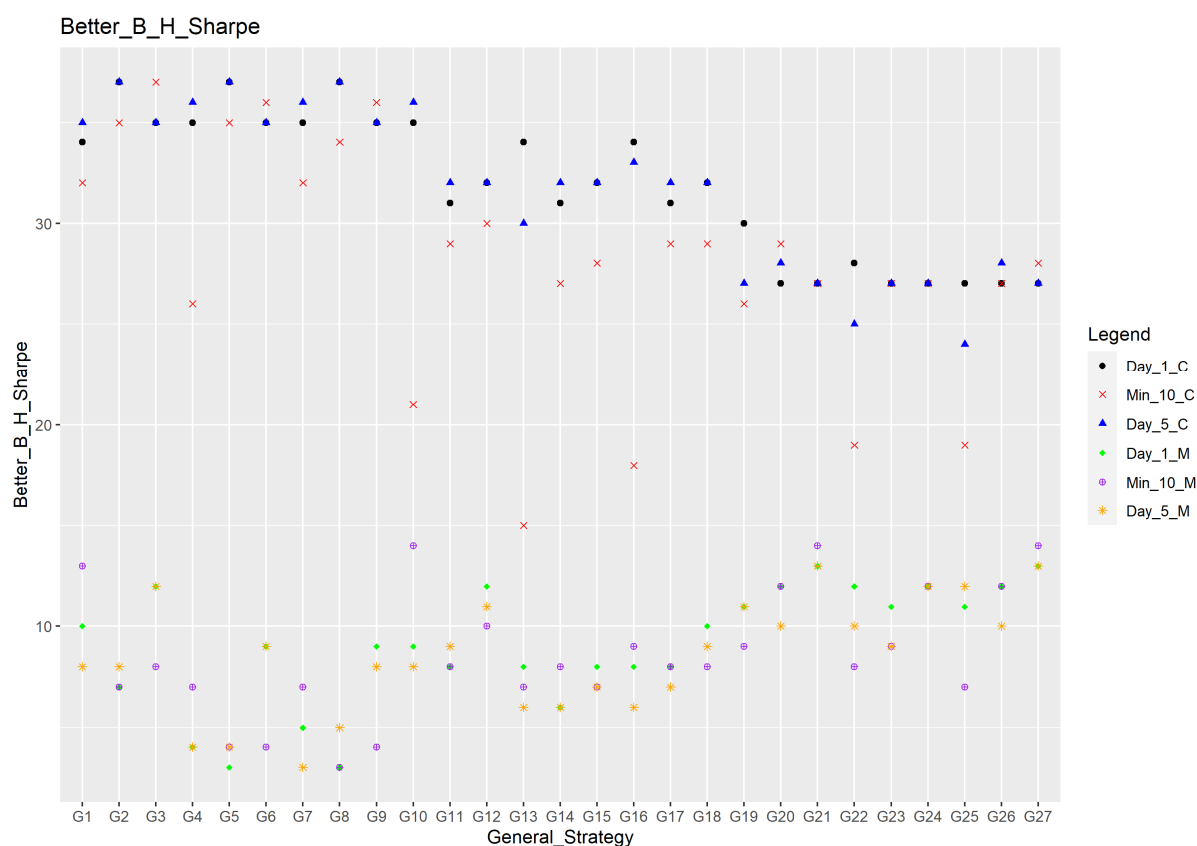
We obtain the same kind of conclusion as for the annualized return, a superiority of contrarian strategies over momentum strategies. The trend indicator does not allow us to obtain better performance for the top performers. The VWAP seems to be better than the MA probably because the VWAP is more flexible and therefore less hinders the position changes necessary to capture the variations in the contrarian case. The trend indicators in the momentum case seem to allow a better performance even if the performance is smaller than the benchmark.

In the top performers for the same reasons explained in the previous section, once again the 5th-95th percentile stands out as the best performer and the impact of stop-losses is generally not so significant. In this percentile, the performance of the daily Sharpe Ratio does not seem to be impacted by the choice to use five days or one day. So, there is more or less the same balance between volatility and returns between these two ways.

This is interesting because it means that in addition to offering very good annualized returns, these top performers strategies reward the most the risk taken. Indeed, the Sharpe ratio measures the excess return obtained per unit of risk, for the Sharpe ratio it is the standard deviation. The higher this ratio is, the more the risk taking will be rewarded. You will find in Appendix 3 for each stock, the ten best performing strategies sorted from best to worst.

Concerning the comparison of the strategies with the benchmark we have the following results.

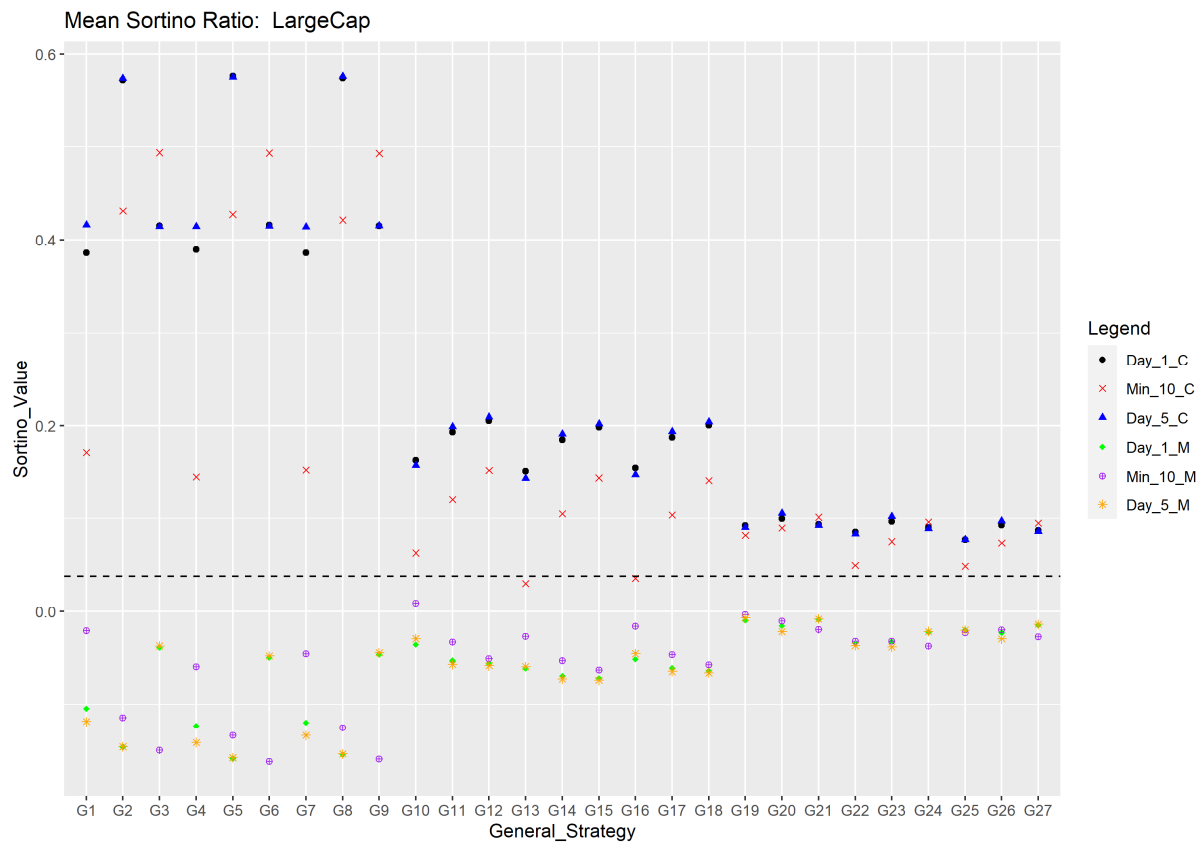
Figure 6 : Number of times that the strategy beats the Benchmark (Sharpe Ratio)



For the same reasons as previously stated for the annualized return analysis, contrarian strategies beat the Benchmark more often than Momentum strategies and in the contrarian case the simplest strategies most often beat the benchmark

5.2.2. Sortino Ratio

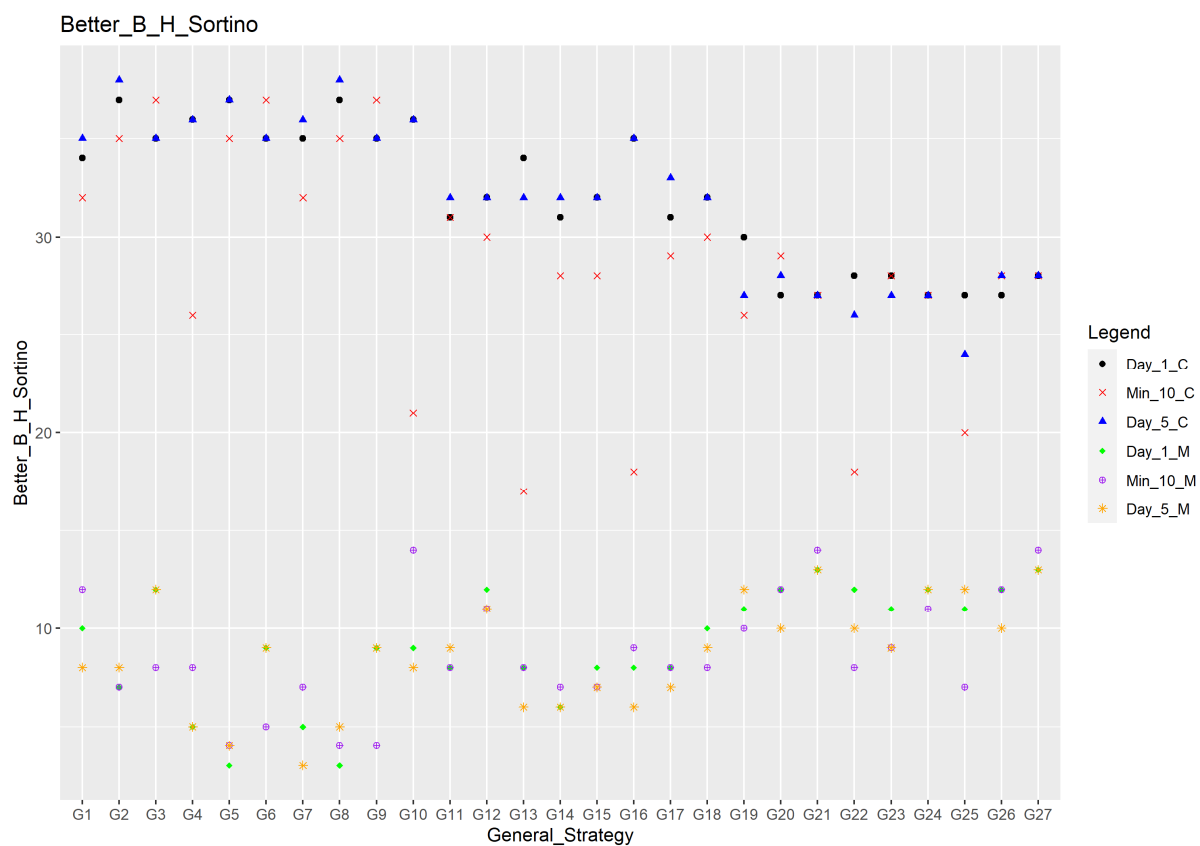
Figure 7: Mean Sortino Ratio



As with the Sharpe ratio, the higher the Sortino ratio the better. The Sortino ratio also tells us what we will get as excess return (compared to our target) per unit of risk, here it will only be the downside risk (negative impact). We can see that the best performing strategies are those using the 5th-95th percentiles calculated on the previous day. We can also notice that the Sortino ratio tends to pull up the top performers. Indeed, once we focus only on the negative risks, those that pull our returns down. We can see that these strategies obtain a better excess return per unit of bad risks. If we compare the Sharpe Ratio and the Sortino Ratio we can conclude that a large part of the volatility in the general sense was due to the positive variation, once we remove these positive variations we see that the negative variations are actually small which is a good thing and this is what explains why the average of the Sortino ratio gives higher values than the average of the Sharpe ratio. If we look at the momentum strategies, we can see that there is no big difference between the Sortino and the Sharpe ratio, which means that the volatility was mainly due to negative variations. You will find in Appendix 4 for each stock, the ten best performing strategies sorted from best to worst.

By looking at each strategy in comparison to the benchmark.

Figure 8 : Number of times that the strategy beats the Benchmark (Sortino Ratio)

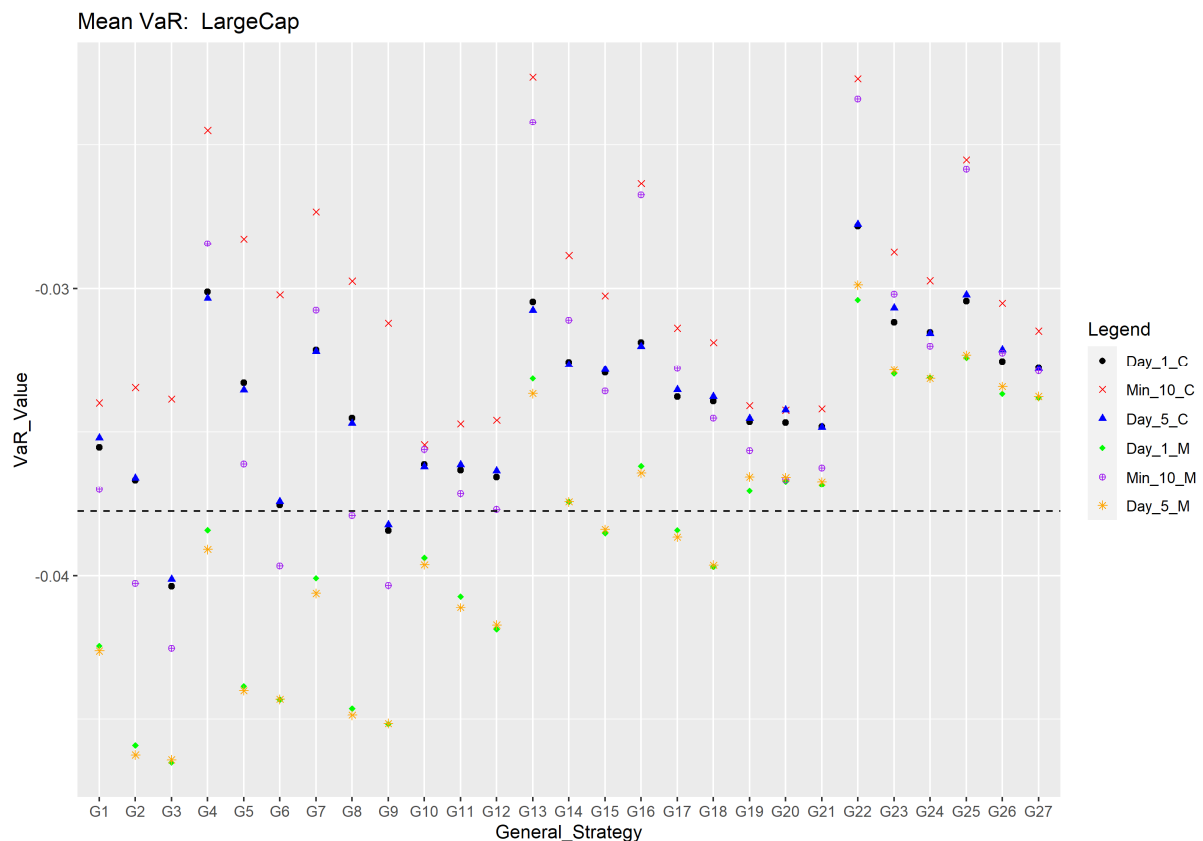


We obtain the same finding as for the Sharpe ratio analysis. The different momentum strategies beat the benchmark by less than fifteen times.

5.3. Risk Measure:

5.3.1. Value at Risk

Figure 9: Mean Value at Risk

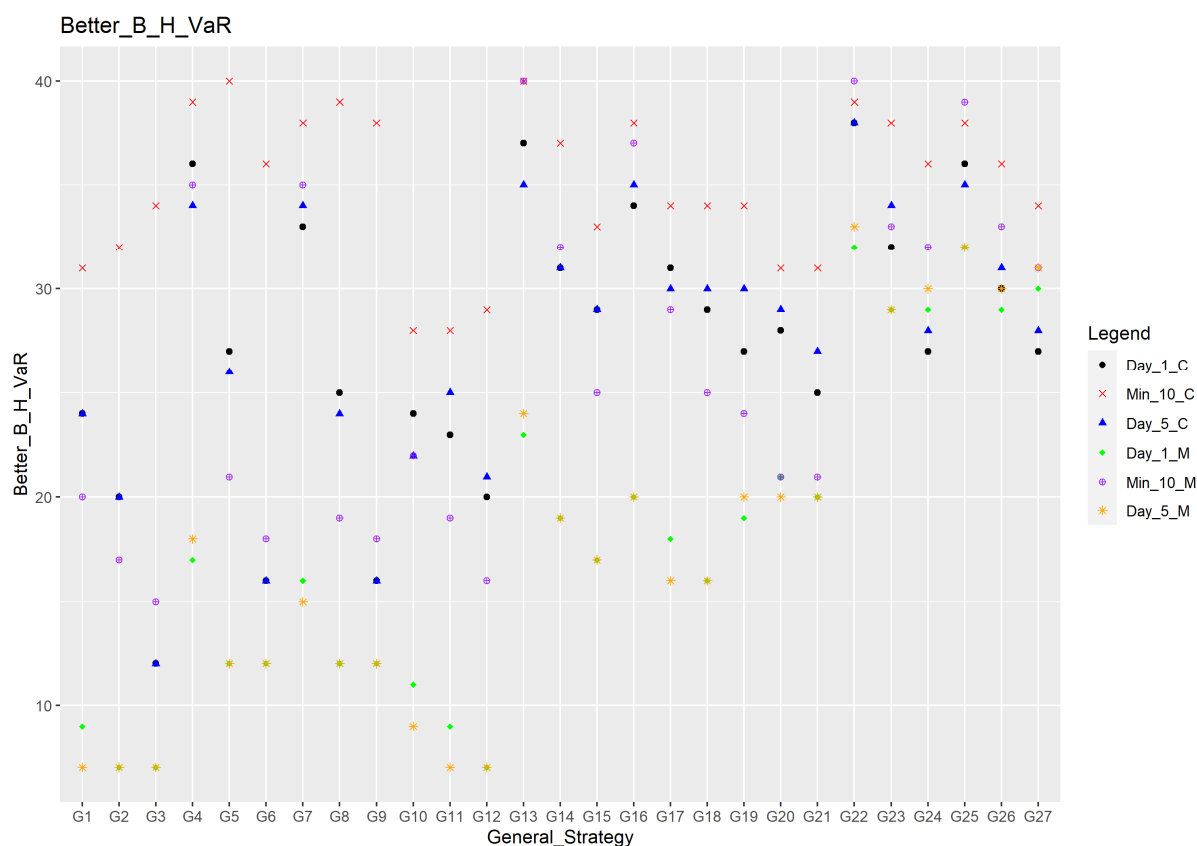


If we look at the VaR, the loss value that we will exceed only in the case of the worst case scenario. We had defined the probability of expecting this worst case scenario at 5%. The higher the VaR value, the better it will be because it means that in the worst case scenario we will have a small loss. Most of the strategies studied have a better average VaR than the average given by the Benchmark. It seems that the trend indicators have a positive impact on the VaR especially the MA. The calculation of the 10 min percentiles seems to systematically produce a better VaR than the other methods. We can also see that putting a stop loss has an interest and that it will allow us to separate the strategies that are in the top given that they seem to give the same kind of results whatever the stop loss. Indeed, we can see that in the case of strategies using the 5th-95th percentile over the last five days or the day before the VaR is much better once we use the stop loss of -1%, there is the same effect with that of -2% but in a lesser effect. Waiting for a 2% loss before exiting the position and then waiting for

the next signal seems to be too long, it is better to exit the position earlier. You will find in Appendix 5 for each stock, the ten best performing strategies sorted from best to worst.

By looking at each strategy in comparison to the benchmark.

Figure 10 : Number of times that the strategy beats the Benchmark (VaR)

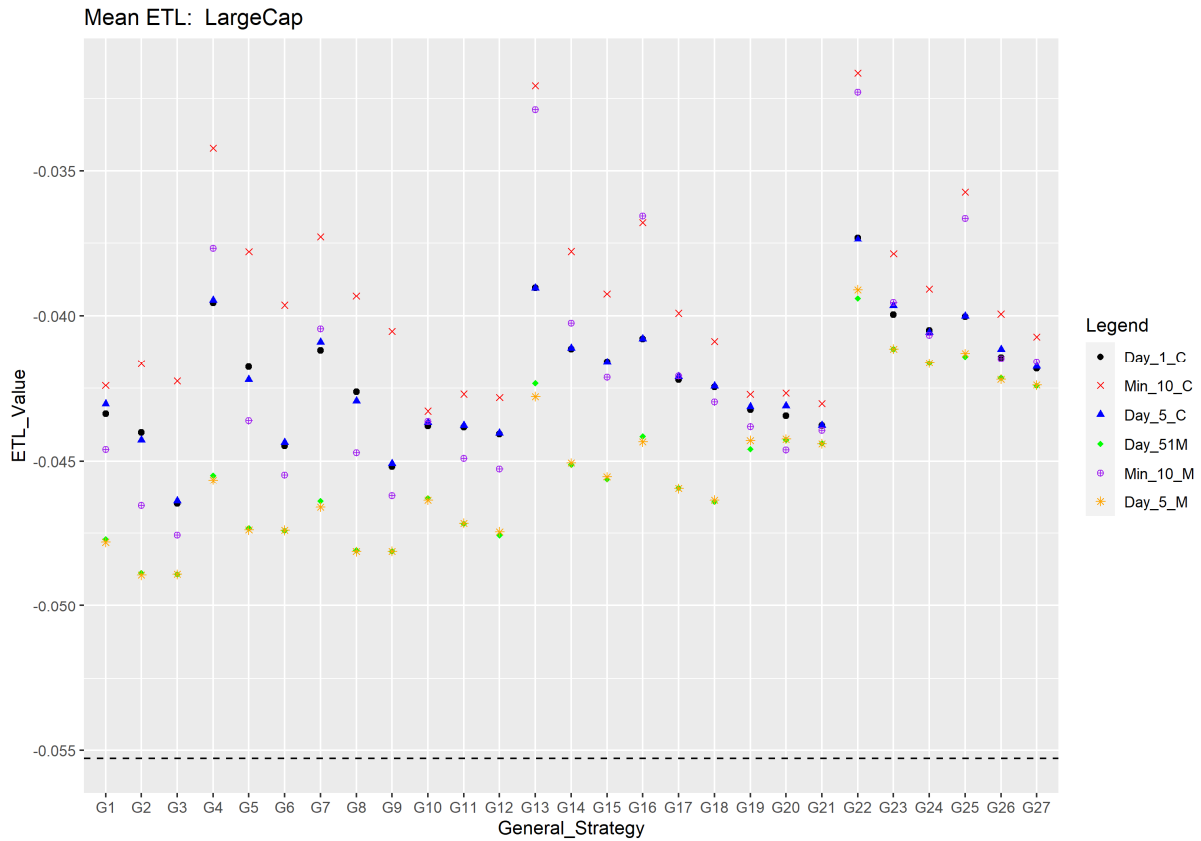


We see many strategies beating the Benchmark at least twenty times, this observation can be explained by the fact that the Benchmark has no stop loss making it leave the market for the day so unlike the tested strategies it can have a return lower than -5% during the day so it has more chance when it falls in an extreme case to have a return lower than -5% which is not the case for the other active strategies. This also explains why in terms of mean VaR the benchmark is often beaten

The trend indicator used that most often allows to beat the Benchmark on average is the MA

5.3.2. Expected Shortfall

Figure 11: Mean Expected Shortfall

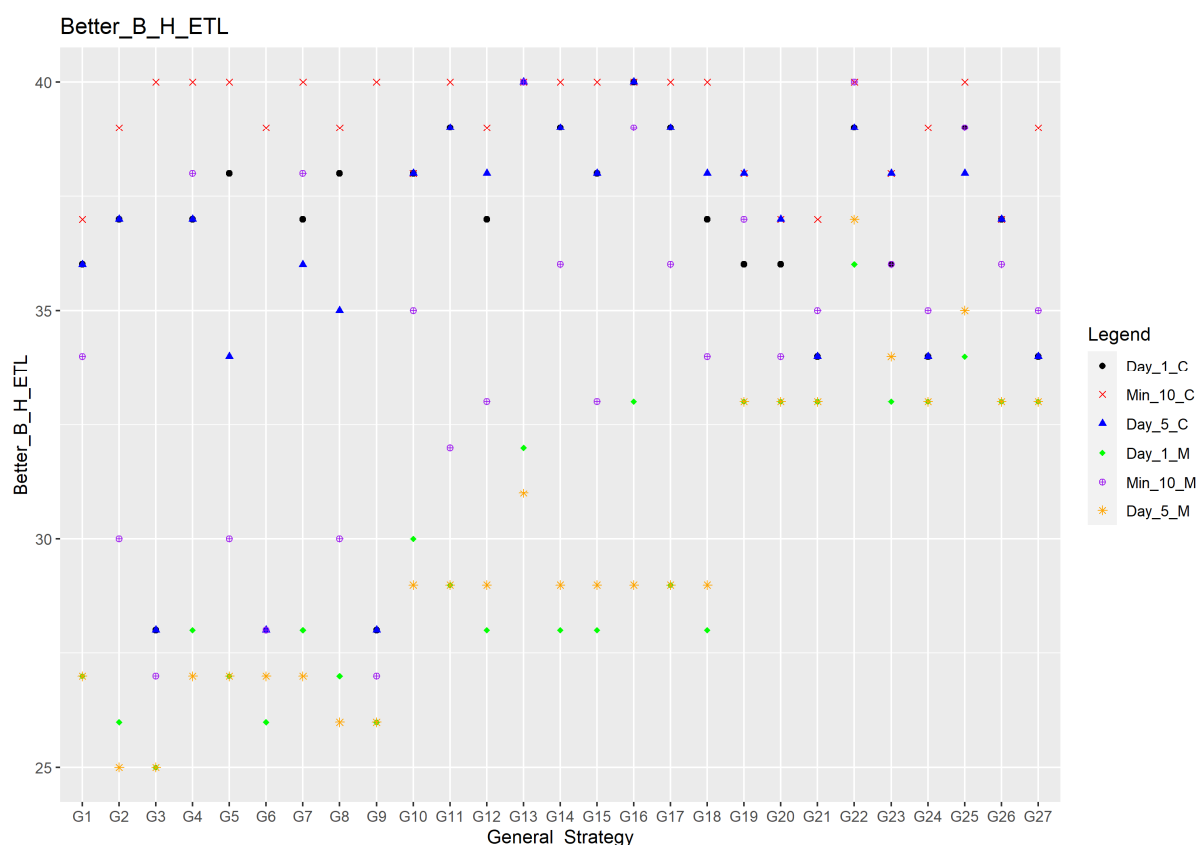


As with VaR, it is preferable to have an Expected Shortfall (ES) as large as possible which will mean that once in the worst case scenarios the average loss will be as small as possible. We can see that the average of the benchmark is systematically beaten as explained above this comes from the fact that since the benchmark has no stop loss on the day it ends up with some days with losses smaller than -5% which will pull the VaR down and therefore the ES as well. The ES confirms that losses smaller than -5% happen because it is smaller than -5%. Concerning the strategies between them, we can see that the order is more or less the same but that the values are pulled down which is explained by the fact that once passed the VaR there are some values lower than the VaR which makes the ES go down. If all the losses once passed the VaR were close to the VaR we would get a high ES close to the VaR.

You will find in Appendix 6 for each stock, the ten best performing strategies sorted from best to worst.

The analysis in comparison to the Benchmark gives us:

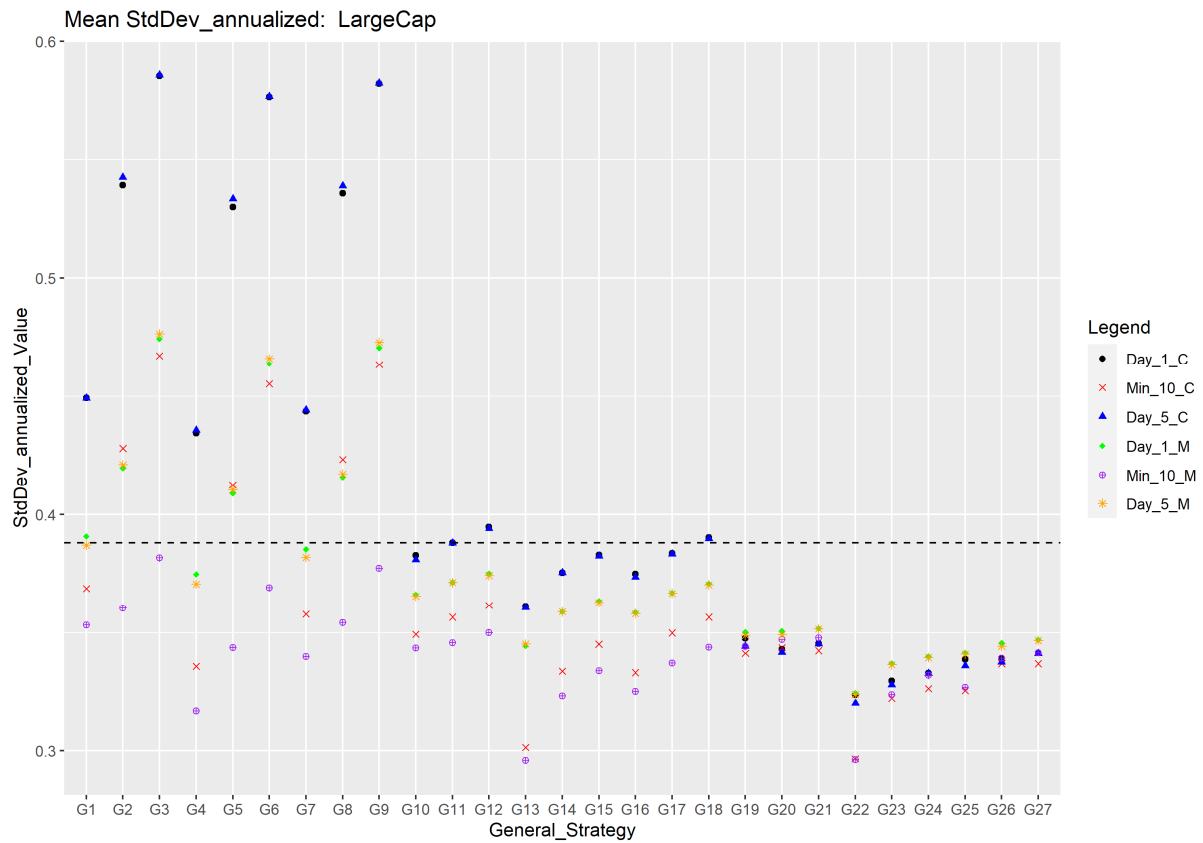
Figure 12 : Number of times that the strategy beats the Benchmark (Expected Shortfall)



Some strategies consistently beat the benchmark on every stock. These are often those that use a ten-minute percentile calculation, a stop loss and a trend indicator (mainly the VWAP). Most strategies beat the benchmark more than half of the time for the same reasons expressed in the analysis of the means.

5.3.3. Annualized Standard Deviation

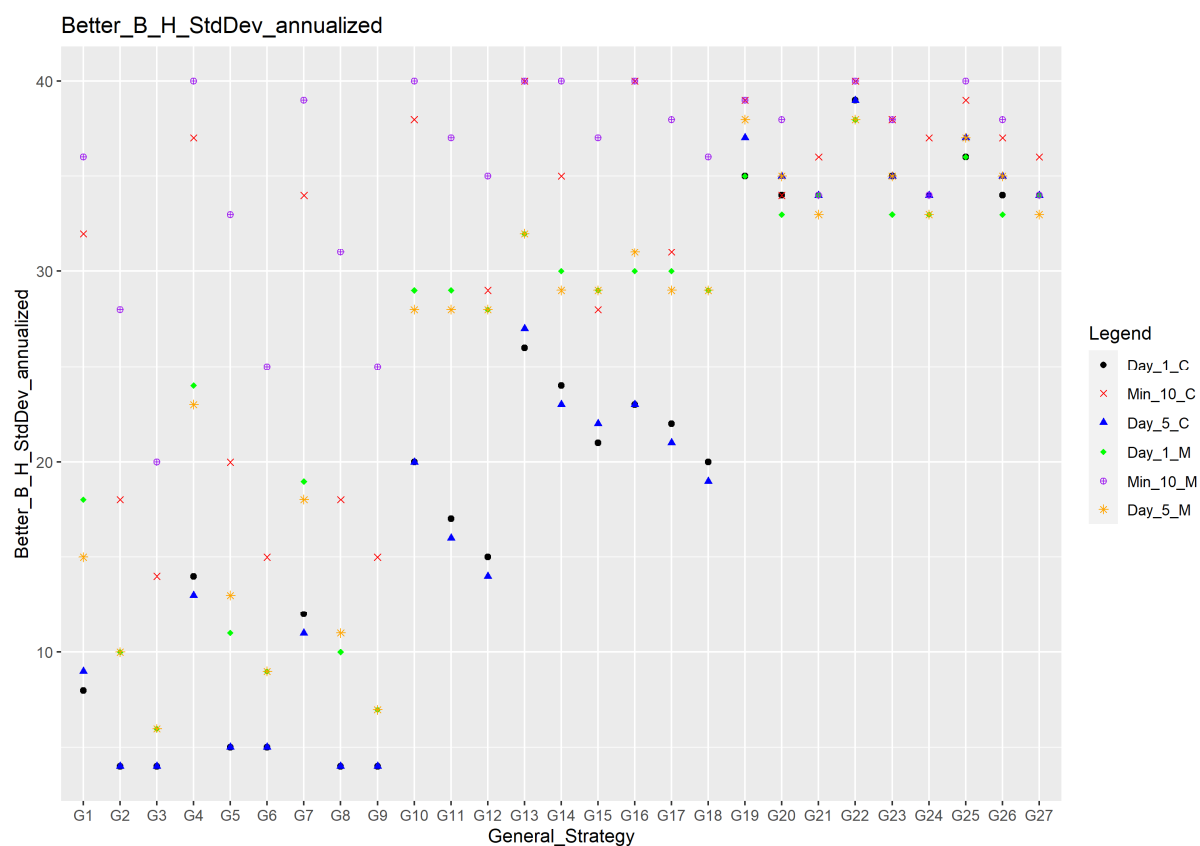
Figure 13: Mean Annualized Standard Deviation



When analyzing the average of the annualized standard deviations, we can observe that there is generally a lot of deviation within the contrarian strategies using the 10th-90th percentiles calculated over the last five days or the last day. These last ways of calculating percentiles seem to give the same average in the case of contrarian strategies. The other strategies are generally below the Benchmark average. The momentum strategies seem to provide almost systematically a smaller standard deviation than their contrarian counterparts and that the MA allows between strategies to obtain the same mean annualized standard deviation. At this stage, it is difficult to know if the large values of average standard deviation imply a negative impact because we do not know the proportion of negative variation and positive variation composing the standard deviation, but it is generally accepted that a large value of standard deviation indicates that there may be a risk of having large negative risks. Although we have already had a glimpse of this in previous analysis, we will see what happens with the other measures. You will find in Appendix 8 for each stock, the ten best performing strategies from the point of view of the annualized standard deviation sorted from the best to the worst.

By looking at each strategy in comparison to the benchmark.

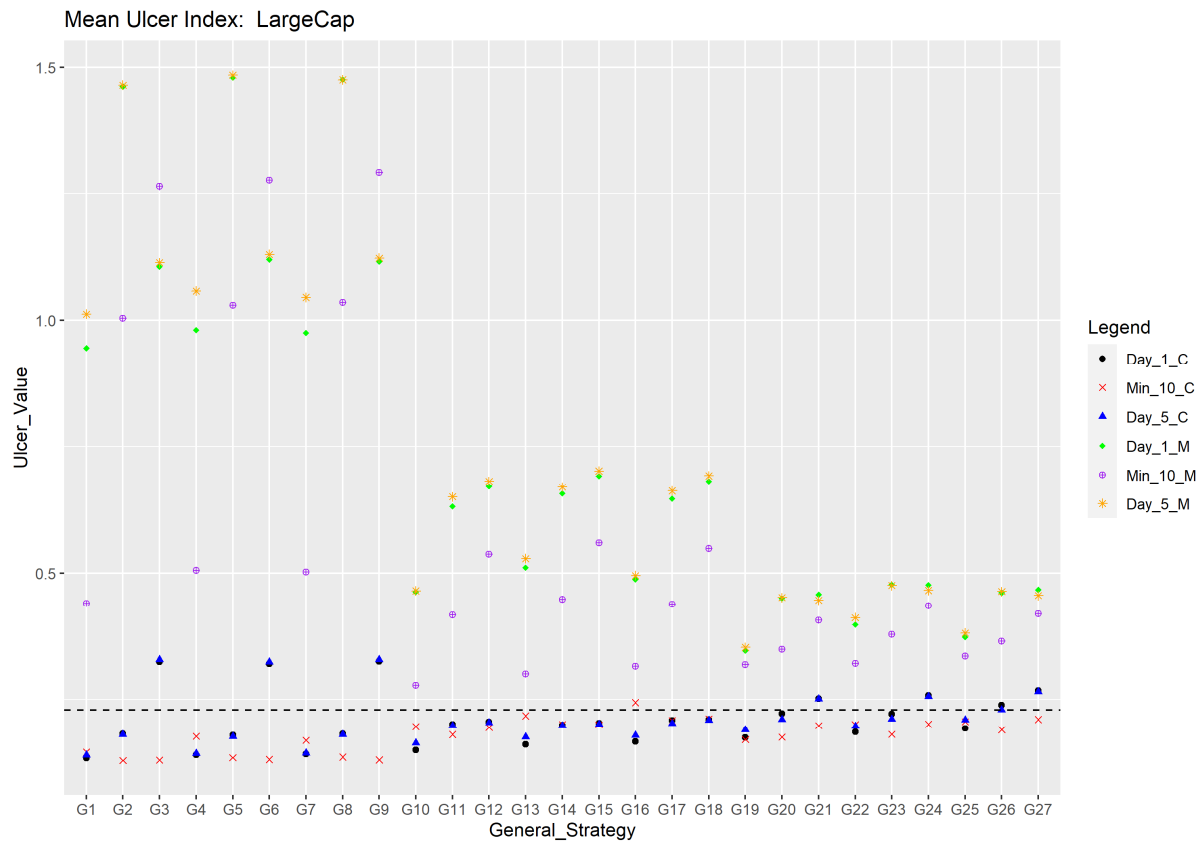
Figure 14: Number of times that the strategy beats the Benchmark (Annualized Standard Deviation)



We obtain again the same kind of conclusion generally on all the strategies, the momentum strategies beat more times the Benchmark on all the broad caps. We can also see that with the MA, the strategies very often have a smaller annualized standard deviation than the Benchmark

5.3.4. Ulcer Index

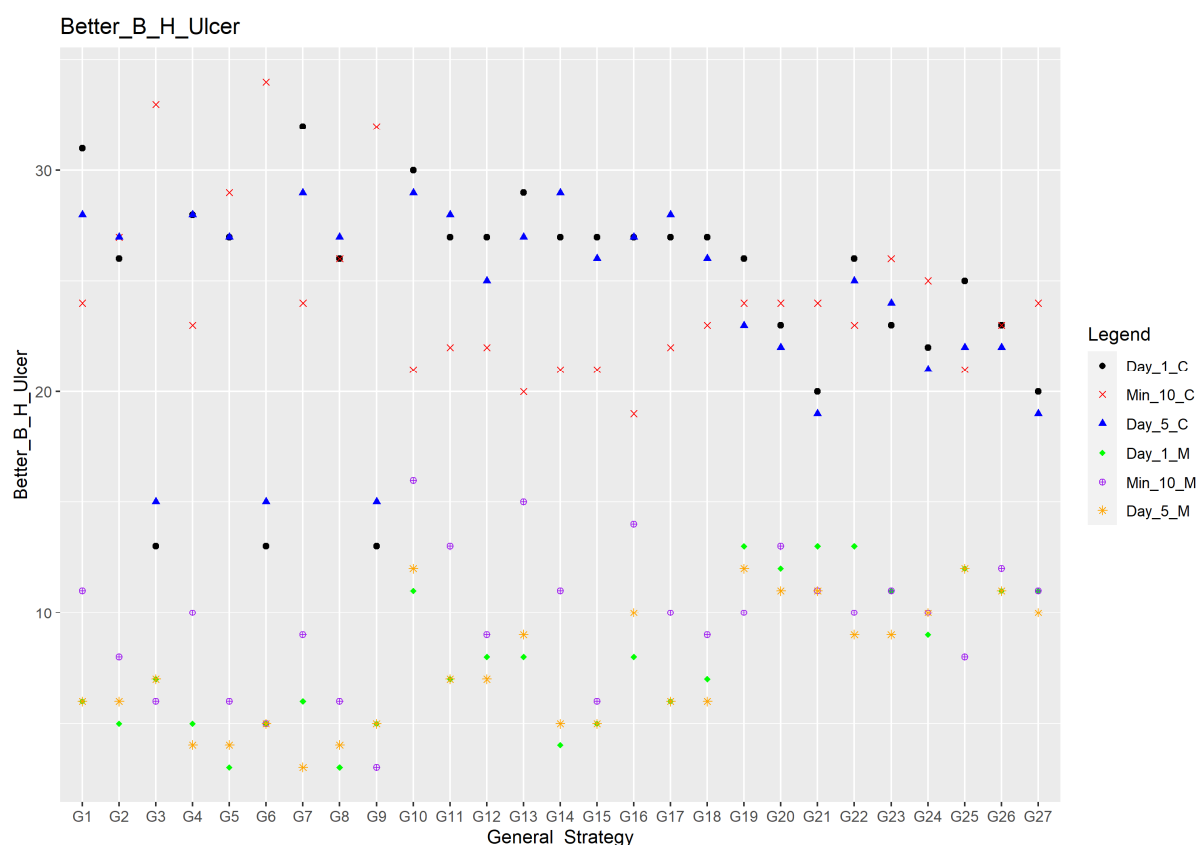
Figure 15: Mean Ulcer Index



The Ulcer Index will indicate the "normal" drawdown that can be expected during the duration of the investment, i.e. the "normal" drawdown value that should be expected after a peak. It is therefore preferable to have the smallest possible value which means that after a peak you will not have a big drop. We can see that if we take the average of all the large caps that the momentum strategies have each time a higher Ulcer Index than the average of the Benchmark which means that the momentum strategies tend to have either big drawdowns and/or a lot of drawdowns. In the contrarian strategies, the Ulcer Index is quite stable among all the strategies, but we can notice that the strategies based on the 10th-90th percentile calculated on the last day or on the last five days almost systematically give a higher Ulcer Index than the benchmark. The contrarian strategies seem in general more conservative, there are only very small drops between the different peaks. You will find in Appendix 8 for each stock, the ten best performing strategies from the point of view of the Ulcer Index sorted from the best to the worst.

When comparing the different strategies with the benchmark.

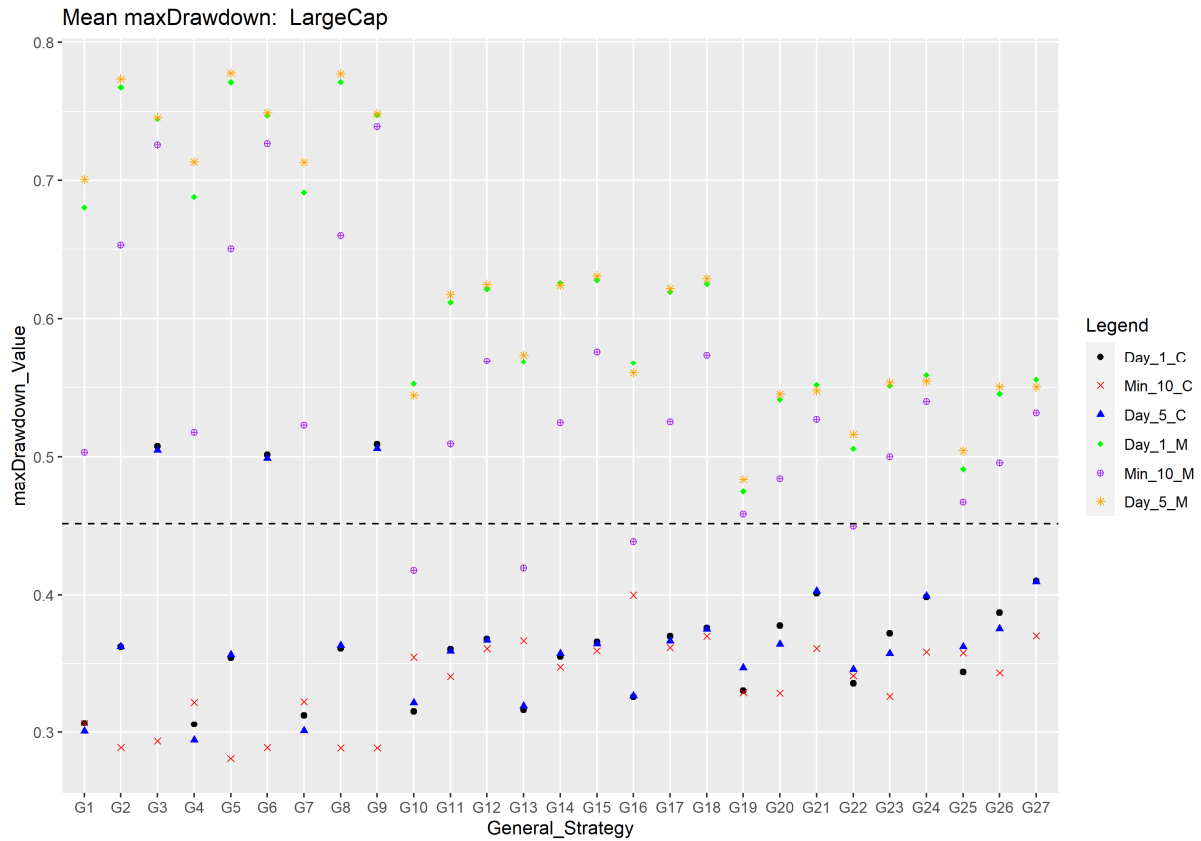
Figure 16 : Number of times that the strategy beats the Benchmark (Ulcer Index)



The same kind of conclusion is reached when we observe how many times the benchmark is beaten by the strategy on all large caps. A large predominance of contrarian strategies despite the underperformance of the 10th-90th percentile calculated over the last 5 days and the day before.

5.3.5. Maximum Drawdown

Figure 17: Mean Maximum Drawdown



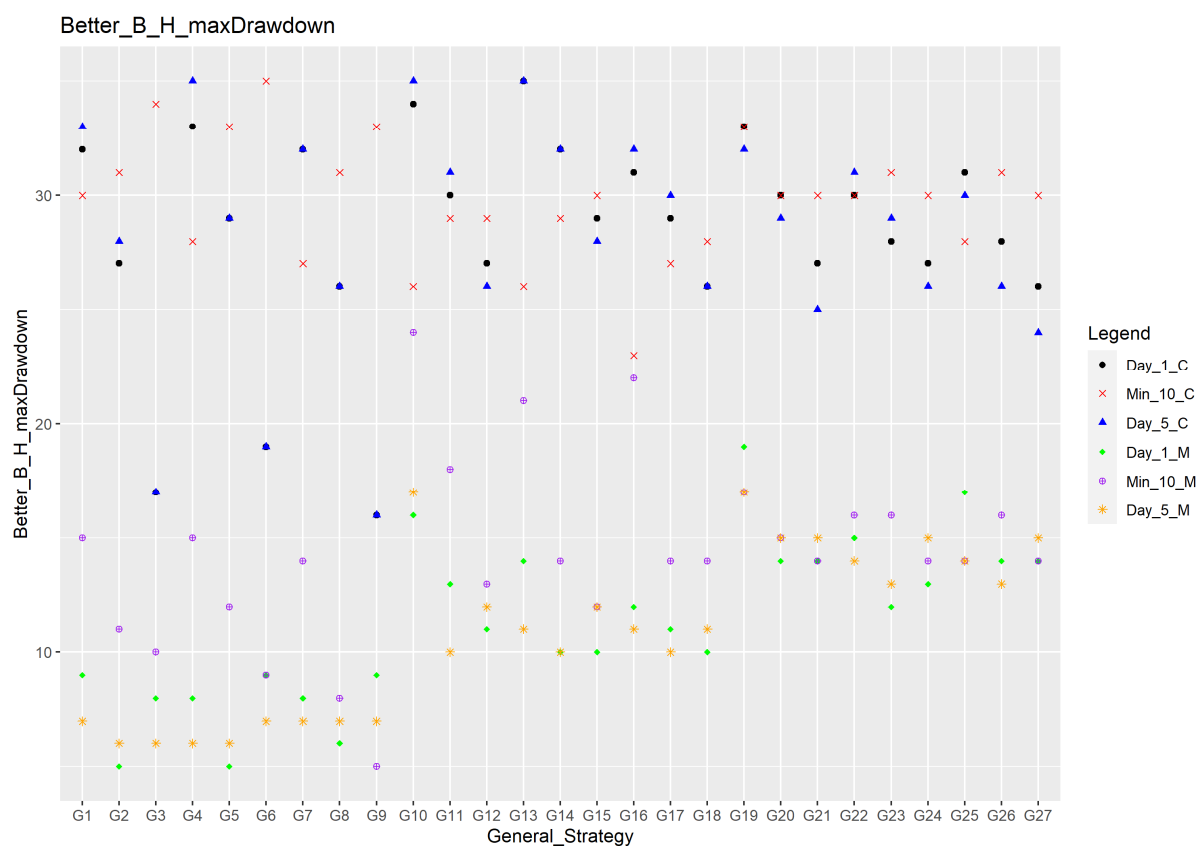
As for the Ulcer Index it is better to have the smallest Maximum Drawdown because it will mean that the biggest loss before returning to the same level as the peak on which the Maximum Drawdown is calculated is the smallest possible. This is an important value because in practice we can absorb a small Maximum Drawdown relatively well and continue the investment to return to the peak but when we meet during an investment a Maximum drawdown that is too large it will dilapidate the capital invested and we will probably end prematurely the investment. It would have been also important to see when this Maximum Drawdown takes place because a big Maximum Drawdown at the beginning of an investment would make that we would abandon very quickly an investment and that consequently we would not be able to see if afterwards it would have been profitable. A strategy could have a very bad Maximum Drawdown at the beginning but afterwards perform very well.

When we compare the average given by each strategy with the average given by the Benchmark, we see once again that the contrarian strategies perform very well compared to the momentum strategies. We obtain the same kind of observation as for the analysis of the

Ulcer Index but if we look at the average values of the Maximum Drawdowns we can see that even for the strategies that are better on average than the Benchmark the Maximum Drawdowns are very large. Appendix 9 shows the ten best strategies for each stock.

If we now compare the strategies with the benchmarks

Figure 18 : Number of times that the strategy beats the Benchmark (Maximum Drawdown)

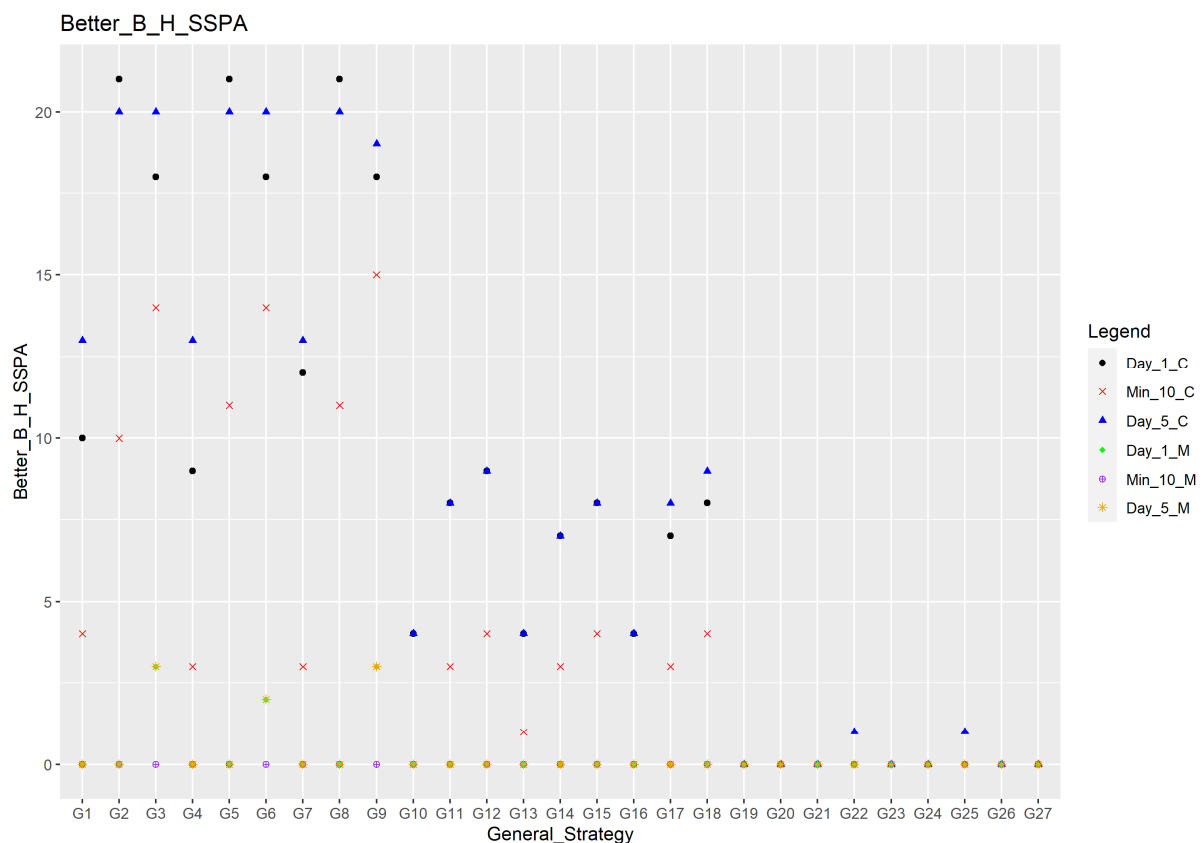


We will see that the benchmarks are beaten a greater number of times by contrarian strategies than momentum strategies.

5.4. Data Snooping

5.4.1. Stepwise Superior Predictive Ability

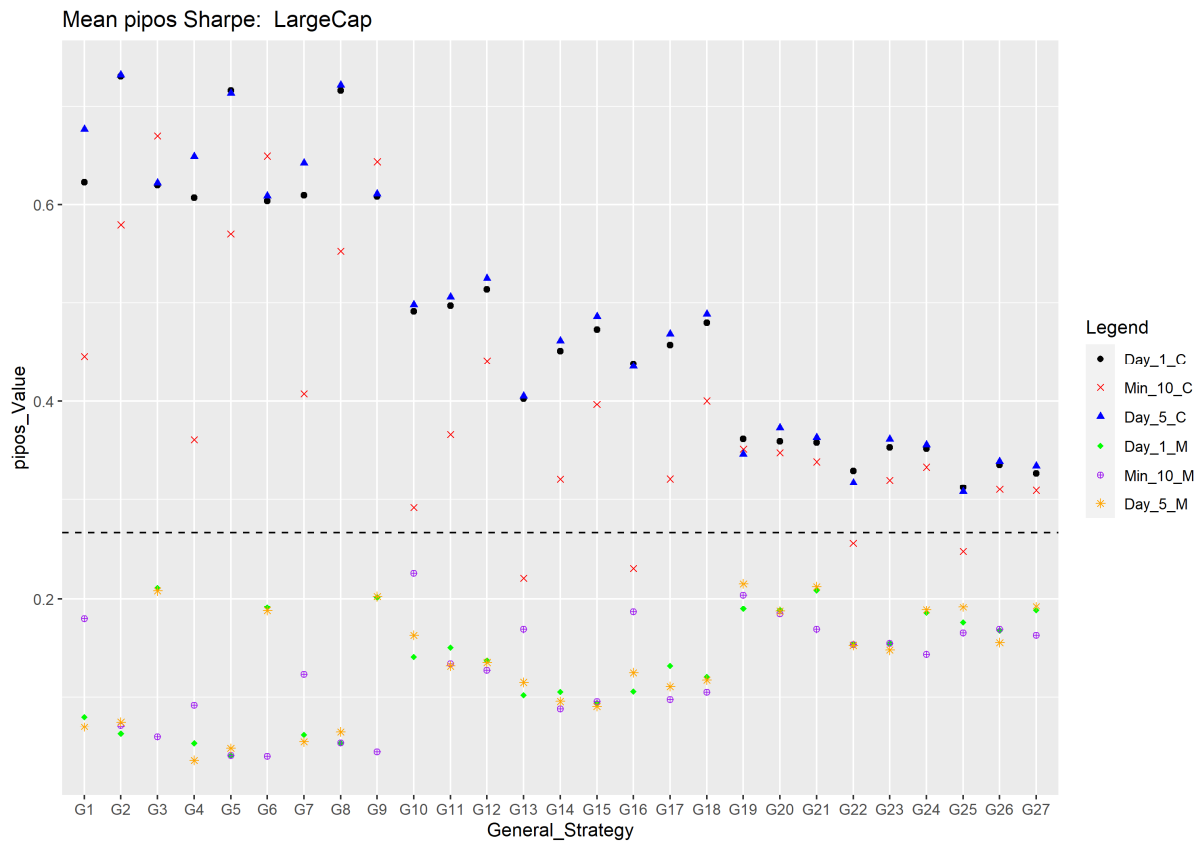
Figure 19: Number of times that the strategy beats the Benchmark (Step SPA)



When you look at the SSPA analysis and compare it with the analysis on the number of times a strategy beats the benchmark in terms of annualized returns. We can see that almost no momentum strategy is able to obtain significantly better returns than the Benchmark. We can see that the strategies using MA no longer allow to obtain significantly better returns. The strategies using the calculation of the percentile over ten minutes are systematically worse than those where we calculate the percentile over the last five days or the last day. As for the analysis of the annualized returns, we can see that the stop-loss does not seem to be very impactful, which seems to apply to the fact that when everything is going well, we do not use them. The contrarian strategy using the 5th-95th percentile calculated on the last day beats the benchmark more often.

5.4.2. Peer Performance

Figure 20: Mean pipos Sharpe Ratio

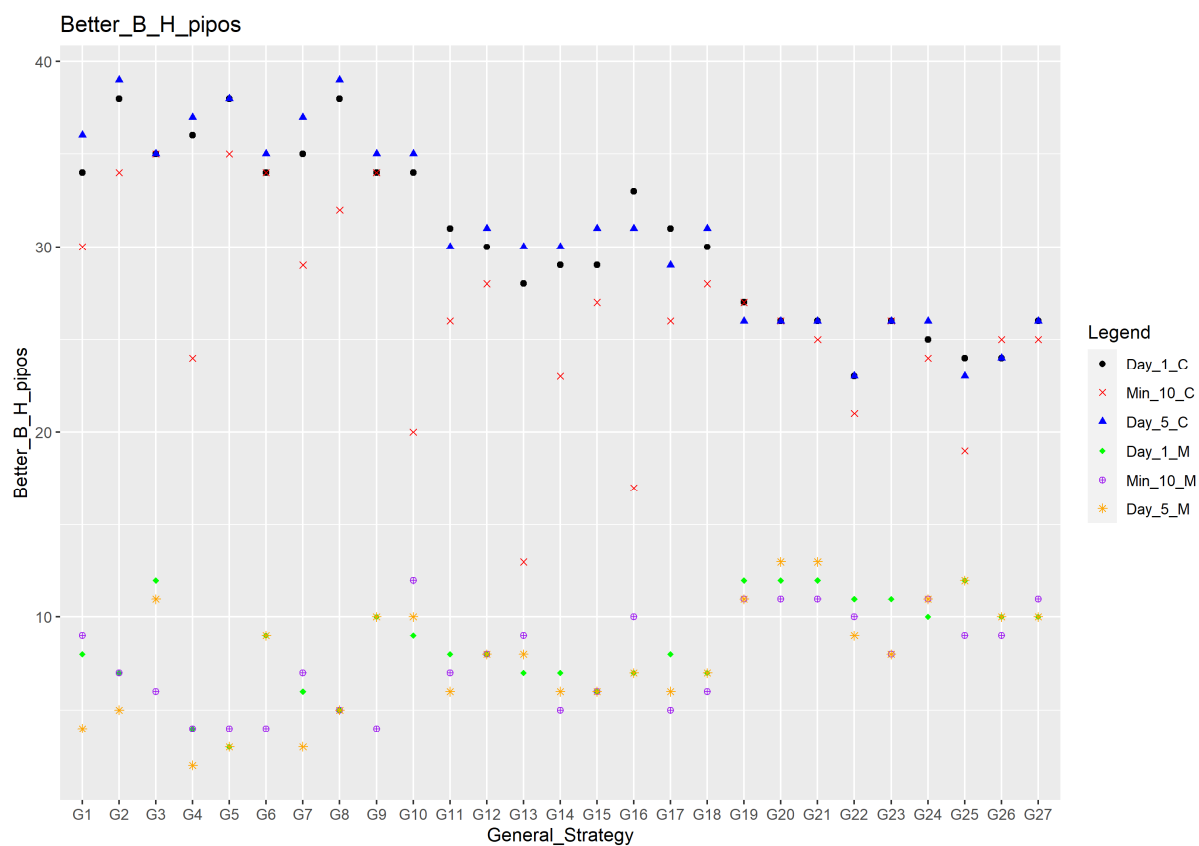


We will look here if statically the strategy of interest is overperforming compared to the others. We will take as for the performance analysis of the strategies, the strategies that have statistically a better Sharpe ratio compared to others so the percentage of strategies that are underperforming compared to it. If the strategy of interest is always superior in performance compared to its peers, the outperformance measure will be 100%.

We see that the simplest contrarian strategies outperform their peers in terms of the Sharpe Ratio. The strategies using the percentiles calculated on the 5th-95th percentiles do once again the best. In the contrarian case, we see once again that in general the use of the first 10 minutes to calculate the percentiles seems to perform less well.

You will find in Appendix 10 the strategies that have compared to their peers have a better Sharpe ratio. They will be ranked from the best to the worst.

Figure 21 : Number of times that the strategy beats the Benchmark (pipos Sharpe Ratio)

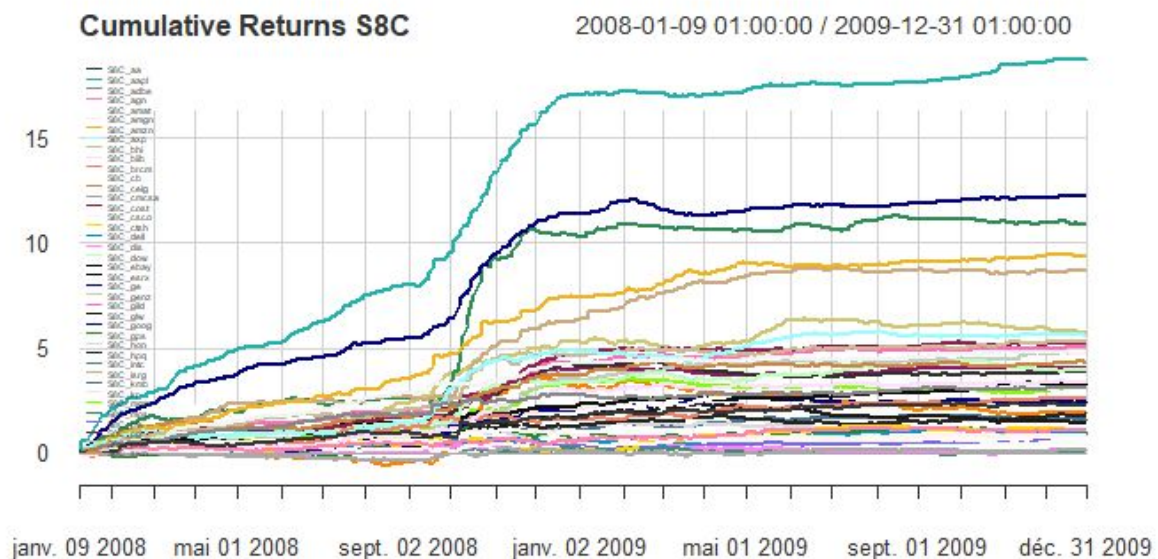


The contrarian strategies beat the benchmark more often. The momentum strategy that will have the most times a better outperformance ratio than the benchmark will be repeated on only thirteen stocks.

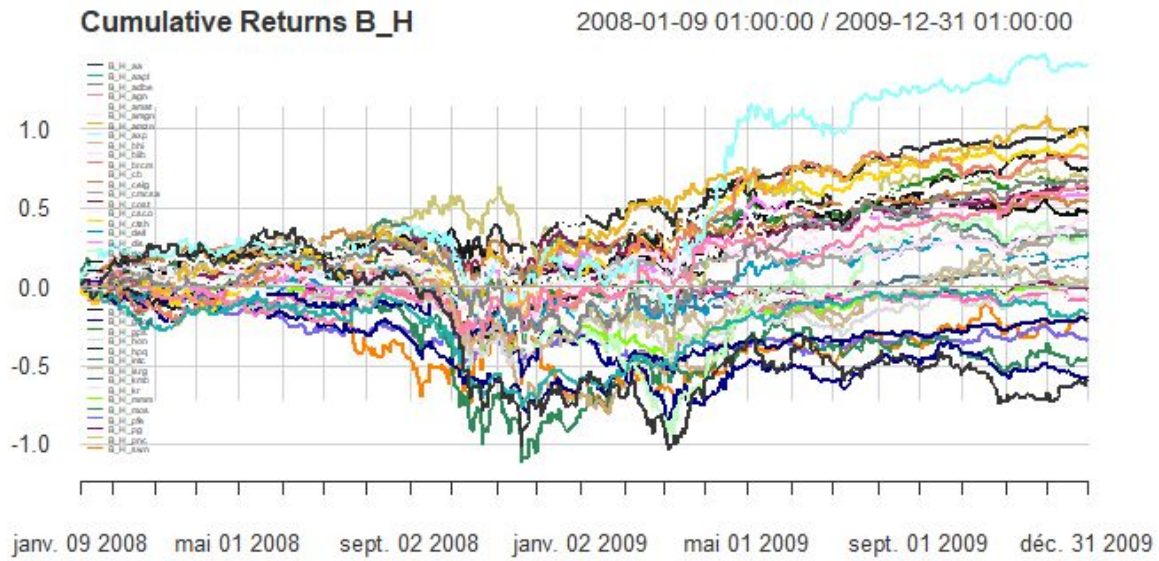
5.5. Analysis one of the “best” strategy

We will now look at the cumulative returns of the G5 contrarian strategy using the previous day to calculate the 5th-95th percentile without the use of a trend indicator and with a stop-loss of 1%. This will be the S8C strategy. We chose it because it is a very successful strategy in terms of the various analyses on returns and risk-adjusted returns. This strategy also showed significant results even after removing the chance effect. In order to better observe what happens we will exceptionally take the non-geometric cumulative return because the geometric does not allow to distinguish well all the curves because of the very high performance of the strategy on the AAPL stock.

Figure 22: Cumulative Return on each stocks by using S8C



We can see that the strategy does not work in an equivalent way in all the strategies which can be explained by the fact that although we are in the large caps, the stocks present in this category are very different from each other. We can also see that there is almost systematically a jump in terms of cumulative returns from October 2008. It would seem that in a period of instability this strategy can obtain great returns in the case of some stocks because they manage to adapt their positions in the market correctly. Nevertheless, we note a relative stability of this strategy after the jump. If we now look at what happens with the Buy&Hold strategy (the benchmark)



The cumulative return movements on each stock seem to follow the same kind of movement. A slight stability followed by a large loss around September 2008 that drives the cumulative return down and then for some stocks a substantial recovery after this shock.

When comparing the two charts, the S8C strategy reacts better to shocks than the Buy & Hold strategy. This can be explained by the dynamic nature of the S8C strategy, and the strategies tested in general. In our case, this allows the S8C strategy to adapt better.

Appendices 11 and 12 will show the cumulative returns of the S8C strategy in a geometric way and during the Buy & Hold

6. Conclusion

We wanted to test in this analysis whether it was possible for an active investor to make a profit by putting himself in the shoes of an HFT by exploiting the inefficiency of the markets. We have therefore tested two main families of strategies, contrarian strategies and momentum strategies.

In order to capture the micro variations in the price that an HFT could take advantage of, we decided to use the following method, using different percentile ranges (1st-99th, 5th-95th and 10th-90th) and calculate them on different time horizons, the day before the trading day, the five previous days before the trading day and the first ten minutes of the day. We also tried to test if the addition of trend indicators would improve our strategies in order to better match the general market trend and the micro variations so as not to have contradictory signals with the market. We will create a set of 162 strategies in total (81 contrarian strategies and their 81 momentum equivalents) that will be applied on forty large caps.

We will also test the different strategies via the Step SPA in order to take into account the chance effect. Here we will use it to see if the returns obtained via our active strategies beat the benchmark in a statistically significant way.

We also compare the strategies with each other via the Outperformance ratio which also takes into account the luck effect when comparing a pair of strategies. In this case, we will use the Sharpe Ratio for comparison.

After testing its different strategies to avoid the luck effect. We came to the conclusion that if we omit the transaction costs, the strategies that work best are the simplest contrarian strategies. It uses the 5th-95th percentiles calculated on the previous day's data without taking into account a trend indicator. The number of times it beats the Benchmark does not seem to depend on the stop loss. If we look at the VaR and the ES, using a stop loss at -1% when taking a position results in beating the Benchmark more often over the large caps. Concerning the Ulcer Index and the Maximum Drawdown, the same happens or at least not significantly worse, the stop loss at -1% is better than the stop loss at -2% or no stop loss.

We can conclude in general that in our case it seems that following a significant variation, the price will tend to return to its equilibrium level rather than continue in the direction of the variation. The 5th-95th percentile calculated on the previous day's data allows us to better appreciate which variation is likely to generate a price reversal. So, we can come to the conclusion that the previous day allows us to better appreciate what is going to happen today

(5 days is also good) and that the 5th-95th percentile allows us to better take advantage of micro price movement between two trades. The trend indicators on the other hand parasitize the strategies because it is forced to react to the variation according to how is the general market trend which prevents it to make a trade to take advantage of micro price movement within a trend.

It is therefore possible to make a profit by taking advantage of the inefficiency of the markets if one does not take into account the transaction costs. Once caught, no strategy works. Nevertheless, we can appreciate the market timing performance coming from the contrarian strategies

In our work, we will analyze past data on a specific market exchange used mainly by HFT firms (68.3% in terms of dollar trading volume in the entire Carrion (2012) database), dating from a rather distant time, and we must therefore take the conclusions with some caution. Moreover, we have to allow a more general analysis of a strategy on the whole of the large caps considered at the same weight a strategy rather than another what does not let us appreciate the different measures in term of value on the various strategies.

Note: You can nevertheless find for each stock the value associated with the analysis for each strategy via this link here : [Master Thesis](#)

Then, the fact of being in a theoretical framework did not allow us to appreciate finely the real transaction costs.

It would have been interesting to see how these different strategies worked on small and mid-caps. It could also be interesting to conduct this analysis using as the maximum transaction costs that could be applied to a strategy to keep it profitable for each strategy to better realize the feasibility of a strategy.

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8. Appendices

Appendix : 1

Strategy	Combination
S1C/M	1-Day Percentile 1-99 NoStopLoss,Contrarian/Momentum
S2C/M	1-Day Percentile 5-95, NoStopLoss,Contrarian/Momentum
S3C/M	1-Day Percentile 10-90, NoStopLoss,Contrarian/Momentum
S4C/M	1-Day Percentile 1-99, StopLoss 1%,Contrarian/Momentum
S5C/M	1-Day Percentile 5-95, StopLoss 1%,Contrarian/Momentum
S6C/M	1-Day Percentile 10-90, StopLoss 1%,Contrarian/Momentum
S7C/M	1-Day Percentile 1-99,StopLoss 2%,Contrarian/Momentum
S8C/M	1-Day Percentile 5-95,StopLoss 2%,Contrarian/Momentum
S9C/M	1-Day Percentile 10-90,StopLoss 2%,Contrarian/Momentum
S10C/M	1-Day Percentile 1-99,NoStopLoss,VWAP,Contrarian/Momentum
S11C/M	1-Day Percentile 5-95,NoStopLoss,VWAP,Contrarian/Momentum
S12C/M	1-Day Percentile 10-90,NoStopLoss,VWAP,Contrarian/Momentum
S13C/M	1-Day Percentile 1-99,StopLoss 1%,VWAP,Contrarian/Momentum
S14C/M	1-Day Percentile 5-95,StopLoss 1%, VWAP,Contrarian/Momentum
S15C/M	1-Day Percentile 10-90,StopLoss 1%,VWAP,Contrarian/Momentum
S16C/M	1-Day Percentile 1-99,StopLoss 2%,VWAP,Contrarian/Momentum
S17C/M	1-Day Percentile 5-95,StopLoss 2%, VWAP,Contrarian/Momentum
S18C/M	1-Day Percentile 10-90,StopLoss 2%,VWAP,Contrarian/Momentum
S19C/M	1-Day Percentile 1-99,NoStopLoss,MA,Contrarian/Momentum
S20C/M	1-Day Percentile 5-95,NoStopLoss,MA,Contrarian/Momentum
S21C/M	1-Day Percentile 10-90,NoStopLoss,MA,Contrarian/Momentum
S22C/M	1-Day Percentile 1-99,StopLoss 1%,MA,Contrarian/Momentum
S23C/M	1-Day Percentile 5-95,StopLoss 1%, MA,Contrarian/Momentum
S24C/M	1-Day Percentile 10-90,StopLoss 1%,MA,Contrarian/Momentum
S25C/M	1-Day Percentile 1-99,StopLoss 2%,MA,Contrarian/Momentum
S26C/M	1-Day Percentile 5-95,StopLoss 2%, MA,Contrarian/Momentum
S27C/M	1-Day Percentile 10-90,StopLoss 2%,MA,Contrarian/Momentum
S28C/M	10 Min Percentile 1-99,NoStopLoss,Contrarian/Momentum
S29C/M	10 Min Percentile 5-95,NoStopLoss,Contrarian/Momentum

S30C/M	10 Min Percentile 10-90,NoStopLoss,Contrarian/Momentum
S31C/M	10 Min Percentile 1-99,StopLoss 1%,Contrarian/Momentum
S32C/M	10 Min Percentile 5-95,StopLoss 1%,Contrarian/Momentum
S33C/M	10 Min Percentile 10-90,StopLoss 1%,Contrarian/Momentum
S34C/M	10 Min Percentile 1-99,StopLoss 2%,Contrarian/Momentum
S35C/M	10 Min Percentile 5-95,StopLoss 2%,Contrarian/Momentum
S36C/M	10 Min Percentile 10-90,StopLoss 2%,Contrarian/Momentum
S37C/M	10 Min Percentile 1-99,NoStopLoss,VWAP,Contrarian/Momentum
S38C/M	10 Min Percentile 5-95,NoStopLoss,VWAP,Contrarian/Momentum
S39C/M	10 Min Percentile 10-90,NoStopLoss,VWAP,Contrarian/Momentum
S40C/M	10 Min Percentile 1-99,StopLoss 1%,VWAP,Contrarian/Momentum
S41C/M	10 Min Percentile 5-95,StopLoss 1%, VWAP,Contrarian/Momentum
S42C/M	10 Min Percentile 10-90,StopLoss 1%,VWAP,Contrarian/Momentum
S43C/M	10 Min Percentile 1-99,StopLoss 2%,VWAP,Contrarian/Momentum
S44C/M	10 Min Percentile 5-95,StopLoss 2%, VWAP,Contrarian/Momentum
S45C/M	10 Min Percentile 10-90,StopLoss 2%,VWAP,Contrarian/Momentum
S46C/M	10 Min Percentile 1-99,NoStopLoss,MA,Contrarian/Momentum
S47C/M	10 Min Percentile 5-95,NoStopLoss,MA,Contrarian/Momentum
S48C/M	10 Min Percentile 10-90,NoStopLoss,MA,Contrarian/Momentum
S49C/M	10 Min Percentile 1-99,StopLoss 1%,MA,Contrarian/Momentum
S50C/M	10 Min Percentile 5-95,StopLoss 1%, MA,Contrarian/Momentum
S51C/M	10 Min Percentile 10-90,StopLoss 1%,MA,Contrarian/Momentum
S52C/M	10 Min Percentile 1-99,StopLoss 2%,MA,Contrarian/Momentum
S53C/M	10 Min Percentile 5-95,StopLoss 2%, MA,Contrarian/Momentum
S54C/M	10 Min Percentile 10-90,StopLoss 2%,MA,Contrarian/Momentum
S55C/M	5-days MA Percentile1-99,NoStopLoss,Contrarian/Momentum
S56C/M	5-days MA Percentile5-95,NoStopLoss,Contrarian/Momentum
S57C/M	5-days MA Percentile10-90,NoStopLoss,Contrarian/Momentum
S58C/M	5-days MA Percentile1-99,StopLoss 1%,Contrarian/Momentum
S59C/M	5-days MA Percentile5-95,StopLoss 1%,Contrarian/Momentum
S60C/M	5-days MA Percentile10-90,StopLoss 1%,Contrarian/Momentum
S61C/M	5-days MA Percentile1-99,StopLoss 2%,Contrarian/Momentum
S62C/M	5-days MA Percentile5-95,StopLoss 2%,Contrarian/Momentum

S63C/M	5-days MA Percentile10-90,StopLoss 2%,Contrarian/Momentum
S64C/M	5-days MA Percentile1-99,NoStopLoss,VWAP,Contrarian/Momentum
S65C/M	5-days MA Percentile5-95,NoStopLoss,VWAP,Contrarian/Momentum
S66C/M	5-days MA Percentile10-90,NoStopLoss,VWAP,Contrarian/Momentum
S67C/M	5-days MA Percentile1-99,StopLoss 1%,VWAP,Contrarian/Momentum
S68C/M	5-days MA Percentile5-95,StopLoss 1%, VWAP,Contrarian/Momentum
S69C/M	5-days MA Percentile10-90,StopLoss 1%,VWAP,Contrarian/Momentum
S70C/M	5-days MA Percentile1-99,StopLoss 2%,VWAP,Contrarian/Momentum
S71C/M	5-days MA Percentile5-95,StopLoss 2%, VWAP,Contrarian/Momentum
S72C/M	5-days MA Percentile10-90,StopLoss 2%,VWAP,Contrarian/Momentum
S73C/M	5-days MA Percentile1-99,NoStopLoss,MA,Contrarian/Momentum
S74C/M	5-days MA Percentile5-95,NoStopLoss,MA,Contrarian/Momentum
S75C/M	5-days MA Percentile10-90,NoStopLoss,MA,Contrarian/Momentum
S76C/M	5-days MA Percentile1-99,StopLoss 1%,MA,Contrarian/Momentum
S77C/M	5-days MA Percentile5-95,StopLoss 1%, MA,Contrarian/Momentum
S78C/M	5-days MA Percentile10-90,StopLoss 1%,MA,Contrarian/Momentum
S79C/M	5-days MA Percentile1-99,StopLoss 2%,MA,Contrarian/Momentum
S80C/M	5-days MA Percentile5-95,StopLoss 2%, MA,Contrarian/Momentum
S81C/M	5-days MA Percentile10-90,StopLoss 2%,MA,Contrarian/Momentum

Appendix 2 : Annualized Return

Ticker	Sorted Strategy by Performance
AA	S57M,S3M,S63M,S9M,S60M,S6M,S55C,S29C,S2C,S8C
AAPL	S5C,S2C,S8C,S59C,S56C,S62C,S3C,S9C,S6C,S57C
ADBE	S60C,S57C,S63C,S8C,S5C,S2C,S6C,S3C,S9C,S55C
AGN	S33C,S9M,S6M,S3M,S36C,S30C,S63M,S60M,S57M,S32C
AMAT	S47C,S19C,S20C,S21C,S48C,S73C,S74C,S75C,S46C,S26C
AMGN	S62C,S59C,S56C,S8C,S2C,S5C,S58C,S61C,S55C,S63C
AMZN	S62C,S56C,S59C,S8C,S2C,S5C,S36C,S33C,S30C,S35C
AXP	S3C,S9C,S6C,S5C,S8C,S2C,S56C,S62C,S59C,S7C
BHI	S62C,S56C,S59C,S2C,S8C,S5C,S36C,S30C,S33C,S1C
BIIB	S62C,S56C,S59C,S8C,S2C,S5C,S60C,S57C,S6C,S63C

BRCM	S62C,S56C,S9C,S63C,S59C,S3C,S57C,S8C,S6C,S60C
CB	S5C,S8C,S2C,S36C,S17C,S30C,S59C,S72C,S33C,S66C
CELG	S59C,S62C,S56C,S8C,S5C,S2C,S60C,S63C,S57C,S30C
CMCSA	S50C,S47C,S51C,S23C,S24C,S77C,S78C,S46C,S22C,S76C
COST	S62C,S59C,S56C,S6C,S9C,S3C,S60C,S63C,S57C,S5C
CSCO	S58C,S5C,S6C,S59C,S60C,S11C,S12C,S65C,S66C,S64C
CTSH	S57M,S60M,S63M,S3M,S9M,S6M,S1C,S55C,S7C,S58C
DELL	S1C,S7C,S10C,S2C,S3C,S55C,S56C,S57C,S38M,S39M
DIS	S47C,S33M,S53C,S30M,S36M,S22C,S19C,S50C,S28C,S3C
DOW	S5C,S2C,S8C,S57C,S56C,S60C,S59C,S3C,S63C,S62C
EBAY	S3C,S56C,S57C,S2C,S9C,S62C,S63C,S8C,S6C,S59C
ESRX	S63M,S57M,S60M,S36C,S33C,S30C,S9M,S3M,S6M,S4C
GE	S2C,S3C,S56C,S57C,S9C,S62C,S63C,S8C,S5C,S6C
GENZ	S59C,S5C,S62C,S56C,S8C,S2C,S60C,S6C,S63C,S9C
GILD	S6C,S9C,S3C,S63C,S57C,S60C,S8C,S5C,S2C,S62C
GLW	S9C,S63C,S8C,S62C,S6C,S60C,S5C,S2C,S3C,S57C
GOOG	S5C,S2C,S8C,S59C,S56C,S62C,S30C,S57C,S33C,S36C
GPS	S12C,S66C,S11C,S65C,S18C,S72C,S71C,S17C,S15C,S69C
HON	S81C,S75C,S78C,S67C,S20C,S64C,S26C,S23C,S70C,S27C
HPQ	S62C,S56C,S59C,S63C,S57C,S60C,S9C,S3C,S6C,S8C
INTC	S11C,S12C,S64C,S65C,S66C,S10C,S17C,S18C,S70C,S71C
ISRG	S56C,S62C,S59C,S8C,S2C,S5C,S30C,S36C,S33C,S55C
KMB	S69C,S66C,S72C,S15C,S12C,S18C,S68C,S65C,S14C,S71C
KR	S12C,S66C,S18C,S72C,S15C,S63C,S69C,S57C,S60C,S9C
MMM	S59C,S56C,S62C,S2C,S8C,S5C,S9C,S6C,S3C,S63C
MOS	S5C,S8C,S2C,S30C,S36C,S33C,S59C,S56C,S62C,S63C
PEF	S2C,S55C,S3C,S56C,S57C,S39C,S38C,S1C,S12C,S65C
PG	S5C,S2C,S8C,S56C,S59C,S62C,S3C,S9C,S6C,S57C
PNC	S33C,S36C,S30C,S59C,S56C,S62C,S6C,S2C,S8C,S3C
SWN	S9M,S6M,S3M,S60M,S63M,S57M,S62M,S8M,S56M,S59M

Appendix 3 : Sharpe Ratio

Ticker	Sorted Strategy by Performance
AA	S57M,S3M,S63M,S9M,S60M,S6M,S29C,S55C,S65M,S30C
AAPL	S5C,S2C,S8C,S59C,S56C,S62C,S33C,S36C,S30C,S61C
ADBE	S60C,S63C,S57C,S8C,S5C,S2C,S30C,S55C,S36C,S6C
AGN	S33C,S9M,S6M,S36C,S30C,S3M,S40M,S32C,S63M,S60M
AMAT	S47C,S19C,S20C,S21C,S48C,S73C,S74C,S75C,S46C,S26C
AMGN	S58C,S61C,S55C,S62C,S4C,S59C,S56C,S8C,S2C,S5C
AMZN	S62C,S56C,S59C,S8C,S5C,S2C,S36C,S33C,S30C,S35C
AXP	S33C,S36C,S30C,S3C,S9C,S6C,S5C,S7C,S4C,S8C
BHI	S62C,S56C,S59C,S1C,S7C,S55C,S2C,S8C,S4C,S36C
BIIB	S62C,S56C,S59C,S8C,S2C,S5C,S60C,S66C,S57C,S72C
BRCM	S62C,S56C,S9C,S63C,S59C,S3C,S57C,S8C,S6C,S60C
CB	S23C,S77C,S74C,S36C,S5C,S26C,S80C,S20C,S30C,S8C
CELG	S59C,S62C,S56C,S8C,S5C,S2C,S30C,S33C,S36C,S55C
CMCSA	S50C,S51C,S23C,S24C,S77C,S78C,S22C,S47C,S76C,S46C
COST	S62C,S59C,S56C,S5C,S8C,S33C,S36C,S2C,S30C,S60C
CSCO	S11C,S12C,S65C,S66C,S64C,S10C,S58C,S19C,S5C,S6C
CTSH	S57M,S60M,S63M,S9M,S3M,S6M,S1C,S58C,S55C,S7C
DELL	S1C,S7C,S10C,S2C,S3C,S55C,S56C,S57C,S38M,S39M
DIS	S47C,S33M,S22C,S30M,S53C,S36M,S19C,S28C,S50C,S45M
DOW	S5C,S2C,S8C,S59C,S56C,S62C,S6C,S55C,S60C,S3C
EBAY	S3C,S56C,S57C,S2C,S9C,S62C,S63C,S8C,S6C,S59C
ESRX	S36C,S33C,S30C,S63M,S57M,S60M,S9M,S3M,S32C,S6M
GE	S30C,S61C,S7C,S55C,S28C,S58C,S1C,S36C,S2C,S3C
GENZ	S59C,S62C,S5C,S56C,S8C,S2C,S33C,S30C,S36C,S60C
GILD	S2C,S8C,S5C,S56C,S62C,S59C,S30C,S36C,S6C,S9C
GLW	S9C,S63C,S8C,S62C,S6C,S60C,S5C,S33C,S59C,S3C
GOOG	S32C,S35C,S29C,S30C,S33C,S36C,S5C,S2C,S8C,S56C
GPS	S12C,S66C,S11C,S65C,S71C,S18C,S72C,S17C,S15C,S69C
HON	S81C,S75C,S78C,S20C,S26C,S23C,S27C,S21C,S73C,S24C
HPQ	S56C,S62C,S59C,S8C,S2C,S5C,S63C,S1C,S57C,S60C

INTC	S11C,S12C,S64C,S65C,S66C,S10C,S17C,S18C,S70C,S71C
ISRG	S62C,S56C,S59C,S30C,S36C,S33C,S8C,S2C,S5C,S55C
KMB	S69C,S66C,S72C,S12C,S18C,S15C,S65C,S14C,S68C,S11C
KR	S66C,S72C,S12C,S18C,S69C,S15C,S65C,S71C,S68C,S11C
MMM	S59C,S56C,S62C,S2C,S8C,S5C,S68C,S71C,S69C,S72C
MOS	S29C,S32C,S35C,S5C,S8C,S2C,S30C,S36C,S33C,S59C
PEF	S2C,S55C,S3C,S56C,S57C,S39C,S38C,S1C,S12C,S65C
PG	S5C,S2C,S8C,S59C,S56C,S62C,S3C,S6C,S9C,S57C
PNC	S33C,S36C,S30C,S59C,S62C,S56C,S29C,S32C,S35C,S2C
SWN	S9M,S6M,S3M,S60M,S63M,S57M,S8M,S62M,S5M,S2M

Appendix 4 : Sharpe Ratio

Ticker	Sorted Strategy by Performance
AA	S57M,S63M,S3M,S60M,S9M,S6M,S55C,S58C,S5C,S29C
AAPL	S32C,S29C,S35C,S5C,S2C,S8C,S59C,S62C,S56C,S61C
ADBE	S60C,S63C,S57C,S8C,S5C,S2C,S58C,S55C,S6C,S61C
AGN	S33C,S40M,S32C,S36C,S30C,S9M,S6M,S3M,S63M,S60M
AMAT	S47C,S19C,S20C,S21C,S48C,S73C,S74C,S75C,S46C,S26C
AMGN	S58C,S61C,S55C,S62C,S59C,S56C,S4C,S8C,S5C,S2C
AMZN	S62C,S56C,S59C,S8C,S5C,S2C,S36C,S33C,S30C,S35C
AXP	S3C,S9C,S6C,S5C,S8C,S33C,S4C,S7C,S62C,S56C
BHI	S62C,S56C,S59C,S36C,S2C,S8C,S30C,S33C,S5C,S1C
BIIB	S62C,S56C,S59C,S8C,S2C,S5C,S60C,S57C,S6C,S63C
BRCM	S62C,S56C,S9C,S63C,S59C,S3C,S57C,S6C,S60C,S8C
CB	S5C,S36C,S77C,S23C,S33C,S30C,S8C,S2C,S17C,S45C
CELG	S59C,S62C,S8C,S5C,S56C,S2C,S30C,S33C,S36C,S61C
CMCSA	S50C,S51C,S23C,S24C,S77C,S78C,S22C,S76C,S49C,S47C
COST	S62C,S59C,S56C,S8C,S5C,S33C,S2C,S36C,S30C,S6C
CSCO	S58C,S5C,S6C,S59C,S60C,S4C,S11C,S12C,S65C,S66C
CTSH	S57M,S63M,S60M,S9M,S3M,S6M,S58C,S1C,S55C,S61C
DELL	S7C,S1C,S4C,S10C,S2C,S3C,S55C,S56C,S57C,S39M

DIS	S22C,S47C,S33M,S53C,S36M,S30M,S50C,S19C,S28C,S3C
DOW	S5C,S8C,S2C,S59C,S62C,S56C,S60C,S6C,S63C,S57C
EBAY	S3C,S56C,S57C,S2C,S9C,S62C,S63C,S8C,S6C,S59C
ESRX	S36C,S33C,S30C,S4C,S7C,S63M,S57M,S60M,S1C,S32C
GE	S8C,S9C,S62C,S63C,S2C,S5C,S6C,S59C,S60C,S3C
GENZ	S5C,S59C,S8C,S2C,S62C,S56C,S33C,S30C,S60C,S36C
GILD	S8C,S2C,S5C,S6C,S62C,S56C,S9C,S3C,S59C,S30C
GLW	S9C,S63C,S8C,S6C,S60C,S62C,S5C,S33C,S59C,S42C
GOOG	S32C,S35C,S29C,S33C,S30C,S36C,S5C,S2C,S8C,S56C
GPS	S12C,S66C,S11C,S65C,S18C,S72C,S71C,S17C,S15C,S69C
HON	S81C,S78C,S75C,S67C,S20C,S26C,S23C,S27C,S64C,S70C
HPQ	S56C,S62C,S59C,S8C,S5C,S2C,S63C,S60C,S57C,S9C
INTC	S11C,S12C,S64C,S65C,S66C,S10C,S14C,S15C,S67C,S68C
ISRG	S62C,S56C,S59C,S8C,S2C,S30C,S5C,S36C,S33C,S29C
KMB	S69C,S66C,S72C,S12C,S18C,S15C,S14C,S65C,S68C,S11C
KR	S66C,S12C,S72C,S69C,S18C,S15C,S65C,S68C,S71C,S60C
MMM	S59C,S56C,S62C,S2C,S8C,S5C,S69C,S68C,S72C,S71C
MOS	S5C,S8C,S30C,S2C,S36C,S33C,S59C,S29C,S32C,S56C
PEF	S2C,S55C,S3C,S56C,S57C,S39C,S38C,S1C,S12C,S65C
PG	S5C,S8C,S2C,S59C,S56C,S62C,S3C,S9C,S6C,S57C
PNC	S33C,S36C,S30C,S59C,S56C,S62C,S29C,S32C,S35C,S2C
SWN	S9M,S6M,S3M,S60M,S63M,S57M,S36C,S30C,S33C,S62M

Appendix 5 :VaR

Ticker	Sorted Strategy by Performance
AA	S40C,S49M,S49C,S40M,S31C,S31M,S22C,S76C,S67C,S76M
AAPL	S32C,S29C,S35C,S55C,S61C,S58C,S4C,S7C,S1C,S34C
ADBE	S31C,S49C,S40M,S52C,S49M,S34C,S31M,S40C,S43C,S43M
AGN	S49M,S40M,S49C,S31C,S43M,S34C,S52C,S40C,S52M,S43C
AMAT	S49C,S22C,S23C,S24C,S50C,S51C,S76C,S77C,S78C,S40C

AMGN	S40C,S31C,S30C,S28C,S32C,S36C,S58C,S41C,S49C,S42C
AMZN	S40C,S49M,S4C,S59C,S62C,S56C,S40M,S5C,S32C,S35C
AXP	S40M,S49M,S40C,S49C,S31C,S52M,S43M,S76M,S76C,S41M
BHI	S49C,S40C,S40M,S52C,S45C,S43C,S39C,S42C,S46C,S50M
BIIB	S49M,S49C,S40C,S43C,S52M,S40M,S52C,S31C,S43M,S50M
BRCM	S49C,S40C,S49M,S31C,S52M,S40M,S76C,S22C,S34C,S52C
CB	S49C,S52C,S22C,S40C,S25C,S76C,S52M,S74C,S35C,S32C
CELG	S43M,S40C,S49M,S49C,S40M,S43C,S52C,S51M,S31C,S52M
CMCSA	S49C,S40C,S50C,S22C,S23C,S24C,S51C,S77C,S78C,S49M
COST	S40C,S49C,S31M,S52C,S34M,S40M,S43C,S49M,S41C,S31C
CSCO	S49C,S22C,S50C,S76C,S40M,S31C,S23C,S24C,S51C,S77C
CTSH	S49C,S40M,S49M,S40C,S52C,S52M,S43M,S43C,S34C,S31C
DELL	S49M,S40M,S43M,S26M,S27M,S53M,S54M,S79M,S80M,S81M
DIS	S49C,S40C,S40M,S52C,S49M,S43C,S31C,S31M,S43M,S52M
DOW	S49C,S40C,S31C,S49M,S52C,S76C,S40M,S43C,S52M,S22C
EBAY	S49C,S43M,S40M,S52C,S34C,S49M,S31C,S52M,S40C,S76C
ESRX	S49C,S40M,S49M,S43M,S31C,S40C,S52M,S34C,S52C,S31M
GE	S49C,S40C,S41C,S42C,S49M,S22C,S40M,S43M,S52M,S50C
GENZ	S40M,S49M,S49C,S43M,S52C,S40C,S34C,S52M,S31C,S43C
GILD	S40C,S32C,S49C,S35C,S43C,S58C,S61C,S31C,S52C,S49M
GLW	S49M,S40M,S49C,S43M,S40C,S52M,S52C,S31M,S43C,S34M
GOOG	S32C,S35C,S31C,S28C,S34C,S61C,S29C,S58C,S55C,S76C
GPS	S49C,S40C,S49M,S52M,S31C,S40M,S31M,S52C,S43M,S43C
HON	S52C,S43M,S49C,S40M,S34M,S40C,S43C,S76C,S34C,S49M
HPQ	S40C,S43C,S49C,S34C,S31C,S49M,S40M,S61C,S7C,S52M
INTC	S40M,S41M,S42M,S22C,S23C,S24C,S50C,S51C,S76C,S77C
ISRG	S49C,S40C,S31C,S49M,S43M,S30C,S40M,S35C,S33C,S29C
KMB	S40C,S49C,S49M,S41C,S51C,S50C,S76C,S12C,S18C,S65C
KR	S49C,S40C,S31C,S40M,S49M,S43C,S52C,S34C,S33C,S25C
MMM	S31C,S49C,S40C,S52C,S40M,S43M,S34C,S43C,S49M,S52M
MOS	S49M,S40C,S52M,S43C,S40M,S43M,S76M,S31C,S25M,S22M
PEF	S49M,S40M,S40C,S49C,S41C,S42C,S31C,S22M,S76M,S32C
PG	S49C,S32C,S29C,S33C,S51C,S76C,S78C,S69C,S30C,S66C

PNC	S49C,S49M,S31C,S34C,S52M,S40C,S52C,S22M,S40M,S43M
SWN	S49M,S40C,S31M,S52M,S49C,S40M,S34M,S43C,S43M,S52C

Appendix 6 : Expected Shortfall

Ticker	Sorted Strategy by Performance
AA	S40C,S49M,S40M,S49C,S22C,S31C,S76C,S67C,S51C,S31M
AAPL	S32C,S29C,S35C,S58C,S61C,S55C,S4C,S7C,S1C,S34C
ADBE	S40C,S49C,S40M,S31C,S49M,S52C,S34C,S31M,S43C,S43M
AGN	S40M,S49M,S40C,S43M,S49C,S52C,S31C,S43C,S52M,S34C
AMAT	S49C,S22C,S23C,S24C,S50C,S51C,S76C,S77C,S78C,S52C
AMGN	S40C,S31C,S49M,S41C,S52M,S32C,S58C,S43C,S44C,S61C
AMZN	S49M,S40C,S52M,S40M,S4C,S59C,S62C,S5C,S56C,S46M
AXP	S49M,S40M,S49C,S40C,S31C,S52M,S43M,S52C,S76C,S76M
BHI	S49C,S40C,S40M,S43C,S52C,S45C,S42C,S49M,S34C,S50M
BIIB	S49M,S40M,S52M,S40C,S31C,S49C,S43C,S43M,S31M,S51M
BRCM	S49M,S49C,S40C,S40M,S52M,S31C,S41M,S31M,S76C,S76M
CB	S49C,S52C,S22C,S76C,S49M,S25C,S19C,S32C,S40C,S31C
CELG	S40C,S49M,S49C,S40M,S43M,S43C,S31C,S51M,S31M,S52C
CMCSA	S49C,S49M,S40M,S50C,S40C,S31C,S22C,S31M,S23C,S24C
COST	S40C,S40M,S41C,S42C,S43M,S49C,S49M,S43C,S44C,S45C
CSCO	S49C,S40M,S50C,S31C,S22C,S76C,S49M,S40C,S52C,S23C
CTSH	S40M,S49M,S40C,S49C,S52M,S52C,S43M,S31M,S31C,S50M
DELL	S49M,S22M,S23M,S24M,S50M,S51M,S76M,S77M,S78M,S40M
DIS	S49M,S31M,S31C,S49C,S52M,S52C,S40M,S40C,S22C,S76C
DOW	S49C,S40C,S49M,S40M,S52C,S22C,S76C,S31M,S67C,S22M
EBAY	S49C,S40M,S40C,S49M,S31C,S22C,S43M,S76C,S50C,S41C
ESRX	S49C,S43M,S49M,S40M,S31C,S40C,S34C,S52M,S22M,S25M
GE	S49C,S40C,S49M,S41C,S42C,S52M,S22M,S31C,S40M,S22C
GENZ	S40M,S43M,S49M,S49C,S52M,S40C,S31C,S43C,S34C,S52C
GILD	S49C,S40C,S35C,S13C,S32C,S43C,S52C,S36C,S33C,S30C
GLW	S40M,S49M,S43M,S40C,S49C,S31M,S41C,S52C,S52M,S31C

GOOG	S34C,S31C,S61C,S28C,S32C,S55C,S58C,S35C,S29C,S49C
GPS	S49M,S49C,S40C,S52M,S40M,S31C,S31M,S43M,S43C,S50C
HON	S49C,S40M,S40C,S52C,S49M,S43C,S31C,S43M,S41C,S44C
HPQ	S40C,S49C,S4C,S49M,S58C,S43C,S74C,S80C,S61C,S7C
INTC	S40M,S22C,S23C,S24C,S50C,S51C,S76C,S77C,S78C,S49C
ISRG	S40C,S31C,S40M,S30C,S36C,S49M,S29C,S33C,S49C,S43M
KMB	S49C,S40C,S40M,S49M,S43C,S43M,S52C,S76C,S41C,S52M
KR	S40C,S49C,S52C,S31C,S49M,S43C,S13C,S50C,S40M,S34C
MMM	S49C,S40C,S31C,S40M,S52C,S34C,S49M,S79C,S31M,S43M
MOS	S49M,S40C,S43C,S52M,S43M,S40M,S76M,S31C,S25M,S70M
PEF	S40M,S49M,S49C,S40C,S31M,S43M,S41C,S42C,S52M,S52C
PG	S49C,S32C,S35C,S29C,S31C,S7C,S52C,S4C,S40C,S36C
PNC	S49M,S49C,S31C,S52M,S34C,S40C,S40M,S52C,S43M,S22M
SWN	S49M,S40C,S31M,S52M,S40M,S49C,S43M,S34M,S41C,S43C

Appendix 7 : Annualized Standard Deviation

Ticker	Sorted Strategy by Performance
AA	1] ,S40C,S49C,S49M,S76C,S22C,S22M,S40M,S42C,S31C,S50M
AAPL	S21M,S27M,S24M,S81M,S75M,S74M,S80M,S78M,S54M,S48M
ADBE	S49M,S40M,S50M,S53M,S40C,S31M,S22M,S76M,S52M,S43M
AGN	S40C,S49C,S43C,S31M,S52C,S49M,S76C,S40M,S22C,S41C
AMAT	S49M,S78M,S77M,S76M,S51M,S24M,S23M,S22M,S49C,S50M
AMGN	S49C,S40M,S40C,S49M,S52C,S31M,S41M,S50M,S46C,S43M
AMZN	S49C,S40C,S52C,S76C,S79C,S73C,S48C,S51C,S46C,S54C
AXP	S49C,S76C,S79C,S77C,S21C,S51C,S24C,S23C,S40C,S27C
BHI	S40M,S31M,S76M,S51M,S49M,S51C,S77M,S74C,S50C,S54M
BIIB	S49C,S40C,S49M,S40M,S31C,S52C,S51C,S77C,S48C,S80C
BRCM	S49M,S40M,S49C,S76M,S22M,S76C,S22C,S41M,S50M,S31C
CB	S22M,S76C,S76M,S25C,S19C,S40M,S22C,S79C,S73C,S50M
CELG	S40C,S40M,S49M,S49C,S43C,S43M,S31M,S31C,S37C,S37M
CMCSA	S49M,S40C,S31C,S40M,S50M,S78M,S77M,S24M,S23M,S49C

COST	S40M,S40C,S49C,S49M,S43M,S37M,S41M,S43C,S52C,S37C
CSCO	S49M,S22M,S40M,S50M,S49C,S42M,S31C,S76M,S51M,S41M
CTSH	S49M,S40M,S49C,S40C,S41M,S43M,S52C,S31M,S52M,S41C
DELL	S78C,S77C,S76C,S51C,S24C,S23C,S50C,S22C,S49C,S49M
DIS	S49C,S49M,S40M,S41C,S40C,S31C,S31M,S41M,S52C,S67C
DOW	S40M,S49C,S49M,S76C,S43M,S40C,S22C,S76M,S22M,S51C
EBAY	S40M,S49C,S49M,S40C,S50M,S41M,S31C,S31M,S43M,S42M
ESRX	S40C,S22C,S40M,S25C,S31C,S31M,S50C,S49M,S49C,S19C
GE	S40C,S40M,S49M,S41M,S51M,S50M,S42M,S22M,S23M,S41C
GENZ	S49M,S40M,S40C,S43C,S31M,S43M,S49C,S37C,S22C,S76C
GILD	S49M,S40M,S40C,S31M,S52M,S43C,S43M,S49C,S41M,S37M
GLW	S40M,S40C,S49C,S31C,S49M,S50C,S31M,S41C,S43M,S76C
GOOG	S48M,S51M,S54M,S22M,S25M,S19M,S74M,S77M,S80M,S26M
GPS	S49C,S49M,S40M,S31C,S40C,S76M,S41M,S22M,S50M,S43M
HON	S40M,S49M,S40C,S31M,S43M,S31C,S50M,S41M,S50C,S52M
HPQ	S40M,S49M,S49C,S42M,S45M,S43M,S40C,S41M,S39M,S52C
INTC	S40M,S42M,S41M,S33M,S32M,S31M,S31C,S78M,S77M,S76M
ISRG	S40C,S49C,S43C,S40M,S31M,S31C,S32M,S52C,S49M,S76C
KMB	S49C,S40C,S40M,S49M,S43C,S46C,S52C,S76C,S52M,S79C
KR	S49M,S40M,S31M,S49C,S52M,S40C,S31C,S76M,S50C,S34M
MMM	S31C,S49C,S40C,S34C,S40M,S28C,S52C,S31M,S43C,S49M
MOS	S40C,S49C,S40M,S49M,S52C,S43M,S41M,S46C,S43C,S44M
PEF	S40C,S40M,S49C,S41C,S42C,S49M,S31C,S42M,S41M,S31M
PG	S49C,S49M,S40M,S52C,S46C,S40C,S43M,S46M,S52M,S77M
PNC	S49M,S22C,S76C,S77C,S74C,S25C,S80C,S23C,S20C,S26C
SWN	S49C,S49M,S31M,S40M,S40C,S34M,S41C,S52C,S31C,S78C

Appendix 8 : Ulcer Index

Ticker	Sorted Strategy by Performance
AA	S71M,S29C,S65M,S18M,S72M,S68M,S17M,S12M,S66M,S11M
AAPL	S61C,S55C,S58C,S4C,S1C,S7C,S32C,S29C,S35C,S45C
ADBE	S30C,S58C,S61C,S51C,S36C,S48C,S54C,S31C,S55C,S34C
AGN	S32C,S33C,S40M,S35C,S36C,S37M,S29C,S30C,S46M,S49M
AMAT	S19C,S47C,S75C,S74C,S73C,S48C,S21C,S20C,S46C,S52C
AMGN	S58C,S61C,S55C,S42C,S39C,S45C,S33C,S4C,S30C,S36C
AMZN	S35C,S29C,S56C,S59C,S36C,S62C,S33C,S30C,S32C,S61C
AXP	S4C,S28C,S32C,S29C,S43M,S31C,S37M,S35C,S19C,S1C
BHI	S36C,S30C,S33C,S29C,S35C,S62C,S72C,S66C,S59C,S45C
BIIB	S33C,S42C,S36C,S30C,S39C,S45C,S8C,S72C,S66C,S5C
BRCM	S34C,S37C,S61C,S7C,S43C,S1C,S58C,S55C,S4C,S46C
CB	S23C,S26C,S77C,S80C,S20C,S74C,S81C,S78C,S8C,S75C
CELG	S61C,S55C,S58C,S33C,S67C,S36C,S50M,S30C,S70C,S47M
CMCSA	S50C,S22C,S51C,S78C,S77C,S24C,S23C,S76C,S49C,S33M
COST	S70C,S67C,S25C,S64C,S16C,S19C,S42C,S13C,S22C,S10C
CSCO	S10C,S66C,S65C,S12C,S11C,S64C,S67C,S69C,S68C,S15C
CTSH	S34C,S28C,S31C,S7C,S32C,S30C,S1C,S39M,S4C,S31M
DELL	S41M,S42M,S45M,S44M,S39M,S38M,S4C,S72M,S71M,S70M
DIS	S47C,S53C,S19C,S50C,S22C,S40C,S33M,S76C,S36M,S25C
DOW	S61C,S32C,S4C,S29C,S58C,S35C,S50C,S55C,S33C,S1C
EBAY	S57C,S56C,S3C,S2C,S63C,S62C,S9C,S8C,S7C,S1C
ESRX	S34C,S28C,S10M,S21M,S16M,S13M,S27M,S70M,S64M,S76M
GE	S28C,S55C,S66C,S65C,S12C,S11C,S10C,S2C,S57C,S56C
GENZ	S5C,S8C,S2C,S59C,S56C,S62C,S36C,S33C,S30C,S29C
GILD	S30C,S36C,S33C,S32C,S29C,S35C,S55C,S61C,S58C,S18C
GLW	S32C,S33C,S36C,S35C,S30C,S39C,S61C,S45C,S29C,S42C
GOOG	S61C,S58C,S55C,S32C,S29C,S4C,S35C,S1C,S7C,S44C
GPS	S65C,S68C,S71C,S66C,S12C,S11C,S69C,S15C,S72C,S18C
HON	S67C,S70C,S64C,S37C,S46C,S43C,S49C,S52C,S13C,S43M
HPQ	S7C,S1C,B_H,S28C,S61C,S34C,S55C,S4C,S31C,S58C

INTC	S22C,S66C,S65C,S64C,S12C,S11C,S78C,S77C,S76C,S51C
ISRG	S33C,S30C,S36C,S4C,S29C,S55C,S7C,S58C,S35C,S1C
KMB	S16C,S64C,S70C,S13C,S67C,S10C,S18C,S72C,S12C,S15C
KR	S21C,S75C,S24C,S78C,S10C,S27C,S16C,S81C,S23C,S64C
MMM	S28C,S31C,S34C,S35C,S29C,S30C,S36C,S33C,S37C,S32C
MOS	S16C,S34C,S28C,S44C,S10C,S13C,S41C,S38C,S31C,S47M
PEF	S2C,S55C,S57C,S56C,S3C,S38C,S39C,S66C,S65C,S12C
PG	S79C,S76C,S73C,S70C,S16C,S64C,S10C,S54C,S51C,S48C
PNC	S32C,S29C,S35C,S33C,S58C,S36C,S30C,S31C,S61C,S55C
SWN	S37C,S14M,S29C,S11M,S17M,S73C,S79C,S55C,S61C,S40C

Appendix 9 : Max Drawdown

Ticker	Sorted Strategy by Performance
AA	S29C,S35C,S40M,S68M,S65M,S11M,S5C,S69M,S15M,S30C
AAPL	S61C,S55C,S58C,S4C,S1C,S7C,S32C,S35C,S29C,S45C
ADBE	S61C,S30C,S58C,S51C,S48C,S55C,S54C,S36C,S31C,S49C
AGN	S40M,S32C,S52M,S29C,S35C,S37M,S49M,S76M,S46M,S43M
AMAT	S75C,S74C,S73C,S48C,S47C,S21C,S20C,S19C,S52C,S46C
AMGN	S39C,S42C,S45C,S4C,S32C,S1C,S19C,S61C,S55C,S58C
AMZN	S30C,S33C,S36C,S35C,S29C,S32C,S65C,S56C,S62C,S59C
AXP	S28C,S37M,S43M,S40M,S31C,S19C,S32C,S21M,S29C,S27M
BHI	S30C,S36C,S35C,S33C,S29C,S45C,S72C,S66C,S32C,S47C
BIIB	S45C,S36C,S33C,S39C,S72C,S16C,S66C,S69C,S30C,S42C
BRCM	S37C,S34C,S43C,S19C,S25C,S46C,S58C,S4C,S73C,S64C
CB	S47C,S23C,S25C,S50C,S19C,S22C,S76C,S77C,S79C,S73C
CELG	S61C,S33C,S50M,S55C,S58C,S36C,S1C,S19M,S30C,S53M
CMCSA	S78C,S77C,S76C,S24C,S23C,S22C,S51C,S50C,S33M,S46C
COST	S67C,S25C,S19C,S70C,S22C,S42C,S64C,S39C,S45C,S13C
CSCO	S66C,S65C,S64C,S12C,S11C,S10C,S67C,S13C,S69C,S68C
CTSH	S34C,S30C,S28C,S44M,S68C,S31M,S49C,S39M,S31C,S45M
DELL	S41M,S42M,S38M,S39M,S72M,S71M,S70M,S18M,S17M,S45M

DIS	S47C,S50C,S40C,S53C,S76C,S22C,S19C,S25C,S40M,S42M
DOW	S50C,S41C,S78C,S24C,S61C,S33C,S22C,S30C,S32C,S53C
EBAY	S22C,S57C,S56C,S3C,S2C,S51C,S63C,S62C,S9C,S8C
ESRX	S34C,S28C,S33C,S76M,S36C,S38M,S79M,S30C,S49C,S37C
GE	S2C,S57C,S56C,S3C,S55C,S30C,S28C,S14C,S69C,S68C
GENZ	S35C,S2C,S8C,S29C,S5C,S61C,S55C,S56C,S59C,S62C
GILD	S32C,S36C,S35C,S30C,S33C,S55C,S61C,S15C,S58C,S29C
GLW	S32C,S33C,S45C,S36C,S35C,S42C,S31M,S67C,S30C,S16C
GOOG	S61C,S55C,S32C,S58C,S29C,S35C,S4C,S34C,S28C,S7C
GPS	S10C,S65C,S11C,S71C,S14C,S66C,S12C,S68C,S17C,S78C
HON	S37C,S67C,S70C,S64C,S43C,S46C,S49C,S52C,S13C,S77C
HPQ	S55C,S10C,S64C,S61C,B_H,S13C,S34C,S7C,S16C,S4C
INTC	S66C,S65C,S64C,S12C,S11C,S10C,S16C,S72C,S71C,S70C
ISRG	S30C,S36C,S33C,S4C,S58C,S55C,S61C,S29C,S7C,S35C
KMB	S16C,S70C,S64C,S10C,S13C,S39C,S72C,S66C,S67C,S69C
KR	S78C,S24C,S55C,S23C,S33C,S81C,S27C,S75C,S21C,S16C
MMM	S28C,S31C,S34C,S30C,S36C,S33C,S37C,S43C,S52C,S47C
MOS	S28C,S34C,S22M,S16C,S47M,S44C,S25M,S13C,S10C,S75M
PEF	S75C,S74C,S73C,S48C,S47C,S21C,S20C,S19C,S81C,S80C
PG	S79C,S73C,S76C,S70C,S25C,S48C,S54C,S16C,S64C,S51C
PNC	S33C,S35C,S29C,S32C,S36C,S30C,S31C,S1C,S7C,S4C
SWN	S37C,S52M,S49M,S29C,S79C,S50C,S43C,S73C,S47C,S19M

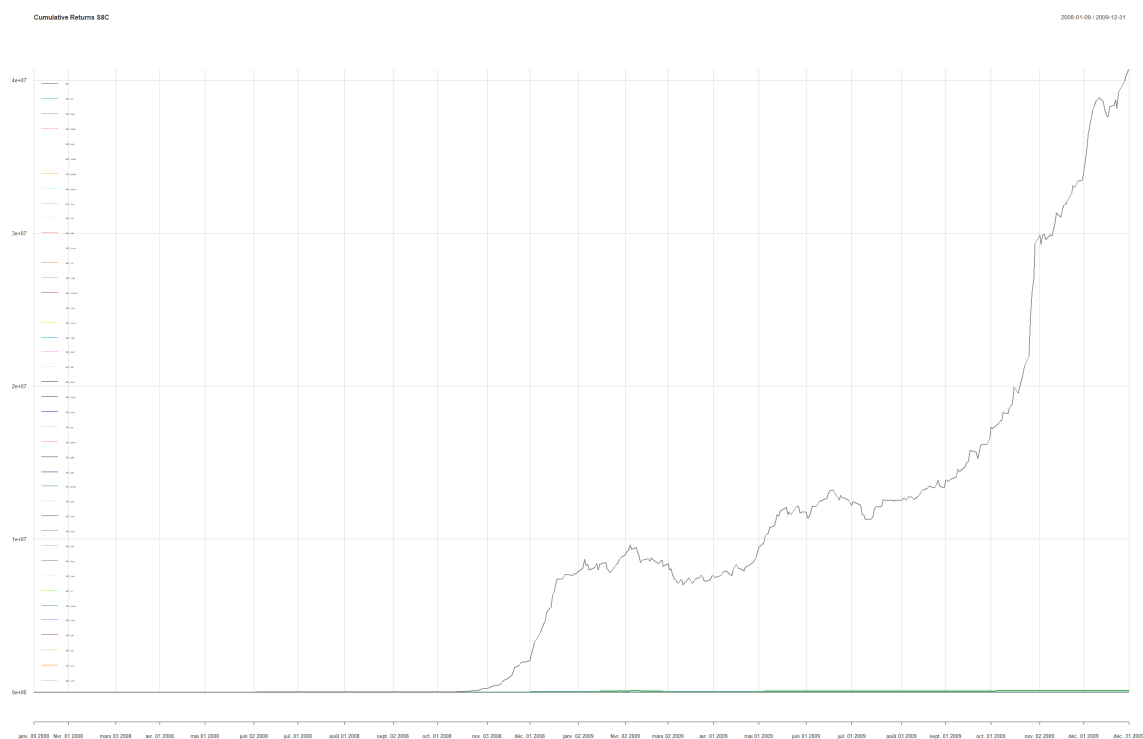
Appendix 10 : Peer Performance pipos Sharpe Ratio

Ticker	Sorted Strategy by Performance
AA	S57M,S3M,S63M,S9M,S6M,S60M,S29C,S55C,S65M,S11M
AAPL	S5C,S2C,S8C,S59C,S62C,S56C,S33C,S36C,S30C,S61C
ADBE	S60C,S63C,S57C,S8C,S2C,S5C,S55C,S6C,S9C,S36C
AGN	S33C,S3M,S36C,S9M,S30C,S6M,S32C,S40M,S29C,S63M
AMAT	S48C,S73C,S74C,S75C,S47C,S21C,S20C,S19C,S53C,S26C

AMGN	S58C,S61C,S55C,S33C,S4C,S62C,S56C,S1C,S30C,S36C
AMZN	S62C,S56C,S59C,S8C,S2C,S5C,S36C,S33C,S30C,S35C
AXP	S33C,S36C,S30C,S55C,S3C,S6C,S9C,S2C,S5C,S56C
BHI	S62C,S56C,S59C,S5C,S2C,S8C,S58C,S30C,S61C,S1C
BIIB	S62C,S56C,S8C,S59C,S2C,S5C,S66C,S72C,S69C,S12C
BRCM	S62C,S9C,S63C,S56C,S3C,S57C,S6C,S60C,S59C,S2C
CB	S23C,S77C,S74C,S26C,S80C,S20C,S36C,S5C,S8C,S21C
CELG	S5C,S56C,S59C,S62C,S8C,S2C,S30C,S33C,S36C,S55C
CMCSA	S50C,S51C,S23C,S24C,S77C,S78C,S76C,S22C,S47C,S48C
COST	S62C,S59C,S56C,S8C,S5C,S2C,S30C,S33C,S36C,S60C
CSCO	S11C,S12C,S65C,S66C,S10C,S64C,S58C,S19C,S5C,S6C
CTSH	S63M,S57M,S60M,S3M,S9M,S6M,S55C,S58C,S4C,S61C
DELL	S1C,S7C,S2C,S3C,S55C,S56C,S57C,S10C,S38M,S39M
DIS	S47C,S33M,S53C,S22C,S19C,S30M,S36M,S50C,S28C,S45M
DOW	S5C,S8C,S2C,S59C,S56C,S62C,S6C,S60C,S3C,S63C
EBAY	S3C,S56C,S57C,S2C,S9C,S62C,S63C,S8C,S59C,S6C
ESRX	S33C,S36C,S30C,S63M,S57M,S60M,S9M,S3M,S6M,S32C
GE	S30C,S61C,S59C,S6C,S60C,S5C,S7C,S3C,S56C,S57C
GENZ	S59C,S5C,S8C,S56C,S62C,S33C,S30C,S2C,S36C,S60C
GILD	S2C,S8C,S5C,S6C,S60C,S9C,S35C,S3C,S63C,S57C
GLW	S9C,S63C,S6C,S60C,S8C,S62C,S3C,S57C,S72C,S18C
GOOG	S32C,S35C,S29C,S30C,S5C,S33C,S8C,S2C,S36C,S56C
GPS	S12C,S66C,S65C,S11C,S18C,S72C,S71C,S17C,S80C,S68C
HON	S81C,S20C,S78C,S75C,S26C,S23C,S74C,S24C,S27C,S21C
HPQ	S62C,S59C,S56C,S8C,S2C,S5C,S63C,S9C,S30C,S57C
INTC	S11C,S12C,S64C,S65C,S66C,S10C,S19C,S16C,S17C,S18C
ISRG	S59C,S62C,S56C,S8C,S55C,S58C,S30C,S2C,S61C,S33C
KMB	S69C,S66C,S72C,S18C,S12C,S17C,S11C,S68C,S71C,S14C
KR	S66C,S72C,S12C,S18C,S69C,S71C,S15C,S65C,S68C,S11C
MMM	S62C,S56C,S59C,S66C,S2C,S65C,S72C,S68C,S8C,S69C
MOS	S29C,S32C,S5C,S35C,S8C,S2C,S30C,S3M,S36C,S59C
PEF	S2C,S3C,S56C,S57C,S55C,S38C,S39C,S1C,S12C,S65C
PG	S5C,S2C,S8C,S59C,S62C,S56C,S3C,S9C,S6C,S57C

PNC	S33C,S36C,S30C,S59C,S56C,S62C,S2C,S8C,S29C,S35C
SWN	S9M,S57M,S6M,S3M,S60M,S63M,S8M,S62M,S64M,S5M

Appendix 11 (Geo) Cumulative returns with S8C



Appendix 12 (Geo) Cumulative returns with the benchmark

