Trading Strategies Optimization Using a Genetic Algorithm under The Directional Changes Paradigm

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Abstract

This thesis is rooted in the Directional Changes (DC) paradigm, focusing on exploring its efficacy in developing profitable trading strategies. In traditional practice, market prices are typically sampled at fixed time intervals to construct physical time data. A method rooted in trading decisions based on this type of data, specifically Technical Analysis (TA), is constrained by the information generated through the selection of these fixed intervals, such as daily or hourly. However, the DC paradigm is an event-driven approach that distinguishes itself from the traditional physical time. It offers a complementary approach for extracting information from data. In the DC paradigm, price movements are recorded when specific events occur, instead of employing fixed intervals. The determination of these events relies on a threshold value, represented as θ, which determines which changes in value qualify as significant and which should be neglected, according to the trader. In this thesis, we begin by introducing our DC-based trading strategies. In the formulation of these strategies, we leveraged two main components of the DC paradigm, namely, scaling laws and indicators. We evaluated the performance of each strategy by employing a single θ. In order to enhance the performance of trading strategies, we proposed a method that utilizes a Genetic Algorithm (GA) to optimize these strategies. As part of our experimental validation, the results of the method were compared against each trading strategy to determine whether there was an

increase in performance. Additionally, we added widely adopted TA strategies from the finance field for comparison, which rely on physical time. In these comparisons, highly used performance metrics were utilized. Results indicate that, when applied to a single θ, certain strategies demonstrated profitability, while others did not. Notably, the method we introduced exhibited superior performance in comparison to both individual strategies and conventional TA strategies. Following this, to investigate whether exposing each strategy to different DC-profiled data generated by various thresholds can enhance the performance, we conducted experiments for each strategy using multiple thresholds. Then, we assessed how various DC profiled data contributed to performance improvements by evaluating each strategy's performance relative to the previous stage. The results at this stage show that using multiple θ improved the performance of certain strategies compared to testing with a single θ. At the final stage, we performed a more fine-grained optimization via GA, which simultaneously employed these strategies with distinct DC-profiled data, each characterized by varying θ. For the final experimental validation, we compared the performances of the previous two stages with this one. In doing so, we again included widely adopted TA strategies from the finance field, which rely on physical time. The results in this final stage demonstrated that the method, which combines multiple strategies and thresholds, not only improved the performance metrics from the previous two stages but also outperformed the TA strategies.

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Chapter 1

Introduction

In this chapter, a fundamental introduction to the research conducted for writing this thesis is provided. As an overview, we begin the discussion by addressing how financial market participants base their decisions on predicting future prices. Subsequently, we will briefly delve into problems that the techniques they use can potentially lead to. We will then discuss how, with a different paradigm, we have introduced a unique perspective in this thesis. The following section outlines the research objectives, and then we provide information about the structure of the thesis in the next section. Finally, we show the publications that preceded the chapters of this thesis.

1.1 Overview

In this thesis, we view "finance" as the mathematical foundation that underlies economical decision-making. Agents that are involved in this area can vary from a "novice" trader to a central bank manager. The aspiration that brings all these different participants of markets together is to foresee the implications of the decisions that are being taken. From the perspective of a novice trader, two main techniques are used for forecasting: Fundamental Analysis (FA) and Technical Analysis (TA). These techniques rely on physical time, which necessitates experiments to be guided by the selection of intervals in the data. However, this opens a possibility of specious outcomes, for instance, the selection of a daily closing price rather than a 5-minute data would neglect some important events on that day. Therefore, we are employing the event-based paradigm, namely Directional Changes (DC), which involves the transformation of physical time into events. In DC, data is recorded whenever there is a price change that exceeds a predefined threshold, denoted by θ.

Research in DC has primarily focused on two aspects: (i) the identification of indicators, which help orient new users, and (ii) scaling laws, demonstrating consistent quantitative relationships between two features in empirical studies. These aspects have guided our focus on trade strategy generation. It is worth noting that we found TA is more accessible for novice traders compared to FA. Hence, the cornerstone of our thesis revolves around the development of DC-based strategies, which operate in a manner reminiscent of strategies based on TA or those with "TA-like" characteristics.

In our contribution chapters, we focus on strategies generated from DC. Initially, of the eight strategies developed using scaling laws or indicators from the DC approach, six are uniquely implemented by us. The other two, though seemed in the field, have distinct implementations compared to existing literature. These strategies were primarily tested under a specific θ. Each strategy operates at a given time based on three recommendations: "Sell", "Buy", or "Hold". At this stage, our aim was not only to evaluate the performance of each strategy individually but also to achieve higher performance through their combined contributions. Therefore, we implemented the Genetic Algorithm (GA) as a weighting mechanism in our model.

By using the fundamental feature (fitness function) employed in the GA's evolutionary process as our performance metric, we aimed to find the optimal weights for the individual strategies that would yield higher performance at the end of the evolutionary process. At the next phase, by applying each of these strategies individually to various θs, we aim to examine the optimization of different thresholds by using GA. Finally, we explore if combining these thresholds and strategies in a model can surpass the outcomes of the previous chapters.

1.2 Research Objectives

The objective of this thesis is to develop DC-based trading strategies based on the scaling laws and indicators from the DC paradigm and improve their performance through the use of GA. Ultimately, the aim is to establish a practical framework for guiding decision-making in the stock market. Therefore, the research questions that we are aiming to answer are the following:

1. As an alternative approach to physical time, DC is an event-based approach that transforms physical time into DC events. The question in Chapter 4 addresses the development of trading strategies within this framework. Among the eight strategies created based on the scaling laws or indicators from the DC approach, six were uniquely implemented by us. The remaining two strategies, although observed in the literature in terms of their transformation from scaling law and indicator to strategy, differ in their overall implementation compared to the existing literature. Additionally, we aimed to improve the overall performance through these strategies combination. We achieved this by implementing a GA, where the chromosomes composed of the number of strategies as genes. Through the evolutionary process, the best chromosome

emerged, representing the optimal weights. We then applied this final chromosome to the Sell, Buy, or Hold recommendations provided by the individual strategies at any given time.

2. The second question addressed in Chapter 5 focuses on the potential to improve the performance of the individual strategies discussed in Chapter 4. Initially, in Chapter 4, the strategies were assessed using a specific θ. However, Chapter 5 introduces multiple θs. In this chapter, we must first note that each strategy was experimented with individually under various thresholds. By leveraging the evolutionary process of the GA again, we addressed the fact that different θs would result in varying recommendations (Sell, Buy, or Hold) from the different DC sample data. We then introduced GA as a weighting mechanism for these θs, allowing the final decision at any given time to be made based on these weights, thereby selecting one of the three recommendations.

3. The last question we will attempt to answer in Chapter 6 is whether it is possible to simultaneously optimize the information coming from strategies and θs by GA to create a superior model. To achieve this, we designed our chromosomes to encompass both the recommendations arising from different strategies and those resulting from various thresholds. This approach integrates the methodologies from the previous two chapters. Our chromosomes included a number of genes equal to the product of the number of implemented strategies and the number of implemented thresholds. This allowed us to test a model that applies the final decision at any given time based on these comprehensive chromosomes.

1.3 Thesis Structure

This thesis is organized into several chapters. Chapter 2 presents a literature review covering the types of financial analysis used in forecasting and their perspective on physical time. Then, the chapter explores the DC concept and its principles, highlighting gaps in current research. Chapter 3 focuses on the genetic algorithm, discussing its principles and application in finance. In Chapter 4, the methodology for setting up DC-based trade strategies and how GA is integrated will be explained. Results will be presented, followed by their interpretation, and finally, the chapter will conclude with a summary. Chapter 5 outlines the method for optimizing each strategy with varying thresholds, presents the results, and concludes with an interpretation of the results and summary. In Chapter 6, we will explain the simultaneous optimization of multiple strategies and thresholds, present the experimental results, and conclude with their interpretation and a summary. The final chapter, Chapter 7, summarizes the thesis, reviews contributions and limitations, and outlines future research directions.

1.4 Publications

The list of publications from the research described in this thesis in Conference Proceedings is as follows:

- Salman, Ozgur, and Kampouridis, Michael and Jarchi, Delaram, *"Trading Strategies Optimization by Genetic Algorithm under the Directional Changes Paradigm"*, 2022 IEEE Congress on Evolutionary Computation (CEC), 2022, pp. 1-8.

- Salman, Ozgur, and Melissourgos, Themistoklis and Kampouridis, Michael, *"Optimization of Trading Strategies Using a Genetic Algorithm Under the Directional Changes Paradigm with Multiple Thresholds"*, 2023 IEEE Congress on Evolutionary Computation (CEC), 2023, pp. 1-8. .

List of Works in Progress

- Salman, Ozgur, and Melissourgos, Themistoklis and Kampouridis, Michael, *"Optimization of Multi-Threshold Trading Strategies in the Directional Changes Paradigm".*

Chapter 2

Literature Review and Background

This chapter examines the evolution of financial forecasting in the literature, focusing on various approaches and their prominent theoretical perspectives. It discusses the use of physical time as data in these approaches. Additionally, it will explore how the use of Directional Changes (DC), as a complementary method to physical time data commonly used in these approaches, can lead to insights. The chapter concludes by identifying gaps in existing literature related to these aspects, followed by a summary.

2.1 Financial Forecasting

By definition, a forecast means a prediction of future events. From a financial perspective, we observe two prominent ways in which this can be interpreted in the context of the stock market. The first approach involves using companies' accounting information, such as balance sheets, income statements, and cash flow statements, to predict the value of a stock (Vanstone & Finnie 2009). The second approach involves using historical prices in the market, often referred to as physical time data in the literature, to predict future movements. This approach relies on the belief that past price patterns can indicate future directions and is graphically displayed (Murphy 1999). Both approaches have a common objective, with the difference lying in the information set used for forecasting.

Respectively to the definitions, in the literature and *the traders' world*, the former approach, namely *Fundamental Analysis* (FA), has a long history and relies on a wide range of information sources, from company financial statements (Abarbanell & Bushee 1997) to macroeconomic variables (Bhargava 2014). The latter approach, namely *Technical Analysis* (TA), can even be traced back to as early as 1882 as Murphy (1999) highlighted, however, it has gained widespread acceptance among regulators and the academic community in recent times. The TA forecast primarily relies on historical price records. In addition to these two main analysis methods, one other method that has recently gained interest is *Sentiment Analysis* (SA), which we would like to briefly mention as well.

As Anbalagan & Maheswari (2015); Ghaznavi et al. (2016) pointed out, the FA centers around the evaluation of the underlying company rather than the stock itself. Therefore, it poses challenges for novice traders with limited knowledge due to the extensive information required. Nevertheless, this does not alter the fact that it serves as an effective predictor of stock price movements (Rather et al. 2015; Ballings et al. 2015; D. Kumar et al. 2016; Zhang et al. 2018; Cao & You 2020). In contrast, TA, practical due to its reliance on market price data, demands inferences from limited information but plays a crucial role in market predictions when used effectively (Wang et al. 2012; Rather et al. 2015; Agarwal et al. 2017; Zhou et al. 2018; Nti et al. 2020). SA primarily uses "news sentiment" from social media and articles (X. Li et al. 2014), classifies sentiments to make stock trade decisions, categorizing opinions as "positive" or "negative" (X. Li et al. 2020).

The predictive capabilities of these methods have been examined in the literature, and three significant theoretical perspectives exist. The first is the *Random Walk Hypothesis* (Fama 1995), which proposes that asset prices in financial markets exhibit a behavior akin to that of a random walk. The second is the *Efficient Market Hypothesis* (Fama 1970), which asserts that asset prices incorporate all available information. Both of these theories, within their definitions, argue that FA and TA lack predictive power in the stock market. The final theory is the *Adaptive Market Hypothesis*, which asserts that stock prices are predictable, and it is possible to generate profits from predictive power of these methods (A. Lo 2017).

This chapter further explores financial forecasting methods in Section 2.2, including a detailed discussion of the earlier-mentioned theories. It also examines the challenges posed by the reliance on physical time data in these methods. Section 2.3 introduces alternative approaches that can be employed instead of using physical time data. Finally, Section 2.4 offers a thorough review of literature related to the Directional Changes paradigm.

2.2 Synopsis of Financial Analyses and Physical Time Data

Over the recent decades, financial forecasting in the context of stock investments has witnessed substantial advancements, particularly in terms of return and risk management. The seminal work of Markowitz (1952a) marked a pivotal moment in the field, and sparked research in creating profitable portfolios for investors while also managing risk. Henceforward, forecasting stock returns for traders has heavily revolved around the two major approaches previously mentioned: Fundamental Analysis and Technical Analysis. In more recent times, with the advancement of Natural Language Processing (NLP) (Chowdhary & Chowdhary 2020), Sentiment Analysis has emerged as a new method that has gained popularity in financial forecasting.

From a trader's perspective, both Fundamental and Technical Analysis serve as key decision-making tools for stock market profits, yet they differ in operation, execution methods, time frames, and tools used (Petrusheva & Jordanoski 2016). In the upcoming Sections 2.2.1, 2.2.2, and 2.2.3, both these analysis methods and the Sentiment Analysis method will be covered comprehensively.

2.2.1 Fundamental Analysis (FA)

FA can be regarded as a more theoretical approach since it aims to ascertain the underlying intrinsic value of a security. Intrinsic value represents an asset's *fundamental worth*, considering its underlying characteristics, financial performance, and economic fundamentals, rather than relying solely on its market price[1] (Mensah et al. 2022). Financial economists widely agree that a stock's intrinsic value aligns with the present value of its expected future cash flows for common shareholders, based on presently available information (Lee et al. 1999). In the literature, methods that derive trading decisions from the present value of future cash flows are commonly referred to as *Present Value Models* (Campbell & Shiller 1987). The other two approaches are *Asset-Based Valuation Models*, and *Multiplier Models* as shown in Figure 2.1. Trading decisions are made by comparing intrinsic values to market

[1]The market price represents the prevailing price at which an asset or service is available for purchase or sale

prices. This yields three possibilities: *undervalued*, *overvalued*, or *fairly valued*. For instance, a stock priced at \$10 with an intrinsic value of \$15 is considered undervalued, suggesting a buying opportunity. In essence, FA informs trading decisions by providing a basis for comparing intrinsic and market values. While there are many models to determine intrinsic value (Pinto 2020), our thesis primarily focuses on the most commonly used ones, as FA is not our central subject.

The *Dividend Discount Model* (DDM) calculates a stock's present value by summing all its future dividend payments, discounted to their present value, considering the time value of money (Farrell Jr 1985). *Preferred Stock Valuation* estimates the value of preferred stock[2] by discounting its future dividend payments at a required rate of return[3]. This is similar to valuing perpetuity, as preferred dividends are typically fixed and paid indefinitely (Emanuel 1983). *The Gordon Growth Model*, a DDM variant, assumes constant dividend growth, ideal for stable-growth companies (Gordon 1962). *Multistage Discount Models*, an extension of DDM, accommodate varying dividend growth rates in different phases before stabilizing. Asset-based company valuation estimates fair values of the company's assets and liabilities (Coulon & Coulon 2022). *Comparables Method*, under the Multiplier Models, essentially involves comparing relative values that are estimated using price multiples. These price multiples are ratios combining a company's share price with particular per-share financial metrics (Liu et al. 2002; Holthausen & Zmijewski 2012). Finally, *Enterprise Value*, considered the takeover value, sums market capitalization[4], preferred stock, and debt values, minus cash and investments.

However, these methods have their limitations. Present value models relying on

[2]Preferred stock is a type of equity, often non-voting, with priority over common stock for receiving dividends and the company's assets in case of liquidation (Linn & Pinegar 1988).

[3]The required rate of return is the minimum return an investor demands for owning a company's stock.

[4]Market capitalization is the total value of all outstanding shares (Reinganum 1999).

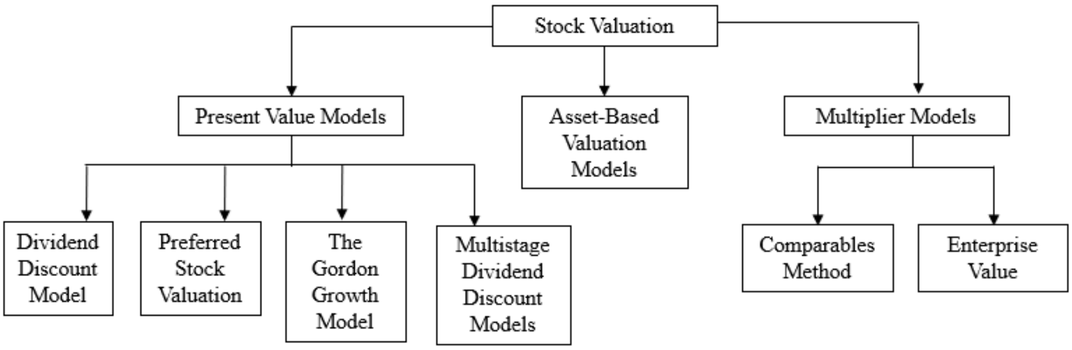

Figure 2.1: Classification of stock valuation methods

dividend assumptions are subject to personal biases. Asset-based models may omit intangible assets[5]. The Comparables method can mislead if firms in the comparison differ significantly. Enterprise value oversimplifies by ignoring sector-specific risks. For example, it may not account for long-term outcomes arising from environmental, social, and governance factors. Additionally, as previously mentioned, it is calculated based on a few main elements, which means it cannot consider the future profits that an intangible asset, such as a patented product, might generate. But more importantly, the most crucial source of information in the use of each of these methods is still the financial statements of the examined stock. For instance, the future potential cash flows are contingent upon opinion-based expectations (De La O & Myers 2021), which eventually raises questions about human errors in interpreting these expectations. Individual traders, the focus of our thesis, often rely on financial statements (Lawrence 2013), which are released quarterly (Ou & Penman 1989). However, the potential impact of subjectivity in financial data, whether deliberate manipulation seen in the Enron Scandal[6] (Rezaee 2005; Vogel 2001) or unintentional

[5] An intangible asset is characterized by its lack of physical presence, such as a patent, or trademark (Choi et al. 2000)

[6] Mark-to-market accounting, seen in the Enron Scandal, updates asset or liability values to match current market prices (Allen & Carletti 2008). This adjustment ensures financial statements reflect real-time values, capturing potential gains or losses from selling assets or settling liabilities at prevailing market rates.

errors (Papik & Papikova 2020), can adversely impact traders. The next section will discuss TA's benefits and drawbacks.

2.2.2 Technical Analysis (TA)

As Brown & Jennings (1989) notes, TA uses historical stock prices to predict future prices and guide trading decisions. Its roots trace back to the late 17th century when Joseph de la Vega first attempted to forecast future prices from historical patterns, as highlighted by A. W. Lo & Hasanhodzic (2010). TA is based on three key propositions: (i) prices are influenced by supply and demand, (ii) causality links price changes to supply and demand shifts, and (iii) prices can be represented using charts and technical tools. These tools can be framed by two subjects; chart patterns, and technical indicators as seen in Figure 2.2.

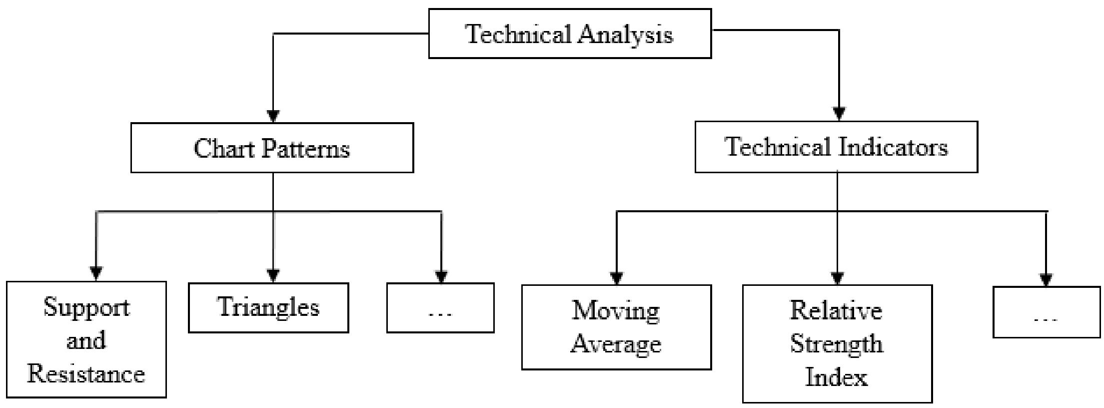

Figure 2.2: Classification of technical analysis tools

Before delving into chart patterns and technical indicators, it is crucial to address the concept of a *trend*. Trends are driven by herd behavior among market participants and typically exhibit persistence over time (Edwards et al. 2018). It signifies a consistent price change in one direction. A rising trend (resp. falling trend), highlighted with a blue dashed line in Figure 2.3, is characterized by a series of progressively higher low prices (resp. successively lower high prices) (Achelis 2001). Here, we have focused on TA concepts relevant to our thesis. Moving forward, we will elaborate on the two key tools in TA: *chart patterns* and *technical indicators*.

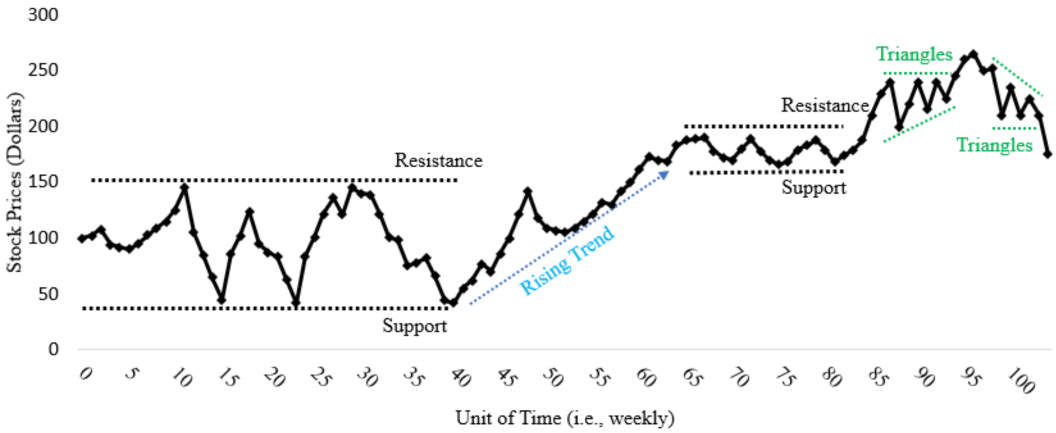

Figure 2.3: Hypothetical weekly stock price

Chart patterns are formations that manifest in price charts, resulting in giving a recognizable silhouette (Kamich 2009). Key concepts include *support* and *resistance*, representing price barriers (Osler 2000; Zapranis & Tsinaslanidis 2012), as shown in Figure 2.3. Another pattern is triangles: A triangle pattern where the high and low price range narrows into a triangular shape, provide insights into future stock price directions (Hartle 2000). In ascending triangles, as illustrated in Figure 2.3 (weeks 82 to 93, green dashed line), consistent selling at a certain price level over time limits price increases. This pattern also signals growing buyer bullishness[7], with their participation at progressively higher prices to counter sell-offs[8] instead of waiting for further price declines. Chart patterns have extensive use in TA; for more information, we recommend “Encyclopedia of Chart Patterns” by Bulkowski

[7]Bullishness, or a bull market, signifies a period of continuous and sustained asset price increases.
[8]A sell-off occurs when a large amount of stock is sold quickly, leading to a rapid and significant price drop.

(2021).

Technical indicators, metrics derived from price data, are used to forecast price changes, often reflecting supply and demand dynamics (Achelis 2001). Indicators are classified into "price-based indicators", "momentum oscillators", and "sentiment indicators" (Fang et al. 2014; Cohen & Cabiri 2015; Feng et al. 2017). However, to stay within the scope of our thesis, we will provide explanations for some of the commonly used ones. Before introducing our indicators, it is essential to emphasize that these indicators are predominantly centered around the identification of trend, which is previously discussed.

Table 2.1: TA indicators, and their insights in forming trade decisions

Indicator	Description and Trading Strategy
Average Directional Index (ADX)	Measures trend strength and direction, aiding in trading decisions by assessing trend strength and potential continuity.
Aroon (Ar)	Comprises by *Aroon up* and *Aroon down* indicators, link the duration between highs and lows. This link's crossover signals potential trend reversals.
Commodity Channel Index (CCI)	Identifies cyclical trends in commodities (Commodities include interchangeable basic goods like grains, gold, oil, and natural gas) and stocks. In trading, used to spot overbought/oversold conditions and potential trend reversals.

Continued on next page...

Indicator	Description and Trading Strategy (Continued)
Moving Averages: Simple Moving Average (SMA); Exponential Moving Average (EMA)	Reveal trends by averaging prices over time, assisting in identifying trend direction and potential reversal points via crossovers and divergences.
Moving Average Convergence Divergence (MACD)	Shows the difference between the MACD line and the signal line. Used in trading for identifying trend reversals and momentum.
Relative Strength Index (RSI)	Measures the magnitude of price movements; and identifies overbought/oversold conditions. In trading, used to spot potential reversals by comparing current and historical strengths/weakness.
Williams %R (Wr)	It is a momentum indicator that assesses the position of the closing price relative to the high-low range within a specified time frame.

Referencing insights from Table 2.1, here, we will briefly explore the indicators that are used in our benchmark strategies' in this thesis. The Moving Average (MA) calculates a stock's average closing price over a specific period, smoothing short-term volatility and clarifying trends (Chiarella et al. 2006), and is foundational for many indicators (Zhu & Zhou 2009). Chapter 4 will detail the mathematical framework of the indicators used to construct our benchmark trading strategies. Briefly, MACD is used for analyzing trend direction and duration by comparing two moving averages. ADX measures trend strength, with higher values indicating stronger trends and lower values suggesting weaker trends or trading ranges. Ar helps in assessing the strength and direction of a trend. CCI identifies emerging trends and signals extreme conditions, particularly useful for detecting overbought and oversold markets. EMA provides a more nuanced trend detection through a weighted average of recent prices. RSI quantifies the pace of price movements, indicating overbought or oversold conditions. Wr is used to identify these market conditions and signal potential reversals. As previously mentioned regarding chart patterns, presenting a comprehensive list of technical indicators is outside the scope of this thesis. However, for a more in-depth examination of the trade strategies that traders can build on these indicators, we would like to refer them to "Beyond Technical Analysis: How to Develop and Implement a Winning Trading System" by Chande (2001).

It is important to underscore that employing TA or FA analysis methods is a viable approach for a trader. Despite their perceived competition, as indicated in Krantz (2023); Rockefeller (2019), it is evident that financial practitioners utilize both, as highlighted by Bettman et al. (2009). However, criticisms are observed in the literature regarding the utilization of both methods. On the TA side, first criticism is the evaluation of the formed patterns on a universal scale. As Kai Jie Shawn et al. (2016) pointed out, the effectiveness of specific cloud charts in the Japanese market may not be replicated in another market. In other words, the identified patterns might be geographically specific and may not be reproducible in different markets. Secondly, as Sehgal & Gupta (2007) highlighted, during an overall market downturn in the Indian stock market, TA strategies fail to outperform the Buy and Hold strategy. However, during an overall market upturn, these strategies can have a significant impact. On the FA side, as the limitations that are discussed in Section 2.2.1, such as assumptions in present value models, preference influence, omission of intangible assets in asset-based models, and the potential for misleading comparables, the primary information source for these methods remains the financial statements of the analyzed stock, which is susceptible to human errors.

Therefore, we consider that the limitations of FA for a novice trader outweigh the limitations that can arise from TA. As a result, we have heavily focused on TA in the financial forecasting literature. Hence, our DC-based trading strategies mainly resemble TA-like strategies. From TA perspective, the advantages can be summarized as follows: (1) the historical data is readily accessible, facilitating the analysis of past price movements and the identification of patterns that may offer insights into future price movements; (2) TA tools are user-friendly and approachable, even for traders who may not possess an extensive understanding of financial statements or other fundamental data; (3) TA relies on market prices, which can provide valuable insights into market sentiment[9].

Lastly, we briefly discuss the types of data used in FA and TA. FA utilizes a wide range of data sources, from macroeconomic indicators to financial statements, and may include specific surveys, like those assessing purchasing behaviors in a tire company. TA, on the other hand, primarily relies on price data based on a *physical time* scale (e.g., weekly, daily, hourly closing prices of a stock). A detailed review of physical time, its limitations, and alternative approaches is covered in Section 2.2.5.

The following section provides a concise overview of sentiment analysis in financial forecasting, and how it integrates with TA and FA.

2.2.3 Sentiment Analysis (SA)

The effectiveness of sentiment analysis is greatly influenced by advancements in Natural Language Processing (NLP), as emphasized by Chowdhary & Chowdhary (2020). An early application of NLP in the scientific field, particularly in medical

[9]Market sentiment refers to the collective attitude of traders toward a particular stock, sector, or the broader financial market (Blasco et al. 2012).

informatics[10], is highlighted by Nadkarni et al. (2011). This research demonstrated NLP's utility in processing complex biomedical language from extensive handwritten records, to create innovative solutions for data processing in various domains. Subsequently, SA's significance in financial forecasting has grown, as shown by Mittal & Goel (2012). This research analyzed "Twitter" to classify market sentiment into "moods" like "calm," "happy," and "alert" using NLP, applying these classifications to stock predictions. Similarly, Rao et al. (2012) demonstrated the early use of SA in classifying sentiments as "positive" or "negative" and using these to forecast stock market trends. Both studies underscore SA's role in market sentiment analysis and its application in financial forecasting.

SA has been used in conjunction with FA and TA methods to enhance analysis. As discussed earlier, FA relies on financial statements, particularly 10-K filings[11], to determine a stock's intrinsic value. SA intersects with FA by classifying the tone of these filings as "negative" or "positive" (Loughran & McDonald 2011), aiding in understanding their impact on stock returns. Additionally, the analysis of management tone in these filings within a litigation[12] context (Loughran et al. 2009) demonstrates how SA can support FA predictions. When SA and TA are utilized together, SA can generate hybrid models using indicators employed by TA. These models enable the tracking of sentiments derived from news sources (Vargas et al. 2017), while also capitalizing on the predictive power of the TA indicators. Some research has also concurrently used SA and TA in trading research (Christodoulaki et al. 2022; Christodoulaki & Kampouridis 2023), showing the effectiveness of these combined analysis methods.

[10]Individuals who use their expertise in data management to improve healthcare processes.

[11]10-K filings are extensive annual reports that publicly traded companies are obligated to submit to the U.S. Securities and Exchange Commission.

[12]The process of taking legal action by the company or directed to the company itself.

Overall, we can briefly state that while SA in stock predictions has garnered recent attention, simultaneous advancements in NLP research as we see in Chowdhary & Chowdhary (2020) suggest its growing relevance in the future. In the next section, we will discuss two theories that challenge the notion of price predictions in the stock market being impossible through both fundamental and technical analysis, and we will also cover another theory that offers a different perspective.

2.2.4 Theories on Stock Prediction

Here, we will focus on theories that are very predominant in stock prediction. While the reasons behind the first two theories differ, they both propose that FA and TA cannot predict future price movements, which ultimately cannot lead to profits. In contrast, the third theory suggests that profits can result from the predictive power of stock prices.

Random Walk Hypothesis (RWH)

The RWH posits that stock market prices move randomly, making consistent prediction impossible (Fama 1965). It asserts that past price movements do not offer a basis for predicting future movements, implying that the stock market's random behavior makes it impractical to outperform the market using TA (Pinches 1970).

Nevertheless, the increasing globalization of financial markets has intensified interest in emerging markets. Research by Urrutia (1995) has provided evidence that developing stock markets have exhibited predictability for specific reasons, thus posing a challenge to the RWH. Meantime, similar findings apply to the Chinese stock market as shown by Darrat & Zhong (2000).

RWH also challenges the notion that expert fund managers can forecast market trends and gain excess returns. It advocates that, since stock price movements are unpredictable, investors are better served by investing in market index[13] funds (Fama 1995).

Efficient Market Hypothesis (EMH)

The seminal work by Fama (1970) is still a cornerstone of modern financial theory, which defines *efficient* market as one where prices "fully reflect" available information. Among the three levels of efficiencies – *weak*, *semi-strong*, *strong* – as emphasized by Fama (1970) each of them categorized by the degree to which stock prices incorporate available information. In the weak form, the EMH posits that all historical trading information is already reflected in stock prices. Consequently, TA is considered ineffective. The semi-strong form states that stock prices swiftly adapt to new publicly available information, rendering it impossible to attain excess returns through FA, which encompasses the evaluation of financial statements. In the strong form, the EMH claims that stock prices encompass all information, including both publicly available and private, insider information. According to this perspective, even individuals with material non-public information cannot consistently attain excess returns. The premises that EMH ground its hypothesis are: i) all information is accessible to every trader; ii) the traders are rational; iii) the market is rational; iv) information transfer costs are uniform for all participants; v) there are no taxes; vi) transaction costs are absent.

However, skepticism towards EMH has grown (Malkiel 2003; Sewell 2011), particularly its claim that profiting from financial forecasting is impossible. Research has demonstrated the feasibility of earning profits (Rossi et al. 2018; Leković 2018), challenging EMH. Critics pointed to anomalies in the market (Yalçın 2010), such

[13] An index fund is designed to replicate or track the constituents of a specific financial market index.

as market bubbles and crashes (Malkiel 2011), and behavioral economics insights (Zafar 2012), which indicate that markets, or also traders (Ying et al. 2019) are not always rational or efficient.

Adaptive Market Hypothesis (AMH)

The AMH, introduced by A. W. Lo (2004), offers a unique perspective on market efficiency. It blends EMH principles with behavioral economics. Unlike EMH's static view of market efficiency, AMH considers it dynamic and evolving with market conditions and adaptive behaviors of participants. It suggests that trading decisions reflect a mix of rational and irrational elements, a notion supported by empirical studies in cryptocurrency markets (Chu et al. 2019). AMH acknowledges that human behavior can lead to market anomalies such as bubbles and crashes, unexplained by the EMH. Moreover, if the market were entirely efficient, there would be no incentive for professionals and investors to engage in trading activities (Grossman & Stiglitz 1980).

2.2.5 Physical Time

The physical time scale used in TA should be perceived as snapshots taken at a chosen frequency on a discontinuous scale. Physical time relies solely on interval-based data, such as daily data depicting the closing price for each day. However, this method risks missing unexpected news events or price fluctuations occurring between intervals, potentially leading to losses. For instance, for daily stock price data, it would be profiled at 252 points in one year. However, this episodic style neglects the important events, or price changes that occur between two intervals. As an illustrative example, consider the events of October 26, 2008, (Gow 2008), when Volkswagen experienced a "short squeeze phenomenon[14]" During this period, Volkswagen's stock price skyrocketed from roughly 200 Euro per share to over 1,000 Euro per share, marking an astounding surge of more than 400% within a single day. However, following the intervention of the firm's, price reverted to a range more closely aligned with its initial levels before the announcement before the day ends. Thus, if we wanted to make a forecast using a firm's daily price data, we would not be able to observe the fluctuations in price.

An alternative approach to the fixed time interval sampling method is event-based data sampling, which involves the sampling of data based on the occurrence of significant events in the market. The underlying concept is to record noteworthy market events that represent substantial price movements which would typically go unnoticed by traditional physical time sampling methods. The next section will cover these alternative approaches.

2.3 Alternative Approaches for Summarizing Data

In the stock market, the seminal paper authored by Mandelbrot & Taylor (1967), which examines the changes in prices at fixed intervals based on a certain number of transactions, suggested a continuity in prices rather than discontinuity (as in physical time), paving the way for future research. From that point on, studies focusing on event-based approaches that take into account this continuity increased.

[14] A short squeeze is when a stock's price rises rapidly because short-sellers, who bet on the stock falling, are forced to buy it to cover their positions, creating a surge in demand and price (Vasileiou et al. 2021).

2.3.1 Event-Based Approaches

The event-based approaches focus on identifying important events within price movements. Data in these approaches are sampled to represent discontinuous shifts in the financial market by reducing changes that are considered substantial by a trader. Various intrinsic time sampling techniques have been documented, including "important points" (Pratt 2001), "perceptually important points" (T.-l. Chen & Chen 2016), "turning points" (Yin et al. 2011), "zigzag" (Özorhan et al. 2019), and more recently, *directional changes* (Glattfelder et al. 2011a; E. P. Tsang et al. 2017; Gypteau et al. 2015; Rostamian & O'Hara 2022; S. Li et al. 2022). From the literature review, our findings suggest that among the event-based approaches, DC has received considerable attention (Palsma & Adegboye 2019). In addition to this, empirical findings in trade strategies have shown that it is possible to create profitable trading strategies (Kampouridis & Otero 2017; Adegboye et al. 2021; Kampouridis et al. 2017).

It is important to note here that, in DC, unlike physical time, time intervals are constituted by price changes. The unique feature that decides the price change to be considered significant is called a threshold, denoted by θ. This allows traders to assess significant events according to their perceptions. In the upcoming section, we will comprehensively explain DC.

2.3.2 Directional Changes (DC)

In this section, we will introduce the definitions in a consistent manner with E. Tsang (2010) to maintain terminology similarity. Also, we will incorporate minor additions to their terminology which are necessary for our thesis' clear exposition.

As a preliminary introduction to more comprehensive discussions to follow, it is essential to note three critical points here: i) After utilizing the threshold parameter onto physical time data, the entire physical time data can be analyzed solely along two directions in DC, namely, *Uptrend* (UT) and *Downtrend* (DT); ii) within these trends, only two types of events are observed, a *Directional Change* (DC) event and an *Overshoot* (OS) event; iii) due to sharp fluctuations in price in different directions subsequently, not every DC should be followed by OS; it is possible to be followed by another DC in the opposite trend. In short, the DC paradigm, given physical time, can profile all data from an event-based approach perspective, as illustrated in Figure 2.4.

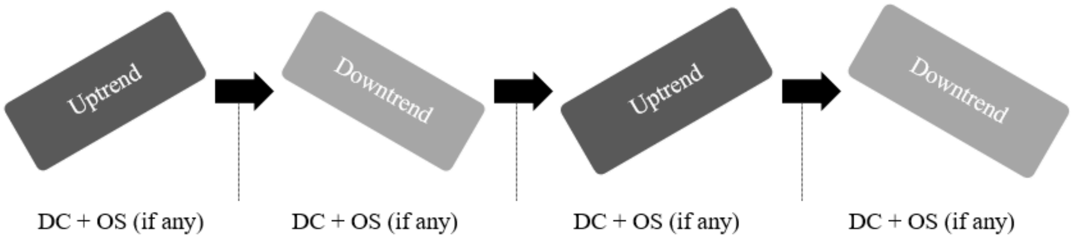

Figure 2.4: DC scheme by sequences of UT-DT-UT-DT

As E. P. Tsang et al. (2017) pointed out in their seminal work, in contrast to physical time, which samples data points at regular time intervals, the DC samples data points from their peak and trough. As mentioned earlier, the paradigm analyzes all data points by incorporating two types of events, DC and OS, and two types of trends, UT and DT. By employing a pre-determined *threshold* (percentage), it becomes possible to decompose the data using these distinct components. In a DT (resp. UT), a last low price (resp. high price) is continuously updated to the minimum (resp. maximum) of the two prices: the current price $p(t)$ and the last minimum (resp. last maximum). The last minimum and maximum in these trends are called *extremum* and are denoted by p_{ext_ℓ} and p_{ext_h}, respectively. The confirmation of a DC event in DT (resp. UT) occurs when the absolute price change between $p(t)$ and the p_{ext_h} (resp. p_{ext_ℓ}), denoted by $\Delta p := |p(t) - p_{ext_h}|$ (resp. $|p(t) - p_{ext_\ell}|$), is at least as high as the given threshold. The region between two DC events defines an OS event, which usually is of non-zero length.

Figure 2.5 demonstrates an example of the formation of consecutive DC and OS events for $\theta = 6\%$. Each data point represented on the graph corresponds to a paired combination of time-step (t) and price (e.g., point $A = (t_A, p_A) = (0, 99.9\$)$). Suppose we have a financial product whose price starts at 99.9\$ at $t = 0$ and decreases to 98\$ at $t = 1$, then to 97\$ at $t = 2$, and finally, to 94\$ at $t = 3$. Since the price change is smaller than the pre-specified value of θ, we do not consider the time interval $0 - 3$ as a DC event. Although the price decrease continues, we only update p_{ext_ℓ} (i.e., at $t = 3$, the lowest price we experienced is 94\$). At $t = 4$, the price jumps to 98\$, but again, due to not seeing the significant price change that is defined by the θ, we still can not conclude a DC event. However, at $t = 5$, from p_{ext_ℓ} to our new price, Δp is at least as high as θ. In other words, within the interval from $t = 3$ to $t = 5$, a substantial price change of 6% is observed. Thus, we can conclude that an uptrend has occurred, and it is evident that the time duration of $3 - 5$ qualifies as a DC event.

To detect the next DC event, this time we should observe a drop greater than the threshold's expected percentage. The event we are currently experiencing until this drop occurs is an OS event. Between $t = 6$ to $t = 7$, which is the first interval where we observe the price drop from $t = 5$ to $t = 9$, there is no DC event validation due to the drop being lower than θ (i.e., $|p(7) - p(6)| < \theta$). Meanwhile, p_{ext_h} keeps updating to the newest high. Therefore, when we reach $t = 9$, p_{ext_h} is at 110\$. From that point forward, we indeed observe a decrease at $t = 10$ and $t = 11$. However, these drops from the p_{ext_h} (110\$) are still not sufficient to conclude a DC event. At $t = 12$, we can observe that the required price change has occurred. Therefore, we can conclude that a DC event has taken place. Retrospectively, we also conclude that the OS in uptrend also occurred between $t = 5$ and $t = 9$. In this context, we would like to emphasize a point within the DC events profiled with the threshold $\theta = 17\%$ in Figure 2.5 (indicated by dotted lines). While we expect that DC events are typically followed by OS events, it is essential to note that this pattern may not always hold true. DC events can occasionally be followed by another DC event in opposite trend due to data fluctuations.

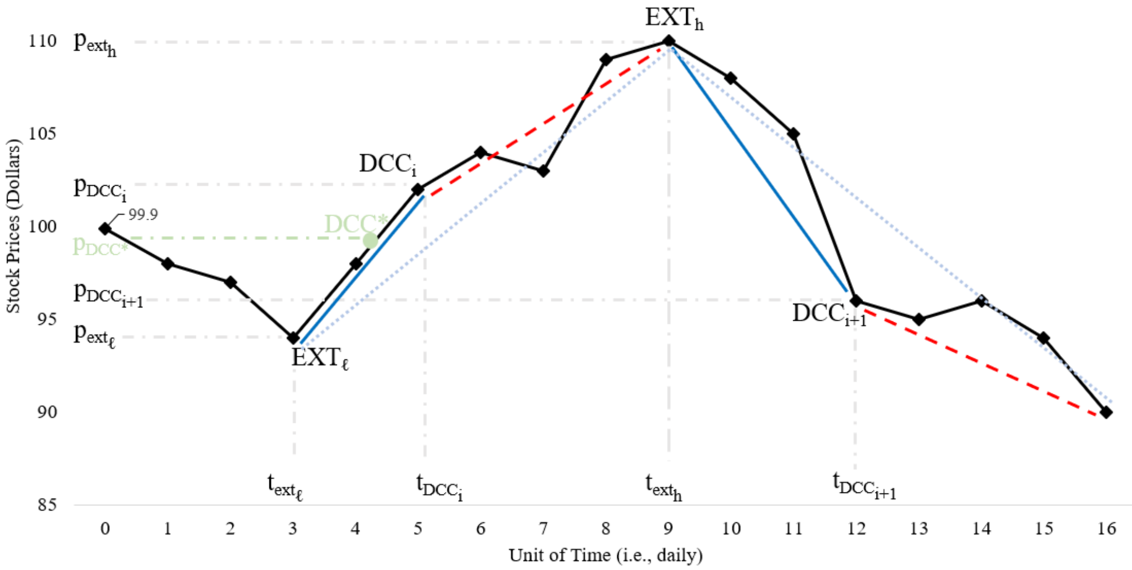

Figure 2.5: Transformation of physical time data into the DC paradigm. The solid and dashed lines represent a set of events defined by a threshold $\theta = 6\%$, whereas the dotted lines correspond to events defined by a threshold $\theta = 17\%$. The solid and dotted lines represent the DC events, while the dashed lines indicate the OS events. For the threshold $\theta = 6\%$, there are two DC event confirmation points, at times 3 and 10. An uptrend takes place between the two extreme points, EXT_ℓ and EXT_h, which are confirmed retrospectively at their subsequent confirmation points, DCC_i and DCC_{i+1}.

Crucial to the definition of directional changes, are the notions of the extremum points (see EXT_ℓ, EXT_h in Figure 2.5), and the *directional change confirmation point* DCC_i. As previously noted, an extremum point refers to the lowest price (resp. high price) in a DT (resp. UT). This point is continuously updated to reflect the minimum (resp. maximum) value between two prices: the current price and the last recorded minimum (resp. last maximum). A confirmation point is a specific point in time at which one confirms the occurrence of a DC event. The interpretation of these points will be useful in our strategies' description in Section 4.2. Another important observation is that Δp can potentially be bigger than the minimum price change (determined by θ) required to identify it as a DC event. To account for this, the concept of a *theoretical confirmation point*, $DCC*$, is introduced. The theoretical confirmation point represents the hypothetical minimum or maximum price level required to confirm a directional change event, either a UT or a DT. It is important to note that the theoretical confirmation point may not actually exist or be encountered in the real market under most circumstances. Instead, it serves as a theoretical reference point used for analysis. This can be seen in Figure 2.5, where a price change of 5.64$ from 94$ to 99.64$, which is exactly 6% more of the price at EXT_ℓ (recall that $\theta = 6\%$ in our example) between points EXT_ℓ and $DCC*$ is sufficient to confirm a DC event. The notation P_{DCC*} signifies the theoretical price that would be enough to conclude a DC event. Let us finally note that, as previously emphasized, DC paradigm encapsulates the entire given data through trends, namely, UT and DT. As an example from Figure 2.5, the boundaries between EXT_ℓ and EXT_h represent UT, and from EXT_h to the upcoming EXT_ℓ will be DT. Algorithm 1 presents the pseudocode for generating DC events, which first appeared (using different notation) in (M. Aloud, Tsang, et al. 2012).

Algorithm 1 Pseudocode for generating DC events given threshold (θ).

Require: Initialise variables (event is Downtrend event, $p_{ext_\ell} = p_{ext_h} = p(t)$, $t_{DC_{duration}} =$ physical time spent in a given DC event, $t_{DCC} =$ specific DC confirmation time point in any trend

if Trend is Downtrend **then**
    if $p(t) \geq p_{ext_\ell} \cdot (1 + \theta)$ **then**
        event $\leftarrow$ Uptrend
        $p_{ext_h} \leftarrow p(t)$ ▷ Price at the DC confirmation point for an Uptrend
        $t_{DCC} \leftarrow t$ ▷ End time for a Downtrend
        $t_{ext_\ell} \leftarrow t - t_{DC_{duration}}$ ▷ Start time for a Uptrend Overshoot Event
    else
        if $p_{ext_\ell} < p(t)$ **then**
            $p_{ext_\ell} \leftarrow p(t)$ ▷ Price at start of a possible Uptrend
else
    if $p(t) \leq p_{ext_h} \cdot (1 - \theta)$ **then**
        event $\leftarrow$ Downtrend
        $p_{ext_\ell} \leftarrow p(t)$ ▷ Price at the DC confirmation point for a Downtrend
        $t_{DCC} \leftarrow t$ ▷ End time for a Uptrend
        $t_{ext_h} \leftarrow t - t_{DC_{duration}}$ ▷ Start time for a Downtrend Overshoot Event
    else
        if $p_{ext_h} > p(t)$ **then**
            $p_{ext_h} \leftarrow p(t)$ ▷ Price at start of a possible Downtrend

In the upcoming Section 2.4, we will begin by reviewing the literature up to the present day. In that part, we will also examine the DC paradigm from the perspective of employing trading strategies that are already based on DC.

2.4 Relevant Literature in DC

The origins of the DC paradigm can be traced back to the work of Guillaume et al. (1997), which aimed at analyzing trend behavior. Since then, research in this field has revolved around three primary aspects: i) *scaling laws*; ii) *indicators*; iii) *trading strategies* based on the previous two aspects.

In the remainder of this section, we will delve into the two key components of these trading strategies, scaling laws and indicators, in Sections 2.4.1 and 2.4.2, respectively. Lastly, in Section 2.4.3, we will delve into the trading strategies that have been previously employed in the literature and are founded on the principles of DC.

2.4.1 Scaling Laws

Scaling laws refer to the functional relationships that exist between two physical quantities that scale together over a significant interval. Specifically, in the DC paradigm, scaling laws are used to establish mathematical connections among price movements, duration, and frequency. Early research findings in this area have yielded a deeper understanding of foreign exchange market behavior. Specifically, among the 13 pairs studied, 12 scaling laws have been identified and exposed to the research community by Glattfelder et al. (2011b). One of the significant findings from this research pertains to the duration of events and its link with the mathematical relationships between DC and OS (see further discussion in Section 4.2).

Following these initial identifications, M. Aloud et al. (2013) identified 4 scaling laws within the foreign exchange markets. Subsequently, in M. E. Aloud (2016b), 5 more scaling laws were identified with stock market instruments. Later research by E. P. Tsang et al. (2017); E. Tsang & Chen (2018) identified five additional scaling laws. These latter studies explored the use of DC in equity products, thereby broadening the applicability of these scaling laws to a wider range of financial instruments.

2.4.2 Indicators

The DC paradigm has been enhanced by integrating indicators, which are statistical metrics used for analyzing conditions and forecasting financial trends. In the context of Technical Analysis, these indicators are mathematical calculations based on a security's price or volume, aimed at predicting future prices. In the realm of DC, while the calculations are based on the metrics derived from DC, the objective remains the same. For this purpose, E. P. Tsang et al. (2017) were one of the first to explore the use of four indicators, and subsequent research by E. Tsang & Chen (2018) added even more indicators to the area. Conceptually, the thesis of Tao (2018) can be thought of as a dictionary of DC-based indicators, providing information on how to extract pattern-based data from the paradigm itself.

2.4.3 Trading Strategies

Recent advancements in trading strategies have increasingly utilized findings from the DC paradigm. Initially, researchers developed trading agents to mimic market traders in response to the rise of high-speed automated algorithms in the financial landscape. To this end, initial efforts were made to model DC trading activity using foreign exchange market data by M. Aloud, Fasli, et al. (2012), subsequently, enhancements were made to that initial model by M. E. Aloud (2016a), which featured more dynamic systems that could react to different thresholds and achieve higher profits. Later, Bakhach et al. (2016) introduced strategies, which leverage DC-based indicators such as overshoot value, while follow-up work has further refined it by addressing its weaknesses, specifically the lack of a size management system and a risk management scheme (Bakhach et al. 2018). More recently, M. E. Aloud & Alkhamees (2021) proposed two algorithmic trading strategies by combining reinforcement learning with DC. Similarly, Rayment & Kampouridis (2023) showed that, when deep reinforcement learning was applied on top of the DC strategy, it outperformed TA-based benchmarks in low-volatility environments.

Another key aspect of DC-based trading strategies is the use of classification tasks. Adegboye et al. (2021) have demonstrated that adding classification tasks has helped traders to identify the right moments to capture the trends. In a recent research involving 20 different Forex pairs under DC, the proposed algorithm by DC trend reversion projection was shown to outperform the majority of DC and non-DC benchmarks in terms of both return and risk (Adegboye et al. 2022).

Another area within DC-based strategies is predicting trend reversal points in DC. Initially, Kampouridis & Otero (2017) attempted to estimate the length of the DC by calculating the average length of DC for each dataset in the training set. They then used this calculated average length as a basis for predicting when a trend would end in the test set. In the subsequent research by Adegboye et al. (2017), the authors expanded upon the work of Kampouridis & Otero (2017) on predicting the reversal of DC events. They utilized a symbolic regression genetic programming algorithm to evolve equations capable of calculating the average DC-OS event length ratio. This ratio was employed for predicting the duration of a trend. The authors identified both linear and non-linear relationships between DC and OS events, which they integrated into a trading strategy, ultimately leading to higher returns. Furthermore, based on the observation that not every DC event is followed by its OS event within a given threshold, the authors extended their work by introducing a DC trend reversal forecasting algorithm. This algorithm combined newly added classification techniques to symbolic regression (Adegboye & Kampouridis 2021).

Overall, the findings from the previous two aspects, namely scaling laws and indicators, are already being utilized to develop trading strategies in the field, and further progress will likely be made in this area.

2.4.4 Critical Review of Literature Findings

In simple terms, a *trading strategy* is a plan designed to facilitate the buying, selling, or holding of assets such as stocks, bonds, commodities, or intellectual property, with the ultimate objective of generating profit. Incorporating these plans into forecasting involves the utilization of three methods, as observed in the literature. Primary methods include fundamental analysis, technical analysis, and emerging sentiment analysis powered by advances in NLP. From the literature, it becomes apparent that for traders with limited finance knowledge, technical analysis is user-friendly. Nevertheless, it should be mentioned that other methods have also demonstrated profitability.

Furthermore, it is crucial to recognize a limitation in these methods, which is their reliance on physical time data. To address this gap in the literature, this thesis aims to utilize an alternative paradigm to data sampling, namely Directional Changes (DC). In our thesis, we emphasize the importance of the DC paradigm in two key ways: Firstly, DC prioritizes data during more significant periods by capturing price changes as soon as they hit a predefined threshold. Secondly, DC bypasses gaps in data. The selection of time intervals may result in the omission of price changes that occur between these defined intervals (e.g., hourly, daily, or weekly). The DC paradigm addresses this limitation by focusing on changes rather than fixed time points.

From the DC literature, it is also noticeable that the strategies that have been constructed based on the DC is very limited. Firstly, mainly because the concept is relatively new and emerging in recent research. In addition to this consideration, from the perspective of a novice trader, it is important to note that DC-based strategies that can be easily implemented are also quite limited. This is in contrast to TA-based strategies, which have undergone extensive research and have been widely adopted in recent times. Therefore, our objective was to address this gap by developing trading strategies based on DC that operate in a manner similar to TA strategies.

Considering these strategies, we will also highlight another aspect that we have identified as a gap in the existing literature. It appears that there is limited integration of these strategies with an optimization process, as opposed to using individual recommendations such as Buy, Sell, and Hold. In Chapter 3, we will introduce the optimization method we have employed, specifically a Genetic Algorithm, to address this limitation. In Chapter 4, we will test the improved model using the recommendations from multiple strategies along with the introduced optimization method to fill this gap. In Chapter 5, we will explore the optimization of recommendations for different DC events by feeding them with different thresholds, a facet that has been scarcely addressed in the literature. Finally, in Chapter 6, we will investigate the contributions of both the strategies and various profiled DC events to our model, a perspective that has not been previously explored in the literature.

2.5 Summary

In this chapter, we have mainly explored two schools of thought in stock forecasting: fundamental analysis, and technical analysis. Additionally, we briefly emphasized sentiment analysis due to its recent advancements alongside natural language processing. While we have highlighted the key areas that fundamental analysis and sentiment analysis used for stock prediction, we have placed a greater emphasis on technical analysis due to its significant overlap with our research interests. Subsequently, we discussed the concept of physical time utilized by each technique and its associated drawbacks. Instead, we introduced an alternative data sampling method called Directional Changes which we also use in our thesis.

Following this, we delved into a review of the literature related to directional changes research and provided a brief overview of scaling laws and indicators, which will serve as the focal points of the upcoming chapters. In conclusion, we have highlighted the constraints identified within the existing literature. In the subsequent chapter, we will introduce the genetic algorithm, a widely employed technique for addressing optimization challenges.

Chapter 3

Genetic Algorithm (GA)

This chapter introduces the Genetic Algorithm (GA), the optimization technique employed in the next three chapters. We begin with an overview of GA's working principles and operations in Section 3.1. Then, in Section 3.2, we review the literature on GA's application as an optimization method in finance.

3.1 Overview of GA

A GA falls under the broader category of Evolutionary Algorithms (EAs). EAs are techniques inspired by Darwin's biological evolutionary theory, where the principle of "survival of the fittest" influences the formation of future generations. Because the scope of evolutionary algorithms is beyond the focus of our thesis, we would like to refer readers to "Introduction to evolutionary algorithms" by Yu & Gen (2010).

A GA operates as a local search algorithm, reflecting the evolutionary process (Holland 1992). This algorithm effectively simulates natural selection and genetic mechanisms, as illustrated in Figure 3.1. Initially, GA generates a population of potential solutions, namely chromosomes, which are typically represented as strings.

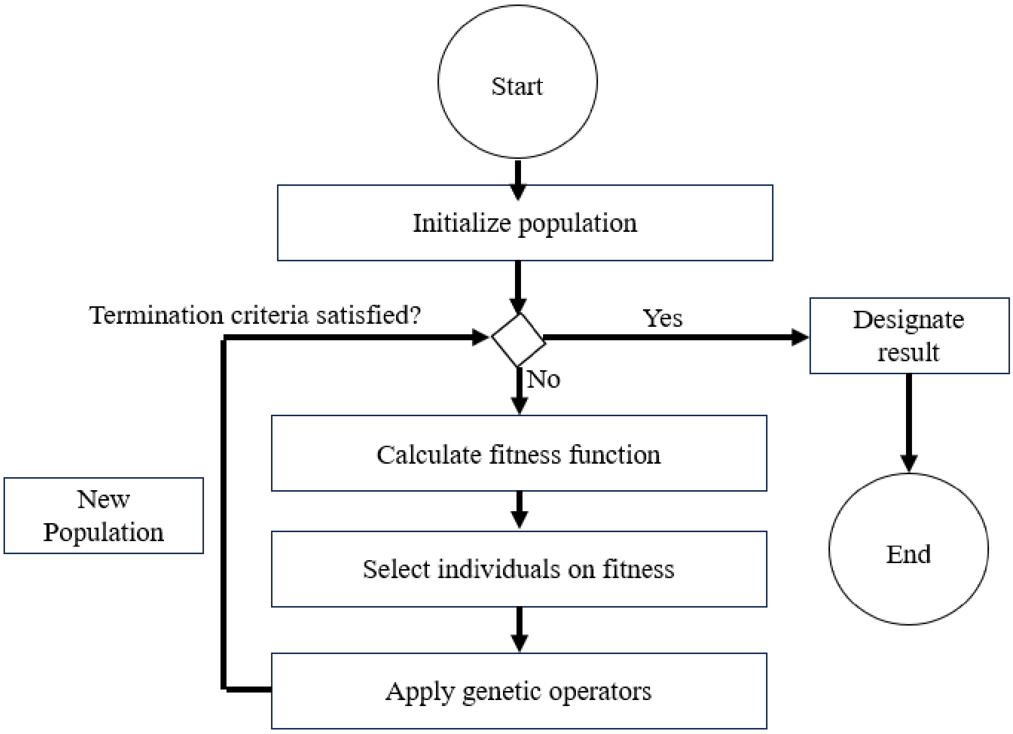

Figure 3.1: GA work cycle.

These chromosomes are produced randomly to initiate the algorithm. Subsequent to generation, each chromosome undergoes evaluation through a fitness function, which assesses the solution's quality. The algorithm then proceeds to select chromosomes for further processing based on their fitness scores. During the phase involving genetic operators, crossover and mutation are employed, leading to the emergence of new offspring. These offspring are subsequently integrated into the population, simultaneously replacing the less fit individuals. This cycle continues over several generations or until a predetermined termination condition is fulfilled.

The rest of this section details the operations fundamental to the GA. We will explore various common variations of these operations, covering population initialization, chromosome selection, crossover and mutation operators, elitism, and the GA's termination criteria.

3.1.1 Chromosome Representation

Before exploring the operations of GA in subsequent sections, this section will provide a concise overview of chromosome representation as outlined in the existing literature. In the GA, a common representation of chromosomes is in the form of an array of binary bits. In this representation, the chromosome consists of values of either 0s or 1s, as illustrated in Figure 3.1. The combination of binary values within a chromosome string determines its uniqueness, defining specific characteristics within the context of the problem addressed by the GA.

Table 3.1: Chromosome representation by binary bits with 8 genes.

0	1	0	0	1	1	0	0

Another form of representation, which is also utilized in our thesis, represents the genetic information as a string of real numbers. Each in a particular range of values depending on the problem at hand; here, their domain is $[0, 1]$. Table 3.2 shows an example of a chromosome with only eight *genes*. Variations in the values of each gene (e.g., the first gene being 0.045, the second 0.001) signify unique weightings assigned to inputs. These variations in weights allow the algorithm to explore diverse solutions, optimizing performance based on a defined fitness function.

Table 3.2: Chromosome representation by real numbers with 8 genes.

0.045	0.001	0.450	0.102	0.130	0.050	0.015	0.207

3.1.2 Population Initialization

Population initialization, while being a comprehensive research area on its own (Kazimipour et al. 2014), in this section, we will focus on three commonly used techniques in the field: i) *random initialization*, which generates chromosomes randomly in the search space, promoting diversity in the initial population (the most commonly used technique); ii) *initialization with known solutions*, which utilizes known good chromosomes to seed the initial population, guiding the algorithm toward promising areas early on; and iii) *hybrid initialization*, which combines random and known solutions, balancing exploration[1] and exploitation for effective search.

3.1.3 Selection of Chromosomes

Commonly used selection methods include: i) *Tournament selection*, which randomly selects a subset of chromosomes from the population, and picks the best among them as visualized in Figure 3.2. The best chromosome with the highest fitness is selected as the parent, which is repeated twice for two different parents. Then, the chromosomes undergo operations to create offspring in the subsequent step. This process is repeated until the new population is created. As pointed out by Miller et al. (1995), this method is straightforward and performs efficiently with large populations. It allows control over the tournament size, affecting selection pressure: larger sizes favor stronger individuals, while smaller sizes offer chances for weaker ones. However, larger tournaments may increase the risk of premature convergence. Furthermore, this method can run in parallel, making it well-suited for managing computationally intensive tasks. Algorithm 2 represents a pseudocode for the method. Notably, in our illustrations, the selection targets the highest fitness value for maximization problems. Conversely, for minimization problems, the selection would focus on the lowest fitness value.

[1] Exploration involves experimenting with new options, exploitation entails selecting the best-known option based on past experiences (Xu & Zhang 2014).

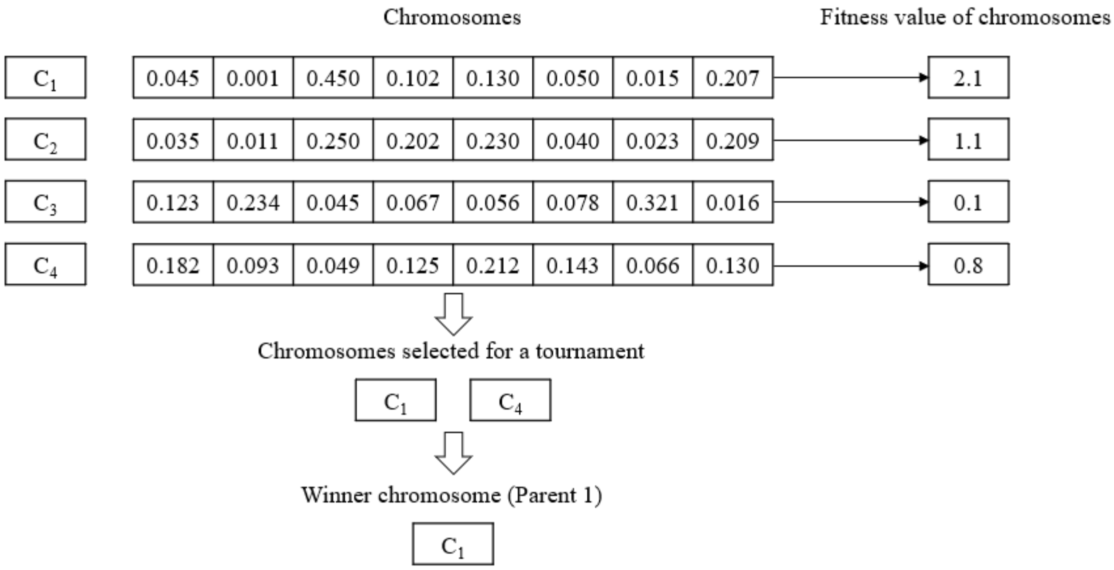

Figure 3.2: An illustration of tournament selection process. Two chromosomes are randomly selected from a pool of four chromosomes as possible parents. Among those, the chromosome with a higher fitness value is assigned as the parent chromosome. For maximization problems, the highest fitness is chosen; for minimization, the lowest.

Algorithm 2 Tournament Selection

$P \leftarrow$ population
$k \leftarrow$ tournament size, $k \geq 1$
$Best \leftarrow$ individual picked at random from P with replacement
for $i = 1$ to k **do**
    $Next \leftarrow$ individual picked uniformly at random from P with replacement
    if Fitness($Next$) > Fitness($Best$) **then**
        $Best \leftarrow Next$
return $Best$ ▷ The "Best" individual is selected as a parent

ii) *Roulette wheel* selection assigns each chromosome a portion of the roulette wheel proportional to its fitness, with higher fitness equating to a higher chance of being chosen. The limitation of this method is that it has the potential to diminish diversity when there are substantial disparities in fitness scores. This bias toward favoring the best chromosome could result in premature convergence (Zhong et al. 2005). While it increases the probability of selecting fitter chromosomes, it significantly reduces the chances of weaker chromosomes. Consequently, this attempt to balance selection may lead to reduced diversity within the population. As depicted in Figure 3.3, the selection of the third chromosome as the parent exhibits a notably low probability. Lastly, it may become computationally expensive for large populations due to the need to compute cumulative fitness.

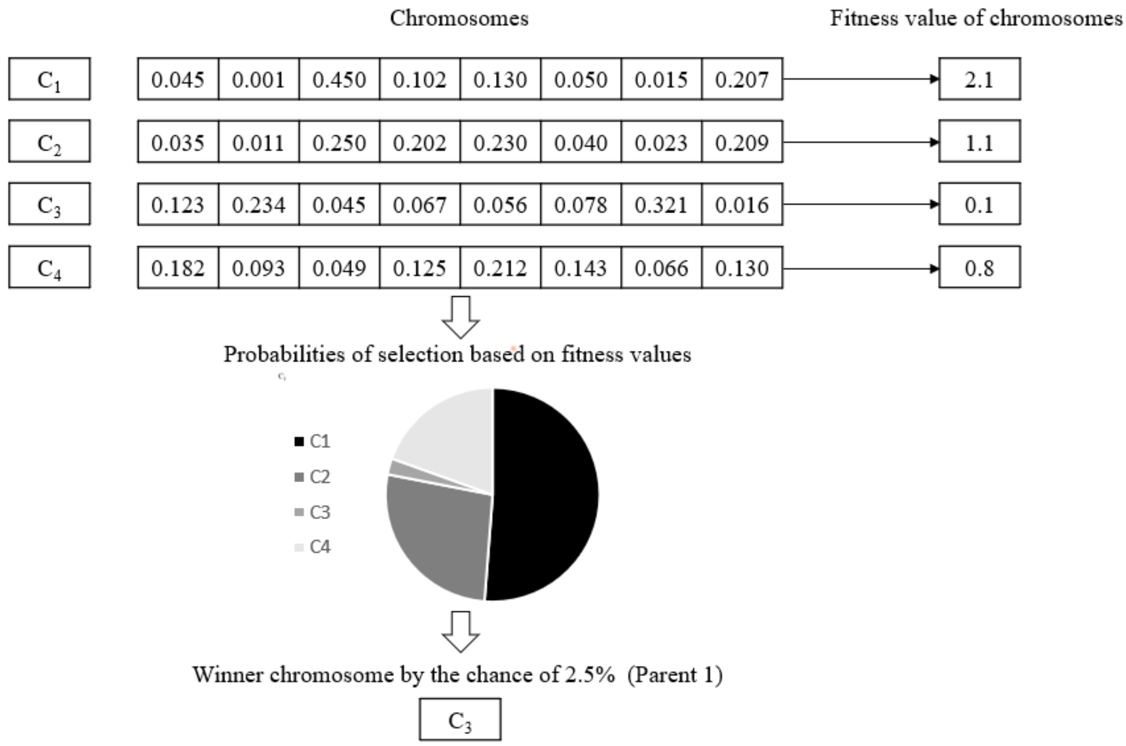

Figure 3.3: An illustration of roulette wheel selection process, where parent chromosome is selected based on its fitness value probability by 2.5%.

iii) In *rank selection*, chromosomes are first organized by their fitness rank. Unlike methods using direct fitness values, this approach bases selection probabilities on each chromosome's rank, similar to roulette selection. However, rank selection allocates probabilities linearly based on rank, not proportionally to fitness values. The probability formula, $P(i) = 2 \times (N - i + 1)/(N \times (N + 1))$, where N is the total number of chromosomes in the population, ensures linear linkage of selection probability to rank, rather than to fitness values. This method reduces the dominance of the best individuals and is less sensitive to fitness value scales. Although it may increase computational time due to the need for ranking (Shukla et al. 2015), it ensures a more balanced selection. As illustrated in Figure 3.4, a chromosome with a rank of 3 would have a 20% chance of being selected, compared to just 2.5% in roulette wheel selection. The probabilities are linearly distributed among the four potential chromosomes, with the fittest receiving 40%, the second fittest 30%, the third 20%, and the least fit 10%.

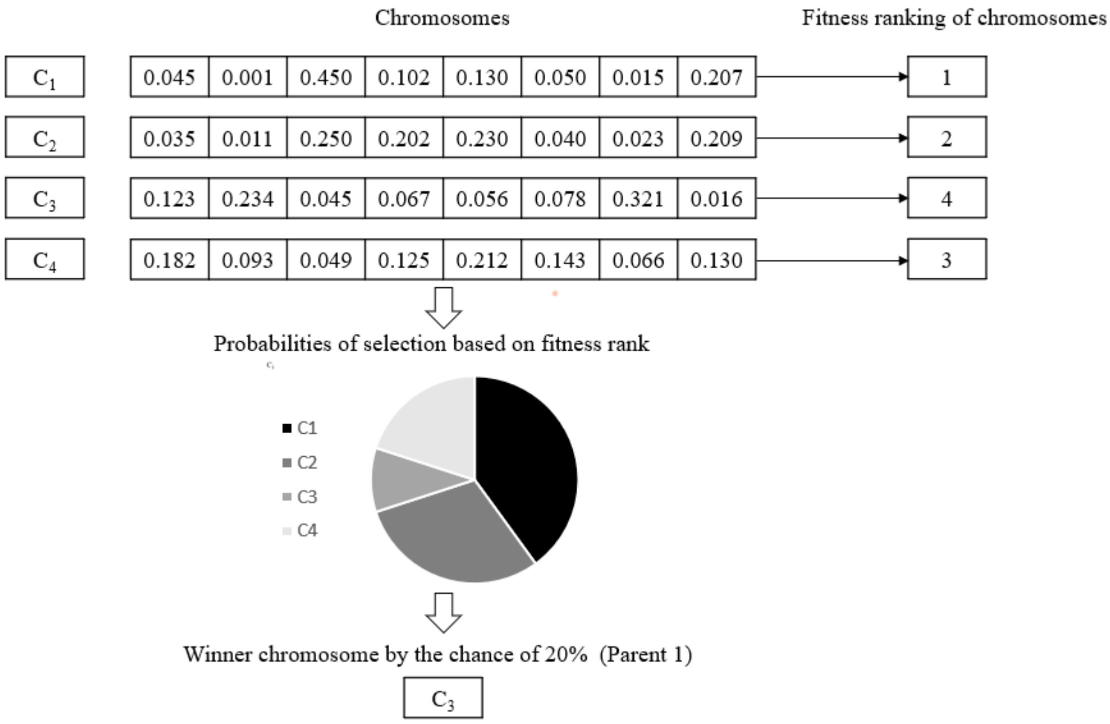

Figure 3.4: An illustration of rank selection process, where a parent chromosome selected by its linear rankings probability by 20%

3.1.4 Crossover and Mutation Operators

Crossover is a genetic mechanism aiming to blend traits from parent organisms to create offspring with potentially enhanced characteristics. As highlighted by Umbarkar & Sheth (2015), increasing the crossover probability indeed enhances the chance of recombination, but it can also disrupt potentially good combinations of genes. It involves various methods:

i) *One-Point Crossover*, depicted in Figure 3.5, involves selecting a random crossover point on the parent chromosomes and swapping all genetic material beyond this point between the parents (Umbarkar & Sheth 2015; Hasançebi & Erbatur 2000). It is straightforward to implement and helps maintain gene sequences, which is beneficial when certain gene combinations work well together. However, the one-point crossover may be limited in its ability to explore the solution space since it always exchanges genes in a single block. In Chapters 4 and 5, we employed chromosomes containing 8 and 10 genes, respectively. Given the relatively modest gene count in each chromosome at each chapter, the one-point crossover technique was adopted for the optimization process within the GA framework to ensure operational efficiency.

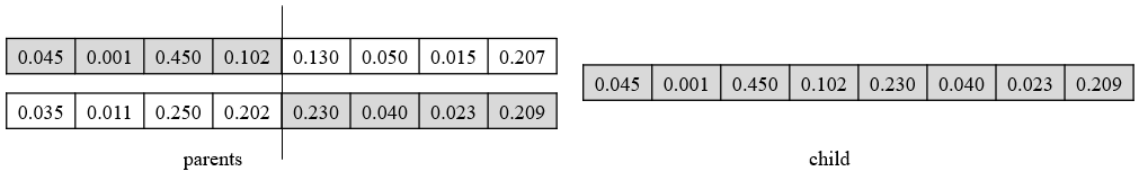

Figure 3.5: An illustration of one-point crossover process, where a child chromosome is created by taking the first four genes from one parent and the last four genes from another parent.

ii) *Two-Point Crossover* is an extension of the one-point method involving two crossover points, facilitating greater mixing of parental genes, as shown in Figure 3.6. Two-point crossover introduces more diversity than one-point crossover by permitting the exchange of genes in the middle segment of the chromosome (De Jong & Spears 1992). In Chapter 6, the chromosomes are composed of a significantly higher number of genes, specifically 70 genes each. Consequently, to enhance the genetic diversity within the population, a two-point crossover method was selected.

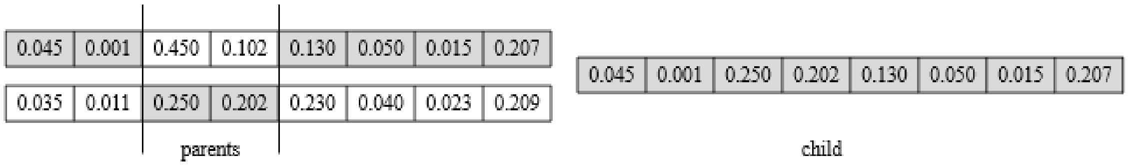

Figure 3.6: An illustration of two-point crossover process, where a child chromosome is created by taking the first two genes and the last four genes from one parent while taking the third and fourth genes from another parent.

iii) *Uniform Crossover* involves individually considering each gene for swapping, as depicted in Figure 3.7, with an adjustable exchange probability. For every gene in the parent chromosomes, there is a 50% chance of selecting that gene from either parent. Subsequently, the genes of the offspring are determined based on the genes selected from the parents. This approach strives to preserve and recombine beneficial traits from the parents in the offspring. Uniform crossover can generate highly diverse offspring by potentially intermingling genes from both parents across the entire chromosome. However, it can disrupt complex gene relationships because it does not preserve the order or grouping of genes.

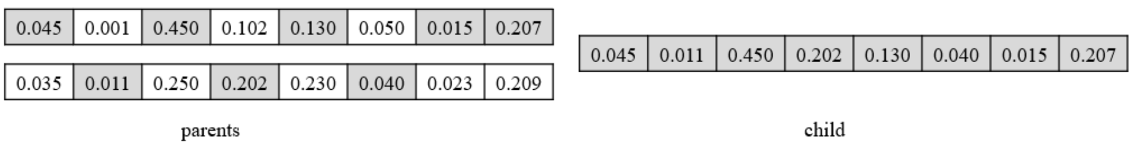

Figure 3.7: An illustration of uniform crossover process, where a child chromosome is created by 1$^{\text{st}}$, 3$^{\text{rd}}$, 5$^{\text{th}}$, 7$^{\text{th}}$, and 8$^{\text{th}}$ genes of one parent, and the 2$^{\text{nd}}$, 4$^{\text{th}}$, and 6$^{\text{th}}$ genes of another parent.

In short, the choice of crossover method in GA impacts the trade-off between exploration and exploitation. One-point crossover preserves genetic blocks for rapid solution improvement, yet it may be limited in exploring the solution space since it only permits a single exchange point. On the other hand, two-point crossover enables more diversity in offspring compared to one-point crossover by combining sequences of genes and allowing for more varied gene swapping. In uniform crossover, each gene is considered separately. While this method is effective for generating diverse offspring, it can disrupt important gene sequences, potentially leading to less optimal solutions in certain scenarios. In the existing literature, a multitude of crossover methods can be encountered as highlighted by Umbarkar & Sheth (2015); nevertheless, in this context, we have opted to introduce the commonly employed ones.

Mutation in GA is another key mechanism for introducing variation into a population. As a secondary operator to crossover, it enhances genetic diversity. Mutation randomly changes one or more gene values in a chromosome. Widely used methods include:

i) *Uniform Mutation*, where a gene is randomly selected and its value is replaced with a random value within predefined bounds (Syswerda et al. 1989). Uniform mutation enables wide exploration of the search space because it allows any gene to be changed to any value within its range (Patil & Bhende 2014). This method is straightforward to implement and can be applied to various types of encoding. Figure 3.8 illustrates the process of uniform mutation on an 8-gene chromosome, where the 5th gene from the left is changed.

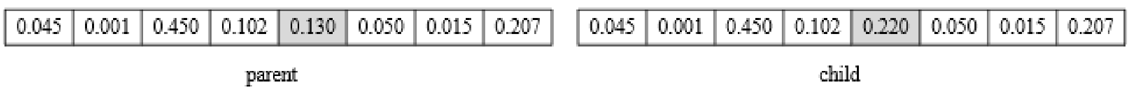

Figure 3.8: An illustration of uniform mutation, where a child chromosome is created by changing the parent chromosome's 5$^{\text{th}}$ gene between the boundaries of 0 and 1.

ii) *Swap Mutation*, involves the random selection of two chromosome positions whose values are then swapped. Swap mutation adds diversity to the population while minimally disrupting the chromosome structure, preserving most of the parent's characteristics (R. Kumar et al. 2020). However, it could potentially lead to stagnation, especially if the algorithm is near a local optimum. Figure 3.9 illustrates the process of swap mutation on an 8-gene chromosome, where the 3$^{\text{rd}}$ and 6$^{\text{th}}$ genes from the left are swapped.

0.045	0.001	0.450	0.102	0.130	0.050	0.015	0.207

parents

0.045	0.001	0.050	0.102	0.130	0.450	0.015	0.207

child

Figure 3.9: An illustration of swap mutation, where a child chromosome is created by swapping parent chromosomes' 3rd, and 6th genes.

iii) *Inversion Mutation* is a mutation type that chooses a segment within the chromosome and reverses the order of the genes in that segment. It is especially well-suited for solving sequence-based problems. Indeed, inversion mutation may become too localized if larger segments are not selected, which can restrict the diversity introduced by the mutation (R. Kumar et al. 2020). Additionally, it can be more complex to implement effectively, particularly in non-sequential problem representations. Figure 3.10 illustrates the method for performing inversion mutation on an 8-gene chromosome, where genes from the 3rd to the 6th position from the left are inverted.

0.045	0.001	0.450	0.102	0.130	0.050	0.015	0.207

parents

0.045	0.001	0.050	0.130	0.102	0.450	0.015	0.207

child

Figure 3.10: An illustration of inversion mutation, where parents genes from third to and sixth genes from the left is inverted to create a child chromosome

Overall, the uniform mutation is well-suited for an explorative search, helping to avoid getting stuck in local optima. Inversion mutation, on the other hand, preserves gene sequence integrity and is more suitable for specific optimization problems but may limit exploration. Swap mutation is more suitable for the tasks where the order of genes is important. While many mutation methods exist in the literature as highlighted by Hassanat et al. (2019), here, we have opted to describe the commonly used ones.

In this thesis, based on the findings from the literature, we employed random initialization as the population initialization method due to its effectiveness in promoting diversity in the initial population. For the chromosome selection process of parents, we used tournament selection due to its ability to reduce the dominance of stronger individuals. We chose one-point crossover as the crossover method for lower-numbered genes in chromosomes, as it provides a straightforward approach and requires less computation time. For chromosomes with a higher number of genes, we opted for a two-point crossover to increase diversity. Finally, for the mutation operations, we selected uniform mutation due to its efficiency in reducing the computational power required

3.1.5 Elitism

Elitism preserves the best individuals by directly copying them from the current generation to the next one (Ahn & Ramakrishna 2003), bypassing crossover or mutation. Its primary aim is to maintain or improve the population's overall quality across generations by safeguarding the best solutions found. The number of individuals transferred to the next generation can be customized. As seen in Figure 3.11, the first chromosome from the population is directly transferred to the new population without undergoing any operations.

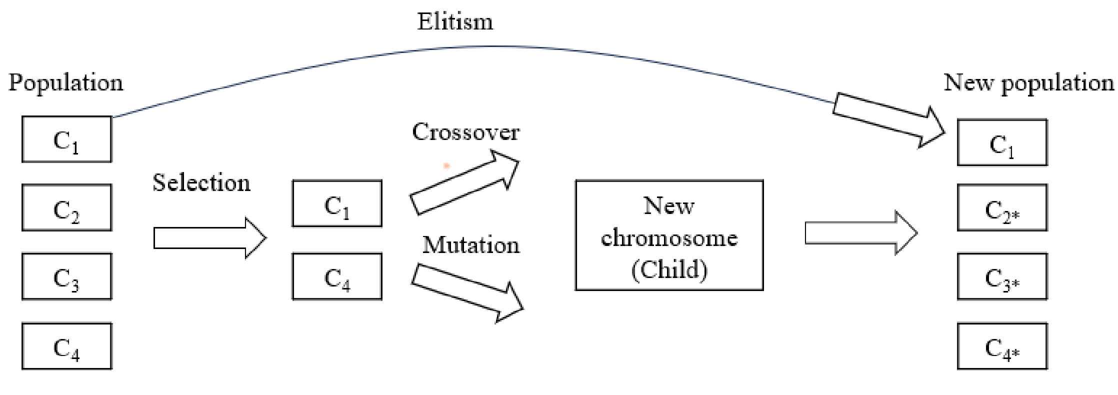

Figure 3.11: An illustration of elitism. Chromosome C_1 directly added to new population.

3.1.6 Termination

Termination conditions determine when an algorithm should conclude its execution, guiding both solution quality and resource use. Several commonly employed termination criteria include:

i) *Maximum number of generations*: The algorithm terminates its execution once a predefined number of generations has been reached. This approach, also employed in our thesis, assumes that following a specific number of generations, the genetic algorithm will have adequately explored and refined solutions in the solution space (Ghoreishi et al. 2017). It offers a predictable runtime and prevents over-fitting.

ii) In *Fitness threshold*: Termination occurs when a solution (or a set of solutions) surpasses a predefined fitness threshold (Bhandari et al. 2012). The termination of the GA is intrinsically linked to the quality of the solution. Therefore, establishing an optimal fitness threshold can pose a significant challenge in the absence of prior knowledge about the problem domain.

iii) *Time limit*: The algorithm halts its operations after a specified time period (Jain et al. 2001). It is useful for real-time systems or limited computational resources. However, this approach does not assure solution quality, as the GA may conclude with a sub-optimal solution in cases where the time limit is too strict.

While there are numerous termination criteria available as highlighted by Ghoreishi et al. (2017), we have explained the commonly used ones here. The next section will overview the literature on GA's use in finance.

3.2 GA on finance

When examining the applications of GA in finance, as presented by Aguilar-Rivera et al. (2015), we observe their presence across a wide spectrum of sub-fields. Some examples of these sub-fields include *fraud detection*[2], *bankruptcy detection*[3], *cash management*[4], *credit scoring*[5], *index tracking*[6], portfolio selection problem optimization, and trading, among others. Our primary focus has been on trading in this thesis, but due to its close connection to stock investments, we have covered the portfolio selection literature as well.

The use of GA in portfolio optimization has shown promising results. Chang et al. (2009) demonstrated that GA optimization with various risk measures can enhance the solving of the "efficient frontier," a concept from Markowitz's research (Markowitz 1952b) that represents the optimal portfolio solutions for a given level of risk. Briefly, the efficient frontier is depicted as a line representing optimal portfolio solutions for expected return and risk levels. In another research, Chou et al. (2017) applied GA to select portfolios, focusing on moderate returns while minimizing risks. C.-H. Chen et al. (2019) introduced a "grouping genetic algorithm" using a diversity function for diversification, enhancing portfolio performance during volatile market periods. Lim et al. (2020) used GA for stock portfolio generation, focusing on stocks' beta[7] values for risk hedging, although it did not outperform benchmarks in profit.

[2]Fraud detection is applied to find the deceptive financial performances of a firm.

[3]Bankruptcy detection aims to identify the indicators that suggest a firm is likely to declare bankruptcy.

[4]Cash management is aiming to manage cash inflows and outflows firm.

[5]A credit score aims to find a consumer's creditworthiness.

[6]Tracker funds, also known as index funds, are investments designed to mimic the performance of broad market indices.

[7]Beta is a concept used to measure the expected movement of a stock in relation to the movements of the overall market. It helps assess how a particular stock is likely to perform in response to market fluctuations.

In index fund management, Chou et al. (2017) found that GA improved performance over traditional methods.

Another important aspect is the exploration of portfolio selection research as a multi-objective optimization problem in the field. Portfolio selection is increasingly viewed as a multi-objective optimization problem, as noted by Ponsich et al. (2012). Rather than seeking a single optimal solution, this approach aims to find a set of solutions offering the best trade-offs among various objectives (Konak et al. 2006; Gao et al. 2000). This reflects the complex nature of financial problems involving multiple conflicting objectives.

Another sub-field, and one of the most important components of our thesis, is the usage of GA in trading strategies. In the literature, what initially stands out is the numerous research that have employed GA in conjunction with Technical Analysis (TA). For instance, Schoreels et al. (2004) combined GA with TA indicators such as RSI (refer to Section 2.2.2 for detailed explanation) for trade decisions, suggesting the addition of more TA indicators could improve performance compared to market indices. Straßburg et al. (2012)) emphasized the importance of increasing the number of TA rules and implementing parallelization, demonstrating an increase in GA implementation speed for enhanced results. Macedo et al. (2020) employed GA to optimize trading strategies in foreign exchange markets, indicating that their GA-optimized strategies outperformed traditional TA methods reliant on a single indicator. Deac & Iancu (2023) focused on optimizing MACD-based strategies for a specific stock using GA. Their findings indicated that employing GA could improve profitability, albeit with a tendency to favor seasonality[8]. In the context of both TA and multi-objective fitness function utilization, Faijareon & Sornil (2019) introduced

[8]Seasonality is a phenomenon of time series data where there are regular and predictable changes that repeat every calendar year.

a method. The focus was on evolving parameters for six widely used technical indicators: slope, EMA, MACD, RSI, stochastic oscillator, and ADX. Authors showcased that with stocks from the Stock Exchange of Thailand, strategies resulting from the GA optimization surpassed the established TA methods in (Faijareon & Sornil 2019).

In the literature, some research were conducted with GA in trading strategies without relying on TA. Mendes et al. (2012) used profit-to-maximum drawdown[9] ratio as a fitness function in their GA, focusing on EUR/USD and GBP/USD forex pairs. Their algorithm implemented ten trading strategies, yielding profitable outcomes in the training set. Iskrich & Grigoriev (2017) applied GA as a "selector" to identify the optimal decision tree from historical data, achieving modest Sharpe Ratio results with simple trading strategies.

Finally, in the context of the DC paradigm, Kampouridis & Otero (2017) utilized GA as an optimizer for a single trading strategy, with chromosomes representing budgeting constraints, differing from our approach. Later, Adegboye et al. (2023) observed statistically significant results in the FOREX market when using GA for the optimization of different strategies compared to DC-based benchmark strategies, particularly in terms of return and risk. Portfolio construction using the GA and DC paradigm is still a relatively unexplored area. To the best of our knowledge, Almeida et al. (2023) is the only research delving into this topic. While their research did not surpass benchmark Sharpe Ratio results, it succeeded in reducing maximum draw-down.

In summary, as highlighted in Sivanandam et al. (2008) some of the advantages of GA are: i) Adaptability for diverse problems; ii) higher global search capability; iii)

[9]Maximum drawdown is a metric that quantifies the most significant decline in the price of an asset, measured from its highest point to its lowest point.

straightforward implementation; iv) efficient parallel computation; v) robust against noise and handles diverse function types.

As seen in the literature, considering the promising results of using GA in trading strategies, both in terms of TA and, more importantly, in the optimization of trading strategies, we will also utilize GA in our thesis. The Algorithm 3 provides a pseudocode for GA that we utilized in our thesis.

Algorithm 3 Pseudocode for Genetic Algorithm

```
Require: Determine number of generations, G, and crossover probability, P_c
  Initialize population with random individuals
  Evaluate the fitness of each individual
  for generation = 1 to G do
      Select elite individuals to carry over to the next generation
      Create a new population
      while new population is not full do
          Select k individuals for tournament
          Perform tournament selection
          Generate random number r between 0 and 1
          if r < P_c then
              Apply crossover to winners to create offspring
          else
              Apply mutation to one of the winners to create offspring
          Add offspring to new population
      end while
      Replace old population with new population
      Evaluate the fitness of each individual in the new population
  end for
```

3.3 Summary

In this chapter, we presented the optimization method we used in the following chapters, which is the Genetic Algorithm (GA). We began with an overview of GA, including the chromosome representation methods. We then outlined the operations including chromosome population initialization, selection, crossover and mutation, elitism, and termination. In this exploration, we presented the methods commonly encountered in the field.

Subsequently, we examined the literature on the application of GA in finance, which we can categorize into three main topics: portfolio optimization with GA, trading strategies with GA, and the integration of GA with DC. We introduced the research findings in each of these areas and elaborated on why we chose GA as the optimization method for our thesis.

Chapter 4

Trading Strategies Optimization on a Single Threshold

4.1 Introduction

As previously mentioned, the cornerstone of our thesis is based on the creation of DC-based strategies, which function in a manner akin to strategies based on TA. Furthermore, these trading strategies provide traders the information based on a set of rules, and the resulting performance can be examined under specific metrics, such as return and risk. The two main pillars contributing to the formation of these strategies are scaling laws and indicator findings in DC literature, as reviewed earlier. In Sections 4.2.1 and 4.2.2, we will delve into strategy formation based on these two pillars. In Section 4.2.3, we will introduce how GA optimization is applied to DC-based strategies. This can be viewed as a process that optimizes the information produced by each strategy to create a more information-rich model. Section 4.3 will detail the data and the experimental setup used in our analysis. We will then present the results in Section 4.5 and provide interpretation and summary in Sections 4.6 and 4.7, respectively.

4.2 Methodology

This section introduces a model for optimizing trading strategies within the framework of the DC paradigm. More specifically, we formed a detailed optimization approach using a Genetic Algorithm (GA). This formation utilizes chromosomes that encompass strategies. We call the current model *Multi-Strategy-Genetic-Algorithm-Model* (MSGAM). MSGAM is employed to incorporate a range of strategies, enabling us to capture distinctive characteristics from various DC-based strategies.

Among the eight trading strategies, two are based on using scaling laws and six based on indicators. The number of genes corresponds to the number of strategies in the chromosome. Each gene holds a weight, which is applied to the trading recommendations – Buy, Sell, or Hold – provided by each strategy when analyzing the price data. By weighting these recommendations accordingly, the final decision is determined by identifying which recommendation has the highest weight.

The chromosome aggregates the weights of genes that recommend Buy, resulting in an aggregate weight W_B. It does the same for genes that recommend Sell and Hold, resulting in aggregate weights W_S and W_H, respectively. In the initial randomly generated population of the GA, the total weights for each chromosome sum to 1. From that point forward, any newly generated child chromosomes, regardless of crossover or mutation operations, are standardized such that their total weight remains 1. Therefore, for every chromosome, the total sum of weights equals 1, which can be expressed as: $W_B + W_S + W_H = 1$. The chromosome's final decision is based on the largest aggregate weight for each time unit in the data. In the event of a tie, it selects one of the recommendations with the highest aggregate weight uniformly at random.

The GA's role in this process is to facilitate the evolution of chromosomes over generations, to maximize the fitness function, which in this case is the *Sharpe Ratio* (refer to Section 4.2.3 for detailed explanation). In Section 4.2.3, a comprehensive discussion regarding the weights assigned to the utilization of three potential recommendations will be presented. In the upcoming Sections 4.2.1 and 4.2.2, we will explain how we initially created these strategies based on scaling law findings and then discuss how we created them using indicators, respectively.

4.2.1 Strategies Based on Scaling Laws

Scaling laws, at their core, explain the inherent connection between two physical quantities that exhibit proportional changes across a substantial range. They are introduced in many areas, spanning from earthquake magnitudes to forest fire extents, as highlighted by Glattfelder et al. (2014), and extending to cancer tumor growth, as evidenced by Pérez-García et al. (2020). In the context of DC, these associations primarily seek to formulate mathematical relationships that encompass price fluctuations, duration, and frequency. Among the 12 scaling laws identified through DC by Glattfelder et al. (2011b), two are highly important in connecting the DC and OS events by their average duration, and the price changes in each event.

The *first scaling law* observed by Glattfelder et al. (2011b) was the identification of a recurring pattern where a DC formed by a threshold (θ) tends to be followed by an OS event with the same price change that θ qualifies, on average. As shown in the Equation 4.1, where the symbol "≈" signifies approximate equivalence.

$$\langle \Delta p_{DC} \rangle \approx \langle \Delta p_{OS} \rangle \approx \theta \tag{4.1}$$

In line with the explanation presented by Glattfelder et al. (2011b, 2014) we assign the symbols $\langle \Delta p_{DC} \rangle$ and $\langle \Delta p_{OS} \rangle$ to represent the price changes in the events of DC and its OS, respectively. To provide a more comprehensive explanation of the scaling law presented in Equation 4.1, we can relate it to work by Glattfelder et al. (2011b). In the research, the authors defined a trend's movement, whether uptrend or downtrend, as the total move. They showed that, on average, a DC event is followed by an OS event of the same magnitude, which makes the total move double the size of the DC threshold. In this context, the price change of a DC event was approximately the same as that of its corresponding OS event.

Considering the scaling law, Strategy 1 (St1) involves buying a stock in a downtrend (DT) when we observe a price change equal to or greater than double the θ from its extremum point (i.e., p_{EXT_h}). The important point to emphasize here is that if a price change of $2 \cdot \theta$ occurs at the confirmation point (DCC) from the p_{EXT_h} (resp. p_{EXT_l}), then the execution of the buy (resp. sell) order takes place at the DCC. To sell, the same process is applied during an uptrend (UT). The underlying rationale behind this strategy is to capture the trend when it reaches the price change as dictated by the scaling laws, and subsequently wait for the opposite trend (i.e., UT) to generate profit. Algorithm 4 represents an overview of how the trading strategy is constructed.

The *second scaling law* demonstrates a consistent pattern: on average, the duration of an OS event was approximately twice the duration of a DC event. Equation (4.2) highlights the scaling law, by aligning the notation of Glattfelder et al. (2011a) let us denote by $\langle T_{OS} \rangle$ and $\langle T_{DC} \rangle$ the average time of an OS and DC event, respectively. Consequently, the previously mentioned scaling law can be expressed as follows:

Algorithm 4 Trading rule for St1

if DC is in DT **then**
    if there is no open position *and* price change reaches $2 \cdot \theta$ from p_{EXT_h} **then**
        buy one amount of share
    else
        Hold
else if DC is in UT **then**
    if there is an open position *and* price change reaches $2 \cdot \theta$ from p_{EXT_l} **then**
        close the position by selling the share
    else
        Hold

$$\langle T_{OS} \rangle \approx 2 \cdot \langle T_{DC} \rangle, \tag{4.2}$$

Equation (4.2) underscores the scaling law, where the symbol "≈" denotes approximate equivalence again.

Strategy 2 (St2) applies the following rationale: Given a DC, to generate an execution signal, we check the time duration of the DC and we Hold for double that time after the confirmation point *DCC*. Then, we Buy if we are in a DT, or Sell if we are in a UT. This strategy is prompted to facilitate informed decision-making through the assumption that the scaling law holds true for every distinct trend. Algorithm 5 illustrates the overview of how the strategy is implemented.

The use of scaling laws in trading strategy development offers promising potential. The primary reason is that the DC paradigm is still a new research area, and the discoveries made so far have been used in trading strategies in a very limited way. Therefore, the realm of DC analysis presents a fertile ground for research, offering the potential for significant improvements in trading performance.

Algorithm 5 Trading rule for St2

```
if DC is in DT then
    if there is no open position and the time spent in OS is more than double the time in its DC then
        buy one amount of share
    else
        Hold
else if DC is in UT then
    if there is an open position and the time spent in OS is more than double the time in its DC then
        close the position by selling the share
    else
        Hold
```

4.2.2 Strategies Based on Indicators

As previously mentioned, indicators, whether derived from directional changes or other financial concepts, are statistical metrics used for analyzing current conditions and forecasting financial trends. This work introduces new DC-based indicators alongside existing ones for improved financial forecasting in traders' decisions. Note that here we only discuss the indicators used in this thesis and the most relevant recent work (Salman et al. 2022, 2023). For a more comprehensive exploration of indicators, we recommend readers to delve into the extensive work of Tao (2018) on the DC indicators. The utilized indicators in this thesis and their insights are as follows:

- Duration of DC events (T_{DC}): Total physical time spent in DC events.
- Duration of OS events (T_{OS}): Total physical time spent in OS events.
- Ratio of duration RD: Total time spent in OS divided by total time spent in DC.

$$RD = \frac{T_{OS}}{T_{DC}} \tag{4.3}$$

- Number of DC events (N_{DC}): The total number of DC events throughout the investigated period.

- Number of Overshoot Events (N_{OS}): The total number of OS events in the profiled data.

- Ratio of a number of events RN:

$$RN = \frac{N_{OS}}{N_{DC}} \tag{4.4}$$

  Notice, that $RN \in [0, 1)$, since in an extreme case it could be $N_{OS} = 0$, and in general, it also holds that $N_{DC} \geq N_{OS} + 1$, since there is at most one OS between two DCs.

- Theoretical Confirmation Point ($DCC*$): The minimum or maximum directional change confirmation price for an uptrend or downtrend after the extreme points (i.e., p_{ext_ℓ} or p_{ext_h}) at which a price change equals θ in the direction opposite to the current trend. At the uptrend:

$$P_{DCC*} = p_{ext_\ell} \cdot (1 + \theta), \tag{4.5}$$

  and at the downtrend:

$$P_{DCC*} = p_{ext_h} \cdot (1 - \theta). \tag{4.6}$$

- Overshoot Values at Current Points (OSV_{CUR}): The main goal of this indicator is to measure the magnitude of an OS event. It can be calculated as follows:

$$OSV_{CUR} = \frac{P_{CUR} - P_{DCC*}}{\theta \cdot P_{DCC*}}, \tag{4.7}$$

where P_{CUR} is the current price of the asset.

- Total Moves Value at Current Points (TMV_{CUR}): The main goal of this indicator is to measure total movement from the eyes of the previous extreme point. it can be calculated as follows:

$$TMV_{CUR} = \frac{P_{CUR} - p_{ext}}{\theta \cdot p_{ext}}, \tag{4.8}$$

where P_{CUR} is the current price of the asset, and the p_{ext} is the previous extreme point that we have observed, for instance, if we are at an uptrend the indicator value is calculated by using the recent p_{ext_ℓ}, if we are in downtrend the extreme point is p_{ext_h}.

The following two strategies are built upon the OSV_{CUR}, (Equation (4.7)) and TMV_{CUR} (Equation (4.8)) indicators. The underlying idea behind their development involves dynamically utilizing the "Best" values observed during the training phase and using them as an execution-triggering mechanism in the test set.

St3 hinges on the employment of the Overshoot Values at Current Points indicator. Within this strategy, we verify whether $|OSV_{CUR}| \geq |OSVbest_{DT}|$ in the test set. The way we determine our $OSVbest$ which is used as threshold in their own way (a value that we decide upon for our trading mechanism) is as follows. Initially, we generate two distributions from the DC-profiled dataset as per Equation (4.7): for every price in OS events in downtrends and uptrends. Therefore, if there is no OS events such that consecutive DC events occur, indicator values are not calculated for that part. These values are then divided into quartiles, each containing a median OSV_{CUR} value, resulting in four indicator values for both trends. Ultimately, the most favourable OSV_{CUR} values is identified through assessment, one for downtrend one for uptrend, denoted as $OSVbest$. This assessment conducted through testing these values by which of them generates the highest sharpe ratio in training set when we use the trading strategy that previously explained. Consequently, we identify two distinct $OSVbest$ values: $OSVbest_{DT}$ for downtrend and $OSVbest_{UT}$ for uptrend.

In instances where this rule is satisfied, we examine the direction of the trend as a signal. If the trend direction is deemed as a downtrend (DT), we initiate a stock purchase and await to see the $|OSV_{CUR}| \geq |OSVbest_{UT}|$ in any upcoming uptrend (UT). In St3, our goal is to detect the trend reversal by observing when the indicator value reaches a certain magnitude. This approach allows us to capitalize on the uptrend shift by purchasing stocks at a lower price and selling them at a higher value. Algorithm 6 provides an outline of the process involved in constructing the trading strategy.

Algorithm 6 Trading rule for St3

```
if DC is in DT then
    if there is no open position and |OSV_CUR| > |OSVbest_DT| [See Equation 4.7]
then
        buy one amount of share
    else
        Hold
else if DC is in UT then
    if there is an open position and |OSV_CUR| > |OSVbest_UT|  then
        close the position by selling the share
    else
        Hold
```

St4 is founded upon the utilization of the Total Moves Value at Current Points indicator, as outlined by Equation (4.8). In the formulation of this strategy, we once more adhere to the condition of verifying whether the magnitude of $|TMV_{CUR}|$ exceeds that of $|TMVbest_{DT}|$, akin to the approach in St3. The methodology for determining $|TMVbest|$ follows a similar process; however, the distinction lies in the calculation of the current value, which is based on Equation (4.8). Again, we find two "best" values, one for downtrend and one for uptrend, denoted by $TMVbest_{DT}$ and $TMVbest_{UT}$, respectively. In the final phase, the trend is assessed once again, and if it is recognized as a DT, a buy order for the stock is executed. We then await the UT, to execute a sell order when the condition is matched again. Similar to the previous strategy, our aim here is to anticipate an uptrend shift upon the indicator reaching a certain magnitude. The distinction lies in the measurement of the TMV_{CUR} indicator, which evaluates the trend from its initial starting point, offering a comprehensive view of the movement's total trajectory. Algorithm 7 shows how trading strategy is integrated.

Algorithm 7 Trading rule for St4

if DC is in DT **then**
  if there is no open position *and* $|TMV_{CUR}| > |TMVbest_{DT}|$ [See Equation 4.8] **then**
    buy one amount of share
  else
    Hold
else if DC is in UT **then**
  if there is an open position *and* $|TMV_{CUR}| > |TMVbest_{UT}|$ **then**
    close the position by selling the share
  else
    Hold

The next two strategies are constructed based on the idea of establishing a relationship between OS and DC within the duration of their connection, as well as considering the overall relationship between the number of observed OS and DC events.

Strategy 5 (St5) is based on the ratio of the total time spent in OS events divided by the total time spent in DC events. We buy the stock in a downtrend whenever we observe that the time duration of OS divided to its DC event time duration is equal or greater than our predefined ratio value. The calculation of this fixed ratio is based on Equation (4.3). For instance, if the duration of any given OS event to its DC duration exceeds the specified ratio RD, we execute a stock purchase if the current trend is DT. Similarly, when the current trend is UT, we wait for the same ratio value to be observed and then sell the stock. Algorithm 8 provides a summary of the process involved in building the trading strategy.

Algorithm 8 Trading rule for St5

```
if DC is in DT then
    if there is no open position and ratio of time spent in OS to its DC ≥ RD [See Equation 4.3] then
        buy one amount of share
    else
        Hold
else if DC is in UT then
    if there is an open position and ratio of time spent in OS to its DC ≥ RD then
        close the position by selling the share
    else
        Hold
```

Strategy 6 (St6) follows a similar process to that of St5. In this case, we establish our predefined ratio by dividing the total number of OS events by the total number of observed DC events, as indicated in Equation (4.4). However, in this instance, the decision to buy stocks depends on a ratio that must consistently fall within the range of 0 to 1. The developed strategy operates based on probability, taking this ratio into account. If the randomly generated number is equal or greater than the predetermined ratio (RN as described in Equation (4.4)) in a downtrend, a stock position is initiated only on DCC points of downtrends. To sell the stock, we await the next confirmation point during a uptrend. The underlying idea behind this strategy is based on the principle that sampling all the data using the DC paradigm gives us a general insight. By taking the number of OS events relative to DC events as a threshold, we aim to capture a quick uptrend in price during downtrends, in an aim not to see OS events when this ratio is met. Nevertheless, the degree of randomness in this strategy depends on the number of OS events observed to DC events observed, with the ultimate goal of capturing the bull market.

Algorithm 9 Trading rule for St6

r is a random variable sampled from the uniform distribution in $[0, 1]$
if DC is in DT **then**
  if there is no open position *and* $r \geq RN$ [See Equation 4.4] at every DCC point for St6 **then**
    buy one amount of share
  else
    Hold
else if DC is in UT **then**
  if there is an open position *and* subsequent DCC confirmed **then**
    close the position by selling the share
  else
    Hold

The final two strategies in our thesis aim to replicate key concepts from Technical Analysis (TA), specifically the indicators of *support* and *resistance*. Support occurs when decreasing prices attract buyers, eventually balancing the demand with the available supply and stabilizing prices (A. W. Lo et al. 2000). Resistance is its counterpart, where rising prices eventually hit a point where selling pressure exceeds buying interest, leading to a potential reversal. Building upon these two primary indicators, we would like to clarify how triangles (3 triangle formation) operate in Technical Analysis and how we developed two strategies that resemble these triangles within the framework of the Directional Changes paradigm.

As shown in Figure 2.3, both ascending and descending triangles are depicted. The strategy based on these triangles is constructed on the concept of "saturation," which can be considered as either support or resistance. In the case of the ascending triangle (weeks 82 to 93, green dashed line), the low price forms triangles with progressively decreasing price differences leading up to the saturation price. The strategy posits that at the end of the third triangle, the saturation point will be broken, resulting in an upward movement.

Similarly, in our constructed strategy, during a trend in a specific direction (e.g., downtrend), we do not observe OS events, whereas we do observe these events in the opposite trends. This indicates that market participants in a particular direction (e.g., buyers) will break the saturation point and drive the price in that direction.

Strategy 7 (St7) is based on the following idea. As previously defined, the saturation point is determined by not observing OS events in a certain trend direction (e.g., uptrends) and observing them in the opposite direction (downtrends). It is important to recall that, as Figure 2.5 also indicates, it is common to observe DC events consecutively without seeing OS events.

Now, consider a sequence of UT-DT-UT-DT-UT. If there are no OS events in all of the DTs and there is an OS event in each of the UTs, then upon noticing the OS event in the final uptrend, we execute the buy. As mentioned earlier, since the triangle indicator in TA is based on the formation of three triangles to reach a saturation point, in this DC-based strategy, we consider three consecutive UTs with OS formations as a saturation point. Once the stock purchase occurs, we subsequently wait for a confirmation point in DT and then sell the stock. The rationale behind the strategy is the indication that market participants in a particular direction (e.g., buyers) will break the saturation point and drive the price in that direction. Algorithm 10 represents the functionality of the strategy.

Strategy 8 (St8) is symmetric to St7, where instead of detecting three OS intervals in UT we detect them in DT. In particular, consider a sequence of DT-UT-DT-UT-DT. If in all of the UTs there is no OS and in each and all of the DTs there is an OS (i.e., three OS intervals), then we buy the stock. The same saturation

Algorithm 10 Trading rule for St7

if DC is in UT **then**
  if there is no open position *and* in the sequence of UT-DT-UT-DT-UT there is no OS in DTs *and* 3^{rd} consecutive OS in UT **then**
    buy one amount of share
  else
    Hold
else if DC is in DT **then**
  if there is an open position *and* the next DCC point is observed in DT **then**
    close the position by selling the share
  else
    Hold

point interpretation is used in a similar manner as in the previous strategy, with the only difference being the direction of the trends. Once the stock purchase occurs, we subsequently wait for a confirmation point in UT and then sell the stock. Algorithm 11 prescribes the actions of the strategy.

Algorithm 11 Trading rule for St8

if DC is in DT **then**
  if there is no open position *and* in the sequence of DT-UT-DT-UT-DT there is no OS in UTs *and* 3^{rd} consecutive OS in DT **then**
    buy one amount of share
  else
    Hold
else if DC is in UT **then**
  if there is an open position *and* when observe the next DCC point in UT **then**
    close the position by selling the stock
  else
    Hold

In summary, these strategies were derived from a combination of scaling laws and indicators from DC. By resembling TA-like approaches in DC, they aimed to provide insights into potential outcomes in the financial markets for traders.

Table 4.1: Execution signals as Buy and Sell

Strategy	Buy Action	Sell Action
St1	In DT, once the price change from p_{ext_h} reaches two θ	Same signal in the UT
St2	In DT, once the duration of its OS event reaches double the duration of the DC event	Same signal in the UT
St3	In DT, once we see the $\mid OSV_{CUR} \mid$ is equal or greater than the $\mid OSVbest_{DT} \mid$	Same signal in the UT by $\mid OSVbest_{UT} \mid$
St4	In DT, once we see the $\mid TMV_{CUR} \mid$ is equal or greater than the $\mid TMVbest_{DT} \mid$	Same signal in the UT by $\mid TMVbest_{UT} \mid$
St5	In DT, once the duration of the OS event over the DC event is equal or greater than RD	Same signal in the UT
St6	In DT, once the randomly generated p is equal or greater than the RN	P_{DCC} in upcoming trend
St7	3$^{\text{rd}}$ consecutive OS in UT	P_{DCC} in DT
St8	3$^{\text{rd}}$ consecutive OS in DT	P_{DCC} in UT

Trading Rules

There are several constraints and considerations to be aware of in the trading process. These are as follows: (i) A new position (i.e., executing a buy, or sell on a stock) cannot be opened if a position is already open; therefore, a position must be closed[1] before a new one can be opened, (ii) *short selling*[2] is not permitted, meaning that all opening positions must involve taking a long position on a stock, and consequently closing the positions, (iii) each trade is subject to a transaction cost of 0.25% applied to the price of the product at the time of the buy execution. This decision was motivated by our intent to embrace a more passive[3] investment approach, which would likely result in a lower number of trades being executed. This approach

[1] Our objective was to treat each trade within a given stock as a single investment, considering the period from the initial purchase to the subsequent sale as a unified investment horizon

[2] For a broader perspective, the concept discussed in (Crace 2021) can be examined from the recent events that have garnered significant public attention.

[3] Passive investing represents an investment strategy aimed at optimizing returns by minimizing the frequency of buying and selling actions.

allows novice traders with limited knowledge about financial markets to have a more transparent view of the performance of their holdings.

4.2.3 GA Optimization

In this section, we will explain how GA is utilized as an optimization method in the recommendations of our strategies.

Action recommendations

In our research, specifically within the MSGAM, chromosomes are composed of eight distinct genes. The number of genes aligns with the number of strategies within a single chromosome. Each gene carries a specific weight that influences the trading recommendations – Buy, Sell, or Hold – given by each strategy during the any given time in the price data. It is possible for different trading strategies to provide different recommendations. Therefore, in an aim to find the most effective weights for the strategies, we used GA optimisation. For visualization purposes, in Table 4.2 we present a hypothetical chromosome consisting of only 8 genes (strategies).

Table 4.2: The chromosome representation includes 8 strategies, and the hypothetical weights assigned to each recommendation.

Strategy	St1	St2	St3	St4	St5	St6	St7	St8
Weight	0.045	0.001	0.450	0.102	0.130	0.050	0.015	0.207

From Table 4.2, imagine the actions of each strategy at a particular time are as follows, from St1 to St8 in sequence: 0, 0, 1, 0, 0, 0, 0, and 2 (Hold:0, Buy:1, Sell:2). In this particular example, the individual recommended actions of the strategies St1, St2, St4, St5, St6, and St7 are to Hold the stock at that given time, while the recommendation for St3 is to Buy, and for St8 is to Sell. To decide which action we take, we sum up the weights of the genes that recommend the same action, i.e., the sum of buying is 0.45; the sum of selling is 0.207; the sum of holding $0.045 + 0.001 + 0.102 + 0.130 + 0.050 + 0.015 = 0.343$. Then, the action that the entire chromosome will perform is the one that has the highest cumulative weight. In this example, buying the position has the highest weight sum with 0.45, therefore, at that specific time, the chromosome would decide to buy the position. Overall, the GA process focuses on optimizing the weights associated with each of the eight individual strategies. This optimization aims to maximize the fitness function, which evaluates the overall performance of the strategy recommendations.

However, in our experiments, the above approach resulted in a problematic situation appearing often: the large majority of the chromosome recommendations within most of the generations were Hold. Therefore, to promote responsiveness, we implement a slight modification of that approach, which encourages a higher frequency of trades by artificially assigning a higher weight to Buy or Sell actions: if at any given time slot and chromosome, we observe more than two genes recommending anything other than Hold, we disregard the Hold-genes, and decide the chromosome's recommendation according to the other genes' weights.

Operators, Fitness Function, and Metrics

Here, we establish the operators and the fitness function employed within the GA framework. We employ a one-point crossover operator with a probability of p and a one-point uniform mutation operator with a probability of $1 - p$. Additionally, we incorporate elitism, which involves preserving the best chromosome from one generation to the next.

To evaluate the fitness of chromosomes, we utilize the Sharpe Ratio (SR) as our fitness function. Firstly, we would like to address how the SR measures performance in a portfolio-based context, which consists of a basket of multiple financial products. Then, we will explain our unique use of the SR as a risk-adjusted metric, highlighting how it differs from the traditional approach and why we needed to vary it to accurately assess the risk-adjusted returns of our trading strategies.

Traditionally, portfolios can include various stocks, for example. The SR assesses risk-adjusted returns by measuring the amount of excess return achieved for each unit of risk (Sharpe et al. 1992). A higher SR indicates superior risk-adjusted performance, making it a crucial tool for evaluating different portfolios. Furthermore, the incorporation of a risk-free asset in the metric establishes a benchmark for evaluating the performance of an investment in comparison to a "no-risk" alternative. This is a vital tool for traders to ensure that the risk taken is proportionate to the returns. It is calculated using the following equation:

$$SR = \frac{R_p - R_f}{\sigma_p} \tag{4.9}$$

where R_p is the portfolio return, R_f is a the return of risk-free asset, which is selected as 2.5% for a two-year dataset to preserve the resemblance of USA government bonds, and σ_p is the standard deviation of returns.

The SR as mentioned above, known also as the "Reward-to-Variability Ratio" (Lim et al. 2020), has emerged as a metric for assessing the risk-adjusted performance of a basket of different products. However, in our thesis, we aim to focus on the core aspect of SR – the reward's variability – without altering it, but with an emphasis on the discontinuity of trades. This approach aligns with the fundamental principle of DC, which transforms discontinued physical time and encapsulates it through events. As E. P. Tsang et al. (2017) highlighted, researchers have long used return and volatility as key indicators in physical time analysis to summarize market price changes. However, DC is a relatively new concept. While an indicator similar to the return concept has been proposed for DC in the same research, a metric for risk-adjusted return is still lacking. In light of these considerations, we used the small variation of traditional SR as a risk-adjusted metric at the trade-level in our fitness function and as a performance metric in our thesis.

In contrast to the traditional portfolio return for SR defined in Equation 4.9, we calculate the Rate of Return (RoR) for each trade by considering the buy and sell prices. RoR is calculated by the following equation:

$$RoR = \frac{P_{t_{i+1}} - P_{t_i}}{P_{t_i}} \tag{4.10}$$

Where, $P_{t_{i+1}}$, and P_{t_i}, represent the prices that we sell, and buy, respectively. We determine the total RoR by summing each trades result that is calculated by the Equation 4.10. The variability of our ratio is then determined based on the standard deviation of these RoRs. This approach was chosen because, throughout the duration of our test set, the realized trades were based on a straightforward rule of buying and then selling (please refer to Section 4.2.2). In other words, at any given time, we would either not hold a stock position or have a buy position, and we would not buy a new stock without first selling the current one.

While using the trade-level rate of returns, we considered three main elements: i) As Christopherson et al. (2009) pointed out, if no cash flows occur during a holding period, the portfolio return can be calculated from the start and end values without considering the effects that the holding period might introduce. This approach allows us to observe the risk-adjusted metric of a portfolio of trades formed from individual trades opened with a buy and closed with a sell, rather than considering the holding periods of each individual trade. ii) Secondly, as shown by A. Cartea & Jaimungal (2013); Á. Cartea et al. (2017), the SR can be calculated without considering holding periods in high-frequency trading (HFT). In HFT, while fixed intervals such as minutely, 5-minutely, and 15-minutely are used for profiling data, the most prevalent and widely used type of data is "tick-by-tick" data, which captures every transaction moment without the constraints of fixed intervals. Given that Directional Changes (DC) focus on event-driven separations rather than fixed intervals, the trade-level Sharpe Ratio we use captures nuances similar to those in HFT. Their approach of calculating the SR based on profit and loss realized over different periods without calibrating for the holding period, similar to DC, convinced us to adopt this method. iii) Lastly, in research conducted on DC, the fundamental characteristic of the concept is its representation through events rather than physical time data (where the traditional SR is suitable for). From a trade-level perspective, researches by Long et al. (2022); Adegboye et al. (2023) demonstrated that within the DC paradigm, the SR calculation can be performed without including the holding period.

In the forthcoming Section 4.5, we will utilize risk metrics alongside the SR and RoR. The first one is Value at Risk (VaR), which is a statistical measure used to assess the level of financial risk within a firm or investment portfolio over a specific time frame. It estimates the maximum potential loss at a specified confidence level, offering a quantifiable measure for the most severe expected loss. It is an essential tool for effective risk management in finance. Its equation is as follows:

$$VaR_{\alpha}(P) = -F_P^{-1}(\alpha) \tag{4.11}$$

where $VaR_{\alpha}(P)$ represents the Value at Risk at a confidence level of α (i.e., 95% in our research) for an investment P. $-F_P^{-1}(\alpha)$ represents the inverse cumulative distribution function (quantile function) of the investment's return distribution evaluated at α. The negative sign is because we are considering the lower tail of the distribution. The last metric is Population Standard Deviation (STD), which quantifies the risk associated with the returns of trades. It measures the extent to which trades' returns can vary from their average return, offering a gauge of its level of risk. A higher standard deviation signifies greater volatility and, consequently, higher risk. Its calculation is as follows:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{4.12}$$

Where σ is the population standard deviation, N is the total number of trade return, x_i is individual trade, and the μ is the average of the trades return.

4.3 Experimental Setup

4.3.1 Data

In this thesis, we use 200 publicly traded stocks listed on the New York Stock Exchange from November 27, 2009, to November 27, 2019, sourced from YAHOO Finance (Aroussi 2017) using the "yfinance" Python module. The selection of these stocks was performed using the "random" module from the broader number of tickers. The reason for selecting 200 stocks is due to time efficiency considerations. Given the extensive number of tests required, a larger number stocks would be impractical, thus, 200 tickers were randomly chosen. The data set for each stock is divided into three parts: 56% for training, 24% for validation, and 20% for testing purposes. The validation set is utilized for parameter tuning of the GA, a topic that will be covered more comprehensively in the upcoming section. After tuning, the training and validation sets (comprising 80% of the total data) are combined to form a final training set, covering the first 8 years. In essence, we concatenate the validation set onto the training set to create the final training set, from which the results of the experiments in upcoming sections are derived. The selection of this specific period aims to exclude any potential distortions in the stock market data that could arise from the COVID-19 pandemic.

4.3.2 Parameter Tuning

The optimal GA parameters were determined via a grid search conducted on the validation set. The validation set interval was determined as follows: 80% of the previously mentioned separated training set, divided into 70% and 30% (The validation set consists of this 30% data, encompassing approximately the last 2.4 years of the first 8 years.), was ensured to not see the test set as discussed in the previous Section 4.3.1. The predetermined values that some strategies, especially $|OSVbest|$ and $|TMVbest|$, will use in the validation set, were also found within this 70% portion of the training set, which corresponds to approximately the first 5.6 years of the entire data-set.

During the parameter tuning phase, we used a subset of 40 stocks. This decision was primarily driven by our constrained computational resources, which played a significant role in optimizing our time efficiency. These stocks were selected at random from the broader pool of 200 stocks that were utilized in the conclusive experiments, as presented in the results sections of Chapters 4, 5, and 6. The selection of these 40 stocks was done as follows: Initially, each of the 200 stocks was assigned to one of three segments based on their market capitalization[4] (Mcap). These three segments are: “small-Mcap” for stocks with Mcap under 2 billion dollars,

[4]Market capitalization is a measure of a company’s total value in the stock market. It is calculated by multiplying the current market price of one share of the company’s stock by the total number of outstanding shares.

"middle-Mcap" for those between 2 and 20 billion dollars, and "large-Mcap" for stocks with Mcap exceeding 20 billion dollars. Following this, stocks were selected in proportion to their respective segments. Since there are a total of 200 stocks, consisting of 58 in the large-Mcap segment, 102 in the middle-Mcap segment, and 40 in the small-Mcap segment, we randomly chose 12 from the large-Mcap, 20 from the middle-Mcap, and 8 from the small-Mcap segments for the tuning phase. In this way, when considering the entire 200 stocks as one group, we employed "stratified sampling" as emphasized by Neyman (1992) to obtain a sample that would be representative of the entire group.

The parameters used for tuning in the grid search for the GA are as follows: population size, with values 100, 150, and 200; number of generations, with values 15, 18, and 20; tournament size, with values 2 and 3; and crossover probability, p, with values of 0.75, 0.85, and 0.95. The mutation probability is equal to $1-p$.[5] We run the GA 50 times for each combination of parameter values to ensure reliable and robust results. From each batch of the 50 runs, we keep the best chromosome (one with the highest SR). We do the same for parameters, and we compare each of their best chromosomes' results within the validation set. However, when subjecting the results of these 54 configurations to the Friedman non-parametric test, we observed that none of the configurations could achieve statistical significance at the $\alpha = 5\%$ level. Our null hypothesis posited that the results of the configuration originated from the same continuous distribution. Consequently, we were unable to reject the null hypothesis. Due to the population parameter being the most important parameter for time efficiency, we selected the lowest value of 100, as we did not observe statistical significance. For the remaining parameters, we chose those that

[5]Because the mutation probability can be derived as 1 minus the crossover probability $(1-p)$, there was no need to include it as a separate parameter in the tuning process.

appeared at the top of the rankings in the 54 configurations tested. For example, since a generation count of 18 came out on top in the rankings more often than others, 18 was selected as the number of generations. The parameters used in the final configuration can be found in Table 4.3.

Table 4.3: Selected parameters from GA tuning

Population size	100
Number of generations	18
Tournament size	2
Crossover probability	0.95
Mutation probability	0.05

As previously mentioned, the validation set was later merged into the training set. As a result, the fixed parameters were applied to experiments conducted on the 200 stocks. In our final experiment, the model was trained using a combined data set, including both the training and validation sets (the first 80% of the whole set) and subsequently tested against a separate test set (the last 20% of the whole set). Lastly, the tuned parameters for GA, have been identified based on a single threshold. The process of selecting this threshold will be explained in Section 4.5.

4.4 Benchmarks

We categorize our benchmarks into two main groups: *DC-based benchmarks* and *Non-DC benchmarks*. This classification is employed to assess whether MSGAM can achieve superior performance compared to both individual strategies designed for DC and traditional TA-based strategies.

4.4.1 DC-Based Benchmarks

Individual Strategies

Previously described strategies, St1, $\cdots$, St8, each representing a distinct approach, will all serve as benchmarks as well. While this might initially seem like a sanity check, it serves to fulfill the two primary objectives of our thesis. The first objective entails the creation of profitable DC strategies that bear resemblance to traditional TA approaches. The second objective focuses on improving performance through the application of GA optimization.

Executions on Confirmation Points

In this specific scenario, our trading approach involves executing trades immediately upon the confirmation of a directional change. Whenever we identify a trend as a downtrend, we initiate a buy at the confirmation point for the stock and then promptly sell it at the subsequent uptrend confirmation point. The benchmark will be abbreviated to "DCC". The primary goal of this scenario is to assess trading profitability when focusing exclusively on DC events.

4.4.2 Non-DC benchmarks

TA Strategies

We use seven popular technical indicators. Based on these indicators, the parameter values for the employed strategies were set to values frequently observed in the field and the work by Achelis (2001) and Di Lorenzo (2013). Their brief descriptions along with how these indicators are utilized in the execution processes of trading strategies as follows:

- *Average Directional Index (ADX)*: ADX quantifies price trend strength. Buy when ADX exceeds 25 upward trend. Sell when ADX surpasses 25 downward. It is highly important to emphasize that the trends elucidated in the explanation of these indicators diverge from those discussed within the context of the DC paradigm. As highlighted by Di Lorenzo (2013), we are utilizing the parameter value set at 25, adhering to the parameter value established by Welles Wilder, the founder of the indicator. Algorithm 12 outlines the execution process in the test set.

Algorithm 12 ADX trading strategy

```
for each time step in physical price data do
    Calculate current ADX value
    if ADX > 25 then
        Execute Buy if the trend is upward, Sell if downward, else Hold
    else
        Hold position
```

- *Aroon*: Buy when Aroon Oscillator is positive (upward trend); sell when it is negative (downward trend). Consists of two components: Aroon Up and Aroon Down. We utilize the same parameters for the Aroon indicator as derived from the work of Di Lorenzo (2013). Algorithm 13 demonstrates the execution in the test set.

Algorithm 13 Aroon trading strategy

```
for each time step in physical price data do
    Calculate Aroon Oscillator = Aroon Up - Aroon Down
    if Aroon Oscillator of previous day < 0 then
        Execute Sell
    else if Aroon Oscillator of previous day > 0 then
        Execute Buy
    else
        Hold position
```

- *CCI*: Buy signals occur when the CCI is below -100, indicating oversold conditions, and sell signals when the CCI is above 100. Following Di Lorenzo (2013), we adopt a parameter value of 100, aligning with the proposition of Donald Lambert, the creator of the indicator. Algorithm 14 illustrates the execution process in the test set.

Algorithm 14 CCI trading strategy

```
for each time step in physical price data do
    Calculate current CCI value
    if CCI < -100 then
        Execute Buy (indicating oversold conditions)
    else if CCI > 100 then
        Execute Sell (indicating overbought conditions)
    else
        Hold position
```

- *EMA*: Computes a 20-period EMA based on closing prices, emphasizing recent data with a designated alpha[6]. Buy when the closing price exceeds EMA (upward trend); sell when it falls below EMA (downward trend). Algorithm 15 outlines the execution process in the test set.

Algorithm 15 EMA trading strategy

```
for each time step in physical price data do
    Calculate 20-period EMA based on closing prices
    if Closing price > EMA then
        Execute Buy (indicating upward trend)
    else if Closing price < EMA then
        Execute Sell (indicating downward trend)
    else
        Hold position
```

- *MACD*: The MACD indicator is computed based on the 12-period and 26-period Exponential Moving Averages (EMAs) of closing prices. According to

[6] Alpha represents a smoothing factor that determines how much weight is given to the most recent data points

the MACD histogram, buy when below zero (potential upward trend), and sell when above zero (potential downward trend). As indicated by Achelis (2001), we employ the same periods for both the EMA and the MACD. Algorithm 16 shows the execution process in the test set.

Algorithm 16 MACD trading strategy

```
for each time step in physical price data do
    Calculate MACD based on 12-period and 26-period EMAs of closing prices
    if MACD histogram < 0 then
        Execute Buy (indicating potential upward trend)
    else if MACD histogram > 0 then
        Execute Sell (indicating potential downward trend)
    else
        Hold position
```

- *RSI*: The RSI is calculated over 14 periods, indicating overbought or oversold conditions. Buy signals are generated when the RSI is below 30 (oversold), and sell signals when the RSI is above 70 (overbought). The parameter values of 30 and 70, along with the period value, are utilized in accordance with the specifications outlined by Achelis (2001). Algorithm 17 outlines the execution process in the test set.

Algorithm 17 RSI trading strategy

```
for each time step in physical price data do
    Calculate RSI over 14 periods
    if RSI < 30 then
        Execute Buy (indicating oversold conditions)
    else if RSI > 70 then
        Execute Sell (indicating overbought conditions)
    else
        Hold position
```

- *Williams %R (Wr)*: The Wr identifies overbought/oversold conditions. Buy signals occur at values below -80 (oversold), and sell signals at values above -20 (overbought). We adopted these parameter values as described in the work of Achelis (2001). Algorithm 18 demonstrates the execution process in the test set.

Algorithm 18 Williams %R (Wr) trading strategy

```
for each time step in physical price data do
    Calculate Wr
    if Wr < -80 then
        Execute Buy (indicating oversold conditions)
    else if Wr > -20 then
        Execute Sell (indicating overbought conditions)
    else
        Hold position
```

Buy and Hold (BandH)

We also consider the BandH strategy as a benchmark, which involves purchasing and holding the product for a certain time without considering market fluctuations. In our model, the trader buys the product at the beginning of the test period and evaluates the performance monthly over the two-year period. Monthly returns are calculated after accounting for a transaction cost of 0.025%.

4.5 Results

Here, it is highly important to mention the selected threshold for this chapter. According to our interpretation, we have selected θ as 0.72%, considering that conventionally for daily stock price, changes between 0.5% and 1% represent an important profit or loss range. When selecting this θ, we uniformly generated a random number between these boundaries using the "random.uniform" function in Python. The generated number was then rounded to two decimal places to obtain the threshold value of 0.72%. In Chapter 5 and Chapter 6, a broader range of thresholds was taken into consideration within their respective models.

4.5.1 MSGAM and DC Based Results

Before we begin discussing the results, we would like to highlight another important aspect. In this chapter, as mentioned in Section , we have divided the 200 stocks into three segments, taking into consideration their Mcap. These 58 small-Mcap, 102 middle-Mcap, and 40 large-Mcap stock can be found in Appendix A.1. Lastly, we must emphasize an important point: Due to spacing constraints in tables, we utilize abbreviations for our MSGAM model when presenting in tables. "MS" denotes the MSGAM model with 200 stocks, while "MS_L", "MS_M", and "MS_S" respectively represent the performance of the MSGAM model considering only stocks within their respective segments: large-Mcap, medium Mcap, and small-Mcap.

Table 4.4 outlines the average performance results of the MSGAM across various metrics such as Sharpe Ratio (SR), Rate of Return (RoR), Standard Deviation (STD), Value at Risk (VaR), and Number of Trades (Tra). The table displays the overall results for all 200 stocks under the MSGAM model in the second column, labeled MS. It then categorizes these results by market capitalization segments, showing performance for each segment's respective number of stocks. Additionally, it details the average outcomes for each of the eight individual strategies and a trading strategy based on confirmation points under 200 stocks again. The results are based on a specific run from a set of 50, specifically using the chromosome with the highest SR from the training phase. This approach is crucial to evaluate the effectiveness of multiple runs and to identify the best chromosome for practical application in real-world trading scenarios. Moving forward, our methodology will follow this pattern: selecting the best-performing chromosome from the training set out of 50 runs and applying it to the test set.

Table 4.4: Average Sharpe Ratio (SR), Rate of Return (RoR), Standard Deviation (STD), Value at Risk (VaR), and Number of Trades (Tra.) results across 200 stocks for the MSGAM (MS) and DC-based strategies. The best value for each row (strategies) is shown in bold.

	MS	MS_L	MS_M	MS_S	St1	St2	St3	St4	St5	St6	St7	St8	DCC
SR	1.71	**2.15**	1.77	1.31	-2.1	0.77	0.13	0.26	0.22	0.5	1.45	1.14	0.19
RoR	0.19	0.19	**0.19**	0.18	-0.09	0.09	0.09	0.09	0.06	0.07	0.1	0.05	0.07
STD	0.1	0.08	0.09	0.12	0.07	0.09	0.1	0.1	0.08	0.07	0.03	**0.02**	0.05
VaR	0.12	0.08	0.1	0.16	0.12	0.13	0.1	0.1	0.13	0.11	0.02	**0.01**	0.06
Tra	8.61	8.28	8.92	8.27	19.9	10.2	5.44	7.01	10.6	16.8	5.52	3.99	35.9

From Table 4.4, the first observation we notice is that the SR metric for MS_L, MS_M, and MS_S, which are 2.15, 1.77, and 1.31, respectively. Additionally, among the 200 stocks, the overall MS performance yielded an SR of 1.71. When comparing this to our individual strategies, St7 and St8 follow closely with SR values of 1.45 and 1.14, respectively. However, considering that the SR is a risk-adjusted metric, as a second observation, we notice that the difference in the RoR for the previously discussed strategies differs from the MS. For example, MS approximately doubles the return of St7 and generates three times more return than St8. Observing the STD of these two strategies, St7 and St8, it becomes evident that their reduced risk has led to an increase in the SR. Furthermore, the low number of trades executed by these strategies is a topic that we will explore in the future to determine if it indeed contributes to lower risk.

Overall, Table 4.4 illustrates that MS exhibits the highest SR with a value of 1.71 when considering the average results of 200 stocks, without taking into account the Mcap segmentation. This value is approximately 1.17 times greater than the second-highest SR and 1.5 times greater than the third-highest SR achieved by St7 and St8, respectively. Similar observations hold true for RoR outcomes: MS achieved an average RoR of 19% across 200 stocks, and the same model again achieved 19% in large-Mcap and medium-Mcap stocks, notably higher than the individual strategies and DCC. However, in terms of risk metrics, MS realized a 10% STD and 12% VaR on average across 200 stocks, which are relatively higher than the individual strategies and DCC. Finally, these performances occurred on average with 8.61 trades for MS, with the highest number of trades on average coming from the DCC strategy.

Figure 4.1 shows that the MS achieved the highest average SR and RoR among large-Mcap stocks, the same observation can be drawn in middle-Mcap stocks. In the small-Mcap segment, MS closely trails St8 and St7 in SR but leads in RoR. However, this higher performance in SR and RoR comes with a relatively increased level of risk, as indicated by the risk metrics in the lower scatter plots of the figure. It is also important to emphasize that in real-world applications when considering aggregate metrics like the Sharpe ratio, relatively high results in risk metrics can often be compensated for.

Figure 4.2 displays the box plot illustrating the distribution of results. As evident from the top boxes, the high median SR and RoR for MS, when compared to the benchmarks, are fairly symmetric around the median. Furthermore, as indicated by the whiskers, the variability in the results of MS is relatively low compared to other benchmarks, except St7 and ST8. One of the primary reasons for this can be observed in the bottom-left box plot, where the risk associated with these strategies scatters around a very low median value compared to other strategies, as well as our MS. Looking at the bottom-left box-plot part of the analysis, we can also conclude that, as indicated by the VaR, the probability of loss for MS is exceeded by these two strategies (St7 and St8), as well as by DCC. Once again, the very limited number of trades executed by these strategies appears to be the reason for this observation. However, the fact that MS demonstrates a mediocre performance on risk metrics encourages further exploration in risk analysis for future research endeavors.

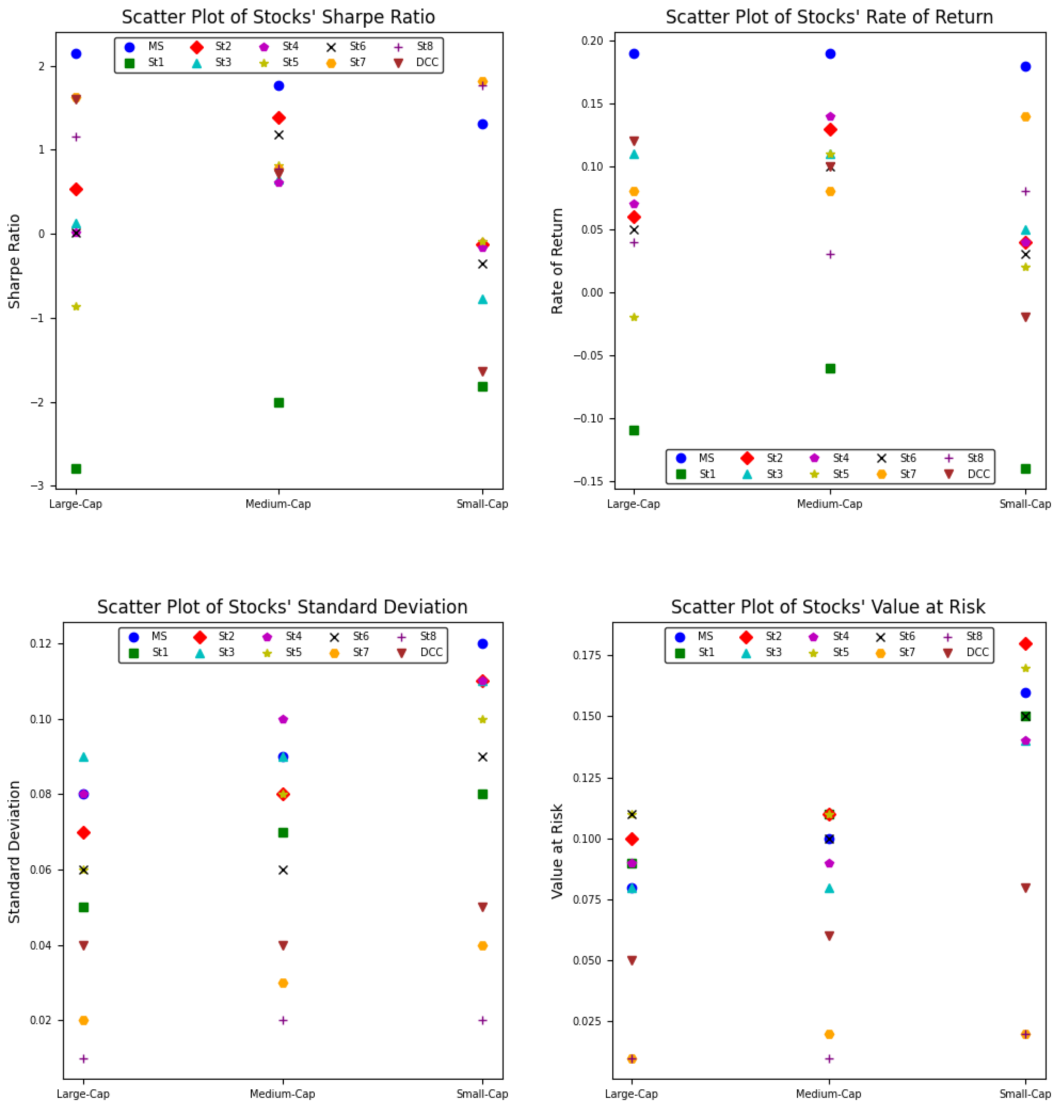

Figure 4.1: Scatter plots of average results for MSGAM (MS) and DC-based benchmarks: Comparison of Sharpe Ratio, Rate of Return, Standard Deviation, and Value at Risk across three market capitalization segments of stocks.

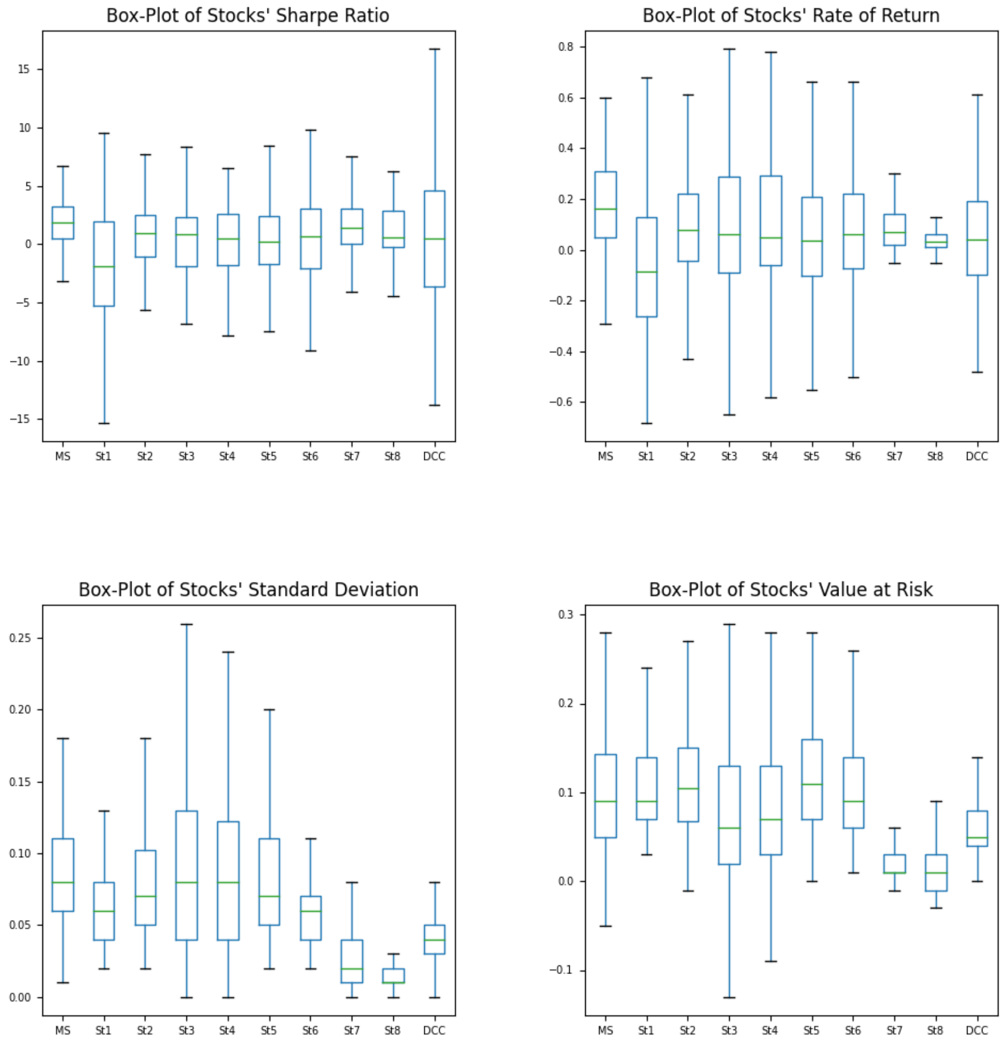

Figure 4.2: Box-plots of MSGAM (MS) and DC-based benchmarks results across 200 stocks on Sharpe Ratio, Rate of Return, Standard Deviation, and Value at Risk.

Table 4.5 illustrates the number of stocks where the MS and individual strategies outperform each other when evaluated among 200 stocks across performance and risk metrics. For the SR, MS demonstrates competitive strength, achieving the highest performance in 29 out of 200 stocks where it competes closely with St6, St7, and St8, each achieving the highest performance on 32, 33, and 32 stocks, respectively. MS emerges as a strong performer in the RoR metric, leading in 48 stocks, significantly outpacing its nearest rival, St6, which comes first in 26 stocks. However, in STD, MS shows limited success, achieving the lowest STD in only 4 stocks, and does not realize superiority in any stocks' VaR. Unlike MS, St7 and St8 show dominance in these risk metrics. Specifically, St7 leads in 40 stocks for STD and 66 for VaR, while St8 significantly outperforms with 137 stocks in STD and 100 in VaR. Overall, considering that SR is a risk-adjusted metric, MS comes first in 29 of the stocks at SR, and the fact that it ranks first in RoR in nearly a quarter of the stocks should be highlighted.

Table 4.5: The number of stocks for which MSGAM (MS) or individual strategies yield the best results on performance metrics among the 200 stocks. The highest number of stocks for the strategy is highlighted in bold.

	MS	St1	St2	St3	St4	St5	St6	St7	St8
SR	29	17	21	11	11	14	32	**33**	32
RoR	**48**	16	21	31	23	15	26	14	6
STD	0	0	0	13	10	0	0	40	**137**
VaR	4	0	1	20	10	0	1	66	**100**

To delve deeper into the results, we performed the Friedman non-parametric statistical tests[7] while assuming the null hypothesis that all algorithms originate from the same continuous distribution. In the tables presenting the statistical Friedman test for SR in 4.6, for RoR in 4.7, for STD in 4.8 and for VaR in 4.9, the second column presents the mean rank of each algorithm. (i.e., GA-optimized model, in-

[7]These tests offer a robust and reliable means to assess differences among related groups. In this work, these groups are distributions from the related test metric results

dividual strategies, DCC) while the third column provides the adjusted p-values derived from the test comparing the average rank of each algorithm with that of the control algorithm (i.e., the algorithm with the highest rank). In adjusted p-values, we used the Post-hoc two-stage False Discovery Rate, abbreviated to *FDR* correction is employed to control the likelihood of making false discoveries (Type I errors) when conducting multiple pairwise comparisons.

Based on the observed results from the SR results of the statistical test at Table 4.6, it is apparent that MS achieves the highest rank and statistically outperforms all other algorithms at a significance level of $\alpha = 0.05$ in terms of the SR. From Table 4.6, MS comes first in ranking with a value of 4.25. It is clear that there are varying degrees of performance among the strategies. The St1, for instance, ranked the lowest at 7.085, and its extremely low adjusted p-value of 3.938284e-19 strongly suggests a significant deviation from the control algorithm. Other algorithms such as St3, St5, St4, and DCC also exhibit significant differences from the control, as evidenced by their very low p-values (ranging from 8.430485e-07 to 2.739033e-05). These findings suggest that benchmark strategies' performances are distinct from that of the control algorithm, which is MS.

Table 4.6: The statistical test results for Sharpe Ratio were obtained using the non-parametric Friedman test, followed by the two-stage FDR correction to calculate adjusted p-values between MSGAM (MS) and DC-based benchmarks. Significant differences between the control algorithm (denoted with (c)) and the algorithms represented in a row at the $\alpha = 5\%$ level are highlighted in bold.

Algorithm	**Rank**	**Adjusted p-value**
MS(c)	4.25	-
St7	**4.745**	9.611118e-02
St8	**5.235**	1.578611e-03
St2	**5.325**	5.507743e-04
St6	**5.465**	9.578207e-05
DCC	**5.565**	2.739033e-05
St4	**5.57**	2.739033e-05
St5	**5.765**	1.449820e-06
St3	**5.815**	8.430485e-07
St1	**7.085**	3.938284e-19

From the RoR results of the statistical test at Table 4.7, MS appears to hold the best ranking with a 3.875. St7 and St8 closely follow MS in the rankings, with values of 4.745 and 5.235, respectively. Their adjusted p-values indicate a statistically significant deviation from MS, with values of 6.116961e-05 and 3.415899e-05, respectively. Meanwhile, St1 has the lowest ranking at 7.19, and its extremely low adjusted p-value of 9.815938e-26 more strongly suggests a significant deviation from the control algorithm.

Table 4.7: The statistical test results for Rate of Return were obtained using the non-parametric Friedman test, followed by the two-stage FDR correction to calculate adjusted p-values between MSGAM (MS) and DC-based benchmarks. Significant differences between the control algorithm (denoted with (c)) and the algorithms represented in a row at the $\alpha = 5\%$ level are highlighted in bold.

Algorithm	**Rank**	**Adjusted p-value**
MS(c)	3.875	-
St7	**5.115**	6.116961e-05
St2	**5.165**	3.415899e-05
St4	**5.19**	2.439752e-05
St3	**5.225**	1.550907e-05
St6	**5.68**	7.705814e-09
St5	**5.69**	7.470163e-09
DCC	**5.795**	1.001861e-09
St8	**6.025**	1.841913e-11
St1	**7.19**	9.815938e-26

In the risk metrics, St8 takes the top position in both rankings, followed closely by St7. Specifically, in the STD results shown in Table 4.8, St8 is ranked the highest with a rank of 1.44. St7 follows closely behind with a notable rank of 2.74 and a highly significant p-value of 8.448027e-10. DCC is ranked third with a rank of 3.685, and its exhibits an extremely low p-value of 1.201893e-24. MS ranks lowest among the strategies with a score of 7.49. From the VaR results Table 4.9, St8, St7, and DCC lead in top three, while MS is sixth with a score of 6.56 and a p-value of 5.294776e-53.It is essential to highlight that despite its shortcomings in terms of risk metrics such as STD in Table 4.8 and VaR in Table 4.9, the model's performance in SR and RoR should be emphasized. Because, practitioners tend to give more weight to aggregated metrics, such as SR, that account for risk in real-world applications. Therefore, the importance of offsetting risk with better returns and a higher SR should be underscored. In the next section, we will discuss the MSGAM model from the perspective of TA-based strategies.

Table 4.8: The statistical test results for Standard Deviation were obtained using the non-parametric Friedman test, followed by the two-stage FDR correction to calculate adjusted p-values between MSGAM (MS) and DC-based benchmarks. Significant differences between the control algorithm (denoted with (c)) and the algorithms represented in a row at the $\alpha = 5\%$ level are highlighted in bold.

Algorithm	**Rank**	**Adjusted p-value**
St8(c)	1.44	-
St7	**2.74**	8.448027e-10
DCC	**3.685**	1.201893e-24
St6	**5.76**	8.225618e-80
St1	**6.0**	1.021062e-87
St3	**6.62**	3.413072e-109
St4	**6.72**	6.668288e-113
St2	**7.05**	5.595941e-125
St5	**7.08**	7.794204e-126
MS	**7.49**	3.547093e-141

Table 4.9: The statistical test results for Value at Risk were obtained using the non-parametric Friedman test, followed by the two-stage FDR correction to calculate adjusted p-values between MSGAM (MS) and DC-based benchmarks. Significant differences between the control algorithm (denoted with (c)) and the algorithms represented in a row at the $\alpha = 5\%$ level are highlighted in bold.

Algorithm	**Rank**	**Adjusted p-value**
St8(c)	1.835	-
St7	2.05	1.088626e-01
DCC	**4.705**	1.605101e-21
St3	**5.175**	2.914773e-28
St4	**5.635**	1.727590e-35
MS	**6.56**	5.294776e-53
St6	**6.715**	1.131776e-55
St1	**7.08**	1.137497e-63
St2	**7.22**	1.991177e-66
St5	**7.445**	4.568826e-71

4.5.2 MSGAM and Non-DC Based Results

In this section, we aim to assess the performance of the MSGAM (MS) model by conducting a comparative analysis with strategies derived from various technical indicators: ADX, Aroon (Ar), CCI, EMA, MACD, RSI, Williams %R (Wr), along with BandH (refer to Section 4.4.2 for detailed explanation).

In Table 4.10, we show the average results of Sharpe Ratio (SR), Rate of Return (RoR), Standard Deviation (STD), Value at Risk (VaR), and Number of Trades (Tra.) across 200 stocks for MSGAM (MS), seven TA-based strategies, and BandH. The highest SR is achieved by MS with 1.71, followed by the SR substantiated by the BandH strategy with 1.62. Two other relatively high SRs are achieved by CCI and RSI, with values of 1.48 and 1.59, respectively. Similar to the findings in the previous section, the Rate of Return (RoR) is best for MS among all strategies, with a value of 19%. Overall, based on all stocks, our MS achieves relatively high SR and RoR compared to other TA-based strategies. When examining the risk metrics, MS exhibits a STD of 0.1, which is equivalent to that of ADX, RSI, BandH, and higher than others such as Ar, CCI, EMA, MACD, and Wr. Although MS's STD is not the lowest, it still signifies a moderate level of risk. Regarding VaR, MS has a VaR of 0.12, which is relatively low compared to other strategies like Ar, CCI, MACD, RS, Wr, and Bandh, all of which have higher VaR values. This suggests that MS carries a lower risk of incurring significant losses than these other strategies, except EMA.

Table 4.10: Average Sharpe Ratio (SR), Rate of Return (RoR), Standard Deviation (STD), Value at Risk (VaR), and Number of Trades (Tra.) results across 200 stocks for the MSGAM (MS), 7 TA-based strategies, and Buy and Hold strategy (BandH). The best value for each row (strategies) is shown in bold.

	MS	ADX	Ar	CCI	EMA	MACD	RSI	Wr	BandH
SR	**1.71**	-1.87	0.55	1.48	-2.64	-0.55	1.59	1.21	1.62
RoR	**0.19**	-0.03	0.06	0.09	0.010	-0.03	0.12	0.07	0.14
STD	0.1	0.1	0.07	0.07	**0.06**	0.07	0.1	0.07	0.1
VaR	0.12	0.12	0.14	0.15	**0.04**	0.15	0.16	0.16	0.13
Tra	8.61	5.59	17.68	12.78	31.97	17.80	6.15	12.31	24

From Figure 4.3, we observe that the median results for SR and RoR are leading, and 50% of the results scatter around this median in a relatively narrow range. In the SR distribution of stocks, EMA scatters over a wider range compared to other strategies, whereas in the RoR, this strategy is BandH. From the bottom two box plots, again, similar to the previous section, we see similar results. While achieving this level of performance, the risk is relatively high. However, this time, the probable loss for the MS strategy is narrower compared to numerous TA-based strategies as illustrated in the VaR box plot.

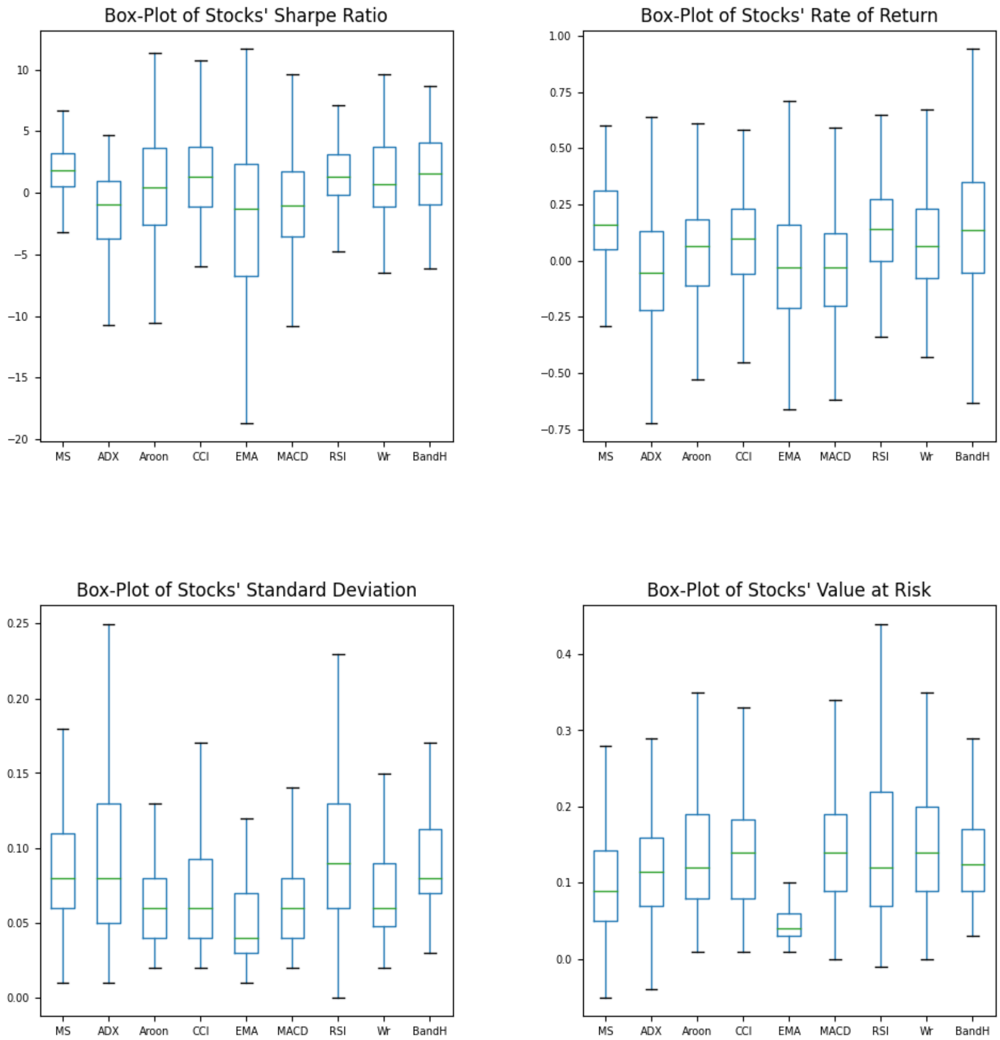

Figure 4.3: Box-plots of MSGAM (MS) and non-DC related benchmarks results across 200 stocks on Sharpe Ratio, Rate of Return, Standard Deviation, and Value at Risk.

To gain a better perspective, we subjected the findings to Friedman non-parametric statistical test. The SR results of the statistical test in Table 4.11, we found that the MS achieved the first rank with 4.105. It is shown that five TA benchmark strategies showed significant deviations from the control algorithm (MS) at the $\alpha = 5\%$ level. This is particularly notable for EMA, MACD, and ADX, as their p-values strongly indicate that their performance significantly differs from the control algorithm. For the remaining strategies, Wr and Ar follow in the ranking by fifth and sixth, respectively, and differs significantly at the $\alpha = 5\%$. However, RSI, CCI and BandH were not able to substantiate statistical significance, while they were following the MS in ranking.

Table 4.11: The statistical test results for Sharpe Ratio were obtained using the non-parametric Friedman test, followed by the two-stage FDR correction to calculate adjusted p-values across MSGAM (MS) and non-DC benchmarks. Significant differences between the control algorithm (denoted with (c)) and the algorithms represented in a row at the $\alpha = 5\%$ level are highlighted in bold.

Algorithm	**Rank**	**Adjusted p-value**
MS(c)	4.105	-
RSI	4.295	2.485e-01
CCI	4.445	1.221e-01
BandH	4.445	1.221e-01
Wr	**4.665**	2.629e-02
Ar	**4.860**	3.541e-03
EMA	**5.880**	4.641e-11
MACD	**6.015**	2.556e-12
ADX	**6.290**	2.458e-15

From the RoR results of the statistical test at Table 4.12, MS ranks first, and it is significantly different from the TA-based strategies at the 5% significance level, except for BandH. Given that stock market bullishness was observed in our test set, and the monthly returns of BandH substantiate a certain RoR in the long run, BandH is closely following MS in rankings. However, MS significantly outperforms every other TA-based strategy, with a ranking of 3.835.

Table 4.12: The statistical test results for Rate of Return were obtained using the non-parametric Friedman test, followed by the two-stage FDR correction to calculate adjusted p-values across MSGAM (MS) and non-DC benchmarks. Significant differences between the control algorithm (denoted with (c)) and the algorithms represented in a row at the $\alpha = 5\%$ level are highlighted in bold.

Algorithm	**Rank**	**Adjusted p-value**
MS(c)	3.835	-
BandH	4.170	7.043e-02
RSI	**4.285**	3.429e-02
CCI	**4.605**	1.577e-03
Wr	**4.900**	3.118e-05
Ar	**5.110**	9.871e-07
EMA	**5.785**	2.533e-13
ADX	**6.155**	7.562e-18
MACD	**6.155**	7.562e-18

When we compare MS with TA-based strategies in Table 4.13 for STD, it did not achieve the highest ranking, similar to the previous individual strategy comparison. Also, from the VaR results of the statistical test in Table 4.14, we would like to emphasize the importance of considering risk while achieving this level of performance. Compared to the previous section, MS performs relatively better under the assumption of a probable loss from the VaR metric with a second ranking. Considering these two rankings, the EMA strategy appears to have the lowest risk in both tables. However, it is essential to bear in mind that this low risk did not necessarily translate into profit, as indicated in Table 4.10.

Table 4.13: The statistical test results for Standard Deviation were obtained using the non-parametric Friedman test, followed by the two-stage FDR correction to calculate adjusted p-values across MSGAM (MS) and non-DC benchmarks. Significant differences between the control algorithm (denoted with (c)) and the algorithms represented in a row at the $\alpha = 5\%$ level are highlighted in bold.

Algorithm	**Rank**	**Adjusted p-value**
EMA(c)	2.015	-
Ar	3.590	9.060e-02
MACD	**3.975**	1.924e-06
CCI	**4.430**	3.891e-10
Wr	**4.700**	2.300e-10
MS	**6.005**	5.548e-14
ADX	**6.055**	1.985e-21
RSI	**6.940**	5.267e-29
BandH	**7.290**	3.044e-70

Table 4.14: The statistical test results for Value at Risk were obtained using the non-parametric Friedman test, followed by the two-stage FDR correction to calculate adjusted p-values across MSGAM (MS) and non-DC benchmarks. Significant differences between the control algorithm (denoted with (c)) and the algorithms represented in a row at the $\alpha = 5\%$ level are highlighted in bold.

Algorithm	**Rank**	**Adjusted p-value**
EMA(c)	1.660	-
MS	**4.155**	6.007e-04
ADX	**4.935**	1.391e-07
RSI	**5.355**	1.193e-07
BandH	**5.400**	6.102e-08
Ar	**5.430**	8.682e-12
CCI	**5.745**	1.907e-12
MACD	**5.815**	3.595e-14
Wr	**5.935**	2.922e-25

4.6 Interpretation

In this section, we will interpret the results mentioned in the previous section. This interpretation will be based on two main pillars. The first is the performance of each individual strategy and the insights drawn from there. The second interpretation is the perspective from MSGAM when these individual strategies are optimized with GA and the results that emerge from this optimization.

Individual Strategies

We first take a look at two strategies, St1 and St2, based on scaling laws. As Section 4.2.1 pointed out, *St1*, involves buying a stock in a DT when its price drops by at least double the threshold θ (refer to scaling law Equation 4.2 for detailed explanation) from its previous high p_{EXT_h} and selling with the same principle on UT by p_{EXT_ℓ}. Given the rule that once a buy occurs, to buy again, it should be sold first (refer the Section 4.2.2 for detailed explanation). From Table 4.4, we can see that on average across 200 stocks, St1 is the strategy that generates the highest number of trades with 19.9 at individual strategies. However, from the same table, we can see that St1 has the worst SR and RoR among the other strategies, with -2.1 and -9%, respectively. From Figure 4.2, it is also evident that the poorly performing stocks have a concentration below the median, which includes 100 stocks. In light of Table 4.7, the strategy we developed based on the expected scaling law performed significantly worse than anticipated. To recall, the strategy involves making a purchase when an OS event is observed after a duration of at least twice that of any DC event, as dictated by the scaling law. The goal is to sell the stock during an uptrend when the duration is twice that of the DC event, aiming to sell the stock bought at a lower price at a higher price. However, due to insufficient time spent in the OS, we were often unable to sell the stock during the immediately following uptrend and downtrend. Additionally, entering another downtrend right after a DC event formed in an uptrend often led to executing the sale at a lower price in the subsequent uptrends, especially at this threshold. Therefore, we can conclude that examining the performance of the scaling law strategy at different thresholds would be beneficial.

St2 generate a Buy when the time duration of that DC doubles from P_{DCC} in DT (refer to scaling law Equation 4.1 for detailed explanation). To sell same principle is used in UT. Tables 4.4 and 4.7 indicate that, in comparison to other strategies, this one performed relatively better, ranking 2nd in RoR with a 9% return. Additionally, its SR of 0.77, and STD of 13% suggest that it maintains a certain level of risk. Based on these results, it can be suggested that in the context of our expectations for OS events within DTs, there is a point at which we reach two durations of DC, and then we capture and sell them in the opposite trend direction.

Among the six remaining strategies, *St3* relies on the use of the OSV_{CUR} (refer to the Equation 4.7 for detailed explanation). The execution of Buy comes from the value of $|OSVbest|$, which is established from the training phase. From Tables 4.4 and 4.7, it is evident that the results support an adequate RoR of 9%. However, the SR performance stands out as one of the worst, which implies that the increase in the absolute values of $|OSVbest|$ in the UT is not as we expected.

St4 depends on the utilization of the indicator denoted as TMV_{CUR}, as indicated in Equation 4.8. The execution of the Buy action is linked to the value of $|TMVbest|$, which is determined during the training phase. The findings presented in Tables 4.4 and 4.7 once again indicate a sub-optimal performance. Although the obtained results were unexpected, particularly in light of the outcomes for St3, it is conceivable that both St3 and St4 encountered a similar challenge due to insufficient increases in the UT, which the $|OSVbest|$, $|TMVbest|$ expected.

St5 and *St6* is based on predetermined ratios. St5 buys a stock when the duration of OS events exceeds a predefined ratio value, namely RD (refer to Equation 4.3 for detailed explanation). From the Tables 4.4 and 4.7, SR, RoR, and VaR are 0.22, 6%, and 13%, respectively, it becomes apparent that the calculated RD possesses limited efficacy when implemented into the test set. This limitation arises despite the initial expectation that the duration of DC and OS would remain consistent throughout the entire time span. However, upon closer examination in Figure 4.2, specifically through the SR box plot, we observe a wider dispersion of data points, with a majority of the stock values deviating from the median, indicating a more significant variability in the stocks.

St6 computes a ratio, namely RN, from the training set by dividing the total number of experienced OS events by the total number of experienced DC events as outlined in Equation 4.4. In this strategy, Buy decisions are based on probability, where a generated random number decides based on RN. From the Tables 4.4 and 4.7 the number of trades for this strategy is notably high; SR, and RoR, 0.5, and 7%, respectively. Therefore, we can conclude that as the sell execution takes place at the respective confirmation points, their previous confirmation points were likely at a lower price. Nevertheless, the profit margins between these points were relatively close to each other.

St7 and *St8* follow the TA resistance and support mechanisms (refer to Section 4.2.2 for detailed explanation). From the Tables 4.4 and 4.7, they are two prominent strategies according to their results in SR, which are 1.45, 1.14. While the RoR parametric test supports this for St7, we cannot make the same assertion for St8. We can attribute the high SR to a low STD in St8, which is achieved through the execution of a low number of trades.

Lastly, DCC executed the highest number of trades on average among the 200 stocks. While doing so, it achieved an average SR of 0.19 and a RoR of 7%. In addition, it ranked at a mediocre level in terms of RoR and SR statistical tests, securing the 6^{th} position in SR and the 8^{th} position in RoR rankings. In terms of risk metrics, despite executing the most trades by a wide margin, it ranked 3^{rd} in both STD and VaR. As evident from the box plots, the variance of the risk metrics is very low.

MSGAM

When the Tables 4.4, 4.7 and Figures 4.2, 4.1 are considered in the context of DC-based benchmarks, it appears that the performance metrics for MS show a SR of 1.71 and a 19% RoR. Additionally, it is worth noting that the deviation from the median for MS seems slightly lower than that of its peers among the DC-based benchmarks at the SR box-plot. However, when we examine Table 4.9, it shows that at VaR, MS ranks sixth. This is further supported by the 12% VaR from Table 4.4. Another important finding from the statistical tests for the risk metric STD is that according to the ranking in Table 4.8, MS appears at the end of the list. Therefore, it can be concluded that MS has outperformed its peers at SR and RoR, albeit with a higher level of risk. As a result, although MSGAM faces higher risks compared to individual strategies, it can be prioritized by less risk-averse traders seeking higher returns and a better Sharpe ratio.

Regarding the non-DC benchmarks on VaR and STD, from Tables 4.13, and 4.14, we arrive at a similar conclusion regarding the risk metrics. Nevertheless, it now occupies the second position in the ranking when compared to TA-based strategies in VaR, whereas it held the sixth in STD. An equally important point is the best performances from MS in terms of SR and RoR, as evident in Table 4.10, and 4.6.

Overall, MS statistically outperforms its benchmarks and is supported by a SR of 1.71 along with a 19% RoR, except for the BandH strategy. The conclusion we can draw from this is that by feeding the chromosomes with different strategies, under $\theta = 0.72\%$, MS improved its performance, albeit with a higher level of risk.

Lastly, we examined the chromosome weights found through GA optimization of 200 stocks. When looking at the average weights of these 200 chromosomes, St2 received the lowest weight at 11%, while St7 received the highest weight at 16% among the 8 strategies. The other strategies had weights between these two values. This indicates that the evolved chromosomes gave relatively more weight to St7, while St2 received the lowest weight.

4.7 Summary

The chapter introduces the Multi-Strategy-Genetic-Algorithm-Model (MSGAM), a model designed for optimizing trading strategies within the DC paradigm using a GA. MSGAM integrates various strategies, two based on scaling laws and six on indicators, into one chromosome. Each strategy, or gene, carries a weight and recommends Buy, Sell, or Hold actions.

Strategies based on scaling laws leverage the regular patterns found within the DC paradigm, such as the average price change or the duration of OS, and DC events. For example, St1 involves buying a stock when a price change exceeds double a threshold from its peak in a Downtrend (DT) and selling in a Uptrend (UT) under similar conditions. St2 operates on the duration of market events, recommending actions based on the time spent in an OS event. The other strategies use DC-derived indicators. For example, St3 and St4 trigger trades based on overshoot and total movement values exceeding set thresholds. St5 and St6 rely on ratios calculated from indicator values, while St7 and St8 are based on indicators signaling saturation-led trend direction changes.

The GA optimization process in MSGAM focuses on maximizing the SR by adjusting the weights assigned to each strategy in the chromosome. The GA employs a one-point crossover and mutation operators, and the fitness of chromosomes is evaluated using the Sharpe Ratio (SR). The optimal GA parameters were determined via a grid search conducted on the validation set.

Results showed that MSGAM achieved high SRs and Rate of Returns (RoR) across various market capitalization segments, outperforming both individual DC-based strategies and traditional TA-based strategies. MSGAM's performance was statistically significant compared to other strategies in terms of RoR, although it assumed a relatively higher level of risk. Moreover, in real-world scenarios where metrics are not viewed in isolation, MSGAM's strong SR (risk-adjusted aggregated metric) performance is particularly relevant to traders. The chapter concludes that MSGAM effectively combines various strategies to enhance trading performance, outperforming numerous benchmarks while managing risks.

Chapter 5

Testing Each Strategy under Various Thresholds

5.1 Introduction

In the previous chapter, we constructed a model using eight genes, namely MSGAM, to process each strategy as a source of information for trade recommendations. We compared strategies and the model that was constructed on these strategies using only one θ. Therefore, the DC profiled data associated with $\theta = 0.72\%$ encompassed only a single set of DC and OS events, specifically characterized by that particular threshold value.

Here, we explore a range of θs instead of using a fixed threshold of 0.72%. This approach allows us to assess each strategy performance under various DC profiled data, derived from the same physical data sets (training and test sets). Afterward, to optimize the actions generated by the strategies under these different thresholds, GA was used. This helps determine if varying θs improves outcomes compared to using a single θ.

It is highly important to emphasize that each strategy will be analyzed individually. For clarity, in the previous chapter, we focused on optimizing recommendations like Buy, Sell, and Hold, which came from various strategies. We addressed conflicting recommendations using GA, encoding the 8 different strategies as 8 genes in a chromosome. However, in this chapter, we shift our focus to optimizing recommendations for each strategy based on DC-profiled data at various θs. We are not combining strategies; instead, we are exploring how different θs (for example, 10 genes representing 10 thresholds in a chromosome for strategy 1) can optimize recommendations within each strategy.

The rest of this chapter covers the methodology in section 5.2, details the experimental setup and results in sections 5.3 and 5.4, and concludes with the interpretation and summary of these findings in sections 5.5 and 5.6, respectively.

5.2 Methodology

It is evident that selecting a fixed value for θ will result in the generation of a single set of DC and OS events. For example, smaller θ leads to more frequent event detection and offers the opportunity to take immediate actions, whereas larger θ detect fewer events but provide the possibility of responding to more substantial price changes. To observe the performance of strategies under different profiled DC data resulting from various θs, we will first explain these θs and the role of GA in the upcoming two sections. We named this model *Multi-Threshold-Genetic-Algorithm-Model* (MTGAM).

5.2.1 Thresholds

This chapter's objective is to encompass a wide range of events by different θ's. In the case of a well-established market like the NYSE, daily fluctuations in stock market indices within the range of 0.5% to 1% (such as the S&P 500 or the Dow Jones Industrial Average) are often considered typical as we used in Chapter 4. To capture a broader spectrum of events, we expanded this range slightly in this chapter, spanning from 0.05% to 2.75%, which encompasses what we view as important events. Subsequently, we randomly selected 10 thresholds from within this range.

This selection process can be summarized as follows: Firstly, to ensure that the thresholds do not closely resemble each other, we divided the range from 0.05% to 2.75% into 10 equal intervals. These intervals are defined as follows: 0.05 for the first, 0.35 for the second, 0.65 for the third, continuing in this sequence up to 2.75 for the final interval (i.e., $2.75\% - 0.05\% = 2.70\%$, and $2.70\%/9 = 0.3\%$, with each interval incrementing by 0.30% and reaching up to 2.75%). Subsequently, we randomly selected the threshold values from 10 different normal distributions, each with a mean (μ) equal to the midpoint of one of these intervals and a standard deviation (σ) of 0.1. For example, the second threshold would be randomly selected from the distribution $\mathcal{N}(0.35, 0.1^2)$. It is important to note two key points: firstly, we included the same threshold from previous chapter as 0.72% for the fourth interval to preserve the comparativeness of the research. Secondly, for the first distribution, we used the right tail, while for the last threshold, we used the left tail. By doing so, the resulting thresholds turned out to be: $\theta_1 = 0.098\%, \theta_2 = 0.22\%, \theta_3 = 0.48\%, \theta_4 = 0.72\%, \theta_5 = 0.98\%, \theta_6 = 1.22\%, \theta_7 = 1.55\%, \theta_8 = 1.70\%, \theta_9 = 2\%$, and $\theta_{10} = 2.55\%$. as in highlighted in Table 5.1.

Here we need to highlight an important point, the early findings of this chapter

Table 5.1: The values of thresholds (%), which were utilized for each strategy, are indicated in bold.

	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8	θ_9	θ_{10}
Values	**0.098**	**0.22**	**0.48**	**0.72**	**0.98**	1.22	1.55	1.70	2	2.55

reveal that, due to their specific construction (as detailed in the Section 4.2.1), St7 and St8 may have had limited – or even no – trading opportunities at larger θs. This is primarily because our data, based on daily closing prices, sees a significant reduction in DC events when θ exceeds 1%. Additionally, there must be no two OS events in downtrends (resp. uptrends) between three consecutive uptrends (resp. downtrends), and these uptrends (resp. downtrends) must also include OS events for St7 (resp. St8) to act. This condition drastically reduces the number of trades, often to near zero. Therefore, St7 and St8 are only applied to the first five thresholds detailed in Table 5.1.

5.2.2 GA optimization on Thresholds

Firstly, it is conceivable that, at a given time, one threshold value may recommend a Buy action while another suggests a Sell or Hold action. However, when a trader wishes to consider recommendations from multiple θs, they may encounter conflicting actions, with one strategy recommending a Buy while another recommends Sell the stock. To address these conflicting recommendations, we assign a weight to each θ and subsequently adjust these weights using GA again (This time, our chromosomes were formed by 10 genes for St1, St2, St3, St4, St5, and St6, and by 5 genes for St7 and St8, as shown in Figure 5.2.). The advantage of incorporating multiple θs is that it can provide a deeper level of information by various profiled data by DC. When it comes to making a decision, we can then follow the recommendation that GA identifies as the optimal chromosome. Once again, it is important to emphasize that in this chapter, each strategy undergoes an optimization process based solely on the recommendations generated by different thresholds. For example, St1 utilizes 10 thresholds, each implemented as 10 genes in the model. In short, each strategy is individually examined.

Table 5.2: The chromosome representation includes 10 thresholds (θs) by the hypothetical weights assigned to each recommendation.

Threshold	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8	θ_9	θ_{10}
Weight	0.023	0.234	0.045	0.356	0.067	0.078	0.089	0.040	0.051	0.001

From Table 4.2, consider that the actions would have taken from the different thresholds at this particular time are as follows, from θ_1 to θ_10 in sequence: 0, 1, 0, 1, 2, 0, 0, 0, 2, and 0 (Hold:0, Buy:1, Sell:2). The genes in the chromosomes are equal to the number of thresholds used for that specific strategy. Again, the total weight for recommendations is $0.023 + 0.234 + 0.045 + 0.356 + 0.067 + 0.078 + 0.089 + 0.040 + 0.051 + 0.001 = 1$, as illustrated in Table 5.2. Subsequently, the action to be executed by the entire chromosome is determined by selecting the one with the highest cumulative weight (i.e., Buy with the weight of 0.590). Similar to the previous chapter, we increase the importance of Buy and Sell recommendations by artificially increasing the responsiveness. When more than two genes suggest actions other than Hold within a time unit, we prioritize the recommendations from the remaining genes and disregard the Hold recommendations for decision-making. In regards to the operators, and fitness function in the GA, please refer to Section 4.2.3 for detailed information.

5.3 Experimental Setup

In this chapter, we utilized the same set of 200 publicly traded stocks listed on the New York Stock Exchange to ensure data consistency (refer to the Table A.1). The time frame considered for the analysis remains consistent, spanning from November 27, 2009, to November 27, 2019. Once again, we adopted the same partitioning strategy, with the first 80% of the data (corresponding to the first 8 years) designated for the training set, and the remaining 20% (equivalent to 2 years) reserved for the test set. We maintained the same parameter configuration as indicated in Table 4.3 for the parameters utilized by the GA as the number of genes closely resembled that of the first chapter.

5.4 Results

Before we begin the results section, we would like to emphasize once again that the purpose of this chapter is to explore whether the performance of each strategy can be improved by using multiple θs. With the help of GA, our goal is to optimize the recommendations that will come from each θ and find the final best-performing chromosome, namely MTGAMs.

In the upcoming two tables, specifically Table 5.3 and Table 5.4, MTGAM will be abbreviated as MT for spacing purposes. In these tables, the performance of the MT is compared with the individual strategies' performances under the thresholds shown in Table 5.1. Essentially, the performances of these individual strategies represent the outcomes resulting from the actions of Buy, Sell, and Hold under their respective thresholds.

Table 5.3 offers a comprehensive view of how each strategy, including MT, performs the best[1] when evaluated among 200 stocks across metrics: Sharpe Ratio (SR), Rate of Return (RoR), Standard Deviation (STD), and Value at Risk (VaR). In the comparison of results between the MT and individual strategies across different thresholds, the highest-performing stock count out of the 200 is emphasized in bold. Additionally, the average number of stocks for which MT vs. each particular θ yields the best performance among the 200 stocks is presented in italics for clarity.

From Table 5.3, MT achieves a notable average of best performances in 35 stocks among the 200 stocks in SR metric, when considering all strategies (St1, $\cdots$, St8). The average result under the $\theta_1 = 0.098\%$ threshold for individual strategies is also 33.6 stocks, which is the closest to MT. In greater detail, MT exhibits a higher peak performance on St2 when compared to the same strategy individually under different thresholds on 59 stocks. Additionally, in St3 and St4, MT achieves the highest SR in 25 and 31 stocks, respectively, when compared to individual strategies with their results under different thresholds. Across all strategies and their respective thresholds, MT shows the second best average outcomes with an average of 33.8 stocks for RoR. In the same metric, MT demonstrates the best performance under St2, St3, and St8, with 60, 24, and 56 stocks, respectively. When considering all single-threshold strategies collectively in the RoR metric, the best performance, on average, is most frequently observed at $\theta_1 = 0.098\%$ with 35 stocks among 200.

When examining these performances from risk metrics, it appears that MT has performed at a mediocre level in comparison to the individual results of strategies based on θs. For STD, MT averages the best performances in 22 out of 200 stocks. The threshold yielding the best average performance for individual strategies is again 0.098%. In this metric, MT's peak performance occurs in St2, where it surpasses the same strategy under different thresholds in 38 stocks. In terms of VaR, MT

[1] The highest value for SR or RoR, and the lowest value for STD or VaR, among the 200 stocks.

Table 5.3: The number of stocks for which MT or individual strategies yield the best results on performance metrics among the 200 stocks. The results of strategies' number of best performance under a specific θ abbreviated by their threshold value in order (0.098% = θ_1, $\cdots$, 2.55% = θ_{10}). The highest number of stocks for the strategy is highlighted in bold.

	Strategies	MT	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8	θ_9	θ_{10}
SR	St1	31	**32**	25	21	17	7	10	12	10	15	20
	St2	**59**	17	13	9	15	22	10	21	9	13	12
	St3	**25**	17	19	23	17	13	15	18	21	13	19
	St4	**31**	16	17	16	20	14	18	16	16	15	21
	St5	28	**31**	26	38	24	17	8	4	9	5	10
	St6	24	**32**	21	19	16	13	17	12	12	21	13
	St7	45	**73**	21	22	22	17	-	-	-	-	-
	St8	37	**51**	30	29	23	30	-	-	-	-	-
	Average	*35*	*33.6*	*21.5*	*22.3*	*19*	*16.6*	*13*	*13.8*	*13*	*12.3*	*15.8*
RoR	St1	23	**33**	20	23	21	8	11	14	12	19	16
	St2	**60**	14	20	10	12	16	10	21	11	11	15
	St3	**24**	21	11	17	19	22	19	13	21	13	20
	St4	25	**31**	14	21	19	8	16	20	12	18	16
	St5	21	**39**	32	30	21	23	11	4	11	2	6
	St6	15	**28**	21	16	13	16	22	13	13	16	27
	St7	46	**61**	26	20	26	21	-	-	-	-	-
	St8	**56**	53	21	25	20	25	-	-	-	-	-
	Average	*33.8*	*35*	*20.6*	*20.3*	*18.9*	*17.4*	*14.8*	*14.2*	*13.33*	*13.2*	*16.7*
STD	St1	32	**35**	27	22	21	12	6	12	9	11	13
	St2	**38**	30	12	22	11	10	11	13	8	21	24
	St3	7	21	14	11	16	13	18	23	20	17	**40**
	St4	9	20	11	12	16	18	18	16	17	21	**42**
	St5	24	**35**	29	30	19	13	9	10	1	8	22
	St6	29	30	**31**	13	13	13	14	9	16	14	18
	St7	24	**50**	14	29	41	42	-	-	-	-	-
	St8	13	33	17	31	40	**66**	-	-	-	-	-
	Average	*22*	*31.8*	*19.4*	*21.3*	*22.1*	*23.4*	*12.7*	*13.8*	*11.8*	*15.3*	*26.5*
VaR	St1	31	46	30	24	11	15	10	6	11	7	9
	St2	**50**	30	19	17	13	14	10	12	13	12	10
	St3	14	**32**	9	13	14	20	13	15	18	20	**32**
	St4	7	19	12	13	15	16	16	15	21	27	**39**
	St5	17	**37**	17	19	20	14	10	9	12	17	28
	St6	26	28	**31**	19	15	29	8	10	11	14	9
	St7	14	42	16	30	39	**59**	-	-	-	-	-
	St8	10	27	23	29	42	**69**	-	-	-	-	-
	Average	*21.1*	*32.6*	*19.6*	*20.5*	*21.1*	*29.5*	*11.2*	*11.16*	*14.3*	*16.2*	*21.2*

shows an average best performance in 21.1 stocks, with its most notable success in St2, achieving the highest VaR in 50 stocks.

Overall, Table 5.3 serves as a starting point for a general framework. MT, when compared to the results of other individual strategies under different thresholds in SR, is ahead in St2, St3, and St4. In St1 and St5, it follows with the highest number of stocks by a small margin. The number of stocks that come out on top for St6 and St8, compared to MT, favors individual strategies by approximately 30%. Additionally, this difference is around 60% for St7.

Table 5.4: Number of trades on average from 200 stocks by MTGAM (MT) and individual strategies.

Strategies	MT	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8	θ_9	θ_{10}
St1	27.16	30.16	27.72	23.36	19.88	16.6	14.38	12.03	11.15	9.78	7.8
St2	13.59	8.29	8.87	9.54	9.88	9.68	9.17	8.52	8.28	7.63	6.66
St3	8.41	5.34	5.23	5.37	5.42	5.28	5.21	5.31	5.32	4.88	4.89
St4	11.71	5.55	5.96	7.29	7.04	8.07	7.91	7.89	7.95	7.71	6.9
St5	14.46	11.41	10.78	10.71	10.43	9.88	9.28	8.35	8	7.16	5.69
St6	24.05	18.41	17.88	17.03	16.7	17.1	14.62	13.8	13.55	13.05	11.71
St7	8.34	8.45	7.81	6.45	5.54	4.44	-	-	-	-	-
St8	6.17	6.2	5.74	4.76	4	3.2	-	-	-	-	-
Average	**14.24**	**11.73**	**11.25**	**10.56**	**9.86**	**9.28**	**10.1**	**9.32**	**9.04**	**8.37**	**7.28**

From Table 5.4 we can observe that MT executed trades more frequently on St1 and St6 compared to the other strategies. As anticipated, MT exhibited the lowest trading activity on St7 and St8. Another crucial validation point to consider is that an increase in the θ corresponds to a reduction in the number of trades.

The primary objective of this chapter is to assess whether optimizing multiple θs can improve the strategies' performances separately. We evaluate this by comparing the MTs results with the outcomes of each strategy from the previous chapter. To reiterate, MTs are models that optimize recommendations across different thresholds for higher performance and reduced risk. For context, in the previous chapter, each strategy's performance was assessed with a θ set at 0.72%. This specific threshold was chosen based on the notion that daily stock price changes between 0.5% and 1% are typically considered significant profit or loss. As mentioned in Chapter 4, we chose θ by generating a random number within this range and rounding it to two decimal places.

For the upcoming tables, it is important to note an adjustment in notation. Until now, "MT" has been used to abbreviate our MTGAM model results. This abbreviation was suitable for the previous two tables, where we focused on MT's overall cumulative performances. However, for more detailed pairwise comparisons moving forward, we will specify these as $\mathrm{MT}_1, \ldots, \mathrm{MT}_8$. For instance, MT_1 will refer to the outcomes of GA optimization using 10 thresholds ($\theta_1, \ldots, \theta 10$) applied to St1. Meanwhile, as previously mentioned, St7 and St8 use only the first five θs. Therefore, MT_7, for example, will indicate the results achieved by optimizing the first 5 thresholds for St7.

Tables 5.5 and 5.6 compare the performance of MT models optimized at various thresholds against individual strategies operating under $\theta_4 = 0.72\%$. Tables show that most strategies improved their SR with MTs, except St5 with a slight decrease. Specifically, MT_3 raised the SR from 0.035 to 0.185, and MT_6 increased it from 0.493 to 1.414. MT_8 more than doubled the SR for Strategy 8, from 1.479 to 2.369. Similarly, MT_7 more than doubled its SR from 1.451 to 3.119. Despite a negative SR, MT_1 improved St1's SR from -2.021 to -1.482. Similarly, most MT models showed higher RoR compared to their respective strategies, except for MT_5. For example, MT_1's RoR improved from -0.085 to -0.032, while MT_2, MT_3, and MT_4 had RoRs of 0.108, 0.086, and 0.102, respectively.

From the Tables 5.5 and 5.6 again, the results of MT models were mixed in STD. MT_1 and MT_4 showed a decrease in STD to 0.062 and 0.073, compared to 0.069 and 0.099. However, MT_2 and MT_3 had a slight increase in STD. For VaR, MTs showed

Table 5.5: MTs ($MT_1 \cdots MT_4$) results comparison with individual strategies ($St_1 \cdots St_4$) results based on $\theta_4 = 0.72\%$ for first 4 strategies. Best value for each comparison is shown in bold.

	MT_1	St1	MT_2	St2	MT_3	St3	MT_4	St4
SR	**-1.482**	-2.021	**0.897**	0.058	**0.185**	0.035	**0.352**	0.215
RoR	**-0.032**	-0.085	**0.108**	0.036	**0.086**	0.084	**0.102**	0.101
STD	**0.062**	0.069	0.079	**0.074**	**0.092**	0.100	**0.073**	0.099
VaR	**0.097**	0.118	0.129	**0.117**	0.107	**0.098**	**0.087**	0.103

Table 5.6: MTs ($MT_5 \cdots MT_8$) results comparison with individual strategies ($St_5 \cdots St_8$) results based on $\theta_4 = 0.72\%$ for last 4 strategies. Best value for each comparison is shown in bold.

	MT_5	St5	MT_6	St6	MT_7	St7	MT_8	St8
SR	0.170	**0.189**	**1.414**	0.493	**3.119**	1.451	**2.369**	1.479
RoR	0.039	**0.063**	**0.131**	0.079	**0.131**	0.098	**0.075**	0.048
STD	**0.074**	0.081	**0.063**	0.070	0.034	**0.031**	0.026	**0.016**
VaR	**0.126**	0.126	**0.079**	0.116	0.027	**0.015**	0.025	**0.013**

varied outcomes again. For instance, MT_1 and MT_4 reduced VaR from 0.118 to 0.097 and 0.103 to 0.087, respectively. On the contrary, MT_2 saw an increase from 0.117 to 0.129.

Overall, as we can see in Figure 5.1, except for St5, each strategy increased its SR and RoR with GA optimization. However, the performance in terms of STD and VaR showed mixed outcomes. Notably, St7 and St8 experienced an increase in VaR, suggesting that optimization has an effect of increasing the volatility of the trades, which eventually experimented higher risk. It is also seen from the Table 5.4.

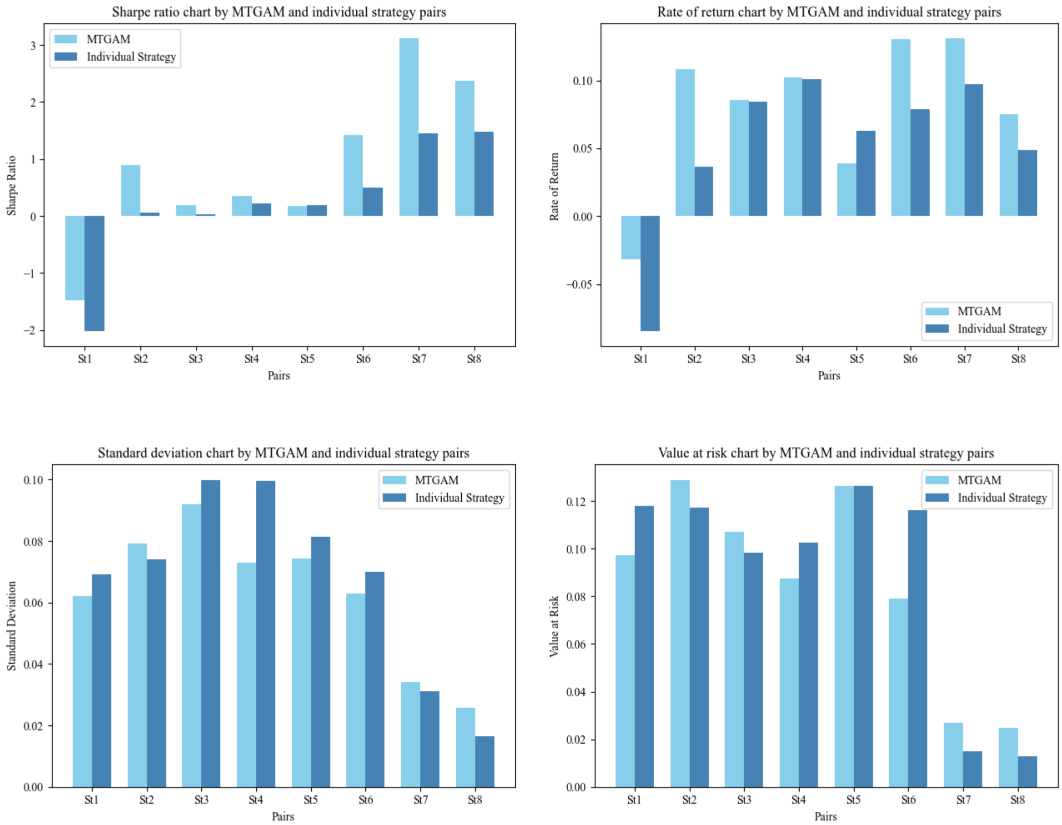

Figure 5.1: Comparison of average results across 200 stocks for MTGAM paired with respective individual strategies performance on single threshold $\theta_4 = 0.72\%$ for Sharpe Ratio, Rate of Return, Standard Deviation, and Value at Risk.

To delve deeper into the outcomes, we conducted the Wilcoxon Signed-Rank non-parametric statistical tests [2] under the assumption that there is no significant difference between the paired groups. Our null hypothesis states that the median of the differences between the pairs of groups is equal to zero, or in other words, the two groups are similar in terms of the median. In Tables 5.7, 5.8, 5.9, and 5.10, the first column displays the pairs, while the second column presents the adjusted p-values derived from the Holm-Bonferroni (Abdi 2010) method to adjust the p-values obtained from multiple statistical tests to reduce the chances of obtaining false-positive results. Notably, pairs that exhibit significance under the chosen significance level of $\alpha = 0.05$ are highlighted in bold.

In the forthcoming tables, St1, $\cdots$, St8 denote the individual performances of strategies under the $\theta_4 = 0.72\%$ threshold. This comparison allows us to evaluate the improvement in performance gained through multiple-threshold optimization, as opposed to the outcomes of each strategy under the threshold in the previous chapter. Table 5.7 shows that for SR, MTs are statistically significant over individual strategies in 3 out of 8 cases, with individual strategies examined under the threshold of 0.72% Particularly, MT_6 with a p-value of 0.029, while MT_7 and MT_8 exhibit extremely low p-values of 7.634e-11 and 1.335e-4, respectively, indicating compelling evidence of their out-performance. MT_1, MT_2, MT_3, MT_4, and MT_5 do not demonstrate statistically significant differences in the SR compared to their respective individual strategies. However, it is noteworthy to emphasize that MT_1 and MT_2, along with their respective individual strategies, exhibit p-values of 0.229 and 0.165, respectively.

From Table 5.8 for RoR, the initial notable finding is that MT_3, MT_4, MT_5 and

[2]This test is employed for conducting pairwise comparisons between two related groups and exhibits robustness against outliers, a valuable feature given the presence of extreme values in our comparison (Woolson 2007).

Table 5.7: Pairwise Wilcoxon signed-rank tests were conducted between MTGAMs (MT_1, $\cdots$, MT_8) and individual strategies under the threshold of $\theta_4 = 0.72\%$ for Sharpe Ratio based on 200 stocks, and significant differences at the $\alpha = 0.05$ level are indicated in bold.

Pair	**Adjusted p-value**
MT_1 - St1	0.229
MT_2 - St2	0.165
MT_3 - St3	0.574
MT_4 - St4	0.802
MT_5 - St5	0.802
MT_6 - St6	**0.029**
MT_7 - St7	**7.634e-11**
MT_8 - St8	**1.335e-4**

their pairs with St3, St4, St5 do not reject the null hypothesis, indicating that they are not significantly different groups, with high p-values. In contrast, for MT_1 and St1, as well as MT_6 and St6 pairs, the p-values are relatively low, with MT_1 and St1 pairs nearly reaching the significance level at 0.060. Moreover, another crucial observation is an increase in RoR and SR, as demonstrated previously in Tables 5.5 and 5.6, and examining the p-values from the table. It becomes evident that the performance improvement of St7 and St8 is significant, with p-values of 8.836e-09 and 1.550e-08, respectively. Similarly, we confirm the enhancement in the RoR performance for St2 through Table 5.8, with a p-value of 0.046.

From the statistical tests tables for risk metrics, particularly Table 5.9 for STD, it's noteworthy that MT_1, MT_4, MT_6, and MT_8 exhibit statistically significant differences compared to their respective individual strategies, as indicated by the adjusted p-values. MT_1 and MT_8 stand out with very low p-values of 2.228e-05 and 2.390e-05, respectively, suggesting strong evidence of their out-performance in terms of STD. Similarly, MT_4 and MT_6 also show significant differences with p-values of 7.516e-06 and 2.202e-04, respectively, indicating their effectiveness in reducing standard deviation compared to the individual strategies. Additionally, as observed in Figure 5.1,

Table 5.8: Pairwise Wilcoxon signed-rank tests were conducted between MTGAMs (MT_1, $\cdots$, MT_8) and individual strategies under the threshold of $\theta_4 = 0.72\%$ for Rate of Return based on 200 stocks, and significant differences at the $\alpha = 0.05$ level are indicated in bold.

Pair	**Adjusted p-value**
MT_1 - St1	0.060
MT_2 - St2	**0.046**
MT_3 - St3	0.960
MT_4 - St4	0.866
MT_5 - St5	0.916
MT_6 - St6	0.115
MT_7 - St7	**8.836e-09**
MT_8 - St8	**1.550e-08**

the MT chromosome optimized with different thresholds not only reduces STD but also has the ability to reject the hypothesis, which is another significant observation. From Table 5.10 for VaR, MT_1, MT_6, MT_7, and MT_8 stand out with very low p-values of 1.662e-08, 2.324e-14, 1.316e-05, and 1.825e-09, respectively, suggesting strong evidence of their out-performance in terms of Value at Risk reduction.

Table 5.9: Pairwise Wilcoxon signed-rank tests were conducted between MTGAMs (MT_1, $\cdots$, MT_8) and individual strategies under the threshold of $\theta_4 = 0.72\%$ for Standard Deviation based on 200 stocks, and significant differences at the $\alpha = 0.05$ level are indicated in bold.

Pair	**Adjusted p-value**
MT_1 - St1	**2.228e-05**
MT_2 - St2	0.529
MT_3 - St3	0.324
MT_4 - St4	**7.516e-06**
MT_5 - St5	0.462
MT_6 - St6	**2.202e-04**
MT_7 - St7	0.177
MT_8 - St8	**2.390e-05**

Table 5.10: Pairwise Wilcoxon signed-rank tests were conducted between MTGAMs (MT_1, $\cdots$, MT_8) and individual strategies under the threshold of $\theta_4 = 0.72\%$ for Value at Risk based on 200 stocks, and significant differences at the $\alpha = 0.05$ level are indicated in bold.

Pair	**Adjusted p-value**
MT_1 - St1	**1.662e-08**
MT_2 - St2	0.485
MT_3 - St3	0.152
MT_4 - St4	0.152
MT_5 - St5	0.641
MT_6 - St6	**2.324e-14**
MT_7 - St7	**1.316e-05**
MT_8 - St8	**1.825e-09**

In this final part of this section, we will present the performance of individual strategies by taking the average of a pool of 50 runs. As previously explained in Section 4.5.1, in this thesis, we will adopt the approach of selecting the best-performing chromosome from a pool of 50 runs in the training set and then applying it in the test set for experimentation. This mirrors real-world scenarios where traders would likely utilize the chromosome with the highest SR achieved during the training phase. Through the analysis of the average performance across these 50 runs, we aim to capture the central tendencies among the runs, instead of solely relying on the chromosome from a single run. The results for the strategies from the best-performed run, denoted as MT_1, $\cdots$, MT_8, will continue to be abbreviated. The average results from the pool of 50 runs will be represented as $MT_{1_{ave}}$, $\cdots$, $MT_{8_{ave}}$.

From Table 5.11, a key observation is that, on average, the strategies showed similar performance metrics across 50 runs compared to the method outlined in the thesis. $MT_{1_{ave}}$ exhibited higher performance in terms of SR, with a value of -1.18 compared to -1.48 for MT_1. Among the remaining seven strategies, MT_5 and MT_8 exhibited SR differences of more than 0.15 in favor of the best-trained chromosome method. When rounding to two decimal places. It is worth noting that the differences are nearly zero for our risk metrics, STD, and VaR. Taking into account these findings, the practice of averaging results from 50 runs may illustrate robustness by reducing the influence of outliers in the St1 comparison. However, what is even more crucial to note is that in the presentation approach we have chosen, to closely mimic real-world scenarios, it is expected that traders prioritize executing the model only once to be in line with best practices. Therefore, the similarity in results between these two methods validates our approach.

Table 5.11: Average Sharpe Ratio (SR), Rate of Return (RoR), Standard Deviation (STD), Value at Risk (VaR) results across 200 stocks for the MT_{ave} (average results for a pool of 50 runs in the test set), and MT (from a certain chromosome that performed in training to experiment in the test set) on 8 strategies. Best value across the metrics between two comparison methods is shown in bold.

	SR	RoR	STD	VaR		SR	RoR	STD	VaR
$MT1_{ave}$	**-1.18**	**-0.02**	**0.06**	**0.1**	MT_1	-1.48	-0.03	0.06	0.1
$MT2_{ave}$	0.75	0.1	**0.08**	0.13	MT_2	**0.9**	**0.11**	0.08	**0.13**
$MT3_{ave}$	0.17	**0.09**	**0.09**	**0.1**	MT_3	**0.18**	0.09	0.09	0.11
$MT4_{ave}$	**0.35**	0.09	0.07	0.09	MT_4	0.35	**0.1**	**0.07**	**0.09**
$MT5_{ave}$	-0.43	0.01	**0.07**	0.13	MT_5	**0.17**	**0.04**	0.07	**0.13**
$MT6_{ave}$	1.37	**0.13**	**0.06**	0.08	MT_6	**1.41**	0.13	0.06	**0.08**
$MT7_{ave}$	**3.13**	**0.13**	**0.03**	**0.03**	MT_7	3.12	0.13	0.03	0.03
$MT8_{ave}$	2.06	0.07	0.03	0.03	MT_8	**2.37**	**0.08**	**0.03**	**0.02**

In the upcoming section, we will focus on the interpretation of the results presented in this section.

5.5 Interpretation

Firstly, as can be seen in Figure 5.4, when we look at the strategies individually, an increase in the threshold value generally leads to a decrease in the actual number of trades. The exception to this is St4 among the 8 strategies. As a validation from Table 5.4, MT achieves the highest number of trades in 5 strategies, averaging across 200 stocks. For St7 and St8, the number of trades at the lowest threshold is nearly the same, while St1 follows with about 10% fewer trades at the lowest threshold.

Table 5.3 shows that, on average, MT has the highest performance, achieving the best SR in 35 out of 200 stocks and the highest RoR in 33.8 stocks. Moreover, the optimization led to a notable improvement in the SR and RoR across most strategies. For instance, St7's SR more than doubled, indicating significant gains from the optimization process. Particularly for St2, St3, and St4, both the SR and RoR metrics have increased. Overall, as shown in Figure 5.1, while only one strategy remained unaffected by the GA, the others experienced improvements in their performance metrics.

Table 5.12: Summary of trading strategies and their aim

	Derivation	*Aim*
St1	1. Scaling law; on average among DC and OS events, price change in the DC event approximately equals in the OS event	Buy when the stock reaches its peak within DT and Sell when it reaches the same saturation point at UT
St2	2. Scaling law; double the duration of the DC event is the OS event duration approximately	Buy in anticipation of a reversal in the DT duration to the opposite direction, Sell occurs when the same duration is captured within that opposite direction.
St3	$\lvert OSV_{CUR} \rvert$ indicator checks the predetermined $\lvert OSVbest \rvert$	The indicator's magnitude, from the theoretical confirmation point, triggers a buy signal in the DT phase due to the expectation of a reversal.

Continued on next page

Table 5.12 continued from previous page

	Description	*Aim*
St4	$\lvert TMV_{CUR}\rvert$ indicator checks the predetermined $\lvert TMVbest\rvert$	The magnitude of the indicator, measured from the extreme point, triggers a buy signal during the DT phase, as it suggests an anticipation of a reversal in the stock's direction.
St5	Predetermined ratio of the total duration of OS to the total number of DC, RN.	When the saturation point obtained from the training set is reached, a buy signal is generated by anticipating the trend's reversal to UT.
St6	A preset ratio of the total number of OS to the total number of DC.	Probabilistically, purchasing at the confirmation point in anticipation of an upcoming UT can yield a profit.
St7	Three consecutive OS events during a UT without any OS events occurring during a DT in between them.	Under the assumption that the resistance level will be breached, Buy the stock.
St8	Symmetric to St7, but focuses on DT, three consecutive OS should be seen in DT.	Under the assumption that the support level will be breached, Buy the stock.

From Table 5.12, we can discern the intended objectives behind the development of each strategy. When we look at the strategies individually from the perspective of thresholds: St1 exhibits a better performance at lower thresholds, displaying increases in the number of stocks for both SR and RoR when subjected to θ_1. St2 consistently demonstrates strong performance across a wide range of thresholds, with a notable emphasis on increasing the number of best performing stocks for both STD and VaR at lower thresholds. St3 and St4 show moderate sensitivity to threshold changes, with no drastic changes in performance across different thresholds. St5 exhibits an increase in both SR and RoR under lower thresholds, alongside an increment in STD and VaR, suggesting a lower risk also higher SR. St6 maintains a relatively stable performance across thresholds, with slight improvements in lower thresholds in SR and RoR. St7 and St8 are highly sensitive to lower thresholds, significantly improving SR and RoR under θ_1, but at the cost of higher VaR.

In this part, we compare the performance and risk metrics results of the stocks to see how they are distributed. To do this, we compared the performances of the MT model, optimized by GA with different thresholds for each strategy, to the individual strategies' metrics that were found on $\theta_4 = 0.72\%$. This enables us to see the improvement in performance from optimizing strategies with multiple thresholds, as opposed to their individual performances under a single threshold, as discussed in the previous chapter. The distributions of metric results for MT_1 to MT_8, representing the first four and last four strategies, are shown in Figures 5.2 and 5.3. These distributions are analyzed using two key concepts: "Skewness", which measures the asymmetry of a distribution to determine its symmetry or skewness; and "Kurtosis", which is a measure of the combined weight of the tails of distribution in relation to the remainder of the distribution, indicating the likelihood of extreme outcomes (Groeneveld & Meeden 1984).

Firstly, as we can see from Figure 5.1 and as examined in detail in the results section, in the individual strategy comparison at a 0.72% threshold with MTs, the average results for 200 stocks were consistently higher for MTs, except for St5 (MT_5 vs. St5). Keeping this in mind, Figures 5.2 and 5.3 show that MT_1, MT_2, MT_4,

MT_5, and MT_6 have more stocks with high performance in the right tail of their distributions, making them more favorable strategies. This comparison is made between the performance of the strategies individually at a 0.72% threshold and their performance when optimized by MTs across multiple thresholds. These MTs also showed moderately stable SRs across 200 stocks. In RoR, The MTs tend to provide distributions leaning towards higher returns in every MT, except for MT_5. Among 200 stocks, especially, MT_7, and MT_8 are associated with the possibility of extreme RoR outcomes, implying a higher potential for earnings. The MTs exhibit varied risk profiles but tend to show a higher level of risk. This is interpreted as a willingness to engage in riskier trades for potentially higher returns. Especially, MT_2, MT_3, MT_7, and MT_8 display more positive skewness in both STD and RoR, when considering their respective single fixed threshold (at $\theta = 0.72\%$) strategies. In summary, MTs exhibit characteristics of potentially higher returns and adaptable risk-adjusted performances compared to individual strategies, albeit with an inclination towards higher risk profiles.

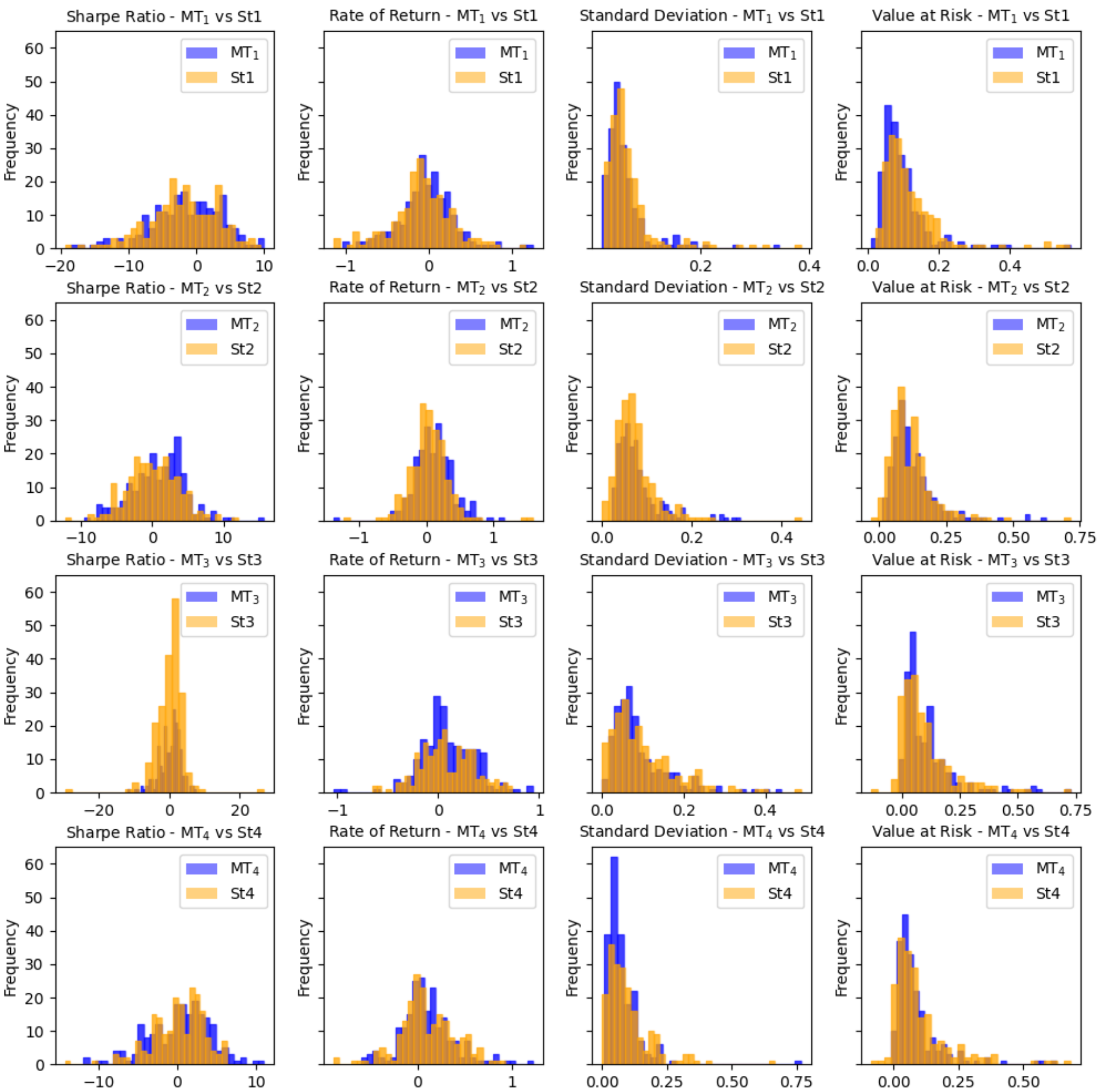

Figure 5.2: MTGAM model performance versus individual strategies performances under $\theta_4 = 0.72\%$ threshold based on Rate of Return, Sharpe Ratio, Standard Deviation, and Value at Risk for the first 4 strategies

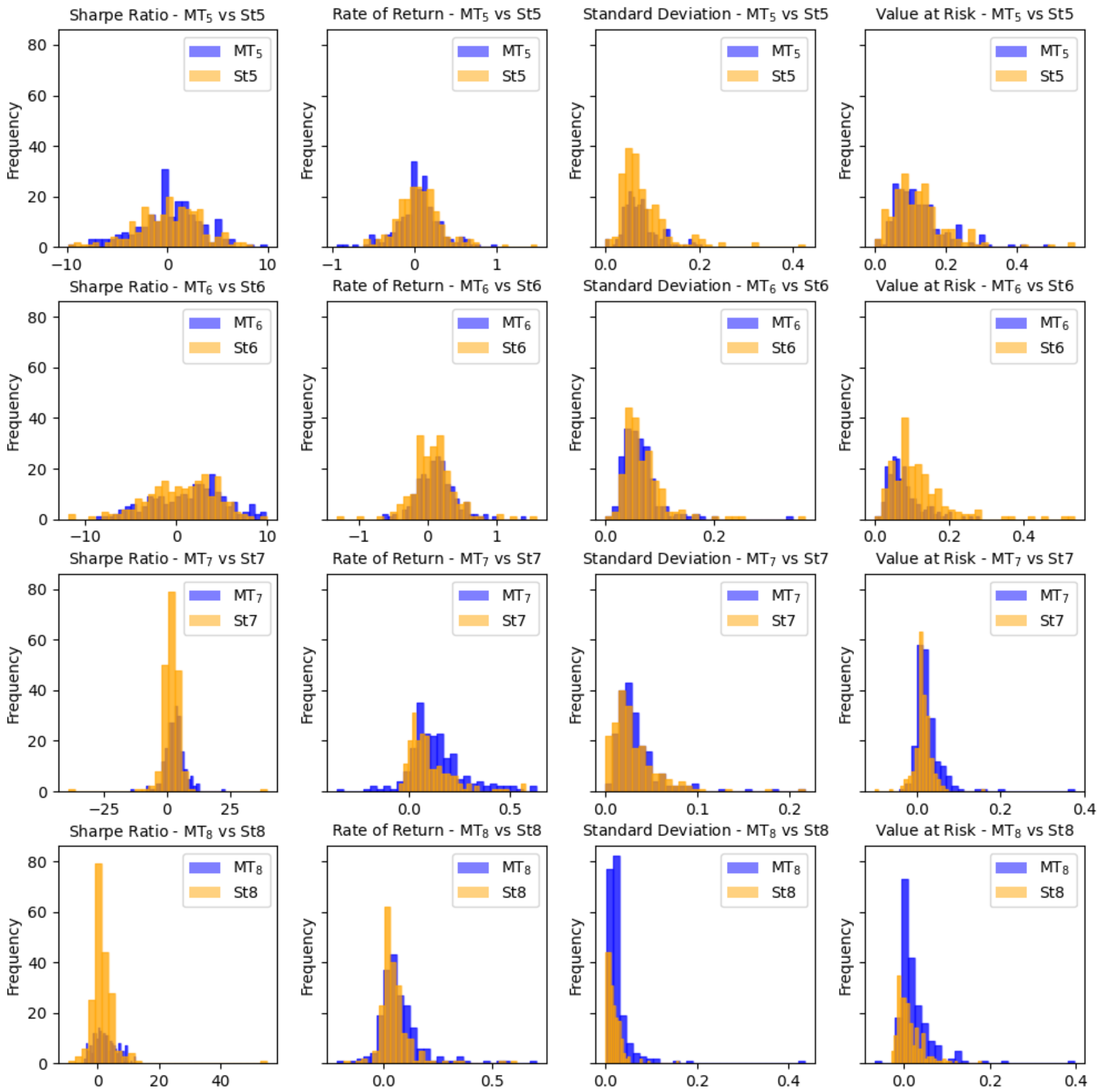

Figure 5.3: MTGAM model performance versus individual strategies performances under $\theta_4 = 0.72\%$ threshold based on Rate of Return, Sharpe Ratio, Standard Deviation, and Value at Risk for the last 4 strategies

The statistical tests confirm significant enhancements introduced by MT across several strategies. Particularly noteworthy are the low p-values for MT_7 and MT_8 in SR and RoR, indicating that the performance disparities between these MT strategies and their corresponding individual strategies are unlikely to be attributed to chance. Consequently, for SR, traders aiming for strategies offering superior risk-adjusted returns may find MT_6, MT_7, and MT_8 particularly attractive based on these findings. Similarly, for RoR, traders seeking strategies delivering enhanced returns may find MT_2, MT_7, and MT_8 notably appealing. The statistically significant findings at $\alpha = 0.05$ observed across MT_1, MT_4, MT_6, and MT_8 in conjunction with their corresponding individual strategies. This indicates an important risk reduction. Similarly, a similar conclusion can be drawn regarding the reduction VaR for MT_1, MT_6, MT_7, and MT_8 with their respective individual strategies. Consequently, from a risk metrics perspective, traders seeking stable risk levels relative to their expectations of SR or RoR may opt for strategies such as St6, St7, or St8 facilitated by the MT model.

Lastly, we wanted to examine which thresholds had the highest average weights for the 200 chromosomes on a strategy-by-strategy basis. First, the weights for St1 to St6 showed small variations within a narrow margin. However, noteworthy observations include St7 and St8, where these strategies, out of the five possible thresholds, had the highest average weights at theta3. Specifically, St7 had 33% of its weight at θ_3, and St8 also showed its highest average weight at the same threshold with with 30%. In summary, the evolution of the chromosomes tended to favor the threshold of $\theta_3 = 0.48\%$ relatively more.

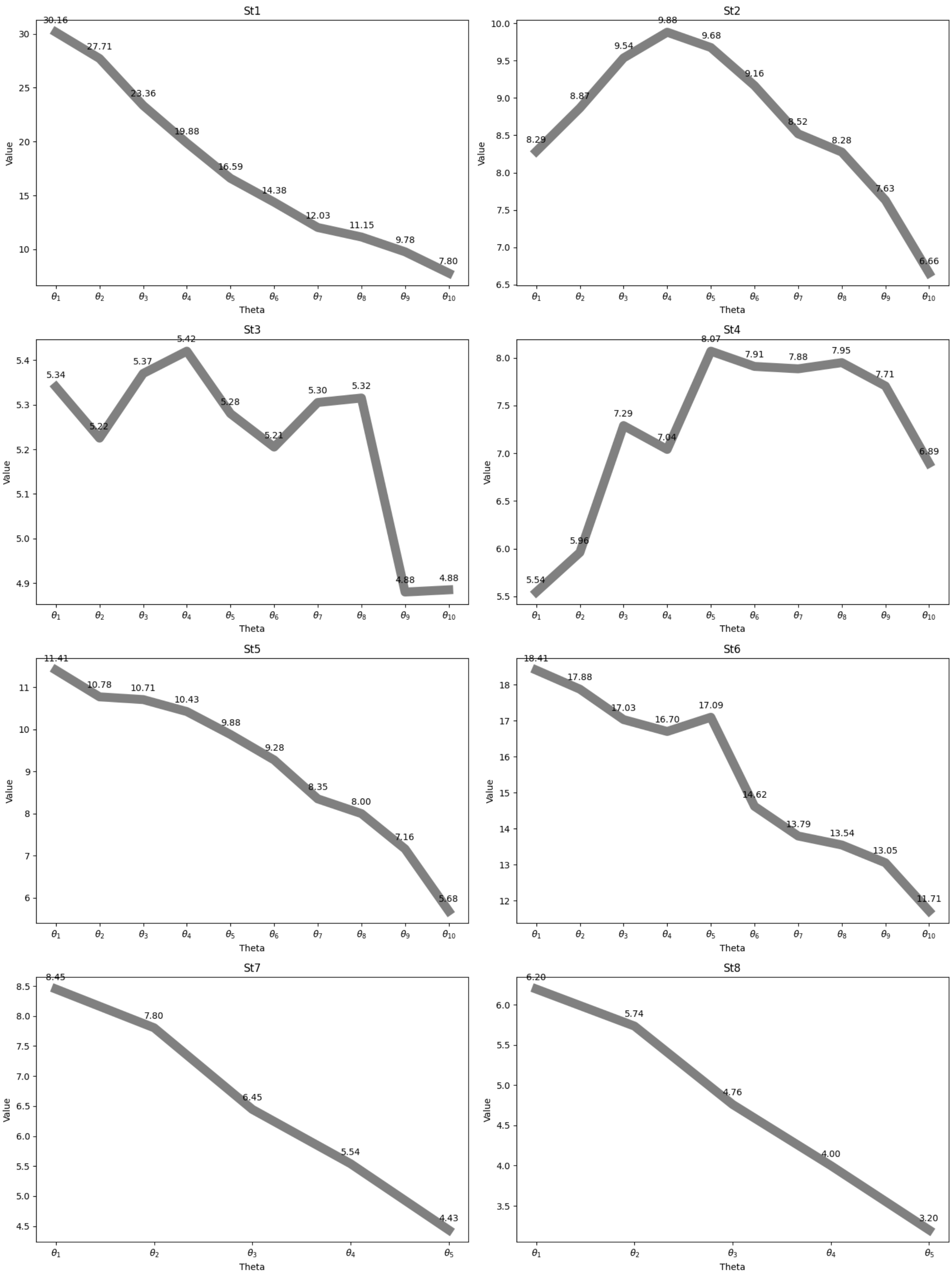

Figure 5.4: Number of trades' average based on 200 stocks respectively to the thresholds by strategies .

5.6 Summary

The chapter focuses on the optimization of trading strategies using different threshold values (denoted as $\theta_1, \cdots, \theta_{10}$). It expands the range of daily fluctuations in stock market indices to 0.05% to 2.75%, with 10 thresholds randomly selected within this range. The strategies St7 and St8, due to their construction, had limited trading opportunities for larger θs. Therefore, they were excluded from using $\theta_6, \cdots, \theta_{10}$. By the GA optimization, the goal was to optimize the recommendations from each threshold and find the best-performing chromosome, namely MTs. The experimental setup used the same set of 200 publicly traded stocks and the same time frame as the previous chapter for consistency.

The performance and risk were evaluated using metrics such as Sharpe Ratio (SR), Rate of Return (RoR), Standard Deviation (STD), and Value at Risk (VaR). MT generally performed well in SR and RoR metrics compared to individual strategies under different thresholds. For risk metrics, the performance was mixed, with some strategies showing an increase in risk. The number of trades also varied among strategies, with MT showing more frequent trades for some strategies. It is worth reiterating that in the practical world, since aggregated metrics like the SR are prioritized for considering both return and risk, the risks that have been seen in the results can be compensated to a manageable level.

Statistical tests (Wilcoxon Signed-Rank tests) were conducted to compare the performance of MT with individual strategies. The tests revealed significant differences in RoR and VaR for some pairings, indicating that the optimization with multiple θs had a notable impact on performance. Overall, the chapter demonstrates the effectiveness of using multiple thresholds for optimizing trading strategies.

Chapter 6

Optimization of the Strategies and the Thresholds Together

6.1 Introduction

In this chapter, our objective is to address the question of whether it is possible to enhance overall performance by simultaneously employing all strategies and making various thresholds equally available to them. Initially, as seen in Chapter 4, performance improved through optimizing trading strategies within the DC paradigm framework. However, this was done using only a single θ. Consequently, all trading strategies were limited by the available information from a specific DC threshold. This approach made it challenging to utilize more effective information that could have come from other thresholds, as we interpreted in Section 4.6.

In Chapter 5, the focus was on acquiring more comprehensive information by introducing multiple distinct thresholds to each strategy individually in Chapter 5. This method exposed the Genetic Algorithm (GA) to a variety of DC summaries, each linked to a distinct θ. As a result, the main limitation of the previous chapter has been addressed through this approach, as we also pointed out at 5.5. However, applying different thresholds to each strategy individually limited the cross-strategy information exchange.

To overcome this, in this chapter, we aim to enhance performance by merging the insights gained from the previous two chapters, creating chromosomes that are richer in information. In doing so, we would like to emphasize our approach: Firstly, as discussed in Chapter 4, we utilize 8 strategies in GA optimization. Each chromosome, representing a potential solution, comprises 8 genes based on these strategies. Secondly, in Chapter 5, we individually optimized each strategy using recommendations from DC data, each tailored to specific thresholds. The chromosome gene count was aligned with the number of thresholds for each strategy (e.g., 10 genes for St1 with 10 thresholds). In this chapter, we combine the two components mentioned above, utilizing both the strategies and their respective number of thresholds. This results in the use of 70-gene chromosomes that are recommendation-rich. As in the preceding sections of this thesis, we will continue to optimize recommendations using GA, with changes in its parameters.

The remainder of this chapter is structured as follows: Section 6.2 introduces the methodology for the optimization of the strategies and thresholds simultaneously. Section 6.3 will discuss the setup of the experiments, followed by Section 6.4, which will illustrate the results of the experiments. In Section 6.5, we will delve into the interpretation of these results. Finally, in Section 6.6, we will provide a summary of the chapter.

6.2 Methodology

In this chapter, we introduce the *Multi-Strategy/Threshold-Genetic-Algorithm-Model* (MSTGAM), an advanced model for optimizing trading strategies in the DC paradigm. Unlike previous models in Chapter 4 and Chapter 5, which focused on a single threshold or solely on threshold optimization, MSTGAM combines both approaches. It utilizes more fine-grained GA optimization by integrating *sub-strategies*, each linked to a specific threshold. A sub-strategy, combining a trading strategy with a particular threshold, contributes to a comprehensive set of 70 possible combinations, expanding our exploration within the DC event-based space.

MSTGAM's structure is built on these sub-strategies, where each one is represented as a gene within a chromosome, assigned a specific weight. These sub-strategies, irrespective of their weights, yield a recommendation: Buy, Sell, or Hold, as discussed in previous chapters. Each chromosome, thus, bases its decisions on these weighted genes. As in the previous chapters, the chromosome aggregates the weights of genes that recommend Buy, Sell, and Hold. This means that within a chromosome, there are as many genes as there are sub-strategies, and these genes are encoded with weights that indicate the extent to which the recommendation of each specific sub-strategy should be considered. Eventually, the sum of these weights for a given chromosome is equal to 1. To reconcile any potentially conflicting recommendations, we utilize the GA once again, to determine the optimal weights to assign to sub-strategies. The GA representation now consists of 70 genes.

Table 6.1 displays only 8 sub-strategies under one threshold (θ_1) due to space limitations. We would like to highlight this essential point once again: In our experiment, we allocated 70 genes for 70 sub-strategies. However, due to spacing constraints, we showcase only 10 sub-strategies in Table 6.1. Imagine that the actions would have taken from the different sub-strategies at this particular time are as follows, from St1θ1 to St1θ10 in sequence: 1, 0, 1, 0, 0, 0, 0, and 2. Thus, from the sequence, recommended actions for sub-strategies St2θ1, St4θ1, St5θ1, St6θ1, and St7θ1, are to Hold the stock at this particular time. In contrast, the recommendation for St1θ1 and St3θ1 is to Buy, and for St8θ1, it is to Sell. Since the sum of Buy actions exceeds those of Sell or Hold, the recommended action is Buy. It is important to highlight a slight modification that we have introduced. Given that, for a given time, the decisions among the 70 genes often tend to lean towards Hold actions. Therefore, similar to the previous chapters, we enhance the significance of Buy and Sell recommendations by artificially increasing their responsiveness. Specifically, if more than two genes recommend actions other than Hold, we disregard the Hold genes and determine the chromosome's recommendation based on the weights of the other genes.

Table 6.1: The chromosome representation includes 8 sub-strategies for θ_1 by the hypothetical weights assigned to each recommendation.

Sub-strategy	St1θ1	St2θ1	St3θ1	St4θ1	St5θ1	St6θ1	St7θ1	St8θ1
Action	1	0	1	0	0	0	0	2
Weight	0.025	0.01	0.10	0.03	0.02	0.02	0.05	0.07

6.3 Experimental Setup

In this chapter, we once again utilized the same set of 200 publicly traded stocks listed on the New York Stock Exchange to ensure data consistency (refer to the Table A.1 for 200 stocks), aiming to preserve similarity to the previous chapters. The time-spans are also the same to avoid negatively impacting the analysis. We have employed the same partitioning strategy, where the first 80% of the data, corresponding to the initial 8 years, is allocated for the training set, while the remaining

20%, equivalent to 2 years, is set aside for the test set.

However, in this chapter, due to the simultaneous generation of 70 sub-strategies coming from the strategies and θs, the number of genes in our chromosomes is set to 70. Furthermore, due to the lack of statistical significance among the configurations, as pointed out in 4.3 by the Friedman test, where the null hypothesis was the configurations originated from the same continuous distribution, we have made two parameter adjustments. These changes aim to avoid extended computational times and to foster diversification, ensuring the population maintains a variety of chromosomes. We chose to use a population size of 150 and opted for a two-point crossover, in contrast to the one-point crossover used in the previous two chapters. The remaining parameters remain the same as those employed in Chapter 4 and Chapter 5. Table 6.2 shows the parameters used for GA in this chapter. Subsequently, we maintain these fixed parameters and conduct GA optimization for a total of 50 runs for our experiments.

Table 6.2: Selected parameters

Population size	150
Number of generations	18
Tournament size	2
Crossover probability	0.95
Mutation probability	0.05

6.3.1 Benchmarks

In addition to the non-DC-based benchmarks explained in Section 4.4, we also used the models from the previous two chapters as benchmarks.

Sub-strategies

For this chapter, we consider the strategies and the trade decisions they provide under different thresholds as individual strategies, as we explained as sub-strategies. Since one of the main goals of optimization is to derive these sub-strategies performance, we will use them as benchmarks in this chapter.

Eight Strategies Optimization on Particular Threshold

In Chapter 4, our optimization process involved 8 trading strategies using a single θ, set at 0.72%. Moving forward, in the subsequent chapter, we introduced additional θs into our experiments. To ensure consistency with our previous work on θs, we expanded our benchmarks by applying MSGAM (i.e., the model that is utilized in Chapter 4) to four other θs: 0.098%, 0.22%, 0.48%, and 0.98%. As mentioned in the previous chapter, due to the inability of St7 and St8 to generate trades above the 1% threshold, we used the first five threshold for these strategies optimization in our benchmark.

Different Thresholds Optimization on Individual Strategies

This benchmark essentially corresponds to the results we obtained in Chapter 5. To ensure the validity of the benchmark, we opted for the two best-performing results derived from the MTGAM model applied to two specific strategies, MT_7 and MT_8, out of the eight (MT_1, $\cdots$, MT_8) evaluated in Chapter 5. The selection criterion is based on whichever yields the highest Sharpe Ratio performances on average among the 200 stocks.

Market Indices

To compare the performance and risk metrics of our model among the 200 stocks with the general movement of the stock market during our test period (November 27, 2017, to November 27, 2019), we used 7 market indices from the New York Stock Exchange. In our model, the trader buys the product at the beginning of the test period and evaluates the performance monthly over the two-year span. Monthly returns are calculated after accounting for a transaction cost of 0.025%. The indices are:

- Dow Jones Industrial Average (DJI): Represents 30 large, publicly-owned companies based in the USA.
- S&P 500 (GSPC): A market-cap-weighted index of the top 500 publicly traded U.S. companies.
- NYSE Composite Index (NYA): Encompasses all NYSE-listed common stocks.
- Russell 1000 Index (RUI): An index monitoring around 1,000 major U.S. equity market companies' performance
- Russell 2000 Index (RUT): A small-cap stock index covering the lowest 2,000 Russell 3000 Index stocks.
- Russell 3000 Index (RUA): An equity index representing the entire U.S. stock market, encompassing the top 3,000 U.S. companies.
- NYSE AMEX Composite Index (XAX): An index covering NYSE American-listed stocks, with a focus on smaller firms.

6.4 Results

From this point onwards, due to space constraints in tables, we will adopt abbreviations for benchmarks as outlined in Section 6.3.1. These abbreviations are: i) $MS_{\theta x}$: represents the Multiple Strategies model (MSGAM) under a specific θ. For instance, $MS_{\theta 1}$ signifies the MSGAM model from Chapter 4, with θ set at 0.098%. We have used ten different θs in this thesis, in order: 0.098%, 0.22%, 0.48%, 0.72%, 0.98%, 1.22%, 1.55%, 1.70%, 2%, and 2.55%. $MS_{\theta 1}$, therefore, specifically denotes MSGAM at 0.098%. To elaborate further, in Chapter 4, we only utilized a single threshold, and the abbreviation MS sufficed for our purposes. However, as we now examine the performance of this model across various thresholds for benchmark, it becomes necessary to employ these notations to distinguish between different θs. ii) For different threshold optimization on individual strategies (MTGAMs), MT with the respective strategy will be used as in Chapter 5. For example, MT_1 means the optimization of strategy 1 with different thresholds. iii) MSTGAM will be shown as MST.

Table 6.3 shows the average results on 200 stocks of various performance metrics, Sharpe Ratio (SR), Rate of Return (RoR), Standard Deviation (STD), Value at Risk (VaR), and Number of Trades (Tra.). These results are presented for our MSTGAM (MST) model in comparison to sub-strategies. We used 8 sub-strategies in the table for illustration purposes because it was not feasible to include all 70 sub-strategies due to spacing constraints. However, here, we would like to add that the results of MST versus 70 sub-strategies for RoR, SR, STD, and VaR metrics for each of the 200 stocks can be found in Tables B.5, B.6, B.7, and B.8, respectively, in Appendix B.

To enhance the credibility of Table 6.3 results, we selected sub-strategies for each strategy based on their highest average SR performance across various thresholds. For example, St1 used 10 thresholds, therefore we considered 10 sub-strategies, selecting the one with the highest average SR. From the table, MST achieves an average SR of 5.59 among the 200 stocks, closely followed by St7θ1 with 3.44, and St8θ1 with 1.67. In RoR, MST leads with 22%, followed by St7θ1 with 0.13 and St8θ1 with 0.06, similarly. In risk metrics, MST ranks third with 4% STD, after St7θ1 and St8θ1, which stand at 3% and 2% respectively. In VaR, MST has a VaR of 5%, compared to 2% for both St7θ1 and St8θ1.

Table 6.3: Average Sharpe Ratio (SR), Rate of Return (RoR), Standard Deviation (STD), Value at Risk (VaR), and Number of Trades (Tra) results across stocks for the MSTGAM, 8 individual DC-based sub-strategies. Best value for each row is shown in bold.

	MST	St1θ2	St2θ4	St3θ4	St4θ3	St5θ3	St6θ3	St7θ1	St8θ1
SR	**5.59**	-0.82	0.76	0.14	0.26	0.75	0.83	3.44	1.67
RoR	**0.22**	-3.3e-3	0.09	0.09	0.09	0.09	0.12	0.13	0.06
STD	0.04	0.06	0.09	0.1	0.1	0.08	0.07	0.03	**0.02**
VaR	0.05	0.09	0.13	0.1	0.1	0.12	0.1	0.02	**0.02**
Tra	70.19	27.48	10.17	5.42	7.24	10.66	18.2	8.36	6.07

Table 6.4 provides insights into how often MST achieved the best performance among the 200 stocks. A key observation is MST's dominance in the SR, where it showed the highest performance in over a quarter of the 200 stocks. Following MST, the two sub-strategies St7θ1 and St8θ1 came closest, with 10 and 11 stocks, respectively. Once again, by validating the results from Chapter 4 and Chapter 5, we observed that the low number of trades provided support for St7 and St8 in achieving better results. In RoR, MST outperformed the sub-strategies more frequently, showing better performance in 20 stocks. From the risk perspective, St7θ1 and St8θ2 recorded lower STD in 3 and 25 stocks out of 200, respectively. For VaR, these sub-strategies again provided the lowest metric values in 6 and 8 stocks respectively. Despite MST not standing out in these metrics, when combined with the findings from Table 6.3, we can propose that STD and VaR results for MST

scatter within a narrow boundary to achieve these SR results.

Table 6.4: The number of stocks for which MSTGAM (MST) or sub-strategies yield the best results on performance metrics among the 200 stocks. The 8 sub-strategies, which are the top-performing sub-strategies according to SR metric as mentioned in Section 6.4. The highest number of stocks for the strategy is highlighted in bold.

	MST	St1θ2	St2θ4	St3θ4	St4θ3	St5θ3	St6θ3	St7θ1	St8θ1
SR	**54**	4	3	3	2	3	5	10	11
RoR	**20**	3	3	2	1	4	6	0	1
STD	0	0	0	3	1	0	0	3	**25**
VaR	0	0	0	5	4	0	0	6	**8**

Table 6.5 presents MST's average metrics results—Sharpe Ratio (SR), Rate of Return (RoR), Standard Deviation (STD), Value at Risk (VaR), and Number of Trades (Tra)—across 200 stocks. It compares these with the outcomes of previous chapters' models: $MS_{\theta 1}$ and $MS_{\theta 4}$ from Chapter 4, MT_7 and MT_8 from Chapter 5, along with TA-based strategies, and BandH strategy. From the table, MST leads with a SR of 5.59, significantly higher than its closest competitors, MT_7 and MT_8, which have SRs of 3.12 and 2.37, respectively. This indicates that MST delivers a much higher return per unit of risk taken. The SR for $MS_{\theta 1}$ and $MS_{\theta 4}$ are notably lower at 1.07 and 1.71, suggesting less efficiency in risk-adjusted returns. TA-based strategies show a mixed performance, with some even having negative SRs. The top three performances in SR, in non-DC based strategies, are as follows: BandH with an SR of 1.62, RSI with an SR of 1.59, and CCI with an SR of 1.48. MST also excels in RoR, with a rate of 22%. This is superior to both $MS_{\theta 1}$ and $MS_{\theta 4}$, which have RoRs of 13% and 19%, respectively. BandH, RoR of 14%, is again one of the top performers. In risk metrics, MST's STD of 0.04 is among the lowest, tied with MT_7 and MT_8. In contrast, other strategies like $MS_{\theta 1}$ and $MS_{\theta 4}$ have higher STDs (0.09 and 0.1), implying higher risk. In VaR, MST shows a moderate VaR of 0.05, which is in line with its low-risk profile indicated by its STD. MST stands out for engaging in a considerably higher average number of trades, with 70.19

trades compared to other strategies. The strategy with the next highest number of trades is the EMA strategy, which averages 31.97 trades across the 200 stocks. This significant difference highlights MST's more active trading approach.

Table 6.5: Average Sharpe Ratio (SR), Rate of Return (RoR), Standard Deviation (STD), Value at Risk (VaR), and Number of Trades (Tra) results across 200 stocks for the MSTGAM (MST) versus strategies optimization on particular thresholds ($MS_{\theta 1}$, $MS_{\theta 4}$), different thresholds optimization on individual strategies (MT_7, MT_8), and TA-based strategies. Best value for each row is shown in bold.

	MST	$MS_{\theta 1}$	$MS_{\theta 4}$	MT_7	MT_8	ADX	Ar	CCI	EMA	MACD	RSI	Wr	BandH
SR	**5.59**	1.07	1.71	3.12	2.37	-1.87	0.55	1.48	-2.64	-0.55	1.59	1.21	1.62
RoR	**0.22**	0.13	0.19	0.13	0.08	-0.03	0.07	0.09	0.01	-0.03	0.12	0.08	0.14
STD	0.04	0.09	0.1	**0.03**	0.03	0.1	0.07	0.07	0.06	0.07	0.1	0.07	0.1
VaR	0.05	0.12	0.12	0.03	**0.02**	0.12	0.14	0.16	0.05	0.15	0.16	0.16	0.13
Tra	70.19	10.27	8.61	8.61	7.02	5.59	17.68	12.78	31.97	17.8	6.15	12.31	24

We presented two Figures 6.1 and 6.2, to visualize the distribution of performance metrics RoR and SR for each stock. The x-axis in these figures represents the stocks, numbered and ordered as listed in Table A.1 in Appendix A. The y-axis shows the SR and RoR values in figures. From Figure 6.1, it can be observed that the MST Sharpe Ratio results across stocks exhibit a higher degree of scatter compared to MT-based and MS-based models. Among these, $MS_{\theta 1}$ stands out due to its low mean, which also operates within a narrower range with smaller variances. In the case of TA-based strategies, EMA results exhibit a high degree of scatter. In Figure 6.2, MST's RoR density is relatively low compared to the MT-based chromosomes. In contrast, MS models show a high density in RoR, similar to MST. Additionally, in this metric, BandH and EMA are among those with a higher scattered profile.

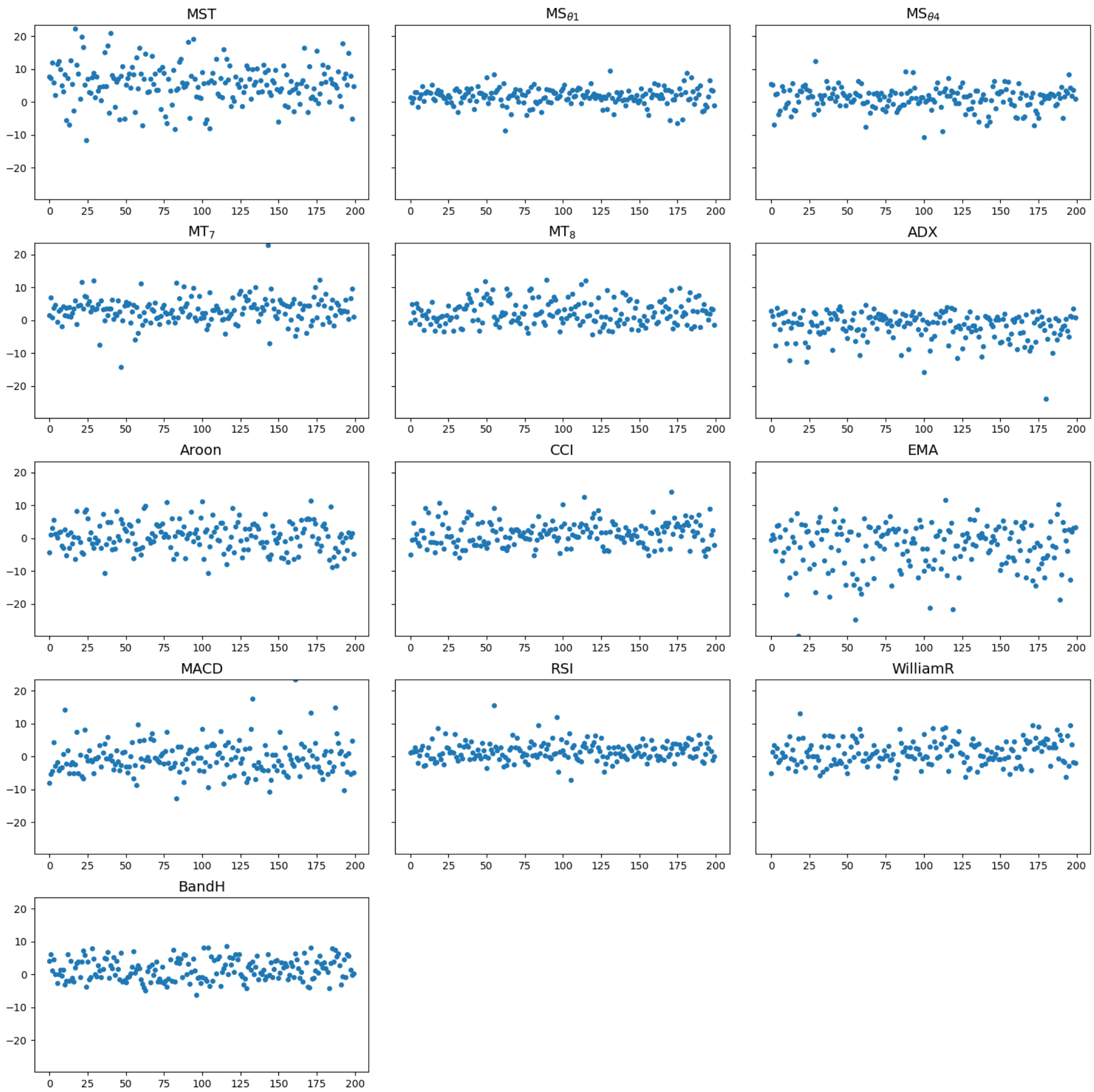

Figure 6.1: Stocks performances plot based on Sharpe Ratio. MSTGAM (MST) versus benchmarks; preceding chapters-models, and TA-based strategies.

Figure 6.2: Stocks performances plot based on Rate of Return. MSTGAM (MST) versus benchmarks; preceding chapters-model, and TA-based strategies.

Figure 6.3 displays the box plot illustrating the distribution of values for the metrics on 200 stocks. Analyzing MST's performance in the upper left part of the figure, it appears that MST's median value is a bit higher than 5, where its average is 5.59, as reported in Table 6.3. The low STD density suggests that the increase in SR could be due to the metric being risk-adjusted. Another key observation is the median of MST's results in SR, which is notably higher than other benchmarks.

In contrast, in the RoR metric, MST is closely followed by the BandH strategy. However, in the other box plots, the BandH strategy shows a lower median SR compared to other strategies, indicating lower risk-adjusted returns. This is due to its moderate RoR coupled with higher volatility, as reflected in the STD plot. When examining the risk metrics represented in the lower box plots, MST's results scatter in a very narrow range around a low median, which is quite distinct compared to the other benchmarks. This indicates MST's effective balance between risk and return, as evidenced by its lower variance and competitive median values across these metrics.

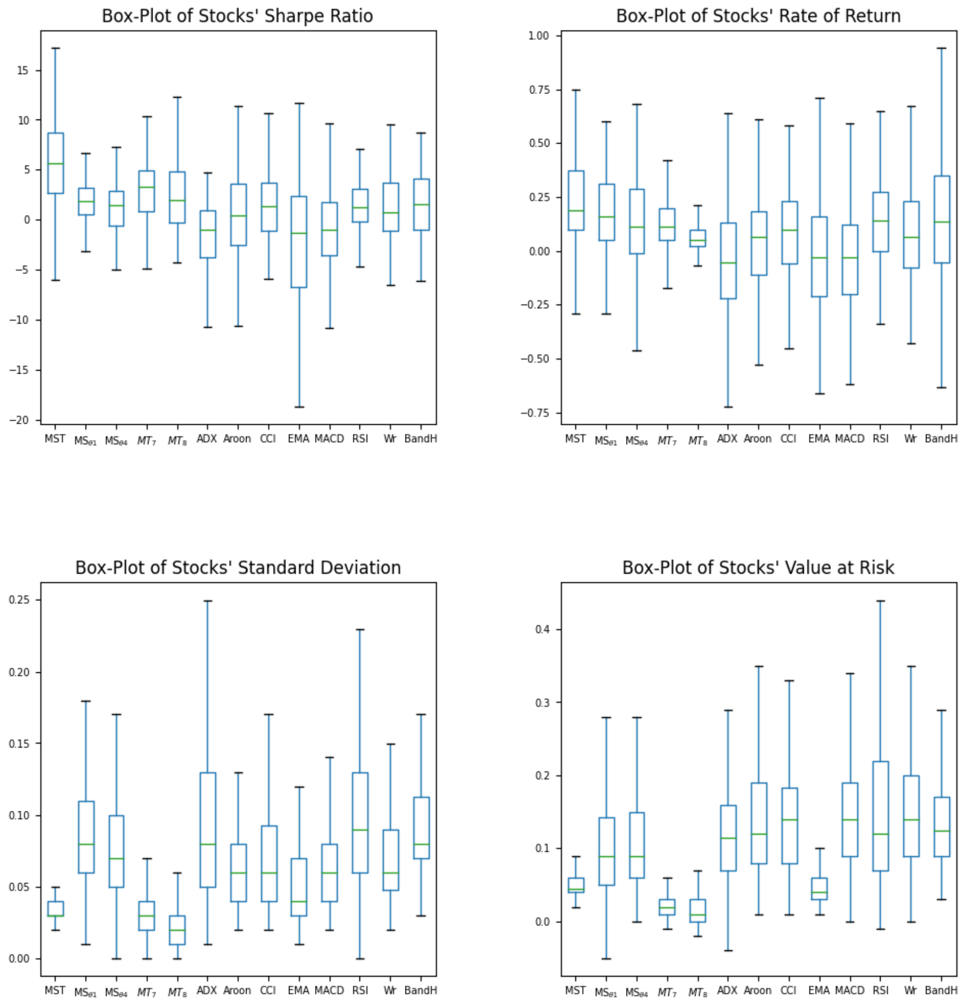

Figure 6.3: Box-plots of MSTGAM (MST), preceding chapters-models, and non-DC related benchmarks results across 200 stocks on Sharpe Ratio, Rate of Return, Standard Deviation, and Value at Risk.

To deepen our understanding of the results, we conducted the Friedman non-parametric statistical test again in this chapter, comparing it with the relevant benchmarks. This test is based on the null hypothesis that all groups, or results for our end, are derived from the same continuous distribution. In Tables 6.6, 6.7, 6.8, and 6.9, the second column presents the average rank of each algorithm. This ranking includes both GA-optimized models and TA-based benchmarks. The third column presents the adjusted p-value obtained from the test, comparing the average rank of each algorithm with that of the control algorithm (the algorithm with the highest rank). In the calculation of adjusted p-values, we once again utilized the Post-hoc two-stage False Discovery Rate method, as described in Section 4.5.

Table 6.6: The statistical test results for Sharpe Ratio were obtained using the non-parametric Friedman test, followed by the two-stage FDR correction to calculate adjusted p-values between MSTGAM (MST), previous chapter models, and non-DC benchmarks. Significant differences between the control algorithm (denoted with (c)) and the algorithms represented in a row at the $\alpha = 5\%$ level are highlighted in bold.

Algorithm	**Rank**	**Adjusted p-value**
MST(c)	3.760	-
MT_7	**5.105**	8.843e-05
MT_8	**6.035**	2.210e-10
$MS_{\theta 4}$	**6.450**	8.542e-14
RSI	**6.760**	1.236e-16
BandH	**6.830**	2.583e-17
CCI	**6.890**	7.284e-18
$MS_{\theta 1}$	**7.140**	1.664e-20
Wr	**7.145**	1.523e-20
Ar	**7.450**	6.126e-24
EMA	**8.860**	1.400e-43
MACD	**8.995**	1.343e-45
ADX	**9.535**	1.537e-54

From Tables 6.6 for SR and 6.7 for RoR, we observe that MST ranks first in both metrics. Furthermore, in doing so, statistically outperforms every other benchmark at $\alpha = 0.05$. In the context of SR, MT_7 and MT_8 follow in the ranks, whereas in terms of RoR, the following two strategies are $MS_{\theta 4}$ and then Bandh.

Table 6.7: The statistical test results for Rate of Return were obtained using the non-parametric Friedman test, followed by the two-stage FDR correction to calculate adjusted p-values between MSTGAM (MST), previous chapter models, and non-DC benchmarks. Significant differences between the control algorithm (denoted with (c)) and the algorithms represented in a row at the $\alpha = 5\%$ level are highlighted in bold.

Algorithm	**Rank**	**Adjusted p-value**
MST(c)	4.81	-
$MS_{\theta 4}$	**5.470**	2.734e-02
BandH	**6.115**	2.034e-04
RSI	**6.150**	1.516e-04
MT_7	**6.340**	2.120e-05
$MS_{\theta 1}$	**6.460**	5.496e-06
CCI	**6.775**	8.568e-08
Wr	**7.185**	1.481e-10
Ar	**7.485**	7.315e-13
MT_8	**7.535**	3.153e-13
EMA	**8.570**	3.297e-23
MACD	**9.030**	1.046e-28
ADX	**9.075**	5.425e-29

In the risk metrics, STD and VaR, as shown in Tables 6.8 for STD and 6.9 for VaR, the results are similar to the findings from Chapter 4. Again, St7 and St8 are leading in the rankings, but this time, it is important to remember that they underwent GA optimization with their respective θs. An important point to note is that MST ranks third in STD and fourth in VaR.

Table 6.8: The statistical test results for Standard Deviation were obtained using the non-parametric Friedman test, followed by the two-stage FDR correction to calculate adjusted p-values between MSTGAM (MST), previous chapter models, and non-DC benchmarks. Significant differences between the control algorithm (denoted with (c)) and the algorithms represented in a row at the $\alpha = 5\%$ level are highlighted in bold.

Algorithm	**Rank**	**Adjusted p-value**
MT_8(c)	1.940	-
MT_7	2.875	5.506e-02
MST	**2.920**	5.915e-06
EMA	**4.700**	7.851e-14
Ar	**6.730**	7.910e-52
MACD	**7.135**	3.657e-62
CCI	**7.660**	8.203e-77
Wr	**7.955**	1.599e-85
$MS_{\theta 1}$	**8.650**	1.679e-107
$MS_{\theta 4}$	**9.440**	9.549e-135
ADX	**9.455**	2.998e-135
RSI	**10.540**	1.782e-175
BandH	**10.940**	6.141e-191

Table 6.9: The statistical test results for Value at Risk were obtained using the non-parametric Friedman test, followed by the two-stage FDR correction to calculate adjusted p-values between MSTGAM (MST), previous chapter models, and non-DC benchmarks. Significant differences between the control algorithm (denoted with (c)) and the algorithms represented in a row at the $\alpha = 5\%$ level are highlighted in bold.

Algorithm	**Rank**	**Adjusted p-value**
MT_8(c)	2.150	-
MT_7	2.400	8.831e-02
EMA	**3.840**	3.632e-10
MST	**4.055**	5.698e-13
$MS_{\theta 4}$	**7.235**	2.010e-32
$MS_{\theta 1}$	**7.510**	3.218e-38
ADX	**8.200**	5.504e-53
RSI	**8.715**	2.932e-66
Ar	**8.900**	3.866e-70
BandH	**9.015**	4.745e-73
CCI	**9.320**	5.216e-82
MACD	**9.365**	8.081e-83
Wr	**9.510**	4.772e-87

Table 6.10 in this part shows the Sharpe Ratio, Rate of Return, Standard Deviation, and Value at Risk of market indices based on the New York Stock Exchange. Among these 7 indices, GSPC, RUI, and RUA demonstrate strong performance following our MSTGAM model, with RoRs of GSPC: 17.91%, RUI: 17.67%, and RUA: 16.43%, compared to our MSTGAM's 22.47%. However, due to their volatile nature, their Sharpe Ratios are relatively low compared to our MSTGAM's SR of 5.59.

Table 6.10: Performance and Risk metric comparison between MSTGAM (MST) and market indices (% for RoR). Best value highlighted by bold.

	MST	DJI	GSPC	NYA	RUI	RUT	RUA	XAX
SR	**5.59**	3.10	3.67	1.06	3.57	0.38	3.22	-2.01
RoR	**22.47**	15.17	17.91	6.74	17.67	4.56	16.43	-6.63
STD	**0.036**	0.041	0.042	0.040	0.042	0.054	0.043	0.045
VaR	**0.050**	0.064	0.070	0.066	0.071	0.105	0.074	0.077

As a final part, similar to Section 5.4, we will take the average of the pool of 50 runs and present the comparative results that we used in our thesis. As previously discussed in Section 4.5.1, this thesis adopts the method of choosing the highest SR performed chromosome from 50 training iterations and using it for experimentation in the test set.

Table 6.11: Average Sharpe Ratio (SR), Rate of Return (RoR), Standard Deviation (STD), Value at Risk (VaR), and Number of Trades occurrence (Trade) results across stocks for the MST (from a certain chromosome that performed in training to experiment in the test set), and MST_{ave} (average results for a pool of 50 runs in test set). The best values between the two presentation methods are highlighted in bold across metrics.

	SR	RoR	STD	VaR	Trade
MST	**5.5892**	**0.2247**	**0.0363**	0.0495	70.1915
MST_{ave}	4.8614	0.1978	0.0363	**0.0495**	70.3943

From Table 6.11, the first noteworthy observation is that MST performs better in terms of SR and RoR, with values of 5.5892 and 22.47%, respectively. Considering that SR is a risk-adjusted ratio, and given the very close values of STD, we can attribute this result to MST yielding higher profits. Another important point to note in these results is that the number of trades per stock is very close, approximately around 70 trades per stock.

In the upcoming section, we will delve into the interpretation of these results.

6.5 Interpretation

From Table 6.3, MST exhibits the highest Sharpe Ratio (SR) with 5.59, outperforming the sub-strategies. This is approximately 1.625 times its closest competitors St7θ1, 3.35 times its second closest benchmark St8θ1. In Rate of Return (RoR), MST again leads with 22%, when comparing with the two best sub-strategies, it adds 9% to St7θ1 and 10% to St6θ3. MST again generally surpasses sub-strategies on SR and RoR. One important point to emphasize is that it generates these results with a very high number of trades relative to its benchmarks. From Table 6.5, the number of trades on average by the 200 stocks is 70.19. The Standard Deviation (STD) of MST shows a mediocre performance trailing after St7θ1 and St8θ1. Table 6.4 reveals that MST performed the best in 54 out of 200 stocks, compared to its peers with a total of 70 sub-strategies for comparison. Therefore, we can conclude that MST has the ability to enhance the performances of sub-strategies.

When we consider all the benchmarks collectively: Firstly, from the Tables 6.6, 6.7, 6.8, 6.9, MST consistently ranks first in the statistical tests for SR and RoR. However, as indicated by the risk test metrics, it is evident that the risk is still trailing after St7 and St8, similar to what previous chapters have shown us. It places third in STD and fourth in Value at Risk (VaR), indicating that there are strategies with a more favorable risk profile. Here, we once again need to emphasize that the SR's effectiveness as a risk-adjusted metric indicates the applicability of results in real-world scenarios where risks are compensated, despite the model's average performance in risk metrics.

When we look at the TA-based benchmarks from Table 6.5, MST SR again is the best among them. For example, RSI has an SR of 1.59, and CCI has 1.48, which is lower than MST's SR. For the same benchmarks, their RoRs are 0.12 and 0.09, which are relatively low when we consider the 22% RoR for MST. In the Friedman test for STD and VaR, MST does not rank as the top model. This suggests that there is a "Risk-Return Tradeoff" compared to TA-based strategies. When we look at the market indices, MST's SR leads with 5.59, while GSPC, RUI, and RUA follow closely with SR values of 3.67, 3.57, and 3.22, respectively. The performance of an analogous index like XAX is notably different, recording a -6.63% RoR and -2.01 SR. In summary, comparing MST's SR and RoR with major market indices reveals that holding these indices from the start would yield lower profits than MST.

We have examined the models' performance and risk metrics of stocks to analyze their distribution, this time comparing results across 4, Chapter 5, and the current Chapter 6. Specifically, we are utilizing the results from the best-averaged models, namely $MS_{\theta 4}$ for Chapter 4, and MT_7 for Chapter 5 with our MST model.

From Figure 6.4, MST shows a nearly symmetrical, lightly-tailed distribution in SR results, highlighting its effectiveness in maintaining a balanced risk-adjusted return profile. This indicates MST's proficiency in optimizing returns while keeping risks in check, compared to the more risk-prone profiles of MT_7 and $MS_{\theta 4}$. In RoR, MST exhibits a slightly right-skewed and moderately tailed RoR distribution, which points out steady gains across 200 stocks. In STD, despite its high skewness and kurtosis, its lower mean suggests a stable risk profile, leading to less volatility and more predictability. In VaR, its right-skewed, lightly-tailed distribution indicates a reduced risk of extreme losses, demonstrating effective downside risk management.

In summary, the results across different chapters indicate that MST has demonstrated improved performance in terms of SR and RoR metrics. Additionally, it has managed to lower the risk compared to the models presented in Chapter 4 and Chapter 5.

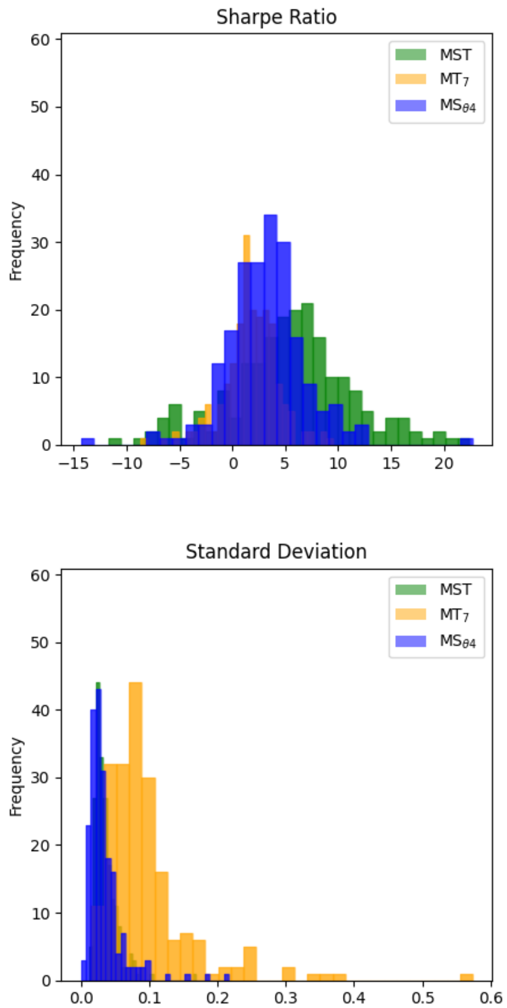

Figure 6.4: Distribution of stocks performance and risk metrics across chapters 4, 5, and 6 using MSTGAM (MST), MSGAM (MS$_{\theta 4}$), MTGAM (MT7)

When we assess the results averaged across the 50 runs in the final part of the results section, it is evident that, the differences in RoR, VaR, and Trade are very narrow. Taking into account that SR is risk-adjusted metric, we can conclude that the results suggest selecting the best chromosome from the training set is the better method for traders.

Lastly, we wanted to examine which sub-strategies had the highest weights in the optimized chromosomes of our 200 stocks. The most notable sub-strategies were St7θ10 with 2.3% and St3θ10 with 2.1%, having the highest weights among 70 genes (sub-strategies weights). In contrast, St4θ9 and St4θ10 had the lowest weights, with 0.05% and 0.06%, respectively.

Overall, while MST excels in terms of SR and RoR, it does carry a moderate risk as indicated by its STD and VaR. However, these relatively moderate risks are outweighed when considering the SR as a risk-adjusted aggregate metric, which is generally preferred in real-world applications.

6.6 Summary

The chapter explores the optimization of both various strategies and θs within the DC paradigm simultaneously. This approach marks a distinct departure from earlier chapters that were either confined to multiple-strategies optimizations on single thresholds or multiple thresholds optimization on each strategy individually.

MSTGAM model integrates a wide array of trading strategies, each paired with specific thresholds, to form a rich set of sub-strategies. This model advances beyond the limitations of previous models by allowing for a more granular optimization process. Unlike its predecessors that were restricted to either single thresholds or singular strategy optimization by thresholds, MSTGAM leverages the GA to use strategy-threshold combinations. Each sub-strategy within this model is encoded as a gene in a chromosome by a weight, which collectively decides what action to take.

The experimental setup for testing is the same as set in previous chapters, utilizing the same 200 stocks listed on the New York Stock Exchange. This consistency in data ensures a reliable comparison across different models and chapters. However, the increase in the number of genes necessitated adjustments in the parameters of the genetic algorithm, notably in population size and crossover probabilities. This adjustment is made to optimize the computational demands.

The results section compares MSTGAM with benchmarks such as DC-based sub-strategies, previous chapter models, and TA-based strategies across metrics like Sharpe Ratio (SR), Rate of Return (RoR), Standard Deviation (STD), Value at Risk (VaR), and number of trades. MSTGAM outperforms all benchmarks in SR and RoR, confirmed by the Friedman non-parametric test. It also surpasses various market indices, highlighting its effectiveness. It is noteworthy that MSTGAM exhibits a relatively average performance in other risk metrics such as STD and VaR. However, it is also crucial to consider that in real-world scenarios, metrics are rarely viewed in isolation. Therefore, the strong performance of our models in terms of the SR results holds considerable relevance for traders. Moreover, the model's higher number of trades implies a more active trading strategy, which might be appealing to certain types of trades or market conditions.

A critical aspect of MSTGAM's performance is its risk-adjusted returns. The model's SR, which accounts for risk, indicates a better performance compared to other strategies. It is noteworthy that MSTGAM exhibits a relatively average performance in other risk metrics such as STD and VaR, suggesting a balanced risk-return profile. However, it is also crucial to consider that in real-world scenarios, metrics are rarely viewed in isolation. Therefore, the strong performance of our models in terms of the SR results holds considerable relevance for traders. Moreover, the model's higher number of trades implies a more active trading strategy, which might be appealing to certain types of trades or market conditions.

In summary, this chapter presents MSTGAM as a model in the realm of trading strategy optimization. By simultaneously combining multiple strategies and thresholds, it not only overcomes the limitations of previous models but also opens new avenues for exploring trading strategies within the DC paradigm. Its superior performance, validated through comprehensive testing and comparison with a range of benchmarks, establishes MSTGAM as a potent tool for traders seeking to optimize their strategies in market environments.

Chapter 7

Conclusion

This chapter offers a summary of the thesis, following a sequential approach that aligns with the insights provided in each chapter. It begins by summarizing the key findings and insights obtained from each chapter. Subsequently, it outlines the contributions made to the field of research by this thesis. Following this, the limitations of the research are addressed. Finally, the chapter discusses the future directions and goals that emerge from the research findings.

7.1 Summary

This thesis centers on the Directional Changes (DC) paradigm, with a primary focus on investigating its effectiveness in the development of profitable trading strategies. To achieve this goal, Genetic Algorithm (GA) is used to enhance the strategies' performances.

Chapter 2 starts with a literature review on financial forecasting, discussing Fundamental Analysis (FA), Technical Analysis (TA), and emerging Sentiment Analysis. It focuses primarily on TA, relevant to our research interests, and highlights the limitations of fixed interval-based data in TA. This led to exploring the Directional Changes (DC) paradigm, examining its components like scaling laws and indicators, crucial for developing trading strategies. Furthermore, a critical feature of DC, the threshold denoted by θ, is highlighted, showcased how physical time data is transformed into event-based data with an example. Chapter 3 introduces the Genetic Algorithm (GA) as our optimization method. It begins with an overview, focusing on chromosome representation, and covers key operations. The chapter also explores GA's applications in finance, and its integration with DC.

Chapter 4 begins by detailing strategies based on scaling laws and DC-derived indicators, outlining their execution via Buy, Sell, and Hold actions. It then discuss GA optimization, using Sharpe Ratio (SR) as the fitness function and examining parameter tuning. The model, tested on ten years of data from 200 NYSE stocks (80% training, 20% testing), *showed superior performance in SR and Rate of Return (ROR), suggests that using this model instead of traditional TA strategies results in higher returns and an improved SR.* It is highlighted that the effectiveness of SR as a risk-adjusted metric underlines the model's real-world applicability despite average performance in other risk metrics.

Chapter 5 transitions from integrating multiple strategies in one model to examining them individually. It introduces the use of multiple thresholds, ranging from 0.098% to 2.55%, instead of the fixed $\theta = 0.72\%$. This approach enables a more comprehensive analysis of how strategies perform under different DC-profiled data. We discuss how this chapter's GA process differs from the previous while keeping the parameters consistent. *The analysis revealed that model generally enhances performance in terms of SR and RoR compared to individual strategies under a single threshold.*

Chapter 6 focuses on enhancing the overall performance of trading strategies by simultaneously employing multiple strategies and various thresholds. We introduced another model, designed to optimize a combination of 70 sub-strategies. *The results underscored the model's improved performance in SR and RoR over both the models from previous chapters and DC-based benchmarks. Moreover, when compared with various traditional TA strategies and market indices, the model outperformed these as well, reinforcing its effectiveness.*

Concisely, our model, optimized through GA based on strategies derived from the DC paradigm and using a single threshold, surpassed benchmarks in the first phase. By incorporating recommendations from multiple thresholds, we generally improved these individual strategies' performances in the second phase. Merging these two phases into a combined model with 70 sub-strategies led to the achievement of peak performance in the final phase.

7.2 Contribution

The primary contributions of this thesis include:

- Newly defined indicators were proposed for the DC field, such as OSV_{CUR} and TMV_{CUR}. These indicators allow traders in the DC paradigm to make practical assessments of trend magnitude, facilitating prompt trading decisions.

- By considering the newly proposed indicators alongside insights from scaling laws found in the literature, DC-based strategies have developed, which operate similarly to TA-like strategies. This allowed for a new addition to traders' decision-making in the stock market through an event-based approach. By the inherent nature of the strategies we have developed, we offer options that can be easily implemented in stock investments by traders without in-depth financial knowledge.

- The optimization of multiple thresholds enhanced the performance of our strategies. Consequently, we introduced traders to a model offering a more comprehensive, event-based perspective. This model's strength lies in its applicability to today's sentiment-sensitive stock pricing. It enables traders to capture market events they deem significant through thresholds and make informed actions based on this model.

- Using GA optimization simultaneously for both the strategies and thresholds, a more effective model, MSTGAM, was introduced. The model's ease of interpretation by traders offers a new managing tool that can be practically utilized in the field. Ultimately, by employing the DC paradigm in the creation of each model, we provided event-based complementary strategies that augment the standard frameworks found in technical analysis.

To summarize, a new information-rich model was created by generating strategies from the DC paradigm through the incorporation of new indicators alongside existing ones and scaling laws.

7.3 Limitations

At present, we observe three main limitations:

- As we have observed throughout each chapter, the model in each chapter lags in terms of risk metrics. We see one of the fundamental reasons for this as follows: due to the usage of a single objective fitness function, in our case, SR, was utilized, the evolution of chromosomes was primarily driven by the pursuit of higher SR. Consequently, the optimization process may have focused on improving the SR aspect while potentially overlooking the goal of minimizing risks or finding lower-risk solutions. Additionally, it is crucial to reemphasize that traders often prioritize aggregated metrics like the SR in the practical world, which takes into account both return and risk. Therefore, in light of the SR results obtained, the demonstrated risk performances can be compensated.

- Due to the rules we have implemented, we can only observe a Buy signal and need to wait for a Sell signal before we can see another Buy. However, in real-world applications, simultaneous Buy signals can certainly occur, and in some cases, considering short selling, the initial execution could even be a Sell.
- For a trader who does not have access to resources like those provided by a high-performance computing environment, computational times can be a significant concern.

7.4 Future Aim

Firstly, the foundation of our research relies on creating a limited number of thresholds. However, in continuous-time stock market data, such as tick data, we would have a vast number of data points compared to the daily closing prices we are currently using. To better test and expand our approach, we aim to work on an extensive range of thresholds. In doing so, we prioritize the distribution of a significantly large number of thresholds. This approach will allow us to expand our research by examining the varied profiles provided by different thresholds through the occurrence of distinct Directional Changes and Overshoot events.

Secondly, as demonstrated by the performance of strategies St7 and St8, which resemble resistance and support principles, it is evident that simple trading strategies based on the fundamental principles of market demand and supply can still be developed. Therefore, we will be able to offer traders easily interpretable strategy variations within the domain of Directional Changes.

Thirdly, our objective is to advance our model by adapting it to incorporate short-selling capabilities. While the practice of short-selling remains a subject of debate among some practitioners in financial markets, it is generally permitted in developed markets. Consequently, developing a model that integrates budget constraints with short-selling opportunities is among our planned future endeavors.

Fourthly, given the involvement of 200 stocks and performance improvements highlighted in each chapter, our model could be a strong contender for portfolio selection. The enhanced model can allow for a classification task to determine whether to include certain stocks in our portfolio. We aim to observe this and compare it with benchmarks commonly used in this sub-field, such as mean-variance portfolio, as part of our future endeavors.

Finally, instead of relying solely on single-objective fitness functions, we will shift our focus toward multi-objective fitness functions. By doing this, we aim to enhance the explanatory power of fitness functions that incorporate multiple objectives. In many real-world optimization problems, optimizing multiple conflicting objectives simultaneously is essential. Our research indicates that by concentrating on a single objective, our models achieve significant Sharpe Ratio outcomes. For the next phase of our work, the multi-objective fitness function will allow for the incorporation of budget constraints and prioritize performance indicators.

Appendix A

Stocks Related Information

In this appendix, we have provided descriptions of the stocks employed in our experiments across all three chapters: Chapter 4, Chapter 5, and Chapter 6. For each stock, we have included their stock ticker listed on the NYSE, along with the complete name of the corporation, as categorized by the segmentation presented in Section 4.5 in Table A.1.

Table A.1: Stock tickers, corporation's full name, and their market capitalization segments.

#	Ticker	Corporation	Segment	#	Ticker	Corporation	Segment
1	AAON	AAON, Inc.	Middle	2	AAPL	Apple Inc.	Large
3	ACM	AECOM	Middle	4	AG	First Majestic Silver Corp.	Middle
5	AGEN	Agenus Inc.	Small	6	ANDE	The Andersons, Inc.	Small
7	ASGN	ASGN Inc.	Middle	8	AWI	Armstrong World Industries, Inc.	Middle
9	BANR	Banner Corporation	Small	10	BCPC	Balchem Corporation	Middle
11	BG	Bunge Global SA	Middle	12	BHLB	Berkshire Hills Bancorp, Inc.	Small
13	BHP	BHP Group Limited	Large	14	BKR	Baker Hughes Company	Large
15	BMI	Badger Meter, Inc.	Middle	16	BMY	Bristol-Myers Squibb Company	Large
17	BSAC	Banco Santander-Chile	Large	18	BSBR	Banco Santander	Large
19	BSX	Boston Scientific Corporation	Middle	20	BX	Blackstone Inc.	Large
21	BYD	Boyd Gaming Corporation	Large	22	CBZ	CBIZ, Inc.	Middle
23	CCEP	Coca-Cola Europacific Plc	Large	24	CCI	Crown Castle Inc.	Large
25	CCL	Carnival Corporation Plc	Large	26	CHH	Choice Hotels International, Inc.	Middle
27	CMP	Compass Minerals, Inc.	Middle	28	CNK	Cinemark Holdings, Inc.	Middle
29	CNXN	PC Connection, Inc.	Small	30	COST	Costco Wholesale Corporation	Large
31	CRK	Comstock Resources, Inc.	Small	32	CSV	Carriage Services, Inc.	Small
33	CUBE	CubeSmart	Middle	34	D	Dominion Energy, Inc.	Large
35	DCOM	Dime Community Bancshares	Small	36	DDS	Dillard's, Inc.	Small
37	DENN	Denny's Corporation	Small	38	DIOD	Diodes Inc.	Middle
39	DIS	The Walt Disney Company	Large	40	DRQ	Dril-Quip, Inc.	Small
41	EAT	Brinker International, Inc.	Middle	42	EBR	Centrais Elétricas Brasileiras	Middle
43	EC	Ecopetrol S.A.	Large	44	EFSC	Ellington Financial Inc.	Small
45	EGHT	8x8, Inc.	Small	46	EGO	Eldorado Gold Corporation	Middle
47	EMN	Eastman Chemical Company	Middle	48	EQR	Equity Residential	Large
49	ERII	Energy Recovery, Inc.	Small	50	ERJ	Embraer S.A.	Small
51	ET	Energy Transfer LP	Middle	52	EVR	Evercore Inc.	Middle
53	FARO	FARO Technologies, Inc.	Small	54	FBNC	First Bancorp	Small
55	FELE	Franklin Electric Co., Inc.	Middle	56	FFIN	First Financial Bankshares, Inc.	Middle
57	FISI	Financial Institutions, Inc.	Small	58	FIX	Comfort Systems USA, Inc.	Small
59	FLO	Flowers Foods, Inc.	Middle	60	GCO	Genesco Inc.	Middle
61	GD	General Dynamics Corporation	Large	62	GE	General Electric Company	Large
63	GSAT	Globalstar, Inc.	Small	64	GTE	Gran Tierra Energy Inc.	Small
65	GTLS	Chart Industries, Inc.	Middle	66	GTN	Gray Television, Inc.	Small
67	HA	Hawaiian Holdings, Inc.	Small	68	HELE	Helen of Troy Limited	Middle
69	HIW	Highwoods Properties, Inc.	Middle	70	HLX	Helix Energy Solutions, Inc.	Small
71	HMY	Harmony Gold Mining	Middle	72	HOPE	Hope Bancorp, Inc.	Small
73	HRI	Herc Holdings Inc.	Middle	74	HWC	Hancock Whitney Corporation	Middle
75	IART	Integra LifeSciences Holdings	Middle	76	IDT	IDT Corporation	Small
77	IMAX	IMAX Corporation	Small	78	IMGN	ImmunoGen, Inc.	Small
79	INSM	Insmed Inc.	Middle	80	IOSP	Innospec Inc.	Middle
81	IP	International Paper Company	Middle	82	IPAR	Inter Parfums, Inc.	Middle
83	IRBT	iRobot Corporation	Small	84	IT	Gartner, Inc.	Middle
85	ITGR	Integer Holdings Corporation	Middle	86	ITT	ITT Inc.	Middle
87	JKHY	Jack Henry and Associates, Inc.	Middle	88	KAI	Kadant Inc.	Small
89	KBR	KBR, Inc.	Middle	90	KFRC	Kforce Inc.	Small
91	KLIC	Kulicke and Soffa Industries, Inc.	Small	92	LANC	Lancaster Colony Corporation	Middle
93	LBAI	Lakeland Bancorp, Inc.	Small	94	LMAT	LeMaitre Vascular, Inc.	Small
95	LOW	Lowe's Companies, Inc.	Large	96	LRN	Stride, Inc.	Small
97	LSI	LSI Industries Inc.	Middle	98	LYG	Lloyds Banking Group Plc	Large
99	MCY	Mercury General Corporation	Middle	100	MDC	M.D.C. Holdings, Inc.	Middle
101	MGM	MGM Resorts International	Middle	102	MGRC	McGrath RentCorp	Small
103	MIDD	The Middleby Corporation	Middle	104	MRO	Marathon Oil Corporation	Middle
105	MSA	MSA Safety Inc.	Middle	106	MT	ArcelorMittal S.A.	Large
107	MTZ	MasTec, Inc.	Middle	108	MYGN	Myriad Genetics, Inc.	Small
109	NBIX	Neurocrine Biosciences, Inc.	Middle	110	NEOG	Neogen Corporation	Middle
111	NFLX	Netflix, Inc.	Large	112	NG	NovaGold Resources Inc.	Middle
113	NGD	New Gold Inc.	Small	114	NGG	National Grid Plc	Large
115	NICE	NICE Ltd.	Middle	116	NNI	Nelnet, Inc.	Middle
117	NNN	NNN REIT, Inc.	Middle	118	NOG	Northern Oil and Gas, Inc.	Small
119	NRG	NRG Energy, Inc.	Middle	120	NVMI	Nova Ltd.	Middle
121	NVS	Novartis AG	Large	122	NWBI	Northwest Bancshares, Inc.	Small
123	OGE	OGE Energy Corp.	Middle	124	OMCL	Omnicell, Inc.	Middle
125	PAYX	Paychex, Inc.	Large	126	PB	Prosperity Bancshares, Inc.	Middle
127	PCH	PotlatchDeltic Corporation	Middle	128	PDCE	PDC Energy, Inc.	Middle
129	PDFS	PDF Solutions, Inc.	Small	130	PDS	Precision Drilling Corporation	Small
131	PERI	Perion Network Ltd.	Small	132	PHG	Koninklijke Philips N.V.	Large
133	PNM	PNM Resources, Inc.	Middle	134	POR	Portland General Electric	Middle

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#	Ticker	Corporation	Segment	#	Ticker	Corporation	Segment
135	PRGS	Progress Software Corporation	Middle	136	QCOM	QUALCOMM Inc.	Large
137	RAMP	LiveRamp Holdings, Inc.	Middle	138	RGR	Sturm, Ruger Company, Inc.	Small
139	RHI	Robert Half Inc.	Middle	140	RJF	Raymond James Financial, Inc.	Middle
141	RL	Ralph Lauren Corporation	Middle	142	ROG	Rogers Corporation	Middle
143	ROIC	Retail Opportunity Investments	Small	144	RPM	RPM International Inc.	Middle
145	RPT	RPT Realty	Small	146	RTX	RTX Corporation	Large
147	RUSHA	Rush Enterprises, Inc.	Middle	148	RY	Royal Bank of Canada	Large
149	SAH	Sonic Automotive, Inc.	Small	150	SAIA	Saia, Inc.	Middle
151	SASR	Sandy Spring Bancorp, Inc.	Small	152	SBH	Sally Beauty Holdings, Inc.	Middle
153	SBRA	Sabra Health Care REIT, Inc.	Middle	154	SBS	Companhia de Saneamento	Middle
155	SCI	Service Corporation International	Middle	156	SCVL	Shoe Carnival, Inc.	Small
157	SEIC	SEI Investments Company	Middle	158	SIEGY	Siemens Aktiengesellschaft	Large
159	SITC	SITE Centers Corp.	Small	160	SKYW	SkyWest, Inc.	Middle
161	SNX	TD SYNNEX Corporation	Middle	162	SO	The Southern Company	Large
163	SRPT	Sarepta Therapeutics, Inc.	Middle	164	STC	Stewart Information Services	Small
165	STLD	Steel Dynamics, Inc.	Middle	166	STM	STMicroelectronics N.V.	Large
167	STT	State Street Corporation	Large	168	STX	Seagate Technology Holdings Plc	Middle
169	SYNA	Synaptics Inc.	Middle	170	TDC	Teradata Corporation	Middle
171	TEX	Terex Corporation	Middle	172	THG	The Hanover Insurance, Inc.	Middle
173	TITN	Titan Machinery Inc.	Small	174	TLK	Perusahaan Perseroan	Large
175	TREE	LendingTree, Inc.	Middle	176	TREX	Trex Company, Inc.	Middle
177	TRMK	Trustmark Corporation	Small	178	TSM	Taiwan Semiconductor Limited	Large
179	TTC	The Toro Company	Middle	180	TU	TELUS Corporation	Large
181	TXN	Texas Instruments Inc.	Large	182	TXRH	Texas Roadhouse, Inc.	Middle
183	UBSI	United Bankshares, Inc.	Middle	184	UGP	Ultrapar Participações S.A.	Middle
185	UHS	Universal Health Services, Inc.	Middle	186	UHT	Universal Health Trust	Small
187	UNF	UniFirst Corporation	Middle	188	WEC	WEC Energy Group, Inc.	Large
189	WELL	Welltower Inc.	Large	190	WEN	The Wendy's Company	Middle
191	WIRE	Encore Wire Corporation	Small	192	WLK	Westlake Corporation	Middle
193	WMK	Weis Markets, Inc.	Small	194	WMT	Walmart Inc.	Large
195	WOR	Worthington Industries, Inc.	Middle	196	WPC	W. P. Carey Inc.	Middle
197	WSM	Williams-Sonoma, Inc.	Middle	198	WTI	W and T Offshore, Inc.	Small
199	WW	WW International, Inc.	Small	200	XPO	XPO, Inc.	Middle

Appendix B

Extended Results of Chapter 6

In this appendix, the first four tables present the metric performances achieved through GA optimization for each stock. Table B.2 displays the Sharpe ratio, Table B.1 showcases the Rate of return, Table B.3 outlines the Standard deviation, and Table B.4 provides insights into the Value at risk. Each table begins with the stock tickers in the first columns, followed by the following order of information: MSTGAM (MST): Optimization of strategies on a single threshold, as explained in Chapter 4 (MS); Optimization of strategies with individually different thresholds, as experimented in Chapter 5 (MT1, $\cdots$, MT8); TA-based strategy results; and confirmation point strategy (DCC).

As discussed in Section 6.4, due to spacing constraints, we have presented the results for 8 sub-strategies. In this appendix, we present all 70 sub-strategies' Sharpe Ratio results. However, due to spacing constraints, the 70 sub-strategies were divided into four different tables, and MST results for each stock were presented in these four tables. Specifically, the first 18 sub-strategies were in Table B.5, sub-strategies 19 (inclusive) to 36 (inclusive) were in Table B.6, sub-strategies 37 (inclusive) to 53 (inclusive) were in Table B.7, and finally, the results for sub-strategies 54 (inclusive) through 70 (inclusive) were presented in Table B.8.

Table B.1: Rate of Return results for MSTGAM (MST) versus MSGAM (MS), MTGAMs (MT1, $\cdots$, MT8), TA-based strategies (TA1, $\cdots$, TA7, represent the TA-strategies in the following order: ADX, Ar, CCI, EMA, MACD, RSI, and Wr), and confirmation point strategy (DCC), BandH (B&H) for each stock.

Ticker	MST	MS	MT1	MT2	MT3	MT4	MT5	MT6	MT7	MT8	TA1	TA2	TA3	TA4	TA5	TA6	TA7	DCC	B&H
AAON	0.23	0.19	-0.05	0.29	0.34	-0.03	0.38	0.19	0.06	0.02	0.3	-0.32	-0.21	0	-0.48	0.1	-0.22	-0.12	0.37
AAPL	0.23	0.01	-0.04	-0.16	0.06	0.1	0.03	0.07	0.15	0.1	0.21	0.12	-0.02	0.1	-0.29	0.16	0.14	0.48	0.58
ACM	0.37	0.07	0.04	0.31	-0.22	0.22	-0.09	0.38	0.05	0.06	-0.09	0.12	0.19	0.03	-0.17	0.15	0.14	0.04	0.14
AG	0.63	0.93	0.27	0.25	0.31	-0.02	0.58	0.86	0.13	0.03	-0.41	0.61	0.01	-0.23	0.4	0.25	0.02	1.11	0.61
AGEN	0.18	0.54	-0.51	-0.02	0.29	0.05	0.6	-0.25	0.25	0.27	0.64	0.29	0.38	1.57	-0.41	0.53	0.63	-0.36	0.03
ANDE	0.46	-0.03	0.03	0.04	-0.18	-0.28	0.06	0	0.02	0.09	0.23	0.05	-0.1	0.23	-0.12	-0.26	-0.19	0.19	-0.25
ASGN	0.41	0.11	0.2	0.14	0.09	0.26	0.12	-0.22	0.09	-0.02	-0.07	0.12	-0.15	0.04	-0.2	0.06	-0.07	0.05	0.04
AWI	0.29	0.22	0.13	0.35	-0.03	0.04	0.03	0.14	0.09	0.07	0.44	0.08	0.12	-0.16	-0.2	0.09	0.06	0.04	0.13
BANR	0.16	0.18	0.05	-0.05	0.02	0.01	0	-0.03	-0	0.05	-0.03	-0.04	0.14	-0.09	-0.13	0.27	0.02	-0.18	0.01
BCPC	0.14	0.04	-0.3	0.44	-0.01	-0.12	0.05	-0.18	0.1	-0.07	0.32	-0.16	0.04	0.16	0.07	-0.29	0.03	0.25	0.15
BG	0.21	0.13	-0.23	-0.13	-0.26	-0.09	0	0.04	0.06	0.05	-0.37	0.14	0.27	-0.52	0.5	-0.12	0.17	-0.03	-0.15
BHLB	-0.13	0.16	-0.36	0.04	-0.02	-0.07	-0.02	-0.14	0.14	0.03	-0.04	-0.16	-0.18	-0.1	-0.07	0.09	-0.19	0.15	-0.14
BHP	0.2	0.16	0.12	0.37	0.27	0.25	0	0.19	0.06	0.11	-0.47	0.06	0.36	-0.32	0.11	0.29	0.31	0.18	0.43
BKR	-0.21	0.33	-0.21	-0.13	0.12	0.31	-0.13	-0.11	0.15	-0.02	-0.25	-0.26	-0.11	0.57	-0.4	-0.07	-0.04	-0.03	-0.2
BMI	0.34	0.44	-0.06	0.29	0.04	0.15	0.09	0.46	0.05	0.06	-0.03	0.1	0.12	0.04	-0.11	0.45	0.14	0.11	0.35
BMY	0.17	0.14	-0.1	0.33	0.2	0.14	0.1	-0.26	0.08	0.04	0.17	-0.07	-0.04	-0.04	-0.06	-0.04	-0.05	0.17	-0.05
BSAC	-0.06	0.06	-0.37	-0.01	0.04	-0.12	-0.29	0.2	0.07	-0.07	-0.24	0.05	-0.2	-0.22	-0.15	-0.12	-0.22	-0.11	-0.11
BSBR	0.74	0.27	-0.2	0.53	0.07	0.34	0.44	0.35	0.13	0.02	-0.05	-0.44	-0.13	0.6	-0.2	-0.2	-0.2	-0.1	0.32
BSX	0.31	0.23	0.24	-0.02	0.18	0.42	0.2	0.15	0.01	0.03	-0.04	0.32	0.29	-0.5	0.26	0.43	0.27	0.29	0.22
BX	0.3	0.19	0.04	0.34	-0.1	0.18	0.15	-0.13	0.24	0.01	0.12	0.05	0.5	-0.06	-0.24	0.06	0.47	0.19	0.34
BYD	0.07	0.18	-0.37	0.14	-0.06	0.09	-0.52	0.24	0.23	0.04	-0.16	-0.09	-0.12	0.26	0.06	-0.11	-0.11	0.37	-0.07
CBZ	0.5	0.17	0.73	0.67	0.35	0.11	0.31	0.46	0.18	0.06	0.12	-0.22	0.25	-0.09	-0.36	0.08	0.28	0.15	0.3
CCEP	0.39	0.05	0.33	0.21	0.08	0.29	-0.02	0.05	0.36	0.02	-0.29	-0.19	-0.15	0.18	-0.25	-0.14	-0.16	0.27	0.36
CCI	0.15	0.06	-0.01	0.26	0.25	0.26	0.05	0.15	0.1	0.02	-0.46	0.32	0.29	0.1	0.24	0.25	0.09	0.08	0.27
CCL	-0.29	0	-0.45	-0.23	-0.05	-0.19	-0.28	-0.33	0.12	0.05	-0.57	0.58	0.06	0.1	0.03	0.17	0.02	-0.11	-0.27
CHH	0.17	0.14	0.14	0.06	0.22	0.16	0.01	0.06	0.11	0.04	-0.12	0.16	0.11	-0.16	-0.02	0.14	0.1	0.05	0.23
CMP	0.15	0.17	-0.15	-0.09	-0.15	0.01	0.22	0.32	0.17	0.03	-0.06	0.01	0.05	-0.06	0.21	0.18	0.22	0.06	-0.14
CNK	0.1	0.01	-0.26	0.16	0.03	0.16	-0.11	-0.1	0.08	0.03	-0.11	0.14	0.06	-0.05	-0.01	0.11	0.03	-0.05	-0.03
CNXN	0.35	-0.1	0.57	-0.05	0.43	0.53	0.2	0.37	0.24	-0.22	0.21	-0.08	-0.06	-0.34	-0.13	0.19	0.02	0.04	0.85
COST	0.23	0.54	-0.07	0.38	0.38	0.5	0.12	0.59	0.29	0.05	0.16	-0.16	-0.24	-0.28	-0.16	0.32	-0.28	0.72	0.26
CRK	0.14	0.71	0.48	0.65	-0.19	-0.17	-0.53	0.04	0.63	0.48	-0.25	0.05	-0.28	0.21	-0.05	-0.01	0.04	-0.6	0.05
CSV	0.4	-0.24	-0.43	0.06	0.28	0.36	0.03	0.22	0.34	0.09	-0.12	-0.06	-0.03	0.27	-0.02	-0.23	-0.06	0.14	-0.04
CUBE	0.11	0.1	0.25	0.07	0.08	-0.04	0.04	0.1	0.07	0.05	-0.26	-0	-0.18	0.22	0.02	0.11	-0.18	0.16	0.16
D	0.1	0.01	-0.09	-0.13	0.25	-0.12	0.15	-0.06	-0.06	0.02	-0.02	0.17	0.16	0.02	0.14	0.07	0.14	0.1	0.07
DCOM	0.05	0.14	-0.2	-0.19	-0.18	0.07	-0.13	-0.03	0.26	-0.03	-0.21	-0.13	-0.17	0.12	-0.2	-0.04	-0.22	-0.08	-0.03
DDS	0.27	0.14	-0.56	-0.03	0.08	0.09	-0.19	0.36	0.23	0.36	-0.26	0.65	0.53	-0.37	0.16	0.39	0.62	0.06	0.23
DENN	0.47	0.18	-0.08	-0.05	0.36	0.31	0.06	0.37	0.02	0.05	0.33	-0.32	-0.11	0.12	0.22	0.52	-0.2	0.05	0.42
DIOD	0.17	0.27	0.15	0.01	-0.16	0.35	0.08	0.63	0.2	0.11	-0.18	-0.1	0.31	-0.37	-0.03	0.38	0.19	0.08	0.57
DIS	0.46	0.34	-0.29	0.1	-0.03	-0.07	-0	0.12	0.05	0.1	0.22	0.16	0.21	-0.24	0.18	0.31	0.2	0.03	0.48
DRQ	-0.13	0.06	-0.01	0.38	-0.14	0.3	-0.02	0.22	0.15	0.18	0.07	0.02	-0.07	-0.1	-0.03	-0.15	-0.22	-0.1	-0.11
EAT	0.72	0.33	-0.31	-0.16	0.1	0.26	-0.1	0.21	0.09	0.14	-0.45	0.36	0.38	-0.39	0.03	0.35	0.35	0.44	0.28
EBR	0.48	0.45	0.23	0.02	0.91	0.81	0.22	0.2	0.32	0.02	0.98	-0.39	-0.07	0.77	-0.14	0.16	-0.09	0.59	0.45
EC	0.27	-0.16	-0.04	-0.1	0.25	0.26	0.09	0.52	0.03	0.09	0.27	-0.06	-0.16	0.73	-0.37	-0.09	-0.23	0.57	0.71
EFSC	-0.02	0.06	0.13	-0.18	0.12	0.09	0.18	-0.06	0.15	0.09	0.04	-0.16	-0.11	0.1	-0.11	0.07	-0.15	-0.07	0.02
EGHT	0.25	0.28	0.29	0.68	0.21	0.11	0.16	0.03	0.06	0.03	0.34	0.58	0.46	-0.17	0.15	0.29	0.31	0.11	0.45
EGO	0.54	1.67	1.25	0.76	0.66	1.23	0.3	1.43	0.53	-0.13	0.88	0.15	0.05	0.94	-0.26	0.13	-0.22	1.39	0.35
EMN	-0.11	0.15	-0.09	-0.3	-0.15	0.05	-0.38	-0.16	0.09	0.07	0.22	0.01	-0.12	0.07	-0.16	-0.04	-0.1	0.03	-0.11
EQR	0.18	0.37	0.15	0.17	0.42	-0.09	0	0.33	-0.36	0.01	-0.08	0.25	0.2	0.19	-0.08	0.25	0.22	0.34	0.35
ERII	0.6	0.17	-0.62	-0.08	0.16	-0.14	-0.13	0	-0.02	0.19	-0.04	0.3	-0.05	-0.28	0.1	0.21	0.11	-0.38	-0.22
ERJ	-0.14	0.12	0.05	0.2	-0.01	0	0.23	-0.07	0.2	0.25	-0.28	0.15	-0.09	-0.38	0.12	0.02	-0.14	-0.17	-0.11
ET	0.19	0.36	0.08	-0.06	-0.01	-0.04	-0.05	0.12	0.14	0.11	-0.11	0.12	-0.1	0	-0.17	-0.29	-0.25	0.21	-0.14
EVR	0.24	0	0.25	0.08	-0.21	0.07	-0.32	-0.18	0.08	0.1	-0.18	-0.03	-0.11	0.17	-0.3	-0.04	-0.11	-0.03	-0.06
FARO	0.47	0.13	-0.73	-0.01	-0.11	-0.15	-0.23	0.1	0.23	0.14	-0.12	0.39	0.68	0.18	-0.28	0.55	0.37	-0.1	-0.04
FBNC	0.14	0.1	0.3	0.33	0.04	0.01	0.02	-0.11	-0	0.11	0.03	0.16	0.16	-0.2	0.02	0.14	0.23	-0.21	0.05
FELE	0.39	0.12	-0.13	0.3	0.06	-0.12	0.08	0	0.2	0.21	0.07	0.1	0.13	-0.39	0.33	0.1	0.02	0.19	0.21
FFIN	0.24	0.51	0.2	0.16	0.26	0.14	0.32	0.19	0.15	0.06	-0.26	-0.27	0.35	-0.38	-0.31	0.59	0.2	-0.15	0.49
FISI	-0.04	0.26	-0.05	-0.18	0.04	-0.01	0.1	0.19	-0.15	-0	-0.32	-0.04	0.1	-0.28	-0.09	0.19	0.17	-0.15	0.05
FIX	0.67	0.33	0.53	0.1	0.29	-0.02	-0.14	0.03	0.21	0.03	-0.11	-0.14	-0	0.08	-0.62	0.19	0.08	0	0.2
FLO	0.13	0.2	0.21	0.12	0.01	0.18	-0.01	0.29	-0.01	0.01	-0.32	0.22	0.27	-0.32	0.38	-0.01	0.34	-0.15	0.16
GCO	0.53	0.11	0.16	0.26	0.16	0.12	-0.1	-0.09	0.05	0.03	0.23	-0.16	0.21	-0.66	0.31	0.3	0.5	-0.22	0.19
GD	0.2	-0.05	-0.14	-0.3	0.08	-0.04	0.02	0.07	0.15	0.04	-0.15	-0.12	-0.09	-0.15	-0	0.06	-0.03	0.07	-0.09
GE	-0.28	0.96	-0.75	-0.12	0.23	-0.41	0.36	-0.11	-0.04	0.1	-0.45	-0.27	-0.31	0.71	-0.3	-0.49	-0.12	-0.23	-0.33
GSAT	1.23	-0.95	-0.77	0.6	-1.04	-0.49	0.33	-0.65	0.2	0.11	0.99	1.39	0.09	-0.34	0.87	-0.07	0.16	-0.48	-0.77

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Ticker	MST	MS	MT1	MT2	MT3	MT4	MT5	MT6	MT7	MT8	TA1	TA2	TA3	TA4	TA5	TA6	TA7	DCC	B&H
GTE	0.58	-0.49	-0.66	-0.32	-0.33	0.24	0.35	0.18	0.01	0.3	-0.68	0.49	-0.45	-0.59	-0.07	-0.67	-0.4	0.1	-0.55
GTLS	0.15	0.22	-0.52	0.13	-0.04	0.05	0.03	0.81	0.11	0.14	0.13	0.03	-0.09	0.38	0.02	-0.06	0	1.07	0.13
GTN	0.22	0.35	-0.59	0.05	0.06	-0.2	0.28	0.27	0.52	0.15	0.28	-0	0.04	0.37	-0.1	0.37	0.01	0.41	0.42
HA	0.39	-0.39	0.28	-0.02	-0.25	0.08	0.12	0.49	0	0.02	-0.05	-0.04	0.18	-0.25	0.35	0.18	0.07	-0.24	-0.27
HELE	0.39	0.25	0.37	0.49	0.15	0.63	0.5	0.57	0.07	0.02	0.56	0.1	0.15	-0.48	0.48	0.35	0.25	0.06	0.29
HIW	0.19	0.22	-0.15	-0.06	0.1	0.04	0	0.15	0.12	0.03	0.07	-0.02	-0.09	0.1	0.18	-0.13	0.09	-0.16	0.02
HLX	0.57	0.52	0.45	0.47	-0.21	0.24	0.19	0.07	0.23	0.1	-0.18	0.1	0.22	-0.07	-0.02	0.33	0.16	-0.02	0.27
HMY	0.2	0.31	-0.51	0.65	0.66	0.75	0.67	0.73	0.05	0.02	1.01	0.43	0.31	0.59	-0.04	0.6	-0.4	0.54	0.69
HOPE	0.15	0.03	0	-0.09	-0.14	-0.07	-0.05	-0.22	0.04	0.15	0.06	0.17	0.14	-0.06	-0.05	0.16	0	-0.28	-0.17
HRI	0.5	0.6	-0.01	0.18	0.42	0.15	-0.47	-0.52	0	-0.03	0.31	0.3	0.12	0.08	-0.17	0.43	-0.04	-0.45	-0.21
HWC	-0.03	0.07	-0.23	-0.04	-0.04	0.02	-0.15	-0.3	0.05	0.07	0.03	0.12	0.08	0.08	0.04	0.02	-0.03	-0.05	-0.17
IART	0.32	0.02	0.09	-0.08	0.14	0.19	0.26	-0.09	0.14	0.05	0.2	0.3	0.19	-0.09	0.09	0.12	0.21	-0.06	0.25
IDT	0.69	0.78	-0.25	0.3	-0.13	-0.44	-0.94	-0.18	0.39	0.13	0.18	0.09	0.04	0.93	-0.41	-0.24	0.1	0.13	-0.53
IMAX	-0.12	-0.18	-0.05	0.01	-0.17	-0.37	-0.47	-0.35	0.13	-0.01	-0.07	0.09	0.03	0.13	0.14	0.06	0.04	-0.21	-0.16
IMGN	-0.34	0.34	-0.58	-0.2	-0.31	0.07	0.15	-0.04	0.11	-0.03	-0.72	1.8	0.52	0.51	1.05	-0.59	0.67	-0.44	-0.34
INSM	0.64	-0.16	0.84	-0.52	-0.16	-0.22	-0.25	0.14	0.01	0.1	0.02	0.08	-0.02	0.64	-0.15	0.69	-0.12	0.51	-0.29
IOSP	0.12	0.46	0.28	0.13	-0.05	0.43	0.31	0.55	0.1	0.14	-0.23	-0.15	0.13	-0.34	-0.22	0.37	-0.01	-0.11	0.4
IP	-0	-0.14	-0.37	-0.07	0	-0.03	-0.34	0.05	0.14	0.34	-0.36	0.37	0.21	0.14	0.12	0.04	0.06	-0.07	-0.12
IPAR	0.41	0.51	0.34	0.38	0.45	0.3	0.29	0.12	0.06	0.02	0.48	-0.34	-0.36	0.14	-0.18	0.29	-0.43	0.29	0.58
IRBT	-0.52	0.05	0.13	-0.45	0.21	-0.1	-0.36	-0.46	-0.11	0.12	-0.1	0.11	-0.44	-0.19	-0.13	0.16	-0.57	0.35	-0.34
IT	0.14	0	-0.11	0.47	-0.03	0.04	-0.1	0.33	0.39	0.04	-0.09	-0.33	0	0.14	-0.54	0.02	-0.1	-0.06	0.33
ITGR	0.18	0.31	0.31	0.04	0.39	0.52	0.12	0.2	0.05	0.16	0.01	0.12	0.45	-0.38	0.25	0.5	0.56	0.21	0.57
ITT	0.45	0.05	-0.37	-0.19	0.48	0.52	0.2	0.08	0.22	0.05	-0.57	0.21	0.08	-0.37	-0.28	0.13	0.23	0.08	0.32
JKHY	0.33	-0.13	-0.44	-0.19	0.01	0.25	-0.16	0.42	0.11	0.11	0.19	0.1	0.05	-0.09	0.12	0.23	0.09	0.17	0.33
KAI	0.18	0.08	0.1	-0.18	-0.15	0.05	0.29	0.25	0.07	0.02	-0.1	0.08	0.13	-0.01	-0.08	0.3	0.1	-0.31	-0.04
KBR	0.17	0.16	-0.4	-0.15	0.05	0.6	0.3	0.96	0.29	-0.02	0.17	0.22	0.26	0.17	-0.59	0.05	0.15	-0.32	0.65
KFRC	0.2	0.52	0.25	0.37	0.37	0.01	0.2	0.29	0.21	0.09	-0.09	-0.35	0.15	-0.18	-0.03	0.28	0.05	0.32	0.58
KLIC	0.23	0.03	-0.29	0.24	0.16	0.02	-0.17	-0.07	0.29	0.19	-0.4	0.03	0.14	-0.25	-0.18	0.42	0.03	-0.14	0.03
LANC	0.5	0.32	0.07	0.21	0	0.17	0	0.09	0.04	0.21	-0.06	0.07	0.14	-0.19	0.05	0.01	0.16	0.21	0.23
LBAI	-0.09	0.02	-0.2	-0.09	-0.27	-0.21	-0.08	0.18	0.11	0.08	0.23	0.07	0.14	-0.03	0.11	-0.07	0.03	-0.02	-0.16
LMAT	0.39	0.22	0.21	-0.22	-0.05	0.07	-0.01	0.25	0.26	0.06	0.19	0.44	0.36	0.03	0.12	0.48	0.34	-0.25	0.11
LOW	0.6	0.31	0	0.23	0.08	0.48	-0.21	0.72	0.27	0.15	0.04	-0.04	0.08	-0.03	-0.11	0.13	-0.02	-0.06	0.46
LRN	0.39	0.52	0.28	0.06	0.28	0.02	-0.18	-0.13	0.04	0.7	0.18	0.16	0.32	0.34	0.22	0.18	0.36	-0.08	0.17
LSI	0.06	0.09	-0.05	0.09	-0.06	0.05	0.06	0.11	0.02	0.26	-0.07	0.12	0	-0.23	0.11	0.39	0.11	0	-0.32
LYG	0.16	0.12	-0.15	-0.14	0.21	0.19	0.01	-0.23	0.13	0.06	0.26	0.04	0.04	0.31	-0.01	-0.21	0.08	-0.07	-0.05
MCY	0.09	0.21	-0.49	0.34	0.14	-0.12	-0.01	-0.02	0.2	-0	-0.22	-0.11	-0.31	0.26	-0.3	0.14	-0.27	0.03	-0.03
MDC	0.06	0.45	-0.18	-0.14	0.29	0.44	0.3	-0.03	0.04	0.03	0.05	0.41	0.28	-0.09	-0	0.49	-0.01	-0.15	-0.24
MGM	0.33	0.27	-0.04	0.22	0.09	-0.02	0.17	0.25	0.09	0	-0.25	0.44	0.44	-0.23	0.34	0.15	0.33	0.19	-0.04
MGRC	0.15	0.57	0.37	0.5	0.43	0.37	0.23	0.58	0.04	0.31	-0.23	-0.39	0.19	-0.19	-0.24	0.06	0.03	-0.19	0.63
MIDD	-0.23	0.08	0.11	0	0	-0.15	-0.01	-0.03	0.13	0.03	-0.01	0.17	-0.15	-0.1	-0.1	0.27	0.02	-0.15	-0.09
MRO	-0.17	0.12	-0.08	-0.36	-0.2	0	-0.03	0.25	-0.05	0.14	-0.11	0.21	0.02	-0.47	0.23	-0.03	-0.17	-0.41	-0.19
MSA	0.16	0.3	-0.06	0.21	0.1	0.38	0.05	0.21	-0.01	0.05	-0.6	-0.35	0.11	-0.38	-0.27	0.38	0.12	-0.19	0.49
MT	-0.39	-0	-0.55	-0.36	-0.43	-0.48	-0.51	-0.23	0.18	0.13	-0.52	-0.19	-0.35	0.55	-0.22	-0.75	-0.22	-0.11	-0.42
MTZ	0.27	0.25	0.13	0.53	0.41	0.59	0.16	0.25	0.04	0.16	-0.04	0.07	0.1	-0.28	0.2	0.2	0.42	-0.03	0.48
MYGN	0.68	0.29	0.22	0.21	0.34	0.2	-0.03	-0.03	0.14	0.07	-0.46	0.8	0.58	-0.59	0.4	0.58	0.67	0.16	-0.26
NBIX	0.24	0.44	0.04	0.08	0.19	0.32	-0.22	0.32	0.11	0.13	0.16	0.26	0.1	0.08	0.27	0.11	0.28	0.09	0.59
NEOG	0.38	0.38	-0.23	0.26	0.13	0.02	0.25	0.08	0.16	0.03	-0.1	0.18	0.06	0.09	-0.12	-0.03	-0.01	0.14	0.06
NFLX	0.14	0.4	-0.85	0.62	0.06	0.21	0.17	0.59	0.37	0.09	0.13	-0.01	0.06	0.16	0.08	-0.2	0.04	0.55	0.66
NG	0.1	1	0.86	-0.3	0.69	0.96	0.18	0.61	0.07	-0.07	0.7	-0.02	0.3	-0.35	0.14	0.11	0.36	0.96	0.75
NGD	0.65	-0.03	-0.98	-1.38	-0.58	-0.43	-0.59	-0.59	0.56	0.35	0.9	0.84	0.78	-0.46	1.32	-0.34	1.14	-1.06	-0.74
NGG	0.06	0.12	-0.01	-0.03	0	-0.04	0.14	0.11	0.03	0.02	0	0.19	0.1	0.02	0.01	0.2	0.24	0.19	0.07
NICE	0.39	0.1	0.23	0.47	0.51	0.2	0.36	-0.08	0.03	0.07	0.17	-0.17	0.34	0.44	-0.37	0.18	0.3	0.08	0.13
NNI	0.19	0.24	-0.1	-0.22	0.07	0.26	-0.1	0.2	-0.07	0.04	0.19	0.13	0.21	-0.25	0.15	0.16	0.15	-0.08	0.18
NNN	0.29	0.14	0.05	-0.22	0	-0.08	0.17	0.2	0.09	0.04	-0.24	-0.29	0.14	0.1	-0.06	0.32	-0.22	0.32	0.46
NOG	0.42	0.34	0.03	0.18	-0.18	0.85	0.64	0.58	0.07	0.14	0.01	-0.33	0.1	0.26	0.58	0.51	0.44	0.16	0.06
NRG	0.37	0.21	0.27	0.06	0.17	0.1	0.11	0.14	0.06	0.07	0.18	-0.12	0.14	0.2	-0.33	0.13	0.05	0.03	0.41
NVMI	-0.02	0.19	0.03	0.51	0.31	0.4	0.02	0.38	0.07	-0.05	-0.31	0.06	0.32	-0.43	-0.02	0.27	0.24	-0.3	0.28
NVS	0.06	0.07	-0.18	0.22	0.42	0.01	-0.03	-0.05	0.18	0.02	0.17	0.22	0.19	-0.07	0.1	0.15	0.13	0.13	0.27
NWBI	0.03	0.07	-0.07	-0.02	-0.04	0.03	0.14	0.1	0.05	0.02	-0.13	-0.06	0.14	-0.02	-0.12	0.22	0.14	-0.05	0.06
OGE	0.15	0.19	-0.12	0.12	0.08	0.14	-0.1	0.21	0.01	0.04	-0.2	0.12	0.03	-0.02	0.02	-0.02	0.14	0.15	0.26
OMCL	0.22	0.17	0.09	0.17	0.64	0.37	0.01	0.18	-0.18	0.19	-0	0.35	0.5	-0.37	0.14	0.22	0.65	0.76	0.53
PAYX	0.11	0.09	-0.07	0.37	-0.05	0.07	0.03	0.36	0.13	-0.05	-0.07	0.2	0.19	-0.1	0.18	0.06	0.06	0.34	0.35
PB	0.2	0.07	-0.07	0.28	0.07	0.14	0.06	0.32	0.23	0.04	-0.4	-0.01	0.09	0.06	-0.09	0.32	0.05	-0	0.04
PCH	-0.01	-0.06	-0.03	-0.23	-0.08	-0.06	-0.2	0.32	0.04	0	-0.11	-0.15	-0.06	-0.1	-0	0.03	-0.06	-0.41	-0.02
PDCE	0.19	0.23	0.24	0.35	-0.21	-0.52	-0.37	-0.51	0.09	-0.02	-0.35	-0.24	-0.37	-0.04	-0.52	-0.83	-0.79	0	-0.23
PDFS	0.24	0.3	-0.42	0.64	0.49	-0.2	0.22	-0.2	0.5	0.05	0.12	0.3	0.23	0.13	0.21	-0.32	0	-0.59	-0.13
PDS	0.75	-0.4	-0.2	-0.46	-0.93	-0.6	-0.74	0.07	0.2	0.55	-0.37	0	-0.63	0.04	-1.09	-0.04	-0.7	-0.19	-0.63
PERI	0.79	0.58	1.15	0.91	0.26	0.73	0.99	-0.14	0.46	-0.11	0.97	-0.38	-0.4	1.08	-0.91	0.29	-0.61	0.11	0.56
PHG	0.16	0.16	-0.42	-0.04	0.11	0.27	0.03	-0.11	0.15	0.03	-0.07	0.15	0.11	-0.15	0.15	0.1	0.19	0	0.24

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Ticker	MST	MS	MT1	MT2	MT3	MT4	MT5	MT6	MT7	MT8	TA1	TA2	TA3	TA4	TA5	TA6	TA7	DCC	B&H
PNM	0.05	0.09	-0.04	0.14	-0.08	0.15	0.09	0.17	0.1	0	-0.01	0.06	0.29	-0.03	0.23	-0.13	0.29	0.01	0.11
POR	0.22	-0.13	0.04	0.11	0.35	0.39	0.1	0.02	0.08	0.09	-0.07	0.18	0.2	0.21	0.35	0.16	0.14	0.07	0.18
PRGS	0.2	0.05	0.38	0.23	-0.15	0.07	-0.13	0.26	0.27	0.08	-0.27	0.38	0.4	-0.09	-0.16	0.13	0.34	-0.23	0.03
QCOM	0.19	0.74	0.46	0.31	0.29	-0.25	0.42	-0.16	0.22	0.01	0.13	0.09	0.13	0.89	-0.56	-0.09	-0.32	0.66	0.36
RAMP	0.45	0.11	0.42	0.01	0.55	0.33	0.6	0.45	0.15	-0.02	-0.6	0.44	0.34	0.08	-0.3	0.16	0.46	0.2	0.84
RGR	0.12	0.31	0.04	-0.39	-0.03	-0.09	-0.5	0.19	0.02	0.03	-0.16	0.29	0.06	0.04	-0.15	0.09	0.05	0.06	-0.15
RHI	0.21	0.26	0.16	0.13	0.05	0.19	-0.03	-0.02	0.1	0.05	-0.11	-0.06	0.03	0.1	-0.19	0.04	-0.12	0.22	0.06
RJF	0.1	0.05	0.15	0.18	0	0.01	0.11	0.28	0.16	0.09	-0.24	-0.05	0.04	0.04	-0.2	0.2	0.03	0.07	0.04
RL	0.57	0.11	-0.16	0.17	-0.16	0.18	-0.07	0.16	0.14	-0.03	0.18	-0.2	-0.05	0.03	-0.29	0.05	-0.12	-0.06	0.18
ROG	0.49	-0.09	-0.58	0.36	-0.43	-0.15	-0.84	0.1	0.29	0.1	0.15	0.89	0.24	0.41	0.4	-0.02	0.2	0.01	-0.19
ROIC	0.12	0.06	0.08	-0.09	0.09	0.02	-0.02	-0.02	0.13	0.03	0.04	-0.01	0.06	-0.08	0.05	-0.03	-0	0	-0.01
RPM	0.25	0.5	-0.32	0.55	0.1	0.41	0.01	0.25	0.14	0.08	0.04	-0.29	0.11	-0.1	-0.18	0.2	0.01	-0.02	0.47
RPT	0.15	0.16	0.03	0.32	0.22	0.23	0.09	-0.15	-0.17	0.07	-0.09	-0.21	0.07	-0.02	-0.33	0.2	0.08	0.11	0.01
RTX	0.08	0.15	0.22	0.2	-0.03	-0.02	-0.02	0.33	0.2	-0.11	-0.1	-0.21	0.01	0.05	-0.35	0.18	-0.02	-0.15	0.27
RUSHA	0.21	0.06	-0.15	-0.33	-0.11	-0.11	-0.32	0.23	0.19	0.04	-0.32	0.22	0.1	0	0.05	0.02	0.02	-0.2	-0.05
RY	0.1	0.09	-0.18	-0.09	-0.02	0.09	0.03	0.11	0.07	0.04	0.03	0.07	0.1	0.08	-0.06	0.05	0.04	0.01	0.11
SAH	0.55	0.8	0.53	1.16	0.94	-0.14	0.12	0.76	0.07	0.09	0.16	-0.02	0.07	-0.09	0.05	0.38	0.38	1.15	0.59
SAIA	0.16	0.02	0.41	-0.21	0.38	-0.11	0.19	0.5	0.05	-0.03	0.05	-0.11	-0.16	0.33	-0.36	0.17	-0.03	-0.12	0.46
SASR	-0.09	0.05	-0.04	-0.12	0.03	0.04	0.07	0.04	0.09	0.02	-0.25	0.03	-0.01	-0.18	-0.03	0.24	-0.01	-0	-0.04
SBH	0.19	0.28	0.16	0.41	0.16	0.03	-0.23	0.14	0.47	-0.01	-0.48	0.13	0.34	-0.44	0.59	0.04	0.23	0.42	0.09
SBRA	0.14	0.19	0.15	0.17	0.05	0.02	0.13	-0.14	0.13	-0	0.07	-0.26	-0.06	0.38	-0.08	0.31	-0.31	0.02	0.35
SBS	0.45	-0.01	0.71	0.23	0.03	-0.22	0.25	0.6	0.19	0.05	0.37	-0.63	-0.3	0.3	-0.53	0.14	-0.05	0.36	0.34
SCI	0	0.18	0.04	-0.05	0.26	-0.01	-0.14	0.14	0.06	-0.01	-0.1	-0.01	0.13	-0.15	0.12	0.16	0.19	0.13	0.23
SCVL	0.51	-0.19	0.45	0.71	0.78	0.17	0.47	0.31	0.41	0.02	-0.49	-0.23	-0.21	-0.28	-0.62	-0.25	0	0.34	0.4
SEIC	-0.02	-0.29	-0.25	0.31	0.02	0.04	-0.25	-0.12	-0	0.2	-0.22	-0.32	-0.28	0.03	-0.33	-0.03	-0.29	-0.08	-0.08
SIEGY	0.1	0.16	0.06	0.18	0.05	-0.02	-0.14	-0.07	0.14	0.37	-0.25	0.26	0.13	0.09	0.05	0.04	0.15	-0.27	0.01
SITC	0.26	0.15	0.05	0.12	-0.13	0.18	0.06	-0	0.03	0.07	0.04	0.03	0.14	-0.23	-0.03	0.44	0.16	0.03	0.35
SKYW	0.14	0.27	0.15	0.2	0.44	-0.06	0.3	0.31	0.23	0.04	-0.04	0.27	0.4	-0.22	-0.11	0.21	0.23	-0.11	0.25
SNX	-0.09	0.32	0.06	0.38	-0.35	0.15	0.11	-0.33	0.34	0.11	0.13	-0.46	-0.29	0.37	-0.26	0.14	-0.23	0.21	-0.08
SO	0.1	0.19	-0.05	-0.18	0.42	-0.08	0.1	-0.06	-0.2	-0	-0.3	0.14	0.13	-0.18	0.45	0.04	0.01	0.33	0.33
SRPT	0.34	0.57	-0.17	-0.08	0.27	0.52	0.63	0.36	-0.06	0.01	0.2	0.08	0.26	-0.08	-0.02	-0.17	0.01	0.47	0.94
STC	0.08	0.07	-0.11	0.03	-0.09	-0.02	0.08	-0.04	0.05	0.04	-0.09	-0.16	0	-0.08	-0.03	0.03	-0.11	0.09	0.13
STLD	-0	0.27	-0.25	0.21	-0.39	0.01	0	0.08	0.21	0.13	0.01	-0.13	-0.23	0.28	-0.45	-0.09	-0.25	0.06	-0.09
STM	0.25	0.13	-0.12	0.06	0.39	-0.47	0.09	0.4	0.05	0.06	-0.15	0.49	0.36	0.15	0.34	0.62	0.52	0.05	0.12
STT	0.3	0.52	-0.08	0.11	-0.26	-0.01	-0.43	-0.13	0.17	0.09	-0.46	0.13	0.18	0.26	-0.03	-0.08	0.17	-0.14	-0.19
STX	0.8	0.5	-0.06	0.17	-0.23	0.03	0.15	0.36	0.16	0.09	0.25	0.14	0.23	-0.53	0.22	0.26	0.27	0.61	0.7
SYNA	0.23	0	0.21	-0.02	0.18	0.27	0.65	-0.3	-0.12	0.04	-0.27	0.56	0.43	-0.46	-0.17	0.62	0.49	0.53	0.54
TDC	-0.08	0.46	-0.34	-0	-0.19	0.23	0.21	-0.04	0.09	0.09	-0.57	0.52	0.27	-0.17	-0.15	0.03	0.26	0.15	-0.29
TEX	0.41	-0.52	-0.14	-0.48	-0.17	-0.2	-0.49	-0.17	0.23	0.07	-0.59	0.3	-0.27	0.31	0.22	0.11	-0.4	-0.04	-0.38
THG	0.04	0.24	-0.01	0.19	0.37	0.09	0.12	-0.01	-0	0.06	0.17	0.26	0.28	-0.2	0.31	0.17	0.23	0.45	0.37
TITN	0.11	0.11	-0.13	0.07	-0.08	-0.23	0.23	-0.21	0.02	-0.05	-0.04	0.09	0.19	-0.21	0.07	0.43	0.3	0.31	-0.2
TLK	0.17	0.05	0.1	-0.03	-0.14	0.03	0.01	0.09	0.21	0	-0.08	0.27	0.34	-0.51	-0.13	-0.14	0.33	0.06	-0.03
TREE	0.06	0.25	-1.03	0.33	-0.03	0.18	0.59	0.06	0.43	0.06	0.08	0.6	0.4	-0.07	0.41	0.47	0.29	0.25	0.22
TREX	0.71	-0.42	0.25	0.26	-0.06	0.38	0.53	0.42	0.05	-0.02	0.56	-0.1	0.42	-0.61	-0	0.14	0.86	0.15	0.48
TRMK	0.02	0.18	0.23	0.01	-0.02	-0.19	-0.18	0.14	0.13	0.15	-0.05	0.02	0.18	-0.05	-0.14	0.27	0.21	-0.04	0.06
TSM	0.11	0.4	-0.1	-0.17	0.42	-0.05	0.06	0.4	0.33	0.1	0.1	-0.24	0.07	-0.21	-0.27	0.23	0.12	0	0.45
TTC	0.18	-0.14	-0.12	0.18	0.24	-0.1	0.21	-0.17	0.16	0.04	-0.01	-0.06	0.09	-0.1	-0.21	0.09	0.15	-0.08	0.22
TU	0.16	0.22	-0.1	0.03	0.03	-0.03	0.02	-0.1	0.01	0.04	-0.14	0.13	0.14	-0.14	-0.11	0.09	0.13	0.19	0.09
TXN	0.24	0.25	-0.04	0.31	-0.09	0.13	0.15	0.16	0.16	0.05	-0.12	0.24	0.31	-0.17	0.05	0.28	0.26	0.17	0.28
TXRH	0.16	0.38	-0.18	0.05	0.1	0.16	0.24	0.13	0.16	0	-0.36	0.16	0.33	-0.08	0.12	0.22	0.26	0.21	0.17
UBSI	0.26	0.05	0.03	0.04	0.25	0.16	-0.04	0.24	0.04	0.11	0.04	0.05	0.18	0.03	-0.25	0.29	0.13	-0.06	0.08
UGP	0.03	0.13	-0.46	-0.41	-0.41	-0.58	-0.22	-0.36	0	0.21	-0.2	-0.84	-0.81	1.19	-0.15	-0.58	-0.58	-0.76	-0.5
UHS	0.2	0.43	0.02	0.36	0.16	0.05	-0.04	0.17	0.17	-0.02	-0.33	0.28	0.26	-0.07	0.09	0.3	0.12	-0.03	0.29
UHT	0.16	0.32	0.15	-0.08	-0.21	0.86	0.1	0.13	0.42	0.1	-0.09	-0.53	0.16	-0.25	-0.2	-0	0.28	-0.1	0.71
UNF	0.18	-0	-0.18	0.27	0.48	0.28	-0.06	0.38	0.01	-0.02	0.09	-0.29	0.06	-0.1	-0.15	0.2	0.19	-0.09	0.27
WEC	0.14	0.08	0.06	0.2	0.38	0.56	-0.16	0.15	0.04	0.04	-0.3	-0.1	0.21	0.28	0.3	0.02	0.3	0.06	0.36
WELL	0.12	0.36	0.22	0.21	-0	0.28	0.11	0.25	0.16	0.08	0.02	-0.33	0.1	0.45	0.23	0.21	-0	0.37	0.38
WEN	0.21	0.11	-0.04	0.18	0.37	0.11	0.14	0.39	0.07	0.08	-0.11	-0.11	0.26	-0.36	0.16	0.33	0.21	0.07	0.49
WIRE	0.08	0.3	-0.01	0.2	0.3	-0.1	0.01	0.26	0.12	-0.03	-0.15	0.04	0.26	-0.34	0.06	0.41	0.35	-0.1	0.23
WLK	-0.03	-0.2	-0.81	0.05	-0.36	-0.47	-0.28	0.13	0.1	0.11	-0.16	0.12	-0.02	0.35	0.15	-0.23	-0.11	-0.23	-0.27
WMK	0.57	-0.16	-0.06	-0.2	-0.1	-0.06	-0.14	0.03	0.08	0.06	-0.12	-0.07	-0.21	0.2	-0.1	-0.2	-0.09	-0.21	-0.01
WMT	0.18	-0.01	-0.19	0.27	0.14	0.12	0	0.06	0.07	0.18	0.05	-0.22	-0.19	0	-0.28	0.07	-0.19	0.19	0.27
WOR	0.27	-0.05	-0.21	0.12	-0.09	0.18	-0.34	0.01	0.32	0.07	-0.11	0.03	-0.14	-0.11	0.04	0.35	0.28	-0.15	-0.04
WPC	0.14	0.19	-0.12	0.09	0.41	0.25	0.08	0.28	0.1	0.03	-0.22	-0.08	-0.07	0.09	-0.12	0.16	-0.09	0.26	0.33
WSM	0.57	0.49	0.31	0.7	0.33	0.55	0.75	0.11	0.04	0.08	0.1	0.16	0.32	-0.34	0.1	0.65	0.43	0.06	0.47
WTI	0.58	0.29	-0.21	0.52	0.43	1.04	0	0.07	0.45	0.16	0.19	0.08	0.18	0.24	-0.62	0.47	0.53	0.6	0.37
WW	-0.34	1.05	-0.7	-0.19	0.3	-0.32	-0.25	0.44	0.62	0.55	1.17	0.3	0.53	1.04	0.63	-0.3	-0.41	0.08	-0.02
XPO	0.28	-0.18	-0.31	0.12	0.08	-0.18	0	0.18	0.06	-0.01	0.06	-0.38	-0.32	0.6	-0.46	0.05	-0.28	-0.05	0.06

Table B.2: Sharpe Ratio results for MSTGAM (MST) versus MSGAM (MS), MTGAMs (MT1, ···, MT8), TA-based strategies (TA1, ···, TA7, represent the TA-strategies in the following order: ADX, Ar, CCI, EMA, MACD, RSI, and Wr), and confirmation point strategy (DCC), BandH (B&H) for each stock.

Ticker	MST	MS	MT1	MT2	MT3	MT4	MT5	MT6	MT7	MT8	TA1	TA2	TA3	TA4	TA5	TA6	TA7	DCC	B&H
AAON	7.68	1.31	-1.53	4.15	2.72	-1.63	4.79	2.78	1.4	-0.67	2.8	-4.26	-4.86	-0.48	-7.93	1.08	-5.06	-3.28	4.16
AAPL	7.18	-0.18	-1.45	-2.93	1.86	3.23	0.03	0.9	6.85	4.75	1.26	1.03	-0.38	1.02	-5.27	1.33	1.36	3.9	6.21
ACM	12.04	1.17	0.32	2.87	-6.56	10.2	-1.64	4.71	0.85	2.38	-1.26	3.11	4.81	0.07	-4.35	1.48	3.48	0.5	1.31
AG	5.94	2.92	1.65	3.19	3.41	-0.8	3.27	5.16	3.69	0.23	-7.71	5.63	-0.18	-3.89	4.41	2.73	-0.03	6.22	4.53
AGEN	2.12	3.06	-2.88	-0.25	4.3	0.29	3.14	-1.73	4.67	5.17	3.77	1.43	1.37	3.87	-2.77	1.67	2.49	-4.99	0.02
ANDE	11.49	-1.43	0.17	0.16	-2.28	-3.38	0.72	0	-0.44	3.82	1.68	0.28	-1.35	3.94	-1.67	-2.05	-1.79	5.44	-2.57
ASGN	12.32	1.23	3.22	1.24	1.53	3.42	1.11	-3.13	2.76	-1.3	-2.81	1.74	-2.36	0.32	-4.13	0.28	-1.09	0.8	0.13
AWI	9.95	2.27	1.65	6.96	-0.67	0.3	0.09	2.64	3.25	3.15	2.17	2.02	2.56	-6.8	-3.53	2	1.1	0.6	1.55
BANR	5.07	4.8	0.94	-1.53	-0.26	-0.25	-0.42	-1.92	-1.86	1.51	-0.69	-2.2	2.43	-4.32	-3.27	3.16	-0.23	-8.06	-0.28
BCPC	3.31	0.23	-4.77	5.75	-1.57	-3.12	0.35	-3.83	4.21	-2.92	2.62	-2.89	0.21	2.75	0.75	-2.9	0.01	4.1	1.56
BG	8.3	2.79	-7.16	-3.44	-5.35	-4.12	-0.42	0.34	1.42	1.72	-6.94	2.74	9.14	-17.13	14.11	-2.72	3.71	-2.54	-3
BHLB	-5.62	3.32	-7.37	0.22	-0.69	-4.63	-1.08	-2.92	3.67	0.5	-0.29	-5.26	-3.4	-2.94	-2.3	0.49	-3.53	3.31	-1.92
BHP	7.23	2.95	2.3	8.56	6.39	3.78	-0.31	3.06	1.33	2.79	-12.28	1	7.77	-11.94	1.84	2.75	6.04	5.04	6.24
BKR	-6.84	2.8	-4.22	-1.6	1.14	3.52	-1.73	-1.51	3.93	-1.3	-2.42	-2.92	-1.18	5.61	-5.07	-0.72	-0.56	-1.65	-1.93
BMI	12.72	5.13	-1.62	6.65	0.16	1.33	1.16	8.53	1.02	5.49	-0.7	1.73	1.61	0.42	-2.48	5.4	1.97	3.63	4.16
BMY	5.4	0.95	-3	3.13	3.99	2.44	0.97	-4.19	2.21	0.8	2.04	-1.61	-1.17	-1.25	-1.73	-0.62	-1.13	3.4	-1.06
BSAC	-2.73	0.46	-7.24	-0.36	0.27	-2.26	-5.64	2.56	3.43	-3.24	-7.09	0.52	-4.25	-10.67	-5.24	-1.89	-4.46	-2.17	-2.19
BSBR	22.42	2.8	-3.82	3.74	1.13	2.6	3.99	4.57	6.08	-0.41	-0.83	-6.33	-1.32	7.59	-2.46	-1.7	-2.35	-3.53	2.23
BSX	11.32	3.56	4.23	-0.9	2.04	11.08	3.99	2.69	-1.28	0.55	-1.14	8.31	6.76	-29.64	7.49	8.57	5.48	8.99	3.49
BX	8.57	2.27	0.23	7.48	-2.52	2.2	2.38	-4.58	4.36	-1.59	0.83	0.31	10.71	-2.81	-5.19	0.59	13.08	6.16	3.98
BYD	1.06	3.25	-6.23	1.23	-1.11	0.46	-6.9	3.49	4.66	1.07	-1.27	-1.22	-1.42	4.35	0.4	-0.91	-1.46	6.21	-0.73
CBZ	19.88	1.86	9.1	7.23	4.4	2.19	5.19	5.71	11.71	1.28	3.02	-4.36	4.2	-6.44	-5.99	0.9	5.6	4.21	3.84
CCEP	16.63	1.13	10.03	4.19	1.1	2	-1.41	0.58	3.52	-3.44	-6.76	-4.83	-3.24	3.94	-6.76	-2.37	-3.32	7.49	7.23
CCI	5.21	1.25	-0.96	3.87	3.31	3.13	0.4	4.01	7.22	-0.93	-12.62	8.11	7.82	1.92	8.18	7.11	1.35	1.5	5.87
CCL	-11.68	-0.26	-13.37	-4.66	-0.85	-2.96	-3.15	-5.79	7.15	1.45	-8.15	8.65	0.69	2.24	0.13	2.69	-0.01	-6.61	-3.78
CHH	7.14	2.11	3.19	1.06	2.94	1.73	-0.3	1.31	4.76	4.39	-3.36	6.11	3.04	-9.32	-1.4	2.47	2.37	1.14	3.91
CMP	3.09	1.52	-2.45	-2.14	-5.12	-0.72	4.83	6.55	5.8	0.05	-0.62	-0.31	0.44	-1.28	1.78	1.11	3.46	1.27	-1.5
CNK	2.78	-0.24	-7.35	1.9	0.18	4.06	-2.96	-3.4	2.56	0.72	-1.33	1.76	0.74	-2.08	-1.04	1.36	0.14	-2.24	-0.69
CNXN	7.55	-1.34	7.7	-0.91	1.68	2.36	2.59	3.89	3.9	-3.33	2.42	-1.68	-1.07	-7.78	-1.63	1.06	-0.04	0.28	7.87
COST	8.91	3.59	-2.97	4.47	3.66	5.83	1.94	5.43	11.94	3.2	1.91	-2.94	-4.54	-16.47	-5.06	6.8	-3.32	9.98	4.85
CRK	1.43	4.19	2.53	2.56	-0.92	-1.63	-3.09	0.15	3.31	1.03	-1.56	0.15	-2.5	1.78	-0.54	-0.15	0.1	-6.17	0.1
CSV	7.82	-3.16	-5.78	0.29	1.38	1.76	0.05	2.83	3.55	4.06	-3.71	-1.35	-0.51	4.9	-0.62	-1.32	-1.04	4.16	-0.66
CUBE	3.5	3.14	5.24	1.33	1.05	-3.75	0.3	2.31	4.91	4.23	-4.24	-0.63	-5.93	6.46	-0.15	3.33	-5.71	3.37	2.82
D	4.54	-0.17	-3.83	-4	1.44	-7.81	2.24	-3.66	-7.55	-2.67	-0.74	3.76	2.66	-0.29	3.53	0.59	2.95	3.88	1.14
DCOM	0.6	1.46	-4.52	-4.48	-2.75	0.69	-2.15	-1.37	5.93	-2.67	-3.51	-2.98	-3.59	2.4	-3.06	-0.67	-4.71	-2.98	-0.7
DDS	4.79	1.46	-7.87	-0.59	1.3	0.92	-2.56	6.01	3.32	3.43	-3.59	7.48	4.96	-6.78	1.26	3.05	6.31	0.7	1.69
DENN	15.18	2.24	-2.72	-1.85	4.39	3.23	0.9	5.32	-0.16	3.42	3.23	-10.49	-3.51	2.42	3.8	4.93	-3.82	0.78	5.11
DIOD	4.69	4.07	1.9	-0.26	-5.54	8.19	0.57	7.98	3.6	4.66	-2.61	-1.73	6.34	-10.51	-0.58	3.42	2.65	1.46	4.83
DIS	17.16	3.03	-13.86	2.46	-3.13	-4.53	-0.88	4.78	1.46	7.94	2.09	4.89	8.02	-17.66	5.83	3.06	6.29	0.04	6.77
DRQ	-3.26	0.44	-0.49	3.48	-2.76	3.25	-0.48	2.56	3.6	6.66	0.35	-0.05	-0.76	-2.61	-0.65	-0.96	-2.69	-2.3	-1.07
EAT	21	4.05	-5.98	-2.05	1.55	6.71	-1.83	3.02	3.42	5.43	-9	5	7.19	-9.79	0.18	4.43	6.07	10.75	2.83
EBR	8.17	1.76	2.36	-0.06	2.63	2.84	1.45	2.04	6.15	-0.12	2.24	-3.45	-0.55	5.25	-1.31	1.13	-0.82	8.06	1.87
EC	7.2	-2.21	-1.3	-0.82	4.79	5.45	0.53	9.82	0.43	3.07	1.53	-1.19	-1.96	9.03	-4.1	-0.65	-2.16	6.83	5.22
EFSC	-1.44	0.33	1.35	-2.43	4.57	3.92	3.96	-1.88	1.9	9.14	0.28	-3.13	-1.98	1.41	-2.37	0.35	-2.31	-2.25	-0.09
EGHT	6.19	4.77	3.47	10.87	1.89	2.21	1.68	0.06	1.5	0.22	3.2	8.37	4.4	-3.69	1.75	2.16	3.39	1.67	4.13
EGO	6.93	2.86	3.55	2.69	1.45	1.56	2.4	4.09	5.94	-3.19	4.15	0.76	0.12	3.25	-1.6	0.4	-1.34	4.8	1.61
EMN	-5.29	2.87	-2.35	-4.41	-2.84	1.54	-6.36	-3.55	2.63	4.83	2.86	-0.38	-2.26	1.41	-4.12	-0.72	-1.98	0.12	-1.48
EQR	7.99	2.59	3.57	3.11	1.93	-5.82	-0.42	3.71	-14.33	-0.67	-2.53	5.81	4.92	5.32	-2.65	4.13	6.12	5.37	6.69
ERII	10.87	1.47	-11.5	-1.41	1.42	-2.83	-1.17	-0.36	0	6.86	-0.35	4.5	-0.99	-7.33	1.19	1.73	0.96	-7.31	-2.18
ERJ	-5.21	2.14	0.54	2.93	-0.28	-0.3	2.42	-3.05	4.33	11.82	-3.22	2.86	-1.71	-14.24	1.34	-0.06	-2.99	-3.74	-1.63
ET	5.18	7.52	1.52	-1.13	-0.61	-1.31	-1.34	2.42	5.46	7.91	-5.54	2.13	-3.02	-0.57	-3.2	-3.51	-5.23	5.35	-2.37
EVR	7.37	-0.36	3.67	1.12	-2.83	0.68	-4.81	-3.41	4.61	5.94	-2.13	-0.7	-1.46	2.05	-4.99	-0.49	-1.2	-2.01	-0.77
FARO	8.64	1.29	-14.2	-0.52	-1.95	-4.72	-2.46	1	5.18	6.72	-2.4	4.19	5.03	2.01	-3.2	3.83	2.92	-2.3	-0.53
FBNC	4.39	2.77	5.37	9.95	0.1	-0.24	-0.09	-2.87	-0.71	5.26	0.04	3.85	4.3	-10.88	-0.04	2.01	6.28	-7.92	0.39
FELE	10.66	1.12	-3.06	3.92	0.78	-4.94	1.02	-0.34	2.69	9.32	2.11	1.64	2.54	-14.16	4.23	0.98	-0.11	6.02	2.43
FFIN	8.36	8.5	3.99	2.45	3.17	2.55	4.86	3.64	4.66	1.11	-6.41	-6.1	9.28	-24.7	-6.71	15.61	5.48	-7.92	6.97
FISI	-2.98	2.98	-1.45	-5.77	0.36	-1.95	2.2	3.02	-5.86	-1.17	-2.95	-1.68	2	-12.48	-2.68	2.94	4.36	-6.21	0.46
FIX	13.55	3.59	5.28	2.07	3.44	-2.19	-3.48	0.34	4.06	0.16	-2.79	-3.48	-0.49	1.03	-8.61	1.87	1.01	-0.95	1.79
FLO	4.23	4.62	4.23	2.33	-0.64	3.12	-1.09	8.3	-3.86	-2.21	-10.69	5.29	5.78	-15.4	9.61	-0.8	8.37	-6.7	2.85
GCO	16.47	0.79	2.87	3.92	3.34	1.7	-1.53	-2.27	1.29	1.26	2.71	-3.25	2.95	-16.86	4.87	2.69	6.29	-6.69	1.94
GD	8.58	-1.07	-6.07	-7.39	0.79	-1.6	-0.2	0.9	11.13	2.43	-4.55	-4.97	-3.01	-6.67	-0.66	0.57	-1.3	0.94	-1.54
GE	-7.2	5.74	-8.67	-1.04	4.26	-9.84	1.74	-1.85	-1.33	1.61	-2.83	-2.79	-3.04	5.95	-3.16	-3.01	-1.37	-3.51	-2.89
GSAT	7.14	-8.73	-6.48	1.85	-7.34	-4.3	1.99	-6.2	2.28	2.06	4.69	9.25	0.36	-2.3	4.92	-0.19	0.96	-5.05	-3.98
GTE	14.62	-1.53	-4.43	-1.92	-1.33	3.53	4.76	1.8	0	9.53	-6.64	9.94	-3.54	-13.93	-1.01	-2.54	-3.06	1.54	-4.86

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Ticker	MST	MS	MT1	MT2	MT3	MT4	MT5	MT6	MT7	MT8	TA1	TA2	TA3	TA4	TA5	TA6	TA7	DCC	B&H
GTLS	2.93	1.22	-9.38	1.56	-1.67	0.62	0.03	8.64	4.21	7.52	0.92	0.04	-2.58	3.63	-0.09	-1.19	-0.56	16.73	1.02
GTN	3.14	1.83	-11.8	0.53	0.35	-6.92	1.82	3.04	4.96	8.06	1.14	-0.24	0.14	3.39	-1.19	2.04	-0.13	6.79	2.45
HA	7.03	-3.78	5.31	-0.57	-5.02	0.8	1.05	8.48	-0.84	-0.46	-0.81	-1.28	2.65	-6.19	5.43	2.73	0.62	-5.38	-2.46
HELE	14.09	2.16	6.81	5.46	1.94	4.97	5.66	9.39	3.38	-0.03	3.51	1.56	1.97	-12.07	6.96	6.66	3.45	1.16	2.99
HIW	5.57	2.77	-3.92	-1.34	1.23	0.45	-0.33	3.76	2.77	2.04	0.73	-0.99	-1.77	2.12	4.94	-2.34	1.23	-6.04	-0.05
HLX	8.54	3.86	4.29	3.27	-2.91	2.36	2.77	0.75	5.3	4.69	-2.49	0.74	2.64	-1.37	-0.45	2.7	1.68	-0.88	1.52
HMY	3.72	1.51	-7.51	2.4	2.8	4.34	5.15	4.02	0.67	-0.16	2.02	4.28	2.65	3.38	-0.68	5.64	-2.88	5.14	3.86
HOPE	3.59	0.02	-0.7	-2.35	-1.92	-2.29	-0.95	-7.31	0.73	0.72	0.32	3.72	2.2	-2.32	-1.33	2.43	-0.49	-9.01	-2.23
HRI	9.7	3.73	-0.53	1.13	3.04	1.05	-5.16	-6.66	-1.19	-0.88	1.7	3.89	0.93	0.62	-1.73	1.81	-0.56	-8.91	-1.24
HWC	-2.18	2.28	-4.89	-1.12	-1.25	-0.14	-3.2	-8.82	1.26	2.07	0.1	1.93	0.72	1.03	0.33	-0.07	-0.57	-2.46	-2.23
IART	10.72	-0.07	1.15	-1.71	1.32	3.44	3.68	-2.31	3.79	1.86	1.31	4.53	1.81	-3.1	0.99	0.84	1.92	-2.89	2.34
IDT	8.86	2.14	-1.81	1.73	-2.23	-4.19	-7.27	-2.14	4.72	4.22	0.64	0.36	0.07	4.87	-2.21	-1.43	0.35	1.38	-2.56
IMAX	-4.33	-4	-1.35	-0.14	-3.96	-11.59	-6.3	-5.2	2.35	-2.24	-0.99	1.37	0.07	1.58	1.6	0.43	0.2	-7.08	-1.87
IMGN	-6.51	3.18	-3.59	-2.49	-3.11	0.28	1.76	-0.9	1.91	-3.96	-3.37	10.99	2.37	2.52	7.42	-2.49	3.15	-7.23	-3.78
INSM	7.11	-2.47	6.3	-6.85	0	-4.95	-2.03	0.87	-0.48	9.09	-0.04	0.42	-0.32	6.83	-1.87	2.8	-1.05	8.77	-1.34
IOSP	3.38	4.59	4.05	1.71	-1.06	3.61	4.95	7.63	2.17	9.47	-1.63	-2.75	1.85	-14.38	-3.53	4.59	-0.92	-5.05	4.51
IP	-0.87	-2.16	-6.9	-2.43	-0.49	-1.05	-5.1	0.57	3.12	6.97	-5.35	6.08	3.9	2.88	1.86	0.17	0.66	-3.32	-2.01
IPAR	9.66	5.37	8.88	5.42	3.39	2.8	3.11	2.74	0.86	-0.93	2.62	-6.31	-5.19	1.89	-3.07	3.58	-6.48	7.38	7.61
IRBT	-8.32	0.1	1.33	-2.71	0.82	-0.79	-1.85	-6.04	-0.86	1.66	-0.75	0.68	-3.48	-1.93	-1.91	0.43	-4.49	4.52	-2.04
IT	3.59	-0.31	-2.67	8.88	-1.3	0.48	-2.05	8.14	11.39	1.76	-1.1	-4.69	-0.41	3	-12.77	-0.15	-2.49	-2.21	3.75
ITGR	4.01	4.11	4.57	0.21	6.83	8.33	1.22	2.98	0.79	7.16	-0.11	2.01	6.69	-9.62	3.02	9.37	8.3	4.2	4.96
ITT	12.15	0.37	-9.52	-5.65	2.54	3.91	3.76	1.26	6.61	2.2	-10.63	5.95	1.28	-10.71	-4.75	0.96	4.14	1.86	3.39
JKHY	13.19	-3.05	-13.03	-7.2	-0.64	4.83	-2.92	7.13	3.45	2.67	2	1.78	0.5	-4.66	2.94	3.29	1.42	4.44	4.89
KAI	5.87	1.21	1.62	-3.01	-2.75	0.45	6.1	4.5	2.66	-0.54	-1.96	1.27	2.36	-0.91	-2.11	4.19	1.64	-10.86	-0.9
KBR	4.61	1.45	-5.32	-2.97	0.71	5.65	2.74	6.46	10.32	-1.52	1.49	3.63	4.35	2.22	-7.87	0.3	2.84	-7.55	6.11
KFRC	4.87	3.96	3	4.91	3.11	-0.5	2.73	4.08	4.1	12.33	-0.72	-6.14	1.26	-3.83	-0.81	2.32	0.25	7.44	5.98
KLIC	5.77	0.01	-5.77	3.4	0.94	-0.11	-4.29	-2.1	5.08	4.86	-8.86	0.04	1.52	-6.84	-3.88	3.59	0.06	-5.43	0.06
LANC	18.2	3.58	1.16	3.65	-0.53	4.79	-0.58	1.86	1.1	1.8	-0.91	1.09	2.47	-8.41	0.83	-0.16	2.65	6.53	3.19
LBAI	-4.97	-0.15	-5.43	-2.75	-2.77	-7.38	-3.33	3.3	1.68	5.82	1.51	1.52	2.6	-1.31	2.06	-0.68	0.04	-1.65	-2.92
LMAT	7.98	3.36	2.58	-3.06	-0.85	0.5	-0.46	3.75	7.25	1.16	2.52	8.03	5.32	0.09	1.72	5.64	4.65	-5.12	0.76
LOW	19.16	2.71	-0.33	2.65	1.57	6.13	-2.53	9.37	9.81	7.14	0.19	-0.92	0.69	-1.26	-1.88	0.81	-0.67	-2.03	4.93
LRN	6.95	2.75	2.87	0.33	1.49	-0.15	-1.68	-1.99	0.85	6.24	0.81	1.54	2.99	3.11	1.95	0.93	2.47	-3.24	1.33
LSI	1.66	1.16	-2.34	2.01	-9.5	0.77	1.01	3.8	-0.05	2.29	-2.74	2.6	-0.71	-11.83	2.22	11.87	2.31	0	-6.13
LYG	4.58	1.34	-6.31	-4.39	2.14	2.18	-0.26	-5.53	3.5	2.91	1.94	0.17	0.21	5.51	-0.45	-4.67	0.68	-4.36	-0.94
MCY	1.44	1.97	-11.33	5.27	1.09	-2.83	-0.47	-0.54	7.39	-3.53	-4.47	-1.81	-4.52	3.59	-4.24	1.44	-4.5	0.24	-0.68
MDC	1.23	3.36	-4.06	-3.18	1.74	1.96	4.49	-0.89	0.48	0.48	0.16	6.28	3.62	-3.06	-0.45	5.29	-0.59	-4.83	-2.69
MGM	9.07	4.02	-1.48	3.24	0.33	-1.27	1.95	3.51	2.15	-0.7	-15.78	11.21	10.4	-9.98	8.27	1.87	6.81	6	-0.74
MGRC	5.6	5.15	6.8	6.05	2.48	3.15	2.45	6.33	0.71	3.23	-2.73	-6.41	4.44	-6.69	-4.48	0.38	0.12	-8.98	8.2
MIDD	-6.39	0.64	1.16	-0.26	-0.34	-3.62	-0.42	-1.32	2.07	0.57	-0.47	2.03	-3.27	-3.23	-1.82	4.33	-0.11	-3.77	-1.14
MRO	-5.24	0.91	-1.67	-3.59	-1.98	-0.23	-0.72	3.29	-2.77	7.09	-1.07	2.66	-0.01	-8.4	2.94	-0.21	-2.28	-5.25	-1.85
MSA	5.97	2.84	-2.03	3.9	2.41	3.13	0.54	2.45	-1.43	1.51	-9.3	-10.56	2.95	-21.11	-9.41	6.92	2.87	-8.63	8.24
MT	-7.92	-0.28	-8.34	-4.85	-3.04	-4.13	-6.99	-4.56	8.43	3.58	-5.66	-2.38	-3.19	4.93	-2.93	-7.2	-2.33	-4.28	-3.56
MTZ	6.7	3.75	1.93	4.76	1.97	4.47	2.99	1.97	0.45	7.91	-0.49	0.68	1.07	-9.17	3.44	2.67	8.54	-1.33	5.57
MYGN	8.93	1.55	1.42	1.86	1.65	1.55	-0.48	-0.76	2.95	1.97	-4.69	7.16	4.17	-6.6	3.76	3.52	4.58	4.83	-1.88
NBIX	5.9	1.81	0.22	0.55	2.28	4.76	-2.86	4.83	3.07	4.13	1.92	1.93	0.68	0.72	3.37	0.52	2.77	1.41	4.37
NEOG	13.1	3.63	-6.12	3.98	1.08	-0.02	5.44	1.23	4.48	0.59	-0.7	3.25	0.41	0.86	-1.8	-0.58	-0.42	4.83	0.4
NFLX	2.57	4.41	-18.45	4.39	0.66	5.86	1.84	6.61	3.41	4.96	1.02	-0.48	0.52	2.33	0.67	-1.16	0.14	8.64	4.86
NG	1.88	4.21	4.43	-5.55	1.67	4.44	1.27	4.52	2.48	-1.47	2.73	-0.73	3.58	-9.27	1.22	1.28	3.95	7.66	5.51
NGD	7.21	-0.3	-9.76	-9.52	-3.35	-7.15	-7.3	-5.06	2.47	10.97	2.46	4.8	4.38	-4.07	7.78	-1.61	8.46	-13.82	-3.42
NGG	1.42	2.07	-0.81	-2.58	-0.83	-2.06	1.75	3.46	0.09	-0.26	-0.72	4.78	2.04	-0.3	-0.43	3.15	5.97	9.51	0.77
NICE	15.95	1.32	4.29	15.73	3.05	4.82	3.75	-2.79	0.25	5.31	2.94	-4.77	12.67	11.66	-8.17	4.04	8.86	1.64	1.81
NNI	5.87	2.18	-4.21	-7.13	2.55	2.69	-3.45	3.86	-4.21	12.11	3.86	3.16	3.97	-11.21	3.42	2.81	2.12	-6.04	3.03
NNN	13.17	3.27	0.69	-7.13	0	-5.12	2.48	5.62	2.88	1.16	-7.65	-7.86	2.89	2.37	-2.42	6.09	-4.39	7.13	8.71
NOG	6.81	1.29	0.03	0.87	-1.31	6.83	5.31	3.29	0.51	1.46	-0.05	-3.2	0.42	2.07	4.42	1.57	2.94	0.95	0.21
NRG	11.15	5.74	5.66	0.56	2.26	1.51	1.99	2.04	1.18	4.92	3.68	-2.54	1.86	4.78	-6.29	1.75	0.32	0.16	5.17
NVMI	-1.38	1.8	0.16	4.36	3.29	4.46	-0.06	4.89	1.88	-4.26	-3.55	0.49	6.29	-21.68	-0.93	3.5	4.82	-7.88	3.14
NVS	1.44	2.5	-7.32	4.33	2.95	-0.48	-1.42	-1.98	6.84	-0.17	3.33	9.23	7.66	-6.09	2.82	4.36	4.56	5.88	5.13
NWBI	0.31	1.19	-4.74	-1.87	-3.29	0.02	4.71	2.11	3.15	-0.26	-2.14	-4.33	3.65	-2.3	-5.7	6.26	3.88	-5.25	0.83
OGE	7.69	2.06	-4.87	2.8	1.29	1.89	-6.5	7.43	-1.26	2.69	-11.59	3.49	0.03	-2.31	-0.13	-1.37	3.81	4.7	6.15
OMCL	5.42	1.55	1.16	1.79	2.75	2.63	-0.11	1.84	-1.65	6.95	-1.58	4.9	8.61	-11.96	1.73	2.8	7.57	14.93	4.71
PAYX	4.56	1.85	-2.97	4.33	-2.79	1.24	0.02	7.96	7.97	-3.48	-2.61	7.18	5.96	-5.42	5.01	1.7	1.21	4.91	6.26
PB	6.8	0.8	-2.45	3.52	1.44	2.59	0.56	8.92	8.8	0.95	-8.72	-0.8	1.72	1.03	-2.02	5.62	0.62	-0.98	0.19
PCH	-1.19	-2.36	-0.8	-6.82	-1.14	-2.09	-4.17	5.28	1.87	-2.13	-1.17	-5.89	-2.47	-3.08	-0.58	0.06	-1.79	-11.58	-0.6
PDCE	2.89	1.68	3.89	3.38	-1.04	-2.57	-3.15	-5.26	3.75	-1.31	-5.25	-3.37	-3.74	-1.01	-5.1	-4.72	-6.3	0	-3.08
PDFS	4.83	1.3	-5.77	2.53	1.64	-7.73	2.96	-2.94	7.31	0.93	0.9	2.94	1.74	1.46	2.35	-2.16	-0.18	-19.99	-1.26
PDS	11.13	-2.06	-2.7	-2.96	-4.06	-2.89	-5.16	0.43	5.88	9.13	-2.43	-0.23	-3.56	0.23	-7.92	-0.21	-3.91	-1.59	-4.09
PERI	10.16	2.27	4.26	3.33	1.61	3.31	4.93	-2.21	6.27	-3.22	2.64	-3.33	-3.86	5.77	-6.7	2.64	-3.49	2.15	2.37
PHG	7.1	9.53	-14.68	-0.96	2.02	7.09	0.06	-4.3	8.77	0.27	-3.53	2.82	1.89	-6.24	2.47	0.87	3.65	-0.7	3.26
PNM	0.95	1.22	-1.4	2.1	-2.41	1.08	1.38	4.51	3.95	-3.51	-1.66	0.88	5.24	-1.79	8.37	-2.94	5.41	-0.3	1.48

Continued on next page

Ticker	MST	MS	MT1	MT2	MT3	MT4	MT5	MT6	MT7	MT8	TA1	TA2	TA3	TA4	TA5	TA6	TA7	DCC	B&H
POR	9.99	-3.68	0.46	1.73	2.55	2.54	1.04	-0.17	3.94	7.05	-1.7	4.28	4.27	5.61	17.56	2.78	2.88	1.26	4.01
PRGS	5.3	0.18	6.66	3.6	-1.21	0.37	-2.05	2.78	4.88	3.22	-3.1	4.55	4.25	-2.27	-2.6	1.03	3.35	-6.63	0.09
QCOM	6.12	2.93	4.84	3.8	2.66	-3.93	3.74	-5.04	10.12	-0.77	0.88	0.47	0.74	8.84	-6.86	-1.57	-4.6	5.22	2.31
RAMP	10.09	0.9	4.14	-0.14	6.08	4.98	6.34	6.56	3.51	-1.61	-4.95	3.88	2.68	0.9	-3.66	3.08	3.97	3.54	5.78
RGR	3.07	2.1	0.37	-7.15	-0.8	-2.25	-5.66	4.03	-0.27	0.17	-2.6	2.99	0.47	0.21	-1.86	0.92	0.34	1.04	-1.53
RHI	6.65	2.99	3	2.57	1.33	3.22	-0.41	-0.96	1.93	2.02	-11.07	-1.45	0.09	1.63	-3.02	0.15	-2.55	5.24	0.5
RJF	3.14	0.48	2.78	3.38	-0.91	-0.64	2.24	5.76	3.9	8.47	-7.99	-1.18	0.27	0.38	-4	2.35	0.14	1.28	0.19
RL	11.37	0.69	-2.79	2.46	-3.13	3.48	-0.78	2.14	3.16	-1.02	1.3	-2.68	-1.1	0.06	-4.14	0.28	-2.12	-2.9	1.55
ROG	9	-1.14	-8.49	2.9	-7.11	-5.23	-9.87	0.94	6.33	7.72	0.88	7.31	3.42	3.83	3.36	-0.34	2.09	-0.14	-1.56
ROIC	5.14	0.64	1.71	-3.76	1.04	-0.24	-0.87	-1.34	4.77	0.3	0.72	-1.08	1.01	-4.29	0.8	-0.86	-0.88	-1.16	-0.56
RPM	9.69	3.49	-7.92	5.23	1.17	4.85	-0.23	3.62	22.73	5.92	0.12	-5.62	2.29	-3.6	-4.24	3.24	-0.43	-1.58	6.1
RPT	2.93	1.32	0.03	3.15	2.78	2.46	1.34	-5.31	-7.04	6.53	-1.31	-6.4	0.89	-1.19	-10.8	2.44	1.3	4.22	-0.18
RTX	1.98	1.6	4.83	4.29	-6.3	-5.24	-1.24	6.61	9.5	-2.72	-1.89	-4.94	-0.36	0.65	-7.18	1.77	-0.79	-6.61	3.61
RUSHA	6.55	0.62	-4.78	-6.82	-1.39	-4.63	-4.62	2.31	5.87	0.82	-5	3.88	1.06	-0.4	0.46	-0.07	-0.12	-4.83	-0.9
RY	5.97	0.82	-8.17	-4.99	-1.07	1	0.2	1.21	3.6	3.83	0.06	1.68	2.74	2.64	-2.81	0.54	0.73	-0.88	1.67
SAH	9.76	2	5.83	3.87	3.12	-4.31	1.68	3.68	1.25	5.74	1.06	-0.54	0.62	-1.75	0.41	2.67	2.75	6.47	4.11
SAIA	3.91	-0.07	5.99	-3.82	2.83	-1.91	1.28	3.32	0.64	-3.07	0.17	-1.4	-1.38	3.46	-4.15	1.23	-0.78	-3.91	4.3
SASR	-6.05	0.53	-1.79	-5.37	0.73	1.41	1.29	0.44	2.61	-0.13	-6.86	0.24	-1.13	-9.61	-1.21	3.25	-0.79	-1.31	-1.1
SBH	3.27	4.15	1.6	6.78	3.35	0.09	-3.99	2.55	6.19	-1.48	-6.69	1.33	3.81	-7.87	7.42	0.07	2.18	9.2	0.55
SBRA	4.13	1.96	3.27	2.05	0.5	-0.02	1.25	-4.47	5.35	-1.44	0.4	-5.84	-1.43	5.44	-2.67	5.42	-3.78	-0.08	3.68
SBS	11	-0.39	9.64	2.82	0.04	-4.8	1.68	7.2	4.89	1.24	1.99	-6	-2.8	3.11	-4.62	0.66	-0.66	5.14	2.03
SCI	-0.96	2.55	0.47	-1.76	2	-3.25	-4.56	3.62	1.97	-2.41	-1.62	-0.86	3.04	-7.41	2.66	3.52	4.43	4.63	3.48
SCVL	8.39	-2.21	4.55	5.32	2.02	1.26	3.28	3.72	4.42	-0.15	-5.8	-4.32	-3.13	-5.58	-5.78	-2.14	-0.29	5.86	2.53
SEIC	-1.53	-4.07	-6.06	3.64	-0.14	0.69	-4.08	-2.91	-2.6	3.98	-7.18	-7.12	-5.14	0.03	-6.24	-0.51	-5.34	-3.14	-1.42
SIEGY	2.93	3.59	0.68	5.43	0.98	-2.53	-2.9	-2.3	4.19	4.23	-4.09	5.26	1.79	1.7	0.49	0.11	2.34	-8.73	-0.19
SITC	6.4	1.39	0.59	1.31	-5	3.43	0.42	-0.59	0.16	4.11	0.09	0.07	1.61	-5.83	-0.88	4.9	1.76	0.22	3.65
SKYW	3.66	2.24	2.98	2.12	4.45	-2.23	4.18	4.33	5	1.03	-0.56	4.52	7.96	-6.72	-2.09	2.26	4.57	-3.18	2.67
SNX	-2.78	5.65	0.53	4.67	-7.34	2.15	1.58	-6.65	6.35	2.28	0.51	-6.38	-3.84	5	-2.83	2.46	-3.45	5.12	-0.85
SO	4.21	2.08	-2.17	-4.42	2.32	-7.66	1.89	-1.94	-4.88	-0.95	-8.79	3	2.65	-10.93	23.44	0.33	-0.27	4.83	6.49
SRPT	5.43	5.35	-2.38	-1.29	2.61	4.11	5.95	6.14	-2.74	-0.56	1.13	0.45	1.64	-0.85	-0.4	-1.09	-0.13	4.43	4.7
STC	2.79	1.27	-3.9	0.05	-5.41	-0.51	0.98	-2.33	1.26	5.68	-3.8	-5.66	-0.64	-3.64	-1.12	0.09	-2.98	2.89	1.84
STLD	-0.7	2.24	-4.51	3.05	-3.89	-0.21	-0.4	1.2	5.18	5.59	-0.36	-2.38	-3.32	3.72	-5.95	-0.71	-3.88	0.89	-1.04
STM	5.74	1.2	-1.6	0.43	2.16	-9.1	0.83	3.73	0.55	2.53	-3.72	5.61	3.5	3.03	3.94	2.96	6.47	0.56	0.87
STT	6.66	4.91	-1.63	1.63	-3.95	-0.81	-5.55	-3.17	3.31	6.37	-8.08	1.67	2.09	4.89	-0.64	-1.16	2.25	-3.97	-2.22
STX	16.55	3.72	-1.71	1.12	-5.6	0.33	2.56	4.24	4.47	4.16	1.69	2.79	4.74	-11.85	2.91	2.61	5.04	6.05	6.53
SYNA	4.88	-0.34	1.26	-0.99	2.49	3.13	3.37	-4.96	-3.91	0.55	-6.14	5.88	3.57	-6.78	-2.34	4.73	4.04	10.54	3.81
TDC	-3.1	3.62	-6.78	-0.42	-3.13	3.95	2.43	-0.7	4.36	3.41	-9.27	5.99	4.68	-3.6	-3.11	0.02	4.57	2.67	-3.62
TEX	10.79	-5.48	-3.45	-6.53	-2.29	-6.89	-7.78	-3.97	4.44	1.19	-8.28	5.87	-3.09	3.97	1.92	0.79	-4.27	-1.77	-3.95
THG	1.1	3.23	-1.21	4.45	4.23	3.31	3.57	-1.85	-1.64	9.08	2.72	11.4	14.02	-12.84	13.36	2.55	9.59	8.59	8.28
TITN	1.56	0.72	-1.46	0.34	-1.34	-3.12	1.91	-3.01	-0.12	-2.46	-0.66	0.6	1.31	-2.62	0.37	3.8	2.26	4.84	-1.33
TLK	4.02	0.83	1.8	-0.82	-2.42	0.06	-0.43	1.72	7.15	-0.85	-6.6	5.87	6.3	-14.36	-3.11	-2.1	5.77	1.25	-1.06
TREE	0.78	2.14	-16.59	2.44	-0.48	0.87	8.23	0.61	10.06	2.67	0.37	4.38	3.66	-1.3	3.98	3.79	2.65	3.06	1.3
TREX	15.52	-6.52	4.03	2.42	-3.86	1.66	6.55	4.96	0.87	-1.37	2.88	-1.61	4.53	-9.18	-0.63	0.8	9	3.03	3.84
TRMK	-0.38	4.03	4.07	-0.21	-0.97	-3.79	-4.1	2.78	4.86	9.85	-1.64	-0.06	3.64	-2.28	-3.09	3.66	4.2	-2.67	0.57
TSM	2.45	2.32	-4.1	-3.35	2.24	-2.07	0.62	3.77	12.31	4.21	0.99	-3.75	0.61	-7.57	-4.44	2.42	1.57	-0.89	5.73
TTC	5.6	-5.23	-4.58	2.36	1.39	-4.89	3.63	-7.74	6.15	1.29	-1.06	-2.19	2.47	-6.18	-4.88	1.24	4.59	-4.77	3.29
TU	11.31	6.67	-5.52	0.08	0.22	-4.97	-0.03	-5.7	-1.2	2.39	-3	3.82	3.96	-11.87	-6.89	2.43	3.71	4.53	2.04
TXN	8.62	3	-2.44	7.06	-1.37	2.52	1.78	2.09	4.38	1.99	-23.85	4.41	6.88	-5.78	0.55	3.91	5.41	4.87	3.81
TXRH	6.2	8.75	-4.86	0.4	1.89	4.91	5.16	2.33	8.01	-1.36	-5.8	2.83	4.9	-5.18	1.58	3.49	5.25	4.97	1.99
UBSI	10.63	0.64	0.22	0.42	3.23	2.1	-1.4	4.96	0.75	6.18	0.2	0.55	4.03	0.16	-5.28	5.67	2.63	-3.62	0.84
UGP	0.02	0.92	-7.87	-2.92	-9.1	-11.91	-1.85	-5.82	-0.49	8.38	-1.66	-6.52	-3.94	5.21	-1.69	0	-2.85	-13.78	-4.13
UHS	7.06	7.56	-0.24	5.26	2.07	0.98	-1.28	4.54	3.75	-2.55	-9.93	9.56	6.47	-2.34	1.72	5.12	2.71	-2.11	3.42
UHT	5.63	3.24	2.31	-1.81	-11.78	4.7	2.09	1.69	6.09	2.94	-4.01	-8.79	2.2	-5.88	-4.55	-0.34	3.85	-4.02	7.93
UNF	5.5	-0.51	-4.12	4.27	2.68	1.86	-1.08	5.4	-1.71	-1.95	0.54	-5.7	0.6	-2.74	-3.13	2.28	2.76	-4.78	3.84
WEC	5.3	1.3	1.12	3.14	2.71	4.51	-3.8	2.98	1.52	7.1	-5.9	-2.85	5.14	7.48	14.88	-0	8.05	1.18	7.63
WELL	4.32	4.19	3.79	3.39	-0.86	2.83	1.79	4.61	5.28	2.53	-0.07	-8.27	1.74	10.29	6.95	2.45	-0.52	6.58	5.55
WEN	9.35	2.23	-2.37	4.34	3.19	3.83	2.32	7.78	4.56	7.5	-4.32	-3.98	7.14	-18.64	3.99	6.52	6.49	1.63	6.3
WIRE	1.86	5.05	-0.86	1.96	3.91	-2.47	-0.12	5.8	3.07	-2.17	-2.88	0.36	4.11	-11.11	0.87	3.98	4.96	-4.65	2.75
WLK	-1.27	-2.77	-13.43	0.59	-4.9	-6.99	-3.31	1.48	2.46	3.06	-1.88	1.35	-0.53	4.97	1.67	-1.61	-1.37	-6.56	-3.08
WMK	17.78	-2.68	-1.73	-3.05	-2.09	-3.91	-2.28	0.08	2.77	4.92	-1.75	-1.2	-3.78	2.34	-2.21	-1.89	-1.78	-6.37	-0.48
WMT	7.37	-0.89	-7.54	3.44	2.05	1.64	0	1.05	2.82	2.9	0.45	-6.11	-5.4	-0.62	-10.32	0.63	-6.33	3.53	4.68
WOR	8.54	-1.43	-5.16	1.77	-2.53	6.03	-6.83	-0.45	6.27	2.16	-3.18	0.2	-3.11	-3.79	0.36	4.11	6.33	-5.22	-0.75
WPC	5.28	1.56	-5.6	1.35	2.24	1.85	0.82	3.39	2.59	0.21	-5.13	-3.63	-3.18	2.67	-4.63	2.59	-2.83	4.66	6.11
WSM	14.85	6.55	6.21	8.17	7.58	5.8	9.99	1.91	0.37	2.02	1.23	1.84	9.04	-12.59	0.93	5.86	9.39	1	5.79
WTI	7.85	3.58	-1.54	2.73	2.03	7.52	0	0.42	6.69	3.61	1.05	0.4	1.02	2.09	-5.46	1.63	3.67	6.9	1.56
WW	-5.01	3.47	-5.31	-1.61	6.03	-3.18	-1.5	5.11	9.53	3.25	3.59	1.45	2.42	3.21	4.71	-0.98	-1.71	1.01	-0.22
XPO	4.71	-1.15	-5.56	0.65	1.16	-4.68	0	2.18	0.97	-1.42	0.71	-4.68	-2.12	3.45	-4.97	0.11	-1.95	-1.83	0.25

Table B.3: Standard Deviation results for MSTGAM (MST) versus MSGAM (MS), MTGAMs (MT1, $\cdots$, MT8), TA-based strategies (TA1, $\cdots$, TA7, represent the TA-strategies in the following order: ADX, Ar, CCI, EMA, MACD, RSI, and Wr), and confirmation point strategy (DCC), BandH (B&H) for each stock.

Ticker	MST	MS	MT1	MT2	MT3	MT4	MT5	MT6	MT7	MT8	TA1	TA2	TA3	TA4	TA5	TA6	TA7	DCC	B&H
AAON	0.027	0.124	0.05	0.064	0.115	0.031	0.075	0.06	0.022	0.012	0.097	0.081	0.047	0.042	0.063	0.066	0.048	0.043	0.082
AAPL	0.029	0.083	0.042	0.064	0.021	0.023	0.123	0.054	0.019	0.017	0.149	0.089	0.11	0.074	0.061	0.103	0.081	0.116	0.089
ACM	0.029	0.042	0.034	0.099	0.038	0.019	0.07	0.075	0.025	0.016	0.093	0.032	0.035	0.035	0.046	0.081	0.033	0.029	0.085
AG	0.101	0.311	0.151	0.071	0.085	0.062	0.169	0.162	0.029	0.02	0.057	0.104	0.098	0.066	0.085	0.084	0.09	0.174	0.13
AGEN	0.075	0.17	0.186	0.166	0.062	0.083	0.183	0.157	0.048	0.047	0.164	0.183	0.26	0.4	0.156	0.3	0.242	0.078	0.257
ANDE	0.038	0.036	0.057	0.092	0.092	0.091	0.056	0	0.013	0.017	0.123	0.086	0.094	0.051	0.088	0.141	0.121	0.03	0.107
ASGN	0.031	0.071	0.054	0.096	0.044	0.068	0.087	0.077	0.022	0.037	0.033	0.053	0.074	0.055	0.054	0.126	0.084	0.037	0.107
AWI	0.026	0.088	0.063	0.047	0.079	0.04	0.05	0.044	0.02	0.015	0.192	0.028	0.037	0.028	0.064	0.034	0.035	0.029	0.069
BANR	0.027	0.032	0.031	0.049	0.031	0.062	0.051	0.026	0.015	0.019	0.075	0.032	0.049	0.028	0.046	0.077	0.039	0.026	0.064
BCPC	0.036	0.062	0.068	0.072	0.024	0.045	0.077	0.054	0.017	0.032	0.112	0.065	0.082	0.047	0.053	0.11	0.097	0.056	0.082
BG	0.022	0.039	0.036	0.044	0.054	0.028	0.055	0.04	0.025	0.016	0.058	0.041	0.026	0.032	0.034	0.053	0.04	0.022	0.06
BHLB	0.028	0.04	0.053	0.081	0.072	0.02	0.041	0.056	0.031	0.017	0.212	0.035	0.062	0.042	0.043	0.136	0.062	0.037	0.084
BHP	0.024	0.045	0.041	0.041	0.039	0.059	0.078	0.053	0.029	0.029	0.041	0.037	0.044	0.029	0.047	0.095	0.048	0.03	0.065
BKR	0.034	0.11	0.056	0.099	0.085	0.081	0.091	0.089	0.032	0.037	0.113	0.098	0.113	0.097	0.083	0.13	0.11	0.036	0.117
BMI	0.025	0.08	0.051	0.039	0.072	0.093	0.058	0.052	0.02	0.007	0.083	0.042	0.056	0.037	0.053	0.079	0.061	0.024	0.078
BMY	0.026	0.125	0.041	0.099	0.044	0.049	0.078	0.068	0.025	0.018	0.069	0.06	0.059	0.053	0.051	0.109	0.069	0.042	0.073
BSAC	0.03	0.085	0.055	0.085	0.049	0.066	0.056	0.068	0.012	0.03	0.037	0.041	0.054	0.023	0.034	0.074	0.056	0.063	0.063
BSBR	0.032	0.087	0.059	0.136	0.039	0.122	0.104	0.072	0.017	0.022	0.088	0.074	0.114	0.076	0.093	0.134	0.098	0.036	0.132
BSX	0.025	0.058	0.05	0.055	0.076	0.036	0.045	0.048	0.016	0.013	0.053	0.036	0.04	0.018	0.031	0.048	0.044	0.029	0.056
BX	0.032	0.072	0.061	0.043	0.049	0.071	0.053	0.033	0.048	0.009	0.111	0.072	0.045	0.029	0.051	0.059	0.034	0.026	0.079
BYD	0.038	0.047	0.063	0.097	0.075	0.145	0.079	0.061	0.044	0.018	0.149	0.091	0.1	0.055	0.084	0.144	0.093	0.056	0.124
CBZ	0.024	0.076	0.077	0.089	0.074	0.038	0.056	0.077	0.013	0.027	0.032	0.056	0.053	0.018	0.064	0.065	0.045	0.029	0.072
CCEP	0.022	0.025	0.03	0.044	0.047	0.134	0.033	0.039	0.096	0.002	0.047	0.045	0.055	0.039	0.041	0.071	0.055	0.033	0.047
CCI	0.024	0.025	0.031	0.06	0.068	0.076	0.072	0.031	0.011	0.004	0.039	0.036	0.033	0.037	0.026	0.032	0.049	0.035	0.042
CCL	0.027	0.088	0.036	0.054	0.085	0.074	0.096	0.061	0.014	0.016	0.073	0.064	0.047	0.033	0.048	0.052	0.041	0.02	0.079
CHH	0.02	0.055	0.037	0.033	0.067	0.076	0.049	0.027	0.018	0.003	0.044	0.022	0.028	0.02	0.031	0.046	0.031	0.021	0.053
CMP	0.041	0.093	0.072	0.054	0.035	0.023	0.041	0.046	0.025	0.016	0.132	0.058	0.06	0.064	0.102	0.136	0.056	0.028	0.109
CNK	0.027	0.057	0.038	0.069	0.051	0.034	0.047	0.037	0.022	0.008	0.1	0.065	0.052	0.035	0.037	0.066	0.05	0.035	0.082
CNXN	0.042	0.091	0.071	0.083	0.239	0.215	0.067	0.089	0.055	0.072	0.075	0.062	0.076	0.047	0.096	0.155	0.081	0.046	0.105
COST	0.023	0.144	0.031	0.079	0.096	0.082	0.05	0.104	0.022	0.007	0.072	0.062	0.059	0.018	0.037	0.044	0.091	0.07	0.048
CRK	0.082	0.163	0.179	0.245	0.233	0.121	0.181	0.104	0.183	0.438	0.179	0.156	0.121	0.106	0.148	0.213	0.129	0.101	0.251
CSV	0.048	0.083	0.079	0.109	0.186	0.19	0.064	0.07	0.088	0.016	0.039	0.06	0.101	0.051	0.08	0.194	0.08	0.028	0.099
CUBE	0.025	0.025	0.042	0.034	0.05	0.016	0.049	0.032	0.009	0.006	0.067	0.046	0.035	0.03	0.04	0.025	0.036	0.041	0.05
D	0.017	0.066	0.029	0.039	0.156	0.019	0.055	0.024	0.012	0.001	0.064	0.038	0.049	0.026	0.032	0.083	0.039	0.02	0.041
DCOM	0.034	0.076	0.051	0.049	0.073	0.066	0.071	0.04	0.04	0.022	0.068	0.051	0.054	0.041	0.073	0.094	0.051	0.037	0.083
DDS	0.051	0.077	0.074	0.085	0.041	0.068	0.085	0.056	0.063	0.098	0.079	0.084	0.102	0.058	0.105	0.12	0.095	0.054	0.118
DENN	0.029	0.07	0.039	0.041	0.076	0.089	0.041	0.065	0.019	0.008	0.094	0.033	0.04	0.038	0.052	0.101	0.058	0.029	0.077
DIOD	0.032	0.061	0.066	0.046	0.033	0.04	0.089	0.076	0.05	0.018	0.077	0.072	0.045	0.038	0.088	0.103	0.063	0.04	0.113
DIS	0.026	0.104	0.023	0.028	0.017	0.02	0.032	0.021	0.019	0.01	0.091	0.027	0.024	0.015	0.027	0.093	0.028	0.027	0.068
DRQ	0.049	0.083	0.079	0.102	0.06	0.084	0.103	0.075	0.034	0.023	0.133	0.067	0.13	0.048	0.082	0.185	0.089	0.053	0.122
EAT	0.033	0.076	0.057	0.089	0.046	0.035	0.068	0.06	0.018	0.022	0.052	0.066	0.049	0.042	0.053	0.072	0.054	0.039	0.091
EBR	0.055	0.244	0.088	0.12	0.337	0.278	0.131	0.088	0.048	0.026	0.427	0.12	0.163	0.143	0.129	0.121	0.137	0.07	0.227
EC	0.033	0.084	0.053	0.146	0.047	0.044	0.125	0.05	0.019	0.021	0.162	0.068	0.093	0.078	0.096	0.175	0.116	0.081	0.132
EFSC	0.031	0.116	0.078	0.085	0.02	0.018	0.04	0.047	0.064	0.007	0.036	0.059	0.07	0.05	0.056	0.129	0.077	0.043	0.079
EGHT	0.036	0.053	0.075	0.061	0.099	0.038	0.079	0.049	0.02	0.009	0.097	0.067	0.099	0.054	0.071	0.123	0.085	0.053	0.103
EGO	0.074	0.574	0.345	0.273	0.44	0.77	0.114	0.344	0.085	0.049	0.206	0.167	0.179	0.281	0.177	0.25	0.181	0.285	0.203
EMN	0.026	0.045	0.047	0.073	0.061	0.015	0.063	0.052	0.023	0.01	0.069	0.052	0.063	0.033	0.045	0.086	0.063	0.028	0.09
EQR	0.019	0.135	0.034	0.048	0.207	0.02	0.05	0.081	0.027	0.018	0.043	0.039	0.037	0.031	0.039	0.054	0.033	0.059	0.049
ERII	0.053	0.098	0.056	0.072	0.093	0.058	0.133	0.064	0	0.023	0.175	0.062	0.072	0.042	0.062	0.109	0.092	0.056	0.114
ERJ	0.032	0.044	0.047	0.059	0.109	0.083	0.085	0.032	0.04	0.019	0.096	0.042	0.065	0.029	0.071	0.157	0.054	0.052	0.085
ET	0.032	0.044	0.036	0.072	0.053	0.053	0.058	0.041	0.021	0.01	0.024	0.046	0.042	0.038	0.061	0.089	0.053	0.034	0.07
EVR	0.029	0.065	0.062	0.051	0.082	0.063	0.071	0.061	0.013	0.013	0.099	0.074	0.095	0.071	0.066	0.136	0.114	0.029	0.107
FARO	0.051	0.081	0.053	0.066	0.068	0.037	0.103	0.071	0.039	0.017	0.061	0.087	0.131	0.078	0.097	0.137	0.118	0.053	0.127
FBNC	0.025	0.028	0.052	0.031	0.117	0.046	0.049	0.048	0.04	0.016	0.138	0.035	0.032	0.021	0.039	0.055	0.033	0.03	0.073
FELE	0.034	0.088	0.052	0.069	0.051	0.029	0.057	0.066	0.064	0.02	0.022	0.045	0.041	0.029	0.072	0.073	0.045	0.028	0.075
FFIN	0.026	0.057	0.044	0.055	0.073	0.045	0.061	0.044	0.027	0.029	0.044	0.048	0.035	0.017	0.05	0.036	0.032	0.022	0.067
FISI	0.021	0.078	0.053	0.036	0.042	0.018	0.033	0.056	0.03	0.024	0.116	0.037	0.036	0.024	0.043	0.057	0.034	0.028	0.061
FIX	0.048	0.084	0.095	0.037	0.077	0.021	0.048	0.019	0.044	0.022	0.048	0.047	0.054	0.054	0.074	0.089	0.059	0.022	0.097
FLO	0.024	0.037	0.043	0.039	0.019	0.051	0.036	0.032	0.008	0.008	0.033	0.036	0.043	0.022	0.036	0.039	0.038	0.026	0.047
GCO	0.03	0.106	0.046	0.06	0.041	0.058	0.081	0.051	0.018	0.002	0.074	0.058	0.063	0.04	0.059	0.102	0.075	0.037	0.083
GD	0.021	0.069	0.028	0.044	0.063	0.039	0.046	0.046	0.012	0.005	0.038	0.029	0.039	0.027	0.041	0.055	0.04	0.047	0.075
GE	0.042	0.163	0.09	0.14	0.048	0.044	0.189	0.073	0.05	0.049	0.167	0.106	0.109	0.115	0.104	0.172	0.109	0.072	0.122
GSAT	0.169	0.111	0.123	0.308	0.144	0.12	0.154	0.108	0.076	0.04	0.206	0.148	0.175	0.161	0.172	0.493	0.139	0.101	0.199

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Ticker	MST	MS	MT1	MT2	MT3	MT4	MT5	MT6	MT7	MT8	TA1	TA2	TA3	TA4	TA5	TA6	TA7	DCC	B&H
GTE	0.038	0.338	0.155	0.178	0.27	0.061	0.069	0.089	0	0.029	0.107	0.047	0.133	0.044	0.097	0.274	0.137	0.049	0.119
GTLS	0.042	0.16	0.058	0.065	0.039	0.039	0.058	0.091	0.02	0.016	0.11	0.101	0.043	0.098	0.108	0.073	0.04	0.062	0.103
GTN	0.063	0.18	0.052	0.05	0.085	0.032	0.141	0.08	0.1	0.016	0.224	0.118	0.122	0.102	0.103	0.168	0.119	0.057	0.161
HA	0.052	0.109	0.048	0.076	0.056	0.071	0.09	0.054	0.029	0.015	0.092	0.049	0.058	0.045	0.061	0.057	0.068	0.049	0.119
HELE	0.026	0.106	0.051	0.085	0.067	0.121	0.083	0.059	0.015	0.011	0.153	0.05	0.066	0.042	0.065	0.05	0.064	0.029	0.088
HIW	0.029	0.071	0.046	0.062	0.061	0.036	0.073	0.033	0.034	0.005	0.067	0.048	0.063	0.034	0.031	0.068	0.051	0.03	0.065
HLX	0.064	0.128	0.1	0.137	0.08	0.091	0.061	0.062	0.039	0.015	0.083	0.096	0.074	0.067	0.103	0.114	0.081	0.046	0.159
HMY	0.048	0.189	0.071	0.261	0.227	0.166	0.126	0.175	0.036	0.033	0.487	0.095	0.108	0.166	0.102	0.102	0.147	0.1	0.171
HOPE	0.034	0.038	0.032	0.048	0.086	0.04	0.084	0.033	0.023	0.176	0.116	0.04	0.052	0.035	0.054	0.055	0.048	0.034	0.087
HRI	0.049	0.154	0.065	0.135	0.131	0.116	0.096	0.082	0.017	0.061	0.17	0.071	0.106	0.081	0.112	0.226	0.124	0.053	0.186
HWC	0.026	0.018	0.052	0.057	0.051	0.036	0.054	0.037	0.019	0.021	0.086	0.051	0.08	0.052	0.057	0.118	0.095	0.029	0.086
IART	0.027	0.078	0.053	0.058	0.089	0.047	0.064	0.049	0.031	0.012	0.137	0.062	0.089	0.037	0.069	0.111	0.099	0.031	0.095
IDT	0.075	0.353	0.153	0.16	0.071	0.112	0.133	0.094	0.076	0.025	0.24	0.193	0.249	0.186	0.197	0.182	0.215	0.077	0.217
IMAX	0.033	0.052	0.057	0.082	0.05	0.034	0.078	0.072	0.043	0.013	0.098	0.051	0.09	0.068	0.073	0.085	0.093	0.033	0.1
IMGN	0.056	0.098	0.168	0.09	0.108	0.159	0.072	0.077	0.046	0.014	0.221	0.161	0.209	0.192	0.138	0.249	0.205	0.064	0.098
INSM	0.087	0.075	0.129	0.079	0.142	0.049	0.136	0.135	0.035	0.008	0.226	0.132	0.139	0.09	0.096	0.239	0.142	0.055	0.236
IOSP	0.03	0.095	0.064	0.062	0.067	0.113	0.058	0.069	0.037	0.012	0.154	0.063	0.055	0.025	0.069	0.076	0.035	0.028	0.084
IP	0.031	0.075	0.057	0.041	0.043	0.057	0.073	0.041	0.037	0.045	0.072	0.057	0.047	0.042	0.049	0.069	0.048	0.029	0.071
IPAR	0.04	0.091	0.035	0.066	0.127	0.1	0.085	0.036	0.045	0.004	0.174	0.058	0.074	0.06	0.066	0.075	0.071	0.036	0.073
IRBT	0.066	0.25	0.077	0.174	0.223	0.158	0.205	0.081	0.155	0.059	0.167	0.132	0.134	0.109	0.082	0.318	0.133	0.071	0.178
IT	0.032	0.073	0.049	0.05	0.041	0.041	0.059	0.037	0.032	0.009	0.105	0.076	0.052	0.038	0.044	0.046	0.05	0.038	0.082
ITGR	0.04	0.07	0.063	0.078	0.053	0.059	0.075	0.06	0.034	0.019	0.139	0.046	0.063	0.042	0.074	0.051	0.065	0.043	0.11
ITT	0.035	0.057	0.041	0.039	0.178	0.126	0.048	0.042	0.03	0.01	0.056	0.032	0.044	0.037	0.065	0.104	0.051	0.029	0.086
JKHY	0.023	0.051	0.036	0.031	0.027	0.047	0.062	0.055	0.024	0.031	0.083	0.042	0.051	0.025	0.031	0.064	0.047	0.034	0.063
KAI	0.027	0.046	0.045	0.068	0.063	0.055	0.043	0.049	0.018	0.012	0.064	0.042	0.045	0.038	0.052	0.065	0.047	0.031	0.073
KBR	0.031	0.093	0.08	0.058	0.04	0.101	0.1	0.145	0.025	0.026	0.099	0.053	0.053	0.064	0.078	0.078	0.046	0.046	0.103
KFRC	0.035	0.125	0.075	0.07	0.112	0.036	0.063	0.066	0.045	0.005	0.165	0.062	0.099	0.054	0.072	0.108	0.102	0.039	0.092
KLIC	0.035	0.155	0.054	0.064	0.142	0.068	0.047	0.047	0.052	0.034	0.048	0.066	0.076	0.04	0.053	0.111	0.086	0.03	0.085
LANC	0.026	0.082	0.036	0.052	0.043	0.031	0.04	0.036	0.015	0.105	0.09	0.037	0.045	0.025	0.034	0.098	0.051	0.028	0.065
LBAI	0.023	0.065	0.042	0.041	0.105	0.031	0.03	0.046	0.053	0.01	0.136	0.028	0.045	0.04	0.041	0.146	0.054	0.026	0.062
LMAT	0.046	0.057	0.072	0.08	0.089	0.099	0.079	0.061	0.032	0.029	0.067	0.052	0.064	0.069	0.053	0.081	0.068	0.054	0.114
LOW	0.03	0.104	0.07	0.078	0.032	0.075	0.091	0.074	0.025	0.018	0.075	0.075	0.077	0.04	0.07	0.131	0.07	0.04	0.088
LRN	0.053	0.181	0.089	0.09	0.175	0.058	0.123	0.076	0.023	0.109	0.195	0.09	0.098	0.1	0.102	0.164	0.135	0.031	0.108
LSI	0.019	0.06	0.034	0.032	0.009	0.036	0.036	0.021	0.014	0.101	0.036	0.035	0.034	0.022	0.036	0.031	0.038	0	0.056
LYG	0.029	0.073	0.028	0.037	0.085	0.074	0.042	0.046	0.029	0.013	0.123	0.067	0.075	0.051	0.067	0.051	0.08	0.023	0.075
MCY	0.045	0.092	0.045	0.06	0.107	0.051	0.077	0.074	0.024	0.007	0.054	0.073	0.075	0.064	0.077	0.083	0.065	0.039	0.076
MDC	0.031	0.125	0.051	0.053	0.15	0.214	0.061	0.06	0.03	0.011	0.142	0.062	0.07	0.039	0.067	0.087	0.061	0.036	0.1
MGM	0.034	0.06	0.046	0.061	0.189	0.035	0.076	0.064	0.028	0.031	0.017	0.037	0.04	0.026	0.038	0.065	0.044	0.028	0.084
MGRC	0.022	0.106	0.051	0.079	0.161	0.11	0.085	0.087	0.021	0.087	0.094	0.065	0.038	0.032	0.06	0.091	0.051	0.024	0.074
MIDD	0.04	0.081	0.069	0.078	0.069	0.048	0.086	0.044	0.051	0.011	0.081	0.074	0.053	0.039	0.072	0.056	0.056	0.047	0.097
MRO	0.038	0.109	0.063	0.108	0.112	0.105	0.072	0.07	0.028	0.016	0.124	0.071	0.068	0.058	0.07	0.247	0.086	0.083	0.115
MSA	0.023	0.096	0.043	0.047	0.031	0.113	0.041	0.078	0.023	0.018	0.068	0.036	0.028	0.019	0.031	0.051	0.032	0.025	0.056
MT	0.052	0.095	0.068	0.08	0.149	0.123	0.077	0.056	0.018	0.03	0.096	0.092	0.118	0.106	0.084	0.108	0.104	0.033	0.124
MTZ	0.037	0.06	0.056	0.106	0.196	0.127	0.046	0.113	0.036	0.017	0.129	0.066	0.066	0.033	0.051	0.065	0.046	0.038	0.082
MYGN	0.073	0.172	0.138	0.101	0.188	0.111	0.107	0.07	0.038	0.023	0.102	0.109	0.134	0.092	0.1	0.157	0.142	0.028	0.149
NBIX	0.037	0.227	0.051	0.109	0.072	0.061	0.086	0.06	0.026	0.026	0.069	0.123	0.106	0.082	0.071	0.156	0.092	0.045	0.13
NEOG	0.027	0.098	0.042	0.06	0.095	0.045	0.042	0.046	0.03	0.008	0.176	0.047	0.091	0.08	0.08	0.094	0.095	0.024	0.096
NFLX	0.046	0.084	0.047	0.135	0.055	0.032	0.076	0.085	0.1	0.013	0.103	0.073	0.065	0.06	0.081	0.195	0.097	0.061	0.13
NG	0.042	0.232	0.188	0.059	0.396	0.21	0.125	0.129	0.018	0.065	0.247	0.063	0.076	0.04	0.095	0.064	0.085	0.122	0.131
NGD	0.087	0.177	0.103	0.147	0.181	0.063	0.084	0.121	0.217	0.03	0.355	0.17	0.173	0.119	0.166	0.227	0.131	0.079	0.225
NGG	0.022	0.048	0.039	0.022	0.026	0.031	0.068	0.024	0.024	0.016	0.031	0.034	0.035	0.023	0.038	0.055	0.036	0.018	0.055
NICE	0.023	0.06	0.047	0.028	0.16	0.037	0.089	0.039	0.02	0.009	0.049	0.042	0.025	0.036	0.048	0.038	0.031	0.032	0.059
NNI	0.027	0.1	0.029	0.035	0.019	0.086	0.037	0.046	0.023	0.002	0.042	0.034	0.047	0.024	0.036	0.049	0.061	0.018	0.051
NNN	0.02	0.035	0.032	0.035	0	0.02	0.057	0.031	0.021	0.015	0.035	0.04	0.041	0.031	0.033	0.049	0.057	0.041	0.05
NOG	0.059	0.242	0.214	0.175	0.156	0.12	0.117	0.168	0.09	0.079	0.221	0.111	0.181	0.115	0.125	0.309	0.142	0.138	0.187
NRG	0.031	0.033	0.044	0.059	0.065	0.051	0.044	0.057	0.026	0.01	0.042	0.059	0.061	0.036	0.056	0.061	0.068	0.034	0.074
NVMI	0.031	0.089	0.033	0.11	0.086	0.084	0.064	0.073	0.022	0.018	0.095	0.063	0.047	0.021	0.05	0.071	0.045	0.041	0.08
NVS	0.021	0.019	0.028	0.046	0.133	0.038	0.039	0.038	0.022	0.006	0.045	0.021	0.022	0.015	0.025	0.03	0.024	0.017	0.049
NWBI	0.016	0.041	0.02	0.024	0.018	0.013	0.025	0.034	0.008	0.013	0.074	0.02	0.031	0.018	0.025	0.032	0.03	0.015	0.048
OGE	0.016	0.079	0.03	0.034	0.042	0.06	0.019	0.026	0.01	0.005	0.019	0.028	0.03	0.021	0.023	0.031	0.029	0.026	0.038
OMCL	0.037	0.092	0.054	0.084	0.225	0.132	0.104	0.083	0.127	0.024	0.018	0.066	0.055	0.033	0.067	0.07	0.083	0.049	0.108
PAYX	0.02	0.037	0.03	0.079	0.026	0.039	0.04	0.042	0.013	0.021	0.038	0.025	0.028	0.023	0.031	0.021	0.032	0.064	0.053
PB	0.026	0.055	0.039	0.073	0.034	0.046	0.055	0.033	0.023	0.012	0.049	0.047	0.04	0.032	0.055	0.052	0.043	0.026	0.066
PCH	0.031	0.036	0.068	0.037	0.094	0.04	0.054	0.057	0.008	0.011	0.115	0.03	0.032	0.039	0.049	0.096	0.049	0.038	0.079
PDCE	0.057	0.121	0.056	0.097	0.228	0.213	0.125	0.101	0.017	0.035	0.072	0.08	0.105	0.063	0.107	0.182	0.13	0	0.085
PDFS	0.045	0.213	0.077	0.242	0.284	0.029	0.067	0.078	0.064	0.023	0.101	0.092	0.117	0.069	0.08	0.159	0.126	0.031	0.125
PDS	0.065	0.204	0.083	0.164	0.235	0.215	0.149	0.099	0.03	0.058	0.163	0.09	0.185	0.063	0.141	0.289	0.184	0.135	0.16
PERI	0.075	0.245	0.263	0.267	0.145	0.212	0.196	0.076	0.07	0.041	0.358	0.122	0.111	0.183	0.139	0.1	0.182	0.04	0.224
PHG	0.019	0.015	0.03	0.068	0.041	0.035	0.078	0.031	0.014	0.011	0.026	0.044	0.045	0.028	0.051	0.089	0.045	0.03	0.067

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Ticker	MST	MS	MT1	MT2	MT3	MT4	MT5	MT6	MT7	MT8	TA1	TA2	TA3	TA4	TA5	TA6	TA7	DCC	B&H
PNM	0.021	0.055	0.045	0.053	0.044	0.118	0.05	0.031	0.02	0.006	0.022	0.044	0.051	0.029	0.025	0.054	0.048	0.033	0.057
POR	0.02	0.042	0.032	0.047	0.127	0.145	0.07	0.037	0.014	0.01	0.053	0.037	0.041	0.034	0.018	0.049	0.041	0.032	0.04
PRGS	0.034	0.156	0.054	0.057	0.142	0.129	0.074	0.083	0.05	0.017	0.096	0.079	0.088	0.051	0.07	0.1	0.095	0.038	0.093
QCOM	0.026	0.246	0.09	0.076	0.099	0.069	0.106	0.036	0.019	0.017	0.12	0.134	0.139	0.098	0.085	0.072	0.076	0.122	0.143
RAMP	0.042	0.096	0.095	0.138	0.086	0.061	0.091	0.065	0.036	0.027	0.125	0.108	0.118	0.057	0.088	0.044	0.11	0.048	0.141
RGR	0.032	0.136	0.043	0.058	0.074	0.053	0.092	0.04	0.027	0.027	0.073	0.088	0.069	0.063	0.092	0.069	0.071	0.037	0.115
RHI	0.028	0.079	0.044	0.041	0.018	0.052	0.128	0.045	0.039	0.012	0.012	0.059	0.06	0.047	0.072	0.115	0.056	0.037	0.077
RJF	0.024	0.045	0.045	0.045	0.024	0.025	0.039	0.044	0.036	0.008	0.033	0.063	0.057	0.032	0.057	0.075	0.052	0.038	0.067
RL	0.048	0.118	0.065	0.06	0.058	0.046	0.124	0.064	0.036	0.051	0.116	0.085	0.071	0.047	0.077	0.09	0.069	0.028	0.102
ROG	0.051	0.103	0.071	0.115	0.064	0.034	0.088	0.081	0.042	0.01	0.145	0.118	0.063	0.1	0.11	0.129	0.083	0.074	0.139
ROIC	0.018	0.062	0.033	0.031	0.06	0.019	0.053	0.033	0.022	0.003	0.026	0.032	0.031	0.025	0.034	0.059	0.033	0.021	0.054
RPM	0.023	0.137	0.043	0.101	0.064	0.08	0.046	0.063	0.005	0.009	0.141	0.057	0.036	0.036	0.048	0.053	0.044	0.031	0.072
RPT	0.042	0.099	0.071	0.093	0.07	0.085	0.045	0.033	0.028	0.007	0.086	0.037	0.05	0.036	0.033	0.071	0.043	0.021	0.057
RTX	0.026	0.077	0.041	0.04	0.009	0.008	0.037	0.046	0.018	0.048	0.064	0.048	0.049	0.037	0.052	0.089	0.052	0.027	0.067
RUSHA	0.028	0.049	0.037	0.052	0.095	0.029	0.074	0.091	0.027	0.02	0.068	0.051	0.067	0.053	0.061	0.115	0.063	0.047	0.086
RY	0.012	0.08	0.025	0.023	0.042	0.063	0.048	0.069	0.014	0.005	0.027	0.029	0.027	0.022	0.032	0.05	0.026	0.019	0.051
SAH	0.054	0.385	0.087	0.292	0.293	0.039	0.058	0.2	0.035	0.011	0.127	0.087	0.079	0.065	0.062	0.134	0.13	0.174	0.139
SAIA	0.036	0.081	0.065	0.061	0.124	0.072	0.132	0.142	0.039	0.017	0.16	0.099	0.131	0.088	0.093	0.116	0.074	0.038	0.101
SASR	0.019	0.055	0.034	0.027	0.008	0.014	0.034	0.027	0.026	0.02	0.039	0.038	0.028	0.021	0.045	0.065	0.05	0.021	0.063
SBH	0.049	0.06	0.081	0.057	0.04	0.051	0.064	0.044	0.072	0.023	0.075	0.081	0.082	0.059	0.076	0.142	0.093	0.043	0.114
SBRA	0.028	0.085	0.038	0.071	0.057	0.036	0.082	0.038	0.019	0.018	0.106	0.049	0.062	0.065	0.041	0.052	0.09	0.037	0.088
SBS	0.038	0.088	0.071	0.074	0.067	0.051	0.135	0.079	0.033	0.018	0.175	0.108	0.116	0.088	0.121	0.173	0.115	0.066	0.155
SCI	0.023	0.059	0.027	0.043	0.115	0.012	0.037	0.033	0.017	0.017	0.075	0.044	0.034	0.024	0.037	0.039	0.038	0.024	0.058
SCVL	0.058	0.097	0.094	0.129	0.372	0.114	0.135	0.076	0.087	0.028	0.089	0.059	0.075	0.055	0.112	0.131	0.072	0.054	0.148
SEIC	0.026	0.078	0.046	0.078	0.064	0.028	0.066	0.049	0.012	0.044	0.034	0.049	0.059	0.038	0.057	0.112	0.058	0.035	0.071
SIEGY	0.026	0.037	0.051	0.029	0.023	0.016	0.058	0.042	0.027	0.082	0.068	0.045	0.059	0.037	0.044	0.112	0.055	0.034	0.069
SITC	0.037	0.09	0.049	0.074	0.031	0.044	0.079	0.049	0.025	0.011	0.121	0.073	0.072	0.043	0.06	0.084	0.076	0.036	0.088
SKYW	0.031	0.11	0.041	0.082	0.092	0.04	0.065	0.066	0.042	0.016	0.122	0.054	0.047	0.036	0.063	0.082	0.045	0.042	0.083
SNX	0.04	0.052	0.07	0.076	0.051	0.06	0.056	0.053	0.049	0.035	0.202	0.076	0.082	0.069	0.102	0.048	0.074	0.037	0.121
SO	0.018	0.081	0.034	0.047	0.169	0.014	0.042	0.042	0.046	0.03	0.037	0.039	0.04	0.019	0.018	0.038	0.046	0.064	0.047
SRPT	0.057	0.103	0.082	0.082	0.093	0.12	0.102	0.055	0.03	0.027	0.151	0.132	0.145	0.121	0.122	0.179	0.157	0.101	0.196
STC	0.021	0.033	0.034	0.049	0.021	0.079	0.058	0.03	0.018	0.002	0.03	0.033	0.038	0.03	0.046	0.056	0.044	0.022	0.055
STLD	0.041	0.11	0.062	0.062	0.107	0.083	0.059	0.049	0.036	0.019	0.055	0.065	0.077	0.067	0.081	0.16	0.07	0.041	0.11
STM	0.039	0.089	0.093	0.072	0.169	0.055	0.08	0.1	0.044	0.014	0.048	0.082	0.096	0.042	0.08	0.201	0.076	0.051	0.109
STT	0.042	0.101	0.067	0.054	0.073	0.042	0.083	0.049	0.043	0.01	0.06	0.062	0.075	0.048	0.081	0.088	0.065	0.042	0.095
STX	0.047	0.128	0.049	0.125	0.045	0.006	0.047	0.079	0.03	0.016	0.136	0.041	0.044	0.047	0.068	0.091	0.048	0.096	0.103
SYNA	0.042	0.063	0.147	0.049	0.062	0.079	0.185	0.065	0.036	0.029	0.048	0.09	0.113	0.072	0.085	0.127	0.116	0.048	0.134
TDC	0.035	0.119	0.054	0.066	0.07	0.052	0.078	0.087	0.015	0.018	0.064	0.082	0.052	0.055	0.056	0.118	0.051	0.045	0.088
TEX	0.036	0.099	0.048	0.078	0.084	0.033	0.066	0.048	0.046	0.034	0.074	0.047	0.095	0.073	0.1	0.104	0.1	0.038	0.102
THG	0.018	0.067	0.027	0.036	0.082	0.021	0.026	0.02	0.016	0.004	0.055	0.021	0.018	0.017	0.022	0.056	0.021	0.049	0.042
TITN	0.057	0.122	0.109	0.144	0.077	0.082	0.109	0.078	0.011	0.031	0.1	0.114	0.124	0.089	0.121	0.107	0.122	0.058	0.172
TLK	0.036	0.036	0.043	0.066	0.069	0.088	0.036	0.038	0.026	0.025	0.016	0.042	0.05	0.037	0.051	0.079	0.054	0.031	0.051
TREE	0.047	0.104	0.064	0.127	0.122	0.174	0.068	0.058	0.04	0.014	0.141	0.131	0.104	0.076	0.097	0.118	0.099	0.073	0.151
TREX	0.044	0.069	0.057	0.097	0.022	0.211	0.077	0.079	0.027	0.035	0.188	0.076	0.088	0.069	0.043	0.14	0.093	0.043	0.118
TRMK	0.02	0.038	0.051	0.048	0.049	0.058	0.051	0.04	0.022	0.013	0.046	0.05	0.044	0.033	0.052	0.068	0.045	0.025	0.067
TSM	0.033	0.163	0.031	0.059	0.178	0.035	0.051	0.101	0.025	0.017	0.076	0.07	0.069	0.031	0.065	0.087	0.061	0.024	0.074
TTC	0.028	0.031	0.031	0.064	0.156	0.025	0.051	0.025	0.023	0.008	0.031	0.039	0.025	0.021	0.048	0.052	0.026	0.022	0.06
TU	0.012	0.029	0.022	0.039	0.023	0.011	0.026	0.021	0.015	0.006	0.056	0.027	0.028	0.014	0.019	0.027	0.028	0.035	0.034
TXN	0.024	0.075	0.028	0.04	0.083	0.04	0.071	0.063	0.032	0.013	0.006	0.049	0.041	0.035	0.041	0.066	0.044	0.03	0.068
TXRH	0.022	0.041	0.042	0.071	0.042	0.028	0.041	0.045	0.016	0.015	0.067	0.048	0.061	0.02	0.063	0.057	0.046	0.036	0.071
UBSI	0.022	0.04	0.038	0.043	0.069	0.065	0.045	0.044	0.018	0.014	0.083	0.049	0.039	0.037	0.053	0.047	0.04	0.025	0.068
UGP	0.039	0.114	0.061	0.148	0.047	0.051	0.13	0.066	0.042	0.022	0.135	0.132	0.212	0.224	0.101	0	0.211	0.057	0.128
UHS	0.024	0.054	0.032	0.063	0.065	0.027	0.051	0.031	0.039	0.016	0.036	0.027	0.036	0.04	0.039	0.053	0.034	0.026	0.078
UHT	0.024	0.09	0.054	0.058	0.02	0.177	0.034	0.064	0.065	0.024	0.029	0.064	0.059	0.048	0.049	0.075	0.066	0.032	0.086
UNF	0.029	0.056	0.05	0.058	0.168	0.139	0.076	0.067	0.011	0.022	0.115	0.055	0.06	0.044	0.055	0.077	0.061	0.024	0.064
WEC	0.022	0.046	0.029	0.055	0.132	0.118	0.049	0.042	0.012	0.002	0.055	0.046	0.035	0.034	0.018	0.031	0.034	0.028	0.043
WELL	0.021	0.079	0.052	0.055	0.035	0.089	0.049	0.048	0.026	0.022	0.081	0.043	0.046	0.041	0.03	0.075	0.051	0.052	0.064
WEN	0.019	0.04	0.029	0.037	0.109	0.021	0.048	0.047	0.01	0.008	0.031	0.033	0.033	0.02	0.034	0.047	0.028	0.027	0.074
WIRE	0.032	0.054	0.038	0.088	0.07	0.049	0.086	0.04	0.032	0.025	0.059	0.042	0.058	0.033	0.04	0.096	0.066	0.028	0.076
WLK	0.044	0.081	0.062	0.041	0.079	0.071	0.092	0.072	0.029	0.027	0.096	0.068	0.084	0.065	0.073	0.161	0.095	0.039	0.097
WMK	0.031	0.071	0.05	0.072	0.06	0.022	0.07	0.065	0.019	0.006	0.084	0.082	0.062	0.074	0.057	0.121	0.067	0.037	0.078
WMT	0.021	0.034	0.028	0.07	0.058	0.06	0	0.032	0.016	0.053	0.064	0.04	0.04	0.034	0.03	0.076	0.033	0.048	0.053
WOR	0.029	0.051	0.045	0.054	0.047	0.025	0.053	0.041	0.047	0.023	0.042	0.037	0.054	0.036	0.042	0.079	0.04	0.033	0.087
WPC	0.023	0.105	0.026	0.046	0.172	0.119	0.066	0.074	0.03	0.017	0.048	0.029	0.03	0.025	0.032	0.053	0.041	0.051	0.05
WSM	0.037	0.072	0.046	0.082	0.041	0.09	0.072	0.046	0.037	0.025	0.063	0.076	0.032	0.029	0.083	0.106	0.044	0.036	0.077
WTI	0.071	0.073	0.155	0.18	0.201	0.135	0	0.105	0.064	0.038	0.156	0.128	0.155	0.101	0.119	0.276	0.137	0.084	0.22
WW	0.072	0.294	0.137	0.133	0.045	0.11	0.183	0.082	0.063	0.161	0.318	0.186	0.208	0.318	0.128	0.329	0.253	0.05	0.208
XPO	0.054	0.18	0.06	0.142	0.045	0.044	0	0.07	0.035	0.024	0.043	0.086	0.162	0.165	0.098	0.231	0.157	0.042	0.132

Table B.4: Value at Risk results for MSTGAM (MST) versus MSGAM (MS), MTGAMs (MT1, ⋯, MT8), TA-based strategies (TA1, ⋯, TA7, represent the TA-strategies in the following order: ADX, Ar, CCI, EMA, MACD, RSI, and Wr), and confirmation point strategy (DCC), BandH (B&H) for each stock.

Ticker	MST	MS	MT1	MT2	MT3	MT4	MT5	MT6	MT7	MT8	TA1	TA2	TA3	TA4	TA5	TA6	TA7	DCC	B&H
AAON	0.036	0.156	0.087	0.141	0.122	0.042	0.112	0.062	0.022	0.023	0.049	0.236	0.14	0.035	0.166	0.103	0.137	0.087	0.102
AAPL	0.045	0.192	0.096	0.155	0.016	0.019	0.3	0.065	0.008	0.003	0.105	0.286	0.294	0.058	0.109	0.166	0.237	0.058	0.123
ACM	0.039	0.055	0.042	0.079	0.1	-0.009	0.163	0.028	0.011	0.01	0.093	0.05	0.028	0.047	0.099	0.148	0.04	0.044	0.106
AG	0.085	0.291	0.172	0.056	0.111	0.095	0.141	0.121	0.037	0.014	0.207	0.225	0.142	0.061	0.141	0.083	0.133	0.085	0.159
AGEN	0.098	0.218	0.351	0.338	0.042	0.138	0.149	0.234	0.004	0.076	0.044	0.411	0.613	0.109	0.373	0.562	0.59	0.173	0.27
ANDE	0.039	0.051	0.076	0.165	0.206	0.312	0.08	0	0.006	0.026	0.131	0.172	0.16	0.039	0.209	0.236	0.186	0.034	0.166
ASGN	0.051	0.118	0.103	0.155	0.06	0.076	0.207	0.125	0.026	0.071	0.08	0.101	0.187	0.036	0.14	0.31	0.217	0.051	0.189
AWI	0.039	0.062	0.073	0.025	0.078	0.059	0.073	0.053	0.022	0.019	0.037	0.053	0.058	0.034	0.188	0.027	0.045	0.068	0.106
BANR	0.037	0.032	0.046	0.123	0.029	0.085	0.101	0.06	0.032	0.007	0.126	0.064	0.067	0.038	0.121	0.104	0.078	0.074	0.106
BCPC	0.052	0.127	0.114	0.1	0.042	0.111	0.209	0.12	0.01	0.082	0.05	0.143	0.242	0.032	0.094	0.251	0.262	0.055	0.131
BG	0.028	0.046	0.076	0.091	0.117	0.067	0.102	0.046	0.041	-0.006	0.164	0.032	0.038	0.054	0.023	0.115	0.093	0.048	0.076
BHLB	0.046	0.035	0.094	0.139	0.121	0.041	0.065	0.103	0.014	0.02	0.194	0.078	0.181	0.034	0.099	0.28	0.185	0.056	0.173
BHP	0.035	0.057	0.057	0.018	-0.007	0.002	0.099	0.062	0.026	0.025	0.14	0.083	0.09	0.043	0.055	0.063	0.093	0.049	0.08
BKR	0.059	0.126	0.104	0.267	0.11	0.098	0.213	0.143	0.029	0.08	0.233	0.277	0.298	0.029	0.189	0.265	0.288	0.053	0.169
BMI	0.027	0.031	0.072	0.041	0.056	0.102	0.119	0.071	0.041	0.003	0.108	0.099	0.059	0.03	0.111	0.073	0.071	0.044	0.103
BMY	0.032	0.16	0.093	0.099	0.026	0.033	0.114	0.153	0.061	0.018	0.058	0.135	0.145	0.039	0.105	0.167	0.154	0.056	0.157
BSAC	0.045	0.26	0.083	0.205	0.161	0.026	0.161	0.092	0.001	0.07	0.089	0.058	0.181	0.035	0.101	0.181	0.181	0.057	0.077
BSBR	0.033	0.111	0.105	0.111	0.016	0.112	0.111	0.075	0.011	0.043	0.135	0.226	0.264	0.038	0.219	0.245	0.268	0.049	0.156
BSX	0.041	0.079	0.058	0.104	0.032	-0.007	0.047	0.078	0.03	0.007	0.079	0.047	0.056	0.033	0.053	0.009	0.074	0.042	0.061
BX	0.059	0.076	0.103	0.046	0.13	0.087	0.092	0.064	0	0.008	0.19	0.132	0.059	0.037	0.101	0.062	0.032	0.047	0.108
BYD	0.06	0.023	0.112	0.146	0.124	0.154	0.216	0.069	-0.003	0.028	0.291	0.231	0.258	0.036	0.201	0.357	0.218	0.051	0.168
CBZ	0.024	0.025	0.009	0.049	-0.015	0	0.057	0.053	-0.002	0.025	0.011	0.136	0.143	0.02	0.163	0.123	0.111	0.047	0.062
CCEP	0.02	0.018	0.068	0.065	0.049	0.046	0.05	0.093	-0.008	-0.003	0.12	0.091	0.148	0.022	0.083	0.153	0.13	0.021	0.054
CCI	0.037	0.03	0.04	0.022	0.04	0.026	0.072	0.035	0.008	-0.002	0.135	0.069	0.047	0.029	0.034	0.023	0.12	0.048	0.044
CCL	0.052	0.091	0.085	0.134	0.124	0.183	0.211	0.124	0.005	0.014	0.222	0.101	0.111	0.03	0.105	0.031	0.111	0.037	0.122
CHH	0.026	0.013	0.079	0.036	0.024	0.048	0.109	0.049	0.01	-0.002	0.081	0.03	0.044	0.025	0.067	0.063	0.044	0.047	0.075
CMP	0.047	0.089	0.098	0.127	0.076	0.054	0.051	0.032	0.009	0.012	0.255	0.147	0.134	0.058	0.237	0.272	0.127	0.056	0.167
CNK	0.046	0.128	0.091	0.14	0.058	0.058	0.084	0.067	0.021	0.005	0.125	0.136	0.08	0.032	0.065	0.082	0.09	0.099	0.107
CNXN	0.035	0.103	0.06	0.201	0.057	0.053	0.093	0.047	0.03	0.232	0.028	0.194	0.175	0.042	0.261	0.169	0.19	0.045	0.138
COST	0.028	0.031	0.041	0.155	0.026	0.036	0.122	0.041	0.006	-0.007	0.077	0.129	0.126	0.028	0.047	0.011	0.225	0.023	0.026
CRK	0.079	0.211	0.398	0.311	0.393	0.263	0.41	0.154	0.03	0.396	0.266	0.35	0.232	0.084	0.339	0.304	0.236	0.227	0.296
CSV	0.056	0.202	0.084	0.154	0.121	0.196	0.066	0.046	0.031	0.015	0.072	0.151	0.325	0.038	0.21	0.393	0.151	0.039	0.101
CUBE	0.047	0.032	0.029	0.057	0.024	0.031	0.082	0.03	-0.008	-0	0.122	0.109	0.074	0.023	0.101	0.014	0.085	0.059	0.067
D	0.03	0.177	0.046	0.078	0.041	0.041	0.101	0.033	0.032	-0.004	0.09	0.082	0.086	0.016	0.078	0.165	0.082	0.031	0.055
DCOM	0.039	0.052	0.064	0.104	0.158	0.073	0.144	0.054	-0.011	0.053	0.11	0.101	0.131	0.032	0.204	0.211	0.137	0.065	0.11
DDS	0.073	0.131	0.155	0.149	0.051	0.047	0.174	0.062	0.057	0.045	0.195	0.024	0.181	0.102	0.204	0.075	0.169	0.08	0.169
DENN	0.018	0.033	0.119	0.094	-0.001	0.031	0.062	0.078	0.016	0.008	0.047	0.068	0.087	0.033	0.168	0.152	0.129	0.038	0.112
DIOD	0.047	0.094	0.106	0.086	0.078	0.025	0.208	0.086	0.033	-0.004	0.183	0.107	0.095	0.033	0.174	0.047	0.126	0.057	0.142
DIS	0.018	0.032	0.043	0.056	0.026	0.038	0.077	0.029	0.015	0.011	0.008	0.033	0.033	0.029	0.045	0.033	0.033	0.04	0.05
DRQ	0.069	0.145	0.121	0.085	0.167	0.088	0.151	0.091	0.032	0.021	0.1	0.108	0.297	0.062	0.143	0.333	0.225	0.083	0.185
EAT	0.044	0.149	0.11	0.164	0.086	0.049	0.137	0.077	0.018	-0.008	0.157	0.063	0.05	0.042	0.12	0.028	0.077	0.044	0.115
EBR	0.079	0.22	0.088	0.249	0.207	0.144	0.143	0.082	-0.006	0.058	0.161	0.142	0.448	0.09	0.373	0.123	0.38	0.068	0.186
EC	0.052	0.137	0.128	0.178	0.08	0.085	0.178	0.077	0.025	0.035	0.095	0.129	0.265	0.037	0.191	0.247	0.283	0.069	0.168
EFSC	0.048	0.229	0.101	0.213	0	0.002	0.025	0.135	0.008	-0.003	0.039	0.151	0.187	0.029	0.142	0.266	0.187	0.076	0.147
EGHT	0.051	-0.053	0.121	0.066	0.051	0.054	0.113	0.064	0.015	0.011	0.035	0.141	0.15	0.054	0.155	0.155	0.146	0.059	0.138
EGO	0.086	-0.031	0.157	0.195	0.352	0.352	0.159	0.139	0.047	0.119	0.06	0.507	0.208	0.073	0.541	0.347	0.499	0.098	0.204
EMN	0.059	0.037	0.105	0.227	0.171	0.038	0.194	0.055	0.008	0.001	0.038	0.086	0.136	0.041	0.107	0.194	0.154	0.055	0.171
EQR	0.031	-0.002	0.029	0.077	0.038	0.044	0.081	0.04	0.085	0.019	0.064	0.118	0.06	0.019	0.078	0.067	0.047	0.036	0.062
ERII	0.062	0.114	0.155	0.167	0.122	0.141	0.298	0.143	0.023	0.033	0.178	0.115	0.134	0.063	0.155	0.085	0.134	0.116	0.174
ERJ	0.067	0.038	0.082	0.121	0.229	0.217	0.113	0.07	0.019	0.009	0.215	0.064	0.156	0.068	0.147	0.222	0.156	0.054	0.124
ET	0.041	0.031	0.07	0.148	0.081	0.116	0.107	0.054	-0.003	-0.007	0.06	0.155	0.108	0.036	0.205	0.141	0.119	0.04	0.106
EVR	0.048	0.095	0.078	0.061	0.211	0.061	0.149	0.118	0.015	0.004	0.152	0.252	0.28	0.033	0.164	0.272	0.31	0.066	0.18
FARO	0.057	0.131	0.149	0.103	0.136	0.099	0.305	0.118	0.012	0.023	0.099	0.14	0.264	0.057	0.27	0.241	0.262	0.159	0.21
FBNC	0.045	0.022	0.04	0.035	0.111	0.073	0.12	0.106	0.095	-0.001	0.128	0.049	0.058	0.027	0.105	0.046	0.058	0.079	0.107
FELE	0.038	0.16	0.095	0.095	0.096	0.076	0.071	0.066	-0.002	-0.002	-0.008	0.086	0.091	0.045	0.117	0.079	0.108	0.045	0.1
FFIN	0.037	0.061	0.047	0.066	0.03	0.03	0.115	0.047	0.011	0.053	0.11	0.138	0.017	0.036	0.114	-0.013	0.024	0.048	0.102
FISI	0.036	0.067	0.062	0.084	0.023	0.028	0.05	0.051	0.079	0.033	0.21	0.122	0.087	0.027	0.112	0.081	0.052	0.068	0.091
FIX	0.041	0.051	0.056	0.078	0.039	0.022	0.078	0.03	-0.016	0.031	0.086	0.116	0.116	0.036	0.161	0.085	0.124	0.038	0.164
FLO	0.031	0.033	0.039	0.056	0.033	0.064	0.061	0.026	0.01	0.01	0.122	0.036	0.044	0.05	0.06	0.045	0.036	0.022	0.073
GCO	0.032	0.158	0.066	0.087	0.049	0.068	0.103	0.077	0.019	-0.007	-0.039	0.138	0.118	0.061	0.124	0.057	0.094	0.056	0.092
GD	0.034	0.111	0.059	0.124	0.021	0.055	0.075	0.1	-0.002	-0.005	0.096	0.068	0.059	0.035	0.067	0.066	0.055	0.101	0.143
GE	0.084	0.013	0.206	0.341	0.058	0.088	0.157	0.104	0.071	0.119	0.325	0.418	0.342	0.044	0.23	0.286	0.317	0.107	0.197
GSAT	0.095	0.277	0.379	0.448	0.302	0.264	0.234	0.158	0.026	0.067	0.195	0.075	0.373	0.161	0.424	0.491	0.165	0.182	0.269

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Ticker	MST	MS	MT1	MT2	MT3	MT4	MT5	MT6	MT7	MT8	TA1	TA2	TA3	TA4	TA5	TA6	TA7	DCC	B&H
GTE	0.051	0.727	0.57	0.559	0.727	0.045	0.081	0.08	-0.013	0.068	0.235	0.058	0.343	0.071	0.191	0.53	0.323	0.082	0.189
GTLS	0.058	0.368	0.146	0.093	0.087	0.053	0.103	0.045	0.034	-0.002	0.102	0.158	0.058	0.076	0.315	0.103	0.056	0.033	0.132
GTN	0.057	0.238	0.107	0.052	0.06	0.084	0.124	0.095	0.018	-0.004	0.137	0.285	0.294	0.041	0.287	0.182	0.282	0.058	0.196
HA	0.055	0.331	0.075	0.143	0.122	0.087	0.176	0.056	0.054	0.017	0.117	0.077	0.123	0.069	0.111	0.034	0.164	0.051	0.134
HELE	0.023	0.125	0.047	0.106	0.043	0.064	0.125	0.044	0.012	0.004	0.021	0.048	0.16	0.097	0.041	0.011	0.154	0.048	0.081
HIW	0.028	0.09	0.091	0.116	0.033	0.049	0.115	0.043	0.014	-0.002	0.073	0.138	0.143	0.019	0.058	0.107	0.114	0.051	0.097
HLX	0.076	0.053	0.084	0.228	0.179	0.138	0.092	0.161	0.027	0.002	0.165	0.214	0.165	0.058	0.235	0.096	0.165	0.059	0.204
HMY	0.066	0.082	0.163	0.193	0.108	0.041	0.193	0.087	0.054	0.08	0.043	0.197	0.14	0.08	0.223	0.116	0.427	0.107	0.182
HOPE	0.038	0.062	0.062	0.103	0.172	0.085	0.12	0.088	0.038	0.127	0.141	0.019	0.113	0.033	0.168	0.089	0.122	0.101	0.102
HRI	0.077	0.097	0.119	0.302	0.192	0.161	0.235	0.17	0.029	0.135	0.156	0.202	0.32	0.052	0.325	0.437	0.399	0.135	0.29
HWC	0.053	0.013	0.078	0.097	0.055	0.062	0.086	0.077	0.019	0.034	0.121	0.095	0.245	0.03	0.156	0.248	0.269	0.044	0.133
IART	0.032	0.155	0.054	0.202	0.043	0.048	0.09	0.058	0.039	-0.002	0.118	0.049	0.161	0.035	0.148	0.212	0.255	0.039	0.152
IDT	0.069	0.341	0.223	0.303	0.181	0.284	0.305	0.202	0.037	0.048	0.229	0.494	0.503	0.055	0.484	0.347	0.431	0.141	0.347
IMAX	0.065	0.153	0.111	0.182	0.144	0.095	0.176	0.14	0.033	0.018	0.181	0.078	0.209	0.045	0.164	0.127	0.209	0.051	0.138
IMGN	0.086	0.143	0.261	0.262	0.296	0.367	0.098	0.163	0.071	0.017	0.524	0.177	0.428	0.106	0.257	0.413	0.437	0.109	0.233
INSM	0.076	0.179	0.124	0.163	0.221	0.099	0.128	0.121	0.056	-0.015	0.272	0.302	0.276	0.067	0.166	0.348	0.276	0.079	0.265
IOSP	0.068	0.051	0.07	0.169	0.097	0.033	0.073	0.077	0.006	0.006	0.216	0.252	0.15	0.042	0.242	0.111	0.068	0.068	0.126
IP	0.046	0.135	0.122	0.111	0.064	0.095	0.196	0.043	0.021	-0.067	0.165	0.078	0.131	0.032	0.116	0.113	0.144	0.047	0.104
IPAR	0.062	-0.02	0.043	0.125	0.003	0.038	0.1	0.09	0.112	-0.004	0.097	0.144	0.182	0.054	0.161	0.076	0.182	0.04	0.103
IRBT	0.113	0.612	0.082	0.626	0.593	0.567	0.491	0.194	0.376	0.012	0.187	0.285	0.289	0.174	0.223	0.545	0.281	0.054	0.218
IT	0.037	0.112	0.056	0.024	0.084	0.052	0.162	0.038	0.013	-0.007	0.188	0.1	0.115	0.02	0.106	0.072	0.112	0.035	0.161
ITGR	0.067	0.11	0.076	0.149	0.035	0.058	0.149	0.099	0.013	0.004	0.209	0.074	0.111	0.109	0.14	0.047	0.111	0.085	0.166
ITT	0.039	0.094	0.067	0.113	0.107	0.077	0.078	0.035	0.013	-0.005	0.201	0.027	0.095	0.055	0.15	0.131	0.128	0.031	0.124
JKHY	0.021	0.121	0.075	0.068	0.045	0.004	0.159	0.025	0.01	-0.002	0.039	0.144	0.136	0.027	0.048	0.155	0.136	0.034	0.09
KAI	0.04	0.082	0.077	0.23	0.143	0.05	0.059	0.072	0.009	0.01	0.138	0.064	0.104	0.029	0.087	0.074	0.115	0.086	0.118
KBR	0.046	0.214	0.175	0.131	0.132	0.021	0.234	0.034	0.032	0.033	0.075	0.117	0.083	0.032	0.203	0.116	0.064	0.109	0.162
KFRC	0.045	0.106	0.059	0.094	0.02	0.05	0.093	0.06	0.02	-0.002	0.253	0.158	0.267	0.043	0.131	0.23	0.244	0.041	0.094
KLIC	0.047	0.254	0.118	0.094	0.049	0.08	0.109	0.084	-0.002	0.064	0.124	0.089	0.143	0.045	0.119	0.175	0.185	0.048	0.138
LANC	0.026	0.065	0.058	0.088	0.06	0.021	0.063	0.044	0.009	0.017	0.11	0.057	0.095	0.03	0.076	0.132	0.093	0.032	0.076
LBAI	0.046	0.068	0.11	0.047	0.236	0.098	0.066	0.04	0.028	-0.001	0.04	0.059	0.125	0.029	0.069	0.226	0.157	0.051	0.102
LMAT	0.044	0.046	0.077	0.19	0.206	0.207	0.23	0.06	0.011	0.049	0.06	0.068	0.128	0.049	0.126	0.086	0.116	0.043	0.15
LOW	0.033	0.138	0.102	0.127	0.056	0.024	0.169	0.052	0.007	-0.02	0.096	0.145	0.143	0.042	0.182	0.175	0.119	0.104	0.164
LRN	0.046	0.117	0.054	0.156	0.186	0.054	0.309	0.027	0.027	0.015	0.15	0.283	0.265	0.064	0.266	0.345	0.281	0.05	0.136
LSI	0.023	0.074	0.063	0.056	0.017	0.033	0.06	0.032	0.019	-0.001	0.059	0.101	0.085	0.031	0.063	0.028	0.101	0	0.241
LYG	0.044	0.079	0.053	0.078	0.035	0.066	0.059	0.073	0.013	0.017	0.083	0.14	0.121	0.039	0.138	0.098	0.121	0.054	0.096
MCY	0.066	0.161	0.133	0.073	0.131	0.139	0.159	0.145	0.012	0.015	0.153	0.176	0.189	0.029	0.191	0.094	0.127	0.049	0.092
MDC	0.039	0.095	0.084	0.145	0.03	0.074	0.1	0.067	0.026	0.007	0.118	0.138	0.146	0.046	0.167	0.08	0.107	0.081	0.154
MGM	0.041	0.026	0.074	0.108	0.154	0.037	0.107	0.063	0.03	0.054	0.067	0.008	0.033	0.042	0.044	0.08	0.047	0.03	0.096
MGRC	0.032	0.043	0.064	0.041	0.021	0.014	0.085	0.059	0.026	0.008	0.1	0.142	0.07	0.031	0.129	0.128	0.126	0.046	0.061
MIDD	0.086	0.151	0.188	0.11	0.118	0.143	0.171	0.086	0.047	0.02	0.143	0.151	0.156	0.04	0.194	0.08	0.139	0.083	0.179
MRO	0.085	0.297	0.106	0.282	0.474	0.26	0.129	0.035	0.065	0.01	0.178	0.215	0.155	0.054	0.185	0.302	0.178	0.12	0.197
MSA	0.035	0.062	0.066	0.067	0.01	0.039	0.057	0.036	0.039	0.021	0.215	0.107	0.044	0.046	0.095	0.041	0.049	0.053	0.098
MT	0.11	0.078	0.221	0.187	0.356	0.422	0.198	0.096	0.022	0.038	0.26	0.236	0.24	0.063	0.173	0.26	0.24	0.057	0.184
MTZ	0.051	0.095	0.09	0.091	0.111	0.111	0.04	0.089	0.023	-0.002	0.13	0.187	0.181	0.059	0.085	0.081	0.076	0.061	0.083
MYGN	0.052	0.138	0.143	0.259	0.114	0.142	0.118	0.11	0.073	0.021	0.242	0.112	0.163	0.187	0.221	0.296	0.27	0.032	0.227
NBIX	0.039	0.3	0.086	0.154	0.035	0.038	0.244	0.063	0.002	-0.013	0.09	0.424	0.286	0.057	0.092	0.3	0.178	0.095	0.18
NEOG	0.04	0.083	0.07	0.077	0.062	0.181	0.055	0.058	0.019	0.008	0.194	0.145	0.286	0.039	0.266	0.183	0.286	0.043	0.147
NFLX	0.079	0.092	0.135	0.152	0.031	0.004	0.145	0.075	0.018	-0.013	0.108	0.136	0.104	0.047	0.167	0.24	0.196	0.078	0.136
NG	0.063	0.069	0.053	0.154	0.069	0.168	0.065	0.091	0.015	0.128	0.019	0.189	0.155	0.057	0.111	0.081	0.177	0.053	0.14
NGD	0.078	0.402	0.31	0.393	0.545	0.151	0.115	0.28	0.043	0.015	0.202	0.363	0.371	0.108	0.17	0.503	0.214	0.262	0.26
NGG	0.028	0.084	0.041	0.039	0.047	0.06	0.084	0.023	0.037	0.011	0.05	0.073	0.051	0.026	0.075	-0	0.07	0.023	0.094
NICE	0.025	0.04	0.032	0.011	0.003	0.001	0.051	0.084	0.018	-0.005	0.031	0.103	0.007	0.017	0.122	-0.001	0.051	0.058	0.068
NNI	0.028	0.081	0.058	0.081	0	0.05	0.085	0.033	0.06	-0.008	0.011	0.057	0.063	0.068	0.027	0.036	0.057	0.035	0.051
NNN	0.025	0.022	0.051	0.081	0	0.043	0.046	0.032	0.019	0.012	0.113	0.105	0.085	0.033	0.057	0.019	0.129	0.029	0.061
NOG	0.089	0.552	0.219	0.245	0.439	0.183	0.107	0.258	0.163	0.18	0.178	0.21	0.413	0.103	0.202	0.219	0.198	0.219	0.236
NRG	0.036	-0.005	0.048	0.083	0.013	0.049	0.081	0.077	0.027	0.002	0.019	0.139	0.165	0.04	0.138	0.097	0.168	0.043	0.101
NVMI	0.044	0.097	0.056	0.093	0.056	0.058	0.098	0.082	0.01	0.043	0.219	0.11	0.092	0.034	0.102	0.113	0.093	0.088	0.104
NVS	0.027	0.021	0.043	0.028	0.052	0.039	0.074	0.046	0.008	0.007	0.028	0.023	0.028	0.021	0.052	0.01	0.028	0.025	0.061
NWBI	0.031	0.055	0.027	0.057	0.046	0.029	0.042	0.038	-0.003	0.009	0.12	0.038	0.072	0.024	0.053	0.029	0.072	0.035	0.075
OGE	0.027	0.064	0.055	0.036	0.022	0.033	0.047	0.021	0.015	0.001	0.083	0.046	0.061	0.023	0.042	0.055	0.054	0.045	0.04
OMCL	0.034	0.08	0.127	0.126	0.042	0.042	0.144	0.189	0.202	-0.007	0.024	0.084	0.087	0.036	0.147	0.047	0.084	0.036	0.124
PAYX	0.036	0.021	0.059	0.023	0.036	0.031	0.062	0.018	0.008	0.039	0.075	0.046	0.054	0.026	0.028	0.015	0.06	0.053	0.076
PB	0.034	0.078	0.084	0.115	0.026	0.04	0.083	0.029	0.011	0.01	0.149	0.095	0.069	0.022	0.151	0.044	0.076	0.044	0.093
PCH	0.049	0.063	0.142	0.092	0.21	0.091	0.104	0.048	0.005	0.014	0.107	0.081	0.093	0.04	0.114	0.178	0.137	0.101	0.128
PDCE	0.082	0.121	0.106	0.095	0.564	0.627	0.276	0.157	-0.007	0.082	0.21	0.158	0.239	0.045	0.287	0.402	0.324	0	0.115
PDFS	0.067	0.246	0.204	0.1	0.113	0.069	0.115	0.092	-0.041	0.037	0.101	0.242	0.308	0.049	0.13	0.253	0.308	0.096	0.164
PDS	0.077	0.507	0.227	0.561	0.572	0.554	0.22	0.116	0.017	0.104	0.424	0.179	0.412	0.05	0.318	0.443	0.412	0.075	0.292
PERI	0.085	0.103	0.125	0.086	0.115	0.095	0.095	0.134	0.037	0.086	0.163	0.447	0.306	0.06	0.36	0.072	0.449	0.049	0.166
PHG	0.033	-0.004	0.06	0.184	0.01	0.024	0.181	0.048	0.01	0.005	0.057	0.062	0.136	0.027	0.162	0.128	0.136	0.064	0.074

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Ticker	MST	MS	MT1	MT2	MT3	MT4	MT5	MT6	MT7	MT8	TA1	TA2	TA3	TA4	TA5	TA6	TA7	DCC	B&H
PNM	0.033	0.071	0.046	0.084	0.1	0.083	0.091	0.024	0.006	0.004	0.031	0.074	0.132	0.028	0.035	0.092	0.118	0.036	0.076
POR	0.036	0.094	0.056	0.05	0.051	0.023	0.125	0.072	0.013	-0.02	0.09	0.03	0.111	0.018	0.002	0.074	0.12	0.046	0.07
PRGS	0.048	0.161	0.044	0.039	0.219	0.193	0.16	0.103	0.027	-0.003	0.208	0.072	0.163	0.07	0.142	0.159	0.193	0.052	0.136
QCOM	0.039	0.093	0.082	0.071	0.081	0.19	0.133	0.053	0.019	0.026	0.128	0.198	0.182	0.021	0.167	0.125	0.184	0.066	0.145
RAMP	0.056	0.094	0.076	0.215	0.013	0.022	0.069	0.144	0.045	0.043	0.289	0.131	0.153	0.045	0.186	0.021	0.091	0.026	0.182
RGR	0.056	0.058	0.059	0.139	0.09	0.09	0.263	0.043	0.05	0.043	0.124	0.207	0.163	0.064	0.185	0.141	0.163	0.073	0.18
RHI	0.04	0.066	0.075	0.06	0.016	0.052	0.146	0.049	0.016	0.009	0.034	0.166	0.138	0.032	0.182	0.152	0.138	0.062	0.128
RJF	0.044	0.107	0.047	0.083	0.031	0.03	0.064	0.043	0.035	-0.003	0.103	0.187	0.131	0.027	0.099	0.155	0.136	0.059	0.094
RL	0.073	0.112	0.121	0.12	0.178	0.053	0.236	0.094	0.023	0.125	0.15	0.188	0.147	0.041	0.217	0.201	0.147	0.059	0.151
ROG	0.063	0.143	0.153	0.169	0.15	0.061	0.231	0.153	0.02	-0.003	0.129	0.278	0.108	0.049	0.328	0.224	0.112	0.173	0.175
ROIC	0.027	0.064	0.042	0.06	0.054	0.026	0.101	0.057	0.007	-0.002	0.007	0.108	0.07	0.028	0.095	0.071	0.074	0.031	0.077
RPM	0.04	0.06	0.099	0.099	0.027	0.063	0.104	0.073	-0.019	-0.007	0.164	0.196	0.063	0.04	0.074	0.05	0.083	0.075	0.101
RPT	0.048	0.104	0.146	0.108	0.041	0.033	0.085	0.048	0.064	-0.008	0.106	0.095	0.129	0.026	0.096	0.108	0.115	0.033	0.185
RTX	0.038	0.142	0.036	0.054	0.025	0.015	0.05	0.037	0.008	0.108	0.129	0.11	0.126	0.024	0.154	0.185	0.118	0.036	0.112
RUSHA	0.035	0.089	0.05	0.126	0.176	0.068	0.166	0.202	0.019	0.028	0.134	0.098	0.151	0.05	0.152	0.139	0.118	0.083	0.156
RY	0.018	0.083	0.072	0.069	0.05	0.042	0.076	0.076	-0.002	-0.002	0.032	0.037	0.061	0.012	0.099	0.089	0.061	0.038	0.077
SAH	0.059	0.295	0.099	0.137	0.111	0.111	0.04	0.107	0.017	-0.002	0.142	0.266	0.108	0.052	0.101	0.131	0.177	0.083	0.13
SAIA	0.062	0.093	0.069	0.156	0.012	0.159	0.194	0.095	0.062	0.031	0.129	0.268	0.332	0.042	0.224	0.222	0.172	0.073	0.116
SASR	0.04	0.103	0.056	0.081	0.002	0.011	0.051	0.034	0.017	0.029	0.104	0.049	0.074	0.034	0.086	0.117	0.15	0.049	0.106
SBH	0.061	0.056	0.096	0.079	0.048	0.043	0.128	0.039	0.061	0.036	0.216	0.194	0.119	0.055	0.095	0.232	0.198	0.039	0.14
SBRA	0.053	0.098	0.057	0.096	0.045	0.054	0.096	0.063	0.006	0.026	0.118	0.12	0.136	0.03	0.063	0.047	0.197	0.059	0.098
SBS	0.055	0.157	0.089	0.108	0.148	0.116	0.28	0.077	0.012	0.013	0.088	0.355	0.335	0.084	0.322	0.241	0.35	0.046	0.125
SCI	0.04	0.056	0.032	0.104	0.011	0.028	0.076	0.034	0.015	0.028	0.128	0.112	0.052	0.029	0.074	0.036	0.059	0.037	0.064
SCVL	0.087	0.185	0.121	0.062	0.115	0.075	0.244	0.046	0.045	0.044	0.234	0.193	0.171	0.049	0.295	0.3	0.169	0.073	0.142
SEIC	0.051	0.151	0.098	0.086	0.121	0.046	0.147	0.077	0.027	0.018	0.071	0.137	0.137	0.034	0.146	0.202	0.137	0.051	0.132
SIEGY	0.042	0.022	0.056	0.04	0.038	0.027	0.163	0.057	0.01	-0.016	0.162	0.099	0.138	0.024	0.07	0.161	0.126	0.069	0.099
SITC	0.05	0.132	0.058	0.091	0.048	0.032	0.143	0.083	0.036	0.009	0.158	0.193	0.166	0.056	0.168	0.097	0.156	0.066	0.091
SKYW	0.045	0.186	0.056	0.117	0.023	0.075	0.14	0.077	0.008	0.018	0.213	0.089	0.074	0.037	0.124	0.142	0.07	0.081	0.095
SNX	0.059	0.052	0.109	0.068	0.149	0.027	0.076	0.107	0.029	0.012	0.161	0.179	0.14	0.064	0.244	0.06	0.139	0.062	0.151
SO	0.029	0.059	0.055	0.14	0.045	0.036	0.063	0.128	0.145	0.052	0.098	0.117	0.106	0.026	0.012	0.056	0.106	0.046	0.071
SRPT	0.109	0.084	0.148	0.149	0.097	0.158	0.148	0.054	0.043	0.034	0.128	0.17	0.445	0.086	0.4	0.335	0.445	0.131	0.174
STC	0.026	0.008	0.063	0.063	0.058	0.112	0.093	0.049	0.013	-0.002	0.066	0.094	0.071	0.036	0.093	0.075	0.092	0.046	0.081
STLD	0.063	0.067	0.107	0.113	0.291	0.094	0.151	0.073	0.023	0.019	0.061	0.123	0.139	0.04	0.211	0.258	0.135	0.059	0.143
STM	0.065	0.096	0.12	0.093	0.105	0.185	0.139	0.087	0.056	0.007	0.125	0.202	0.149	0.041	0.119	0.211	0.136	0.086	0.161
STT	0.048	0.076	0.097	0.101	0.156	0.114	0.238	0.06	0.025	0.005	0.187	0.149	0.136	0.031	0.195	0.127	0.14	0.067	0.172
STX	0.062	0.179	0.121	0.19	0.108	0.003	0.077	0.067	0.011	-0.01	0.167	0.078	0.06	0.061	0.114	0.092	0.078	0.09	0.13
SYNA	0.06	0.151	0.103	0.081	0.061	0.084	0.143	0.182	0.081	0.05	0.143	0.125	0.155	0.098	0.208	0.132	0.231	0.046	0.159
TDC	0.067	0.05	0.082	0.165	0.25	0.057	0.05	0.087	0.006	0.02	0.155	0.205	0.086	0.07	0.127	0.268	0.085	0.104	0.148
TEX	0.056	0.204	0.073	0.187	0.187	0.086	0.149	0.083	0.022	0.061	0.182	0.078	0.216	0.038	0.204	0.141	0.219	0.075	0.179
THG	0.034	0.082	0.034	0.05	0.004	0.017	0.055	0.052	0.027	-0.005	0.003	0.019	0.008	0.027	0.019	0.096	0.001	0.027	0.045
TITN	0.062	0.304	0.177	0.221	0.119	0.251	0.135	0.17	0.015	0.077	0.124	0.216	0.189	0.109	0.256	0.115	0.222	0.048	0.241
TLK	0.04	0.046	0.066	0.117	0.103	0.107	0.055	0.051	-0.002	0.045	0.04	0.119	0.119	0.047	0.177	0.163	0.119	0.036	0.066
TREE	0.083	0.136	0.171	0.136	0.231	0.115	0.062	0.076	0.023	0.006	0.109	0.251	0.262	0.123	0.15	0.128	0.195	0.101	0.224
TREX	0.043	0.222	0.07	0.077	0.034	0.061	0.065	0.057	0.064	0.062	0.095	0.119	0.168	0.161	0.072	0.191	0.194	0.097	0.173
TRMK	0.035	0.033	0.046	0.085	0.042	0.133	0.096	0.063	0.016	0.004	0.07	0.162	0.081	0.033	0.194	0.076	0.096	0.053	0.107
TSM	0.067	0.144	0.068	0.137	0.057	0.057	0.089	0.066	0.004	0.015	0.066	0.208	0.149	0.034	0.127	0.078	0.12	0.04	0.125
TTC	0.035	0.065	0.055	0.071	0.09	0.068	0.074	0.05	0.001	0.009	0.051	0.093	0.038	0.031	0.161	0.089	0.038	0.039	0.09
TU	0.018	0.007	0.046	0.076	0.019	0.033	0.038	0.056	0.029	-0.005	0.115	0.027	0.048	0.023	0.046	0.032	0.031	0.032	0.063
TXN	0.042	0.092	0.06	0.05	0.141	0.035	0.081	0.06	0.061	0.007	0.031	0.09	0.071	0.051	0.076	0.082	0.105	0.046	0.105
TXRH	0.026	0.016	0.075	0.125	0.04	0.054	0.045	0.047	0.011	0.017	0.204	0.065	0.101	0.026	0.137	0.035	0.072	0.055	0.122
UBSI	0.031	0.069	0.065	0.053	0.049	0.041	0.104	0.063	0.028	0.012	0.072	0.13	0.071	0.027	0.171	0.062	0.091	0.054	0.088
UGP	0.069	0.112	0.087	0.367	0.128	0.18	0.378	0.14	0.071	0.029	0.277	0.428	0.528	0.078	0.261	0.583	0.528	0.131	0.22
UHS	0.027	0.019	0.042	0.081	0.048	0.027	0.115	0.05	0.017	0.026	0.114	0.022	0.029	0.046	0.081	0.049	0.037	0.058	0.074
UHT	0.041	0.146	0.082	0.13	0.05	0.066	0.049	0.045	0.005	0.028	0.061	0.205	0.154	0.047	0.116	0.113	0.187	0.041	0.136
UNF	0.042	0.137	0.091	0.094	0.08	0.203	0.199	0.035	0.018	0.042	0.094	0.104	0.122	0.036	0.124	0.155	0.16	0.042	0.071
WEC	0.044	0.043	0.04	0.076	0.047	0.016	0.113	0.026	0.009	-0.009	0.137	0.1	0.073	0.021	0.028	0.028	0.051	0.042	0.05
WELL	0.032	0.082	0.027	0.074	0.062	0.058	0.093	0.066	0.02	0.003	0.072	0.109	0.142	0.016	0.045	0.115	0.142	0.027	0.06
WEN	0.031	0.054	0.062	0.046	0.075	0.019	0.116	0.035	0.001	0.001	0.057	0.081	0.038	0.041	0.074	0.02	0.041	0.039	0.089
WIRE	0.043	0.05	0.045	0.156	0.088	0.08	0.145	0.034	0.015	0.04	0.106	0.068	0.123	0.031	0.076	0.091	0.098	0.05	0.112
WLK	0.067	0.176	0.123	0.058	0.254	0.068	0.159	0.102	0.025	0.064	0.175	0.116	0.198	0.039	0.126	0.363	0.259	0.1	0.14
WMK	0.027	0.196	0.09	0.214	0.169	0.033	0.142	0.177	0.006	-0.002	0.101	0.285	0.143	0.05	0.128	0.214	0.17	0.075	0.094
WMT	0.028	0.042	0.068	0.081	0.028	0.04	0	0.053	0.015	-0.002	0.102	0.108	0.099	0.039	0.078	0.129	0.099	0.064	0.058
WOR	0.049	0.119	0.085	0.071	0.113	0.031	0.138	0.073	0.006	0.02	0.095	0.073	0.093	0.039	0.071	0.092	0.072	0.061	0.148
WPC	0.028	0.052	0.066	0.034	0.06	0.057	0.07	0.068	0.029	0.008	0.092	0.072	0.08	0.027	0.072	0.048	0.106	0.033	0.073
WSM	0.054	0.054	0.058	0.075	0.025	0.035	0.037	0.05	0.062	0.008	0.062	0.135	0.055	0.045	0.215	0.124	0.07	0.059	0.089
WTI	0.101	0.055	0.305	0.204	0.441	0.071	0	0.202	0.049	0.004	0.2	0.35	0.344	0.074	0.344	0.323	0.347	0.196	0.3
WW	0.107	0.118	0.27	0.223	0.055	0.071	0.327	0.105	0	0.001	0.058	0.254	0.518	0.089	0.245	0.679	0.518	0.112	0.241
XPO	0.074	0.363	0.103	0.241	0.033	0.102	0	0.062	0.034	0.044	0.046	0.212	0.477	0.048	0.236	0.436	0.477	0.104	0.232

Table B.5: Sharpe Ratio Results for MSTGAM (MST) versus sub-strategy for St1θ1, $\cdots$ S2θ8 experimented in Chapter 6, where cardinal numbers denote specific sub-strategies (e.g., 1 = St1θ1, 18 = St2θ8) as described in Section 6.4

Label	MST	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
AAON	7.7	7.3	5.5	5.4	2.6	0.1	0.4	8.3	-5.6	0	1	8	0.8	4.8	9.7	8	2.5	3.3	2.9
AAPL	7.2	6.4	-2.1	-4.7	-3.1	-5.2	-5.7	-5.6	-5.6	-5.5	-3.4	4	5.5	2.9	7	5.5	-2	-2.5	3.7
ACM	12	3.8	1.6	-1.5	5.6	4.6	0.7	0.6	-7.3	-2.2	1.6	-8.2	1.3	0.4	1.6	-7.8	1.9	1.6	3.7
AG	5.9	3.2	4.1	2.5	3.4	2.7	2.1	1.4	2	0.9	-8.9	3.9	2.7	3.4	2.6	1.1	2.9	1	5.5
AGEN	2.1	0.9	1.2	-1.5	-3.8	-10.6	-0	0.7	2.4	2	-1.7	1.5	1.5	-0.4	0.1	-1.6	-0.4	0	1.2
ANDE	11.5	-10.2	3.2	-1.7	-1.8	-8.3	-1.3	-1.7	3.3	-2.6	-5.2	4.8	-2.6	-4.7	-2.2	1.3	-3	3.8	1.8
ASGN	12.3	-2.1	-1.2	-2.5	-3.4	-2.2	-6.2	-1	-0.5	-4.1	-1.5	-1.3	-4.1	-2.5	2.4	-0.4	0.2	3.4	1.8
AWI	10	9.2	8	6	4.8	2.7	-1.6	0.8	-3.9	0.3	-2.7	3.2	3.9	3.6	5.1	2.3	3.4	3.3	4
BANR	5.1	-4.6	-1.8	0.4	-5.1	3	-10.7	-6.6	-6.1	-4.6	-0.9	-1.2	4	-1.4	-0.6	-2.4	-1.4	-2.1	-4.1
BCPC	3.3	-4.7	-7.3	-7	-5.2	-4.1	-4.8	-5.4	-5.1	-3.8	-3	-0.9	-1.8	0.8	2.9	-0.2	0.9	-1.7	-0.1
BG	8.3	-11.1	-5.9	-3.5	-9.5	-9.8	-8.1	-5.4	-5.9	-2.9	-1.6	-7.6	-4.8	-7	-5.7	-7	2	0.5	-0
BHLB	-5.6	-2.6	5.5	1.2	-1.6	-2.2	-2	4.6	-7.6	-1.1	-4.1	1.7	-1.1	2.1	1	2.4	1.7	-0.1	-2.6
BHP	7.2	6.4	0.8	-5	-0.3	0.3	-7.8	6.6	4.5	1.7	3	1.1	1.2	10	2.2	1.2	1.2	6.8	1.7
BKR	-6.8	-7	-2.2	-2.9	-4	-1.3	-7.2	-3.6	-3.3	-3.4	-4.9	3.6	4.2	3.2	1.7	-0.4	-2.1	-0.9	2.1
BMI	12.7	6.5	2.8	4.4	-2.8	3.7	6.2	3.7	-5.7	-4.2	-3.9	2.4	0.1	3	3	-1	-5.6	-2.8	7.1
BMY	5.4	-1.2	-0.8	-3	-3.5	-2	-2.6	7.4	-8	-3.1	-2.5	-0.8	0.7	7.1	-0.3	2.8	-4.1	-0.1	1.6
BSAC	-2.7	-6.5	-5.5	-4.2	-3.4	-3.5	-3.5	-1	-3.7	-4.9	-2.6	-2.2	-3.9	-2.7	-2.1	-4	-4.2	-4.8	-4.4
BSBR	22.4	2.1	3.1	-4.1	-4.5	-1	-0.3	3.1	-0.7	1.8	0.5	-0	2	2.1	-0.5	-2.6	1.9	0.4	-4.5
BSX	11.3	8.3	2.8	0.1	4.9	4.7	-2.1	0.9	-1.6	-3	-0.4	2.4	2.2	-0.3	13.7	4.1	6.8	4.2	2.1
BX	8.6	4.7	11.1	8.2	3.8	9.8	9.4	-1.2	0.6	-2.5	-3.7	4.5	-2.3	5.2	4	2.5	0.6	-0.1	-1.8
BYD	1.1	-6.2	-2.1	-19.6	-8.4	-8.3	-4.7	-6	-9.3	-6.3	-6.6	2.2	1.2	-5.7	0.1	0.1	-0.2	-9.3	-5.3
CBZ	19.9	7.6	4.3	4.7	0.3	-3.5	4.9	2.1	2.8	3.5	0.8	5	4.9	3.6	5.6	3.3	6.9	3	4.5
CCEP	16.6	3	2.1	2	0.3	-2	2.7	2.5	-1.8	0.4	0.1	5	5.1	7.3	-0.6	2.3	0.1	0.7	2.2
CCI	5.2	-5.2	1.9	3.1	1	-5.3	-4.4	-0.1	3	4.9	5.4	-2.5	0.6	1.6	3.7	2.5	0.6	-1.5	12.3
CCL	-11.7	-11	-8.4	-2.5	-11.1	-11.1	-7.6	-6.3	-6.2	-6.6	-8.4	-6.9	-4.9	-4.3	-3.6	-6.9	1.5	-4.1	-2.9
CHH	7.1	-0.3	0.1	4.4	-2	1.1	6.1	-1.2	-0.9	-0.9	-3.4	0.1	-2.3	-3.7	-0.9	-1.5	0.6	-3.3	3
CMP	3.1	6.6	6.3	3.2	-2.1	-0	-1.7	3.7	-6.8	4.5	-2.7	-4.4	-2.1	2.9	3.4	-1.2	-1	-4.9	2.4
CNK	2.8	-1.2	-6.6	2.2	0.3	-8.9	-11.9	-5.8	-3.2	-1.4	-2.1	-3.8	-2	-4.8	0.7	0.8	1.7	-0.2	-2.8
CNXN	7.6	9	5.9	6.2	8.3	1	-1.1	-3.5	-2.6	2.7	2	1.5	4.7	4.9	-1.1	4	2.9	-1.5	0.4
COST	8.9	9.1	-16	-9.4	-7.2	-6.9	-4.2	-3.8	-3.7	0.5	4.1	3.1	1.5	7.5	5.4	3.1	6.7	-1.3	-0.6
CRK	1.4	4.1	3.5	2.5	-0.9	-9	1.1	0.7	2.2	2.1	0.6	-0.9	-4.3	0.7	1.5	0.2	1.4	2.3	3
CSV	7.8	-9.9	-7	-3.9	-2.5	-4.8	-4.2	-5.5	-3	-2.2	-2.9	0.5	-3.3	1.3	1.9	0.7	0.1	-1.8	0.1
CUBE	3.5	-0.1	-5.5	-0.7	2.7	-0.9	-4.2	-3.8	-3.7	1.8	-1.8	2.9	5	-0.9	2.2	5.3	-0.9	3.2	0.9
D	4.5	-1	-2.4	-11.7	-6.2	-4.8	-1	-2.7	-0.8	-0.8	-0.4	-0.3	-1.3	-1.7	-3.5	-2.2	-1.8	-1.5	-3.1
DCOM	0.6	-0.4	2.1	-1.2	-0.3	-1.5	-0.6	-5.4	-4.5	-1.2	-3.5	-5.7	-0.7	-0.9	1.1	-5.8	-5.7	-0.6	3.3
DDS	4.8	-12.9	-13	-9.8	-4.2	-21.5	-14.9	-8.5	-5.4	-4	-7.8	2.5	-1.9	1.4	-0.6	0.4	3.4	4.3	6.1
DENN	15.2	4.6	5.3	1.2	-6.7	-2.5	-3.4	0.9	2	1.2	2.9	3.1	1.6	2.3	1.6	-1.3	3.7	-0.5	-2.1
DIOD	4.7	-7.4	-9	-4	0.5	-2.3	2.2	2.5	4.5	1.7	1	4.8	3.1	1.4	1.8	4.9	5	-0.4	0.9
DIS	17.2	6.4	5.7	4.5	1.8	3	4.7	-0.7	4.1	6.9	2.5	-3.2	3.6	0.7	3.6	4.5	-4	-4.4	2.5
DRQ	-3.3	-3	0.6	-4.4	-3.6	-1.2	-0.3	-0.8	-0.2	-1.3	-4.7	-1.8	2.5	2.3	1.4	1.1	-1.1	0.6	-1.2
EAT	21	2.9	0.8	3.6	-10.9	-8.2	-6.5	-2.2	-5.9	-5	-3.5	2.4	6.8	3.5	6.3	0.8	-0.7	-1.3	0.1
EBR	8.2	3.6	4.9	0.9	-6	1.4	3.7	2.7	-0.9	1.2	-1.8	2.3	-0.4	4.2	1.1	1.9	2.9	0.5	4.3
EC	7.2	0.4	-6.2	-2.9	-3.2	-7.1	-1.6	-3.3	-1.8	-1.4	-3.9	-2.7	3.3	2.4	0.9	1.8	2.5	0.5	0.8
EFSC	-1.4	-6.9	3.9	-5.2	3.1	0.5	-3.5	-2.9	-3.2	-3.6	-3.1	1.6	-1.6	0.2	2.6	-5.3	-0.9	-2.3	-7.6
EGHT	6.2	2.9	5.6	1.1	7.2	3.6	6.2	8.4	3.7	9.4	6.8	0.3	1.3	-0.7	3.6	2.5	3.5	7.6	5.8
EGO	6.9	2.6	-1.1	2.5	2.3	2.8	2.8	-2.2	2.2	1.9	3.5	2.6	2.5	2.5	2.5	4.6	2.4	0.9	1
EMN	-5.3	1.4	0.2	-6.1	-3.7	-3.5	-6.7	-8.2	-6.5	0.2	-2.3	-0.5	-1.1	7.1	-3	-4.5	-0.6	1.8	0.3
EQR	8	0.6	-1.9	-0.4	-0.9	-4.4	-3.5	2.1	2.4	3.5	-0.3	2.4	1.4	-0.4	-0.7	-1.8	-1.5	-0.3	0
ERII	10.9	1.4	-3.4	-2.3	-5.8	-0.6	1	-2.1	-0.1	-3.5	-0.6	-2.4	1.1	-1.3	1.3	2	0	-1.2	-3.3
ERJ	-5.2	-6.6	-5.2	-5.8	-0.6	-7.5	-3.6	-4.4	-5.4	-1.6	-5.3	2.1	-1.1	-1.2	2.1	0.9	-0.8	1.5	0.2
ET	5.2	-7.5	-2	-0.9	-2.3	-4	-4.8	-7.2	-6.5	-6.6	-4.3	-3.4	3.1	-1.4	-3.1	1.3	-3.2	0.8	-0.6
EVR	7.4	-2.9	0.1	-1.9	0.9	-9.3	-0.5	-3.9	-9	-4.3	-4.8	-1	-3	2.2	0.2	2.4	-0.2	3.3	3.8
FARO	8.6	-3.4	1	-0.2	-3.6	-1.9	1.7	1.5	2.3	-0.5	-1.2	0.3	-1.1	-0.2	-2.6	4.4	3.3	2.3	1.5
FBNC	4.4	5.1	2.8	-6.8	-13	-7.7	-6.3	-6.9	-3.7	-3	-0.7	2.5	2.7	-1.8	1.4	3.6	1.1	5.2	0.4
FELE	10.7	-1.1	3.2	-4	-2.9	-2.2	-2.7	-2.8	-4.8	-1.7	-0.9	0.4	-0.9	0.8	13.3	2.2	3.4	2.9	1.1
FFIN	8.4	4.3	7.3	8.6	4.2	10.4	7.5	12.5	-1.4	-1.1	1.2	2.5	2.5	4.9	10.9	3.5	2.8	4.1	6.7

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Label	MST	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
FISI	-3	-3.4	-1.6	-8.1	-4.5	-2.5	-3.1	-3.3	-5.7	2.2	-1.3	-3.6	-4.5	0.8	1.1	0.4	-6.6	-3.7	-0.4
FIX	13.6	5	4.8	3.7	4.4	2.5	-3.1	-1.3	3.6	5.5	-1.5	-0.8	3.4	-4.4	2.1	1.2	0.8	0.1	4.8
FLO	4.2	-9.9	2.9	4.3	-1.3	1.5	-2.7	-7.2	-7.1	-12.8	1.5	6.3	1.2	-4.4	1.8	4.2	0.3	0.6	4.2
GCO	16.5	4	-2.9	8.7	5.2	-1	-2.8	-1.8	0.2	-0.4	0.1	-3.9	-2.6	-2.8	-1.5	-1.1	-0.6	-0.5	-1.2
GD	8.6	3.3	-4.9	-11.8	-5.3	-1	-6.2	-6.3	-5.5	-4.4	-1.6	-3.7	-0.5	1.2	0.9	-1.6	-6.3	1.2	0.7
GE	-7.2	-2.2	-4.7	-1.2	-0.8	-2.7	-6.4	-9.6	-2.8	-2.1	-6.3	-4.3	-1	-5.5	-3.2	0.7	-3	-0.1	1.7
GSAT	7.1	-6.3	-6.3	-5.6	-11.8	-9.4	-8.5	-4.3	-3.3	-4.3	-6.2	-3.9	-3.9	-3.9	-3.9	-2.9	-2.9	-2.7	-2.7
GTE	14.6	-4.1	-3.1	-5.1	-2.3	-1.7	1.2	0.7	0.6	-3.9	-3.8	-2.2	-2.2	-2.9	-2	-2.9	-3	-1.4	0.1
GTLS	2.9	-9	-7.9	-15.9	-8.8	-8.7	-5.4	-8.8	-7.1	-9.7	0.5	-4	-12.6	3.7	0.4	-1.2	1.1	-0.8	0.7
GTN	3.1	1.5	3.9	5.6	-8.7	-2.2	-4.2	4.8	3.2	3.3	2.3	1.5	1.8	4	-1.9	-6.1	-3.6	-0.9	0.8
HA	7	3.2	-3.1	-4.2	-4.6	-1	3.2	-6.3	4.9	-8	0.7	-1.1	-4.8	-5.8	-0.8	1.2	-2.3	-0.3	3.5
HELE	14.1	8.1	6.5	6.4	7.7	-6.1	-0.9	5.4	-4.6	2.1	2.1	4.4	4.8	-0.4	5.4	0	3.9	2.7	2.2
HIW	5.6	-7.5	-4.2	-0.9	-4.6	-4.1	-5.3	-4.2	-2.4	-3.8	-7.6	-2.9	-1.1	1	0	-0.2	0.9	3.7	2.1
HLX	8.5	2.2	5.5	-0.1	5	-0.9	2.3	0	3.3	-4.4	1.7	-2	0.4	1.7	-1.6	2	3.6	3.7	0.6
HMY	3.7	3.9	3.3	-4.3	2.4	2	0.5	-1.9	1.7	-1.3	-0.2	1.1	1.1	1.9	2.4	1.8	1.8	3.7	2.9
HOPE	3.6	0.3	1	-2.8	1.8	-4.9	1.2	-1.6	-1.7	0.6	-3.1	0.8	2.4	-1.6	-10.7	-2.7	-0.2	-7.2	-5.4
HRI	9.7	1	1.9	1.8	-1.9	-5.5	-1.8	0.2	1.1	-9.9	-9	-5.4	-3.4	-5.7	0.4	-1.3	0.2	0.2	2.4
HWC	-2.2	0.9	1.8	0.4	3.6	-5.8	-10.2	-5	-5.9	-6.4	-2.1	-5	-1.3	-6.4	1.4	-2.1	-0.2	-10.5	-4.3
IART	10.7	-0.1	-1	2	3.3	2.6	1.2	7.1	5.1	0.7	1.4	2.6	-2.6	-3	-3.5	-0.6	-0.3	-0.6	1
IDT	8.9	-2	-2.5	-3.4	-5.5	-3.8	-2	-6.5	-1.9	-4.8	-0.5	-4.6	-8.8	-2.1	-5.4	0.5	-2.1	0.3	1.9
IMAX	-4.3	-1.6	0.3	-1.2	-1	5.4	6.8	-4	-1.4	-0.8	0.9	-1.5	-1.5	-2.4	-3.5	-3.2	1.9	-1.1	0.3
IMGN	-6.5	2.9	-6.2	-1.4	-3.8	-4.6	-1.1	-4.4	-3.5	-3.2	-4.7	-0.6	-0.5	-0.9	-0.2	0	-2.7	4.5	-0.9
INSM	7.1	-0.4	1.5	-11.3	-8.3	-4.2	2.7	2.1	-8	-7.5	1.6	1.7	1.9	0.8	-2.5	1	1.1	1.2	2.1
IOSP	3.4	0.7	2.9	-0.2	1.9	2.1	2.2	2.6	4.4	-2.5	-1.1	4.4	3.1	10.4	3.9	2.2	-2.5	2.2	5.8
IP	-0.9	3.1	-4.6	-0.8	-3.9	0.5	-12.1	-11.9	-15.3	-7.6	-3.7	-0.7	-1.3	1.3	-4.8	3.7	-6.3	-2.2	-6.1
IPAR	9.7	5.8	2.8	5.3	4.2	1.7	5.7	2.2	5.4	2.9	-1.5	-1	-1.6	0.5	2.2	3.2	4.2	7.2	9.8
IRBT	-8.3	-5.1	0.7	-2.6	-1.2	-14.4	-11.9	4.1	1.1	-0.9	-6.2	-5.2	-1.4	-2.4	-0.1	-0.6	-1.6	-2.8	-4.3
IT	3.6	-8.8	-5	-1.9	-6.4	-7.6	-5.3	-4	-3.2	-4.3	-1.6	-0.7	0.4	5.9	-1.6	-1.2	0.7	6.5	2.7
ITGR	4	-10.5	5.1	6.5	3.8	4.9	4.5	6.3	4.6	2	-1.4	-1.7	1.5	5.7	-0.2	4.5	4.5	2.4	1.5
ITT	12.2	-3.2	-3.9	-7.6	-6	-5	-3.8	-1.2	0.4	-1.9	1	-2.7	1.8	8.1	1	6.2	11.1	11.5	3.9
JKHY	13.2	-11	-10.2	-12.1	-8.6	-6.8	-5.2	-3.1	-2.6	-1.9	-1.6	2.1	2.6	1.8	1.3	1.7	2.7	4.7	0.3
KAI	5.9	-3.8	-4.2	-20.1	1.2	-11	-2.4	1.1	3	-5.6	-2.7	1.6	1.1	2.6	3.9	-1.5	-0.5	0.2	-4.5
KBR	4.6	7.3	-2.4	-6.1	-5.8	-9.8	-11.2	-7.8	-2.5	-0.8	-2.1	-3.9	-1	16.9	2.6	0.1	1.7	2.2	4.6
KFRC	4.9	4.7	5	5	1.7	6.8	5.9	1.3	2.3	3.6	2.2	2.4	4.2	1.3	3.8	7.9	7.1	-0.2	-0.5
KLIC	5.8	-4.8	-2.9	4.8	-2.9	-3.1	-2.5	1.6	1.6	-2.6	-1.7	3.8	1.7	-3	-2.4	0.8	-4.5	0.5	-7.4
LANC	18.2	-0.9	-2.4	-0.8	2.1	4.4	-3.4	0.8	0.1	-1.2	1.1	0.9	5.4	2.4	4.4	0.6	0.9	0.5	3.4
LBAI	-5	1.3	0.3	-3.9	-2.6	-2.9	-3	-5.1	-3.6	1.3	-3.7	-1.2	-0.7	1.4	1.4	-1.4	-1.6	-0.5	-2.2
LMAT	8	-3.1	8.4	-4.3	5.4	1.1	-1.2	0.2	1.3	-3	0.7	1.3	1.4	-1	-1	-1.8	-1.6	0.5	-0.3
LOW	19.2	-0.6	-7.2	-7.9	-5.2	-5.9	-8.1	-3.1	-0.9	-6.3	-2.6	2.2	5.7	0.4	2.7	-1.8	-0.1	1	7.2
LRN	7	3.4	6.8	6.9	5.3	-5.7	-2.9	-1.5	-4.3	-3.9	-2.6	5.5	0.4	1.7	0.1	0.1	0.7	-1.3	-0.8
LSI	1.7	0.1	-5.4	-8.2	-3.5	-2.7	-5.6	-0.8	-2.3	-3.1	1.4	-0.5	3.1	5.3	2.6	0.6	-0.7	2.1	-5.5
LYG	4.6	-7.5	-4	0.5	-9.9	-0.2	0.4	-17.7	0.5	1.2	-1.1	-1	-1	-2.2	-0.7	0.7	-1.4	-2.2	-6.3
MCY	1.4	-10.6	0.5	-3.8	-6	-0.1	-5	-3	-1.1	-4.5	2.2	1.8	-5.2	-2.5	0.2	0.4	-1.2	-0.8	-2.4
MDC	1.2	2.8	6.3	0.9	3.1	-1.1	1.1	3.3	-2.3	2.8	0	2.2	1.8	3.1	1.9	4.9	2.9	7.9	-2
MGM	9.1	-1.2	5.9	0.1	-5.3	-0.1	-5.8	-1.4	-0.8	-0.8	-12.4	2.8	-0.5	-1.1	-1.7	-0.8	-3.6	-1.6	-1.1
MGRC	5.6	3.4	0.6	0.6	-1.1	1.2	2.2	-3.9	-2.4	-1.8	0.8	3.5	2.4	2.6	-0.1	2.3	3.6	0.8	-0.5
MIDD	-6.4	-5.3	-2.9	-3.1	-0.5	-3.8	-6.5	-5.5	-7.5	-5.8	-3.4	-0.4	-1.5	3.9	-4	-3.8	-3	-2	-0.3
MRO	-5.2	-3.2	-0.3	0.9	-4	-6.6	-4.2	-1	0.1	-3.9	-2	-0.7	-0.1	-0.4	-2.2	-1.4	-5.3	-3.4	-6
MSA	6	0.5	-2.2	-4.1	2.4	-4.1	-6.4	-4.8	-5.3	-4.2	1.1	-0	-2.9	-3.5	4.1	-1.7	-0.7	2.8	2.7
MT	-7.9	-8.7	-6.3	2.7	-8.4	-7.3	-13.3	-7.4	-1.8	-6.3	-2.7	-3.3	-3.5	-0.7	-0.6	-2.9	-2.5	-5.9	-4.1
MTZ	6.7	4.3	1.9	-0.1	-6.1	9	7	0.9	1.1	-3	4.2	2.7	2.7	4	5	4.1	3.6	3.9	2.9
MYGN	8.9	7.4	5.2	-4.7	-8.4	3.6	-0.6	1.3	2.2	-3.3	-3.3	1.3	-1.1	-0	-1.8	0.8	0.3	-1.5	-4
NBIX	5.9	-12	1.9	3.5	2.8	-2.5	-1.2	1.8	0.6	-4.5	-3.1	1.4	1.3	2.7	2	2.1	-0.5	1.7	-0.1
NEOG	13.1	-9.7	-3.3	-3.2	0.3	-3.2	-2.5	-1.4	-2	-2.2	-2	4.8	-2.2	-1.4	5.2	-2.6	0	-3	-1.5
NFLX	2.6	-0.4	-2	-17.4	-3	-22.5	-14.6	-14.5	-11.7	-3.2	-1.9	4.1	-1	-3.7	-0.3	0.9	2.1	1.6	3.2
NG	1.9	5.2	-1.9	-2.3	3	3.1	2.6	3.4	6.6	-0.9	5	2.4	3.2	2.4	2.6	2.9	3.8	3.6	2.9
NGD	7.2	-6.4	-7.4	-4.9	-4	-5.5	-3.9	-6.4	-5.5	-3.9	-6.2	-7.9	-7.9	-4.6	-4.6	-1.9	-5.8	-7.2	-8.3
NGG	1.4	2.4	-4.6	-7	-11.9	-3.1	2.4	3.9	-4.2	0.3	-1.7	-2.4	0	0.4	-0.5	3.9	1.7	1.9	9.8
NICE	16	1.7	1.7	5.6	6.1	-1.5	0.5	0.9	3	2.9	-0.3	3.8	4.3	5.3	3.2	7.3	6.1	5.1	2.7
NNI	5.9	2	8.9	0.8	-0.3	-7.7	-3.7	-4.9	-4.1	-4	-1.4	-1.1	-1.6	-6.9	-0	1.5	-8.3	-1.6	2

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Label	MST	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
NNN	13.2	2.1	5.7	10.2	-4	0.4	-0.4	4.7	4.1	1	1.5	5.1	0.3	3.7	-0.3	3.8	6.6	2.8	5.1
NOG	6.8	-4.6	-1.8	1.2	-0.8	0.4	1.4	0.3	2.9	1.9	1.4	2.1	2.1	3.7	2.9	5.5	4.8	2.8	1.2
NRG	11.2	2.7	4.8	8.9	6.7	-2	-3.9	-3.6	-3.5	-2.6	-3.5	1.4	1.9	2.3	-0.2	2.7	-0.4	-1.4	6
NVMI	-1.4	-1	0.3	5.7	-0.8	1.1	-0.2	2.9	2	-1.1	2.7	1.9	2.5	3.1	1.4	2.2	2.3	1	-2.2
NVS	1.4	0.9	4.1	3.7	-5.9	-2.3	-6.7	-0.1	-3.5	-2.1	-1.4	-1.5	0.8	-0.4	2.9	4.9	-0.4	1.3	-0.5
NWBI	0.3	1.3	-1.4	-2.9	-0.2	-0.3	2.1	-2.1	-4	-2.5	-4.2	6.6	0.6	-0.7	-1.2	1	1.6	-1.3	0.5
OGE	7.7	-4.4	-5.6	-2.9	3.3	-7.3	-1.7	-2.9	-2.6	2.4	-1.2	0.4	1.3	4.2	1	3.5	3.1	1.6	-0.1
OMCL	5.4	-0.4	5.8	10	-4.1	3.1	-1.8	-6.9	-10	4.5	-2.2	4.1	3	-1.3	1.4	0.7	1.7	1.6	3
PAYX	4.6	2	11.4	-3.8	0.6	-4.9	-3.5	-7.6	-23.8	-13.3	-1.6	1.4	8.7	0.6	2.2	5.5	1.6	1.3	5.2
PB	6.8	-1.1	-1.1	-6.6	-3.6	-8.6	-3.6	0.6	1.1	1.7	-2.3	-0.8	5.4	0.2	3.9	0.3	2.6	-3.6	2
PCH	-1.2	1	0.3	-1.5	-2.6	-5.2	-1	-3.1	-1.7	-0.3	2.3	-1.9	-10.3	-2.8	1.1	-3.5	-1.9	-1.9	-2.2
PDCE	2.9	0.2	1	0.7	-3.8	-5.8	1.2	0.8	-0.4	-2.1	-1.3	-2.1	-1.8	-1.8	-2.1	-1.7	0.1	-2.2	-1.5
PDFS	4.8	0.1	-1.5	-2.5	-0.3	-4.6	-1	1.7	-3.2	-0.8	-0.9	2.4	1.6	0.6	0.9	3.4	3.4	4.3	1.6
PDS	11.1	-2.5	-4.4	-8.4	-7.9	-3.8	-4.4	-4.2	-6.2	-5.9	-2.6	-2.7	-2.7	-3.9	-3.1	-5.7	-5.6	-0.4	1.3
PERI	10.2	3.1	1.3	4.2	2.2	2.7	3.7	1.5	2.6	2.8	2.9	3.7	3.7	4	3.7	3.4	1.4	0.3	-0.4
PHG	7.1	-4.5	0.9	-1	-1.4	-2.1	2.3	1.6	-2.4	-4.8	-1.9	3.3	5.2	2.2	4.7	5.7	4.4	-1.4	0.6
PNM	0.9	-0.9	-3.2	-0.5	0	0.3	-0.7	-2.1	-7.2	0.4	-1	0.4	-1.4	2.7	-1.8	-2.1	1	-0.4	-4.1
POR	10	-8.4	-4.3	-1.5	-5	-5.9	-1.8	-2.8	-5	-1.7	-1.4	-4.5	-0.5	0.5	-3.6	-1.9	-0.5	-0.9	0.7
PRGS	5.3	-0.4	1.8	-3.2	-2	-2.4	-8.2	-2.2	-1.7	0.7	-3.1	-0.8	-2.6	0.1	2.7	-0.5	2	5	-0.3
QCOM	6.1	-15.4	-7.7	-8	-7.7	-5.2	-3.3	0	0.2	-7.6	-6.5	6.4	5.6	2.6	1.8	2.9	3.3	3.7	5.2
RAMP	10.1	-1	4.2	2.9	4.1	2.7	-9	-2.4	-3.5	-1.5	3.4	6.5	4.1	-0.1	2.5	4.2	5.4	0.2	2.5
RGR	3.1	-1.2	-0.9	-5.1	0.6	-2.4	-1.6	-5.4	-3.1	-5.5	-2.9	0.5	0	2.7	-4.5	-4.1	6.4	-3	0.5
RHI	6.6	-4.7	2.9	-0.8	-2.9	-6.3	-1.9	-6.9	-6.1	-4.7	-4.8	-5.8	-2	1.4	1.6	1.8	1.2	-1.3	0.9
RJF	3.1	-10.5	-8.1	-8.4	-13.5	-2.1	-10.4	-5.5	-5.6	-9	-5.2	0.1	-5.3	-3.4	6.8	-2.4	-4.1	1.6	1.5
RL	11.4	-8.1	-4.9	-14.6	-14.5	-3.5	-3.2	-3.1	-3.3	-5.2	-5.7	0.3	2.5	2.6	3.1	0.9	1.8	0.8	-3.6
ROG	9	-13.2	-13.1	-22.1	-7.7	-8.9	-7.1	-1.4	0.4	2.1	-8.7	-1.7	-0	4.7	1.2	-2.1	4.2	-1.2	-0.4
ROIC	5.1	2.3	4.2	0.7	-1.6	0.6	-4.9	0.6	2	0.3	-1.2	-0.5	2.1	-0.6	-0.7	2.5	0.8	2.6	1.2
RPM	9.7	-6.4	-5.8	-2.8	-6.4	-5	-1.9	2.3	-2.6	-7.2	-10.1	1.2	4.2	4.3	0.8	5.3	3.7	3.7	0.6
RPT	2.9	-3.5	-1.7	0.6	4.2	6.7	4.1	-4.1	-5.3	-2.3	-0.8	2.6	1.9	3.5	1.4	1.5	-2.1	-4.2	2.4
RTX	2	5	3.1	-1.8	1.4	3	-4.2	-4.2	-4.5	-6.6	-4	-2.9	-3.5	-3	-1.1	-6.3	1.5	0.4	0.5
RUSHA	6.5	-6.4	-5.8	-2.3	-5.6	-1.8	3.7	-5.4	-2.4	-1.1	-1.6	-2.5	0.6	1.4	0.3	-4.4	-2.1	-2.5	-0.7
RY	6	-1.1	-11.3	-9.9	-9	-5.9	-6.4	-3.3	-3	-1.7	-2	-1	1.8	-8.6	-2.2	-0.4	-2.3	-8	-3.6
SAH	9.8	5.7	4.1	7.4	3.6	5.8	2	0.8	-1.8	-1.3	-0.3	2.8	2.8	2.2	-3.3	0.8	-1.1	2.5	3.7
SAIA	3.9	4.1	3.5	5.8	2.3	1.8	2	0.3	5.7	7.6	3.9	2.8	3.3	-3.3	1.5	-1.1	-0.5	-2.5	4.8
SASR	-6.1	0.1	-0.4	-1.5	2.2	-3.5	-4.6	-1.3	-0.9	-4.5	-5.8	6.5	-1.5	0.5	-4	-2.6	-8.2	-1	14.5
SBH	3.3	3.5	4.6	-1.7	2.8	4.7	-2.2	4	-6.7	-2.8	4.8	2.2	-2.6	-2	-3	4.3	-1.7	-0.3	1.9
SBRA	4.1	-2.8	-5.5	1.8	-0.5	2.4	2.9	-0.4	0.8	-3.8	-1.1	3	5	1.5	6.3	3.9	3.4	2.8	2.5
SBS	11	4.2	6.9	4.6	6.4	0.6	0.4	-2.1	1.4	-1.2	-2.7	3	-1.9	1	-1.2	-3.6	2.4	0.4	-2.3
SCI	-1	8.2	4.3	4	-4.3	-2.8	-4.2	-3.4	-3.9	-3.6	-2.7	1.8	2	-2.7	5.3	0	-4.7	2.8	-1.8
SCVL	8.4	3.9	9.9	-1.9	-0.4	2.4	3	5.9	-0.9	5.9	-0.2	3.2	4.1	4.3	3.9	4.8	3.4	1.6	1
SEIC	-1.5	-3.1	-4	-8.4	-11.7	-7.9	-11.3	-7.1	-7.5	-4.6	-3.4	-4.8	-4.9	0.9	-1.5	1.4	-1.4	1.8	-2.5
SIEGY	2.9	-2.9	-1.7	-3.6	-7	-3	-4.2	-7.5	-4.4	-6.2	-2.6	-0.9	-2.1	-3.1	-7.7	-2.7	-2.5	-4.2	-5.6
SITC	6.4	2.9	-0.6	1.1	4.4	4.9	3.9	4.1	0.2	-0.5	2.5	1.3	3.3	3.7	1.3	3.1	5.5	-1.7	-2.1
SKYW	3.7	-5.4	-2.3	5	-1.3	3.7	-0.8	5	8.1	-0.6	3.7	-0.1	0.1	1.2	5.4	3.4	5.3	0.5	-1.3
SNX	-2.8	-4.5	-0.8	-4.1	-10.3	-6.5	-10.3	-7.9	-10.2	-8.5	-3.8	-1	-3.6	0.3	-0.5	-0.3	-0.1	-1.7	-3.2
SO	4.2	-0.9	3.6	-0.9	2.4	-2.5	-5.2	-3.7	-2.7	-1.5	-1.1	-2.8	-1.6	2.6	-2.5	-0.1	3.8	2	-3.4
SRPT	5.4	-0.5	-0	1.3	-1.8	0.6	-0.1	-5.1	-5.2	-2.8	-6.6	2.4	2	3.7	1.9	0.4	6.1	4.7	5.5
STC	2.8	3.1	3.8	-3.6	-9.9	-6.9	-2.6	-2.3	-2.1	-1.9	-5.6	2.2	0.7	-1.2	1.1	-2.1	1	-1.9	-2
STLD	-0.7	-16.1	-4.4	-3.2	-15.3	-15.2	-13.8	-12.2	-9.5	-7.4	-4	-0.4	-1.4	-6.3	-10.2	-0.8	-3.4	-1.5	-0.7
STM	5.7	2.4	-2.1	-0.3	-2.6	-2.8	-4.4	-8.9	-7.8	-9	-5.8	0.2	-3.5	-0.3	2.5	-0.7	-3.5	-1.9	0.5
STT	6.7	-2.4	-2.3	-3.1	-2.2	-12.4	-5.6	-4.9	-5.1	-6.6	-4.5	-7.3	-3	-1	0.4	2.9	-2.7	-5.9	-11.7
STX	16.6	0.8	-0	0.5	-9.2	-10.7	-6.7	-5.1	-5.1	-2.4	-1.4	2.2	2.5	3	4.4	-0.4	0.5	2.3	2.4
SYNA	4.9	2.4	2.7	-7.5	2.8	3.2	-2.5	4.6	4.9	1.3	-1.2	-1.5	-0.2	1.6	-0.6	2	2.9	-2.2	2
TDC	-3.1	0.3	-2.2	-6.1	-1.6	-0.3	-4.4	-0.1	0.5	-4.9	-2.6	1.3	0.4	2.1	2.3	-1.5	3.1	-2	-0.6
TEX	10.8	-3.6	-8.7	-4.8	-0.3	-3.1	-6	-7	-1.8	1.3	-5.5	-4.8	-5.7	-0.8	-9.2	-7.4	0.3	-7.1	-7.9
THG	1.1	2.6	-12.4	-6.2	-0.9	0.7	-2	-1.2	-3.6	0.8	-5	-2.7	-5.6	2.5	1.3	-4.4	0.3	2.9	-1.4
TITN	1.6	-4	-3.2	-7.6	-8.2	-2.8	-9.5	-3.6	-2.6	0	-9	-1.2	-7.2	1.5	0.6	0.7	-1.9	-0.1	-6.4
TLK	4	0.8	0.4	-4.3	0.4	0.9	-1.3	-3.4	-0.2	1.3	1.9	-8.5	-3.1	-2.7	0.2	1.9	7.4	-1.9	0.7
TREE	0.8	-11.6	-15.3	-15.5	-16.8	-14.9	-13.8	-9.7	-7.9	-9.1	-5.1	1.4	0.1	2.2	1.5	2.4	0.5	0.4	-2.9
TREX	15.5	1.9	6.5	3.3	3.9	-5.4	-1.1	4	6.2	1.7	-3.9	2.9	2.8	0.8	-1.1	3.4	6.7	2.5	1.7

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Label	MST	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
TRMK	-0.4	1	0.8	4.1	3.1	0.4	1.6	-1.2	0.3	-4.4	-0.8	1.3	4.5	-1.8	-0.3	-2	-2	1.6	-1.4
TSM	2.4	4.4	0.2	4.2	5.7	1.7	-1	-5.3	-6	-3.2	-1.3	-3.7	-2.7	-14.1	-0.5	2.6	-1	3.1	3
TTC	5.6	6.2	-0.2	-4.5	-3.8	-6.9	-7.7	-3.6	-3.5	-0.5	-0.9	-2.6	-0.4	3.4	0.2	-0.3	1.7	0.9	2.2
TU	11.3	-0.5	-0.6	5.1	4.4	-6.1	-7.2	2.5	2.9	3.9	5.6	1.8	1.1	1.3	6.5	1.8	4.9	0.3	5.5
TXN	8.6	-10.1	-7.9	-2.3	-4	-2.1	-7.3	-5.4	-3.8	-1.5	-1.4	-1.1	-5.8	0.5	2	-1.6	4.7	3.9	1.4
TXRH	6.2	-11.1	-8.1	-6.2	9.5	5.1	1.4	-2.8	-3.4	1.5	6.1	-0.3	-5.2	-3.1	-1.8	-1.9	2	0.1	-4
UBSI	10.6	-1.7	-0.1	0.7	4.4	-2.9	-7.8	2.4	0.2	0.9	0.2	1.1	0.7	4.9	4	4	-0.2	1.4	3.2
UGP	0	-5.2	-7.5	-14	-10.1	-4.7	-6.1	-5.6	-4.7	-3.6	-3.1	-3	-1.4	-7.6	-1.7	-5.8	-2.5	-2.9	-5.8
UHS	7.1	0.5	-8.3	-0.2	-2.7	-3.1	-2.7	-3	-4.3	-3.8	-0.7	0.6	5.3	4.7	1.5	4.6	4.6	-0.8	-1.1
UHT	5.6	3	2.6	3.3	2.7	2.7	0	-0.1	-1.8	-0.4	-0.1	-1.6	-1.5	3.2	3.2	-0.6	-2.4	-3.2	6.9
UNF	5.5	-2.5	2	1	-4.2	-2.6	-3.9	-3.4	-1.8	-5	-0.4	3.7	0	8.1	3.4	-3.9	-3.8	1.8	2.9
WEC	5.3	-2.1	0.6	0.4	0.8	-1.9	-2.9	-2	-0.9	3.2	2.9	1.8	0.6	2.3	1.2	-0.4	-1.3	-0.7	1.8
WELL	4.3	-0.1	-6.6	7.1	8.1	-3.8	-3.6	-4.5	-0.8	-3.2	0.2	-0.3	3.4	4.7	-0.2	1.2	0.7	-0.5	-0.2
WEN	9.3	-0.5	0.3	3	5	1.7	-6.3	0.6	0.1	3.5	2.4	6.2	5.8	6.5	7.7	0.3	2.8	4	4
WIRE	1.9	6.4	1.1	1.8	2.1	-6	-8.5	-5.1	-4.8	-3.4	-1.4	3.7	-5.5	7.8	-2.1	-1.4	-0.1	1.7	2.5
WLK	-1.3	-29.1	-24.6	-26	-19.3	-17.9	-17.1	-10	-9.4	-10.9	-8.2	-1.4	-2.2	-2.3	-0.4	-6.2	2.4	-1	1.6
WMK	17.8	-9.3	1.1	3.2	-3.9	-9.2	-3.3	-2.4	-2.5	-5.2	-2.6	-1.3	-2.2	-3.8	-0.5	-0.7	0.2	-1.4	0.7
WMT	7.4	4.2	-3.2	-0.1	-1.1	-1	1.2	-1.6	-2.6	-2.5	-7.3	-5.2	-0.6	-5.9	0.5	-1.9	2.5	2.4	3.5
WOR	8.5	0.6	-2.2	3.7	-4.2	-2.9	4.5	4.1	-6.5	-5	-4.6	0.6	-4.7	-1.4	-1.4	-0	-1.5	-1.3	-0.1
WPC	5.3	-4.4	-8	-7.7	-5.7	-1.1	-3.3	-2.7	-0.3	-1.6	-12.1	1.8	-0.7	3.7	0.3	-1	-1.7	3.2	-0.3
WSM	14.9	2.8	-0.5	9.4	1.5	-1.8	-0.4	-0.1	1.8	-3.4	-1.9	-0.5	5.5	7.7	2.8	9.9	2.9	6.1	3.7
WTI	7.8	-1.1	-5.8	6	-8	-2.7	-2.7	-6	1.9	2.1	-1.3	0.7	-0.2	3.4	0.6	5.4	2.7	1.4	-0.9
WW	-5	-6.6	-7.5	-14.1	-12.3	-6.3	-5.6	-11.1	-11.6	1.7	-6.8	1.1	-0.9	0.9	-0.8	0.3	-0.5	0.9	-0.8
XPO	4.7	-9.6	-4	-7.9	-8.4	-5.4	1.5	1.7	2	-5.5	-2.3	5.2	1.3	-5.1	-3.5	-4.5	1.4	-0.3	1.7

Table B.6: Sharpe Ratio Results for MSTGAM (MST) versus sub-strategy for St2θ9, $\cdots$ St3θ6 experimented in Chapter 6, where cardinal numbers denote specific sub-strategies (e.g., 19 = S2θ9, 36 = St3θ6) as described in Section 6.4

Label	MST	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
AAON	7.7	2.2	0.8	0.3	0.8	1.4	-3.7	-3.2	1	4.5	2.1	-5.3	-1	3.5	3.7	2.3	2.3	2.6	-4.7
AAPL	7.2	1.7	2.3	3.5	3.9	-0.2	2.6	3.2	-0.9	-3.2	5.1	2.1	-0.3	4.8	-0.7	-4.5	3.8	1.8	-0.1
ACM	12	-1.2	-2.5	-3	-3	-6.7	-3.7	-1.4	-6.9	2.1	0	0	1.2	1.5	-1.1	-7.9	2.1	-2.4	-1.2
AG	5.9	-3	-3.6	-5.4	-1.5	-1	1.4	0	-2.1	-7.7	4.1	-7.7	1.9	1.7	1.4	-3.2	-0.6	3.5	-1.7
AGEN	2.1	1.1	-1.6	0.3	-1.8	-0.5	-0.6	-0.6	-0.6	0.4	0.9	1.3	3.5	3.2	3.2	4.4	0.5	-2.3	3.2
ANDE	11.5	-1.4	1.5	2.8	1.6	-1.7	-1.2	0.3	-0.8	0	3.4	3.5	5.8	-11	-2.3	-2.4	-2.9	-0.6	-3.4
ASGN	12.3	-3	-1	-1.3	-1.8	1.7	2	0	0	3.5	-1	-1.8	-0.9	1.1	3.2	3.7	0	0	0
AWI	10	-3.7	1.2	1.5	3.6	2.5	2.5	1.9	2.6	2.6	-2.1	2.8	1.9	-4.6	-8.1	2.8	3.9	-2.2	2.4
BANR	5.1	2.4	2.4	0	0	2.4	0	0.3	1.4	0.8	1.3	0.1	0.5	0.7	0.4	1.4	-1	-0.3	-2.1
BCPC	3.3	4.9	1.6	0.3	4.7	-0.5	1.5	0.6	0.2	1.6	2	0.9	1.4	-0.8	1.8	0.5	1.1	-1.8	-0.5
BG	8.3	0.1	1.5	-3.8	-2.7	-2.4	-3.7	-3.8	-1	-1	-7	-7.8	-5.1	-3.5	-9.1	-4.6	-1.8	-3.4	-2.1
BHLB	-5.6	-4.9	-3.8	-1	-1.1	-1	-3.2	4.4	2.1	-5.3	-2.1	1.1	-0.7	-0.6	-7.4	-1.2	1.8	-0	-1.1
BHP	7.2	2.6	4.4	2.1	2.2	1.2	-1.6	2.6	3	2	2.9	2.8	0.9	1.8	0.9	1.8	6.6	-1.7	-4.8
BKR	-6.8	-2.8	2.7	0.8	-0	0	-2.1	-1.3	-1.4	-2.4	-2	-2.2	-1.7	-1.5	-0.5	-1	-0.4	0.4	-2.2
BMI	12.7	2.9	1.3	2.1	0.9	-0.3	2	2.8	0	0	0	-0.4	1.9	-1.2	5.1	4.1	3.4	2.4	-0.2
BMY	5.4	2.5	-2.9	-1.8	0.4	1.9	-0.2	-0.1	-1.9	-2.4	0.8	0.3	-2	-0.1	-0.3	0.7	0	-0.3	-0.5
BSAC	-2.7	-3.2	-1.9	-1.7	-2.9	-3.1	-1.5	0	0	-2.5	-1.9	-3.5	0	0	-2.2	-4.4	-1.6	-4.7	-2.1
BSBR	22.4	-1.2	-2.3	0	2.3	2.3	1.6	-3.2	0.9	1.4	2	2.1	2.9	4.2	0.3	2.9	3.4	0.6	-12.1
BSX	11.3	5.1	3.3	0	0	4	2.2	2.7	3.3	4	1.2	1.9	3.3	4.7	3.9	6	2.5	6.3	5.9
BX	8.6	5.1	2.3	3.6	-4.3	3.4	4.9	-2.8	4.5	3.1	1.4	1.5	-4.2	2.6	2.8	1	2.8	3.3	-4.6
BYD	1.1	-3.5	-3.6	0	0	0	-1.9	-1.4	0.3	0.5	-0.4	-0.2	-2.9	0.1	0.1	-0.8	-0.8	-1.6	0.1
CBZ	19.9	4.7	3.6	-2.2	4.8	10.7	5.5	3.9	4.5	4.1	2.8	-1.5	0	2.8	-0.5	0	0	5	0
CCEP	16.6	-0.6	1.1	2.1	3.8	2.4	2.3	2.7	2.6	2.5	3.1	2.5	2.1	2.5	2.4	2.4	-0.8	-6.7	2.8
CCI	5.2	4.2	0.7	2.6	2.1	3.5	2.7	2.8	3	2.2	1.7	1.5	4.4	2.5	4.2	3	2.7	2.3	2.4
CCL	-11.7	-2.5	-4.5	-6.4	-4.2	-1.1	-1.8	-3.4	-2.2	-3.1	-6.5	-4.6	-1.4	-5.2	-6.4	-2.5	-3	-1.9	-3.3
CHH	7.1	5.9	-1.7	2.1	1.9	3.5	3.9	1.3	2.7	3.2	2.8	1.8	2.7	1.5	2.5	-1.8	3.4	2.3	3
CMP	3.1	-3	0.2	-2.9	-2.2	-2.8	-6.5	-5.1	-7.7	-3.7	-5.1	-3	-0.8	-1.5	0.7	-0.1	-2.3	-5.1	-3.1

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Label	MST	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
CNK	2.8	-0.7	1.9	0.2	-1.8	-5.4	-2.8	2.6	-4	0.6	-0.5	0.7	-0.1	-0.8	-1.5	-1.4	-0.9	0.7	-2.9
CNXN	7.6	3.5	0.4	1.5	1.9	2.6	1.8	1.7	2	1.6	0.7	1.4	0.6	3.9	1.8	2.9	1.1	2.1	2
COST	8.9	2.5	2.8	4.1	4.4	2.4	4.9	1.8	2.9	-0.1	0.8	2.6	3.1	3.4	4.9	3.4	3.5	4	-3.6
CRK	1.4	6.5	-1.3	2.2	2.2	2.2	-2	-1.7	-0.9	-0.3	-0.2	-1.6	-2.2	1.6	0.1	-0.3	-2	-3.2	-1.4
CSV	7.8	0.6	2.6	0.9	0.7	1.6	0.1	-5.8	-3.4	-2.2	-2.1	-7.2	-3.3	-6	1.5	0.8	-0.2	-6.3	1.5
CUBE	3.5	7.2	-0.2	5.4	4.9	1.4	1.7	1.7	1.4	2.4	-7	1.7	4.5	2.6	0	-4.4	2.6	1.8	1.8
D	4.5	-2.3	-1.5	-5.8	0.3	0.8	0.9	-5.4	0	1.3	0	0	-2	2	1.7	0.6	2.9	1.1	1
DCOM	0.6	-7.2	0.3	1.8	-3.9	1.1	-2.9	-2.4	-4.1	-0.4	-5.6	-4.5	-3.7	-0.9	3.1	0.4	0.5	2	-1.4
DDS	4.8	-0.8	-0.2	-3.7	3.5	1.6	-0.1	1.4	1.4	0.4	-3.2	0.9	1.4	1.8	-2	1.9	-0.9	-2.2	1.3
DENN	15.2	-1.4	2.1	4.3	2	2.3	2.1	2	2	3.4	3.4	3.7	0	2.2	3.7	1.8	2.2	2	2.1
DIOD	4.7	6.3	3.2	4.2	3.2	2.4	5.5	4.8	3.7	1.8	4.3	3.4	3.5	1.7	3.4	1	4.6	2.7	9
DIS	17.2	1.9	2.1	1.9	1.7	1.9	2.7	-3.8	-0.6	-4.3	1.9	-0.8	-6.2	1.9	2.2	2.2	3.2	-0.1	-3.3
DRQ	-3.3	1.5	0.6	-2	-1.7	1.7	-2.1	-2.4	-2	1.6	2.9	0.6	-1.8	-1.3	-3.1	-2.7	-0.2	-0.6	-4.1
EAT	21	-2.9	2	0.1	2.2	-1.2	2.1	-0.4	2.1	0.8	-0.6	1.7	3	-3.7	0.1	-1.5	0.6	1	-1.9
EBR	8.2	1.2	0.8	0	0	-2.3	-0.6	0.9	1	2.2	2	2.3	2.6	0	0	0	-0.5	2	1.9
EC	7.2	-1	2	1.7	2	7.1	3.2	8	4.5	3.8	3.7	1.2	2.1	2	4.8	2.7	0.2	3	4.2
EFSC	-1.4	0.9	4.6	-24.5	-1.3	-0.6	3.9	-1	0.2	1	1	2	-18.5	-6.7	2.1	1.4	5.8	2.2	-0.7
EGHT	6.2	4.8	2.2	0.5	0.2	1.9	3.7	4.5	1.4	-1.4	3.1	-6	6	-1.1	-0.9	0.9	-14.2	3.4	8.9
EGO	6.9	2.1	4.7	-2.1	-2.1	-0.4	-0.7	1.4	1.7	-1.8	-2.4	0.8	2.1	0.8	0.8	-0.4	1.1	-3.2	-1.4
EMN	-5.3	-2	-4.1	-0.5	-3.3	-4.7	3.5	-46.8	-11.4	-13.6	-2.1	-0.2	3.2	-8.1	-3.2	-1.3	-3	-4.9	-2
EQR	8	2.6	0.6	0	0	1.4	1.8	1.8	3.1	1.5	1.9	0	0	1.3	0	1.7	2.6	-1.5	1.8
ERII	10.9	-0.7	1.7	-0.6	-0.6	-0.6	-0.3	-4.5	-1.7	-1.9	-3.1	-7.1	-3.9	-3.6	-1.4	-3.7	-2.7	-0.4	-4.3
ERJ	-5.2	3.4	2.4	0.8	-1.2	-0.5	2	-2	-1.9	-3.4	-3.9	-4.6	-2.8	2.3	0.3	-3.5	-2	-5	-2.9
ET	5.2	1	0.2	-0.3	3.8	-0.1	-1.1	0.4	-1.1	1	1	-7.7	-3.9	-4.1	0.1	-2.2	-0.4	-1.9	-3.8
EVR	7.4	-0.6	0.3	-1.9	-0	-1.1	-2	-0.1	-0.5	-1.1	-1	-0.6	-1	-0.7	-0.4	-1.5	-1.4	-0.6	-1.3
FARO	8.6	2.3	3.4	0.2	-1.4	-0	-4	-1.6	2.2	0.4	3	-2.1	3.2	-2.5	-3.4	0.1	1.8	-2.9	-1.7
FBNC	4.4	-2	1.3	1.1	-0.8	-0.2	0.2	0.5	1.1	0.8	1.3	2.6	0.7	0.3	-1.1	2	0.6	4	2.2
FELE	10.7	3.2	0.4	2.1	-0.5	-2.2	2.5	1.3	1.3	1.3	4.2	4.8	1.4	2	-0.8	1.8	-0.1	3.6	2.5
FFIN	8.4	4.2	1.6	10.2	10.2	11.6	6.2	5	2.6	2.7	2.5	1.3	1.6	3.7	2.4	3.2	3.8	12.7	0.2
FISI	-3	-5.1	1.5	1	-0.6	1	2	-0.1	-4.1	2.5	1.1	-4.1	-0	0	1.7	-6.8	2.6	3.2	-2.6
FIX	13.6	5.1	-0.3	3.2	0.4	0.8	1.8	2.1	1.2	2	1.4	1.5	-0.8	1.6	0.8	1.5	2.1	0.8	2.2
FLO	4.2	2.3	0.9	1.3	1.1	2.1	3.1	2.3	0	1.4	3.8	1.7	0	2.9	4.2	2	3.3	-1.1	-0.5
GCO	16.5	-2.7	-3.3	-1.4	3.8	-3.2	2	3.6	-9.5	3.5	2.6	-1.7	2.3	-0.1	-0.4	-4.1	-2.7	-0.9	-2.8
GD	8.6	0.1	-1.7	-12.2	-14.4	-8.1	-11.3	-0.7	-3.7	-1.7	-0.5	-0.6	-0.8	-7	-4.6	-6.8	-3.2	-4.1	-1
GE	-7.2	-6.1	-1.1	-2.6	-7.6	-6.1	-3.5	-12.7	-2.8	-6.6	-4.1	-5.3	-10.1	-13.3	-3.9	-2.3	-1.3	-4.9	-2.9
GSAT	7.1	-6.5	2.5	-7.3	-7.3	-7.3	-9.8	-10.2	-7.5	-8.6	-3.8	-5	-14.7	-4.3	-4.3	-4.3	-7.1	-13.8	-5
GTE	14.6	3.2	2.2	-0.6	-1.5	-0.8	-1.2	2.7	0.6	3.7	4.6	-2.4	-1.6	-2.2	-0.2	-1.5	-1.4	5.8	2.4
GTLS	2.9	-0.5	0.3	-3.4	1.8	-2.2	0.5	1.6	0.7	-0.3	1.3	2.3	2	1.7	1.2	2.8	0.8	1.1	-1.2
GTN	3.1	0.9	1.9	-163	-163	0.9	1.2	1.2	0.8	0.9	0.9	0.9	0.9	-0.5	-0.8	1.8	1.3	3.1	-8.3
HA	7	0.1	1.2	-6.1	-5.7	-2.3	-2.4	-3.6	-0.4	-0.4	1	-1.3	-1.4	-1.6	-0.6	0.9	-4.1	-2.5	-1.7
HELE	14.1	0.8	4.1	1.4	1.2	1.2	1.6	3.4	1	1.6	1.2	2.3	4.4	2.6	5.1	1.7	2	5.3	4.4
HIW	5.6	-1.7	-3.6	0.3	0	0	-3.2	0.1	0.7	0.7	1.2	1.5	-4	1.1	-0.4	-4.3	-1.5	-5.4	-1
HLX	8.5	-0.6	4.1	1.6	-2.2	1.6	-1.3	0	1.6	-0.2	0.7	-0.2	0.4	-2.7	-0.6	2.4	5	3.5	2
HMY	3.7	0.8	7.2	-0.9	-6.7	1.1	-4.4	2.8	-1.6	-0.7	0.3	1.8	2.1	1.9	1.9	1.9	1.9	-2.9	-2.1
HOPE	3.6	-5.2	-4	0.4	-9.8	-5.6	-2.7	-3.3	-5.3	-0.6	-2.2	0	-2.8	0.1	-6	-10.7	0	-4.2	-4.7
HRI	9.7	1.5	2.2	-0.2	-1.7	-1.7	-0.7	0.6	-0.5	0	-1.9	-1.5	-2.5	0.5	0.6	0	2.5	0.6	0
HWC	-2.2	-1.7	-0.7	-2.6	-2.4	-6.2	-5.3	-7.5	-5.3	-0.8	-1.3	2.8	1.1	-5.4	-2.2	0.4	-2	-1.8	0.6
IART	10.7	6.3	1.2	3.3	4.2	0	1.3	2	1.8	1.7	6.2	2.5	1.9	-2.3	1.2	2.8	5.4	4.9	3.4
IDT	8.9	-0.3	1.4	-7.1	-5	-1.3	-3.9	-7.7	-13.9	-5.3	-5.3	-5.5	-2.9	-1.1	-4.7	-5.2	-3.5	-2.4	0.6
IMAX	-4.3	3	-3.1	-1.7	-1.8	-2.3	-3.9	-1.2	-4.6	-1.9	-1.7	-1.7	-2	-2.7	-2.6	-1.9	0.2	-5	1
IMGN	-6.5	-4.8	0.5	-1.1	0.5	2.2	2.9	3.8	-1.2	-0.1	-4	-2.8	-1.8	-2.3	-1.8	-3.1	-4.2	-3.8	-1.4
INSM	7.1	2.3	2.3	0.3	-0.2	-0.2	-1.5	-1.4	-1.4	-0.9	-0.9	-0.9	-1.3	0.9	1.7	1.7	1.3	-4.4	-1.5
IOSP	3.4	3.1	2.1	1.9	1.6	2.1	2.3	1.5	3.4	1.4	2.3	2.3	3.9	3.3	3.6	5.2	2.8	3.9	2.9
IP	-0.9	-5.3	-2.6	-4.9	-2.1	-0.5	-5.9	-5.2	-3.1	-3.2	0.3	-1.9	6.4	-2.8	-2.7	-5.2	-3.2	-5.2	-0.9
IPAR	9.7	2.5	1.1	1.3	1.5	4.9	2.6	3	3.4	5.4	3.7	-0.6	3	1.9	1.9	1.9	1.9	4.6	2.6
IRBT	-8.3	-2.9	3.7	-1.6	0	1.6	0.3	-1	-2.8	-2.9	-1.5	-1.2	-4.7	-3.4	-0.3	-0.8	5.9	-0.2	-2
IT	3.6	1.6	1.4	-0.2	-2.1	7.4	-0.2	2	0.3	0.4	-3.4	-2.3	-1.1	-2.1	1	-1.8	0.5	-0.6	-2.1
ITGR	4	2	2.4	3.3	4	2.6	3.7	1.5	6.8	2.8	6.3	6.3	2.6	5	6.5	2.6	5.1	1.9	4.9
ITT	12.2	3.3	2.3	2.2	2.2	2.2	3.3	1.4	8.6	1.4	1.8	2.3	2.3	2.3	2.8	-0.4	-2.6	3.5	1.7
JKHY	13.2	0.4	2.5	1.8	1.1	2.1	0.4	1.2	0.9	2.3	2	2.1	1.9	-2.2	4.5	-0.8	0.1	2.7	0.9

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Label	MST	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
KAI	5.9	0.7	-0.5	0	0	-2.9	-29.5	-29.5	-0.5	0	0.2	-0.2	0.2	0	0	1.2	0.5	0.3	-3.6
KBR	4.6	-3.9	-2	5	4.7	4.5	8.4	2.2	-3.9	-1.5	0	0	0	4.3	5	5.2	6.3	0.2	1.8
KFRC	4.9	0.1	0.5	3.4	7	2.9	0	2.8	5.4	4.8	0	8.4	3.9	2.6	2	5.2	1.4	0.5	4.7
KLIC	5.8	-1.6	-2	1.4	1.4	1.6	-1.5	-0	0.6	-0.1	-5	0.8	0	1.1	3	0	0.6	-2.4	2
LANC	18.2	0.1	0.8	-0.5	-2.1	-0.5	2.6	1.5	1.5	-3.7	1.9	1.8	2.1	1.5	2.6	4.3	2.9	4.7	4.9
LBAI	-5	-8.4	1.2	0	-1.1	0	-5.1	-3.9	-3.3	-1.9	0	0	-2.2	-1.7	-5.4	-3.8	-2.1	-7.3	-2.4
LMAT	8	-2.3	-4	-2	-0.8	0.5	0.9	-2	-2.4	-0.1	0	-0.3	2.5	-2.7	-2.4	2.4	5.8	5.5	0.3
LOW	19.2	0.2	2.8	1.3	-0.3	1.6	2.7	2.5	1.5	3.7	3	1.9	2.6	2.1	-0.6	1.9	-1.9	4.7	3.4
LRN	7	0.7	-1.9	1.4	1.1	0	2	2.5	2.2	1.1	3.7	3.6	3.5	-0.6	0	0	3.5	2.9	2.5
LSI	1.7	2.4	3.2	0	0	1.3	2.3	1.4	1.6	1.6	2.1	2	1.8	0	-0.6	2.2	2.9	2.8	0.5
LYG	4.6	-0.6	1	0	0	0	-0.8	0.5	-8	-5.5	-6.3	-5.1	-4.4	-3.7	-3	0.5	0.1	-5.7	-0.4
MCY	1.4	-1.5	0.6	-2.8	-0.2	-0.4	-0.3	1	0.8	-0.6	0.5	-2	0.4	0.3	0	-0.6	0.7	-0.6	2.1
MDC	1.2	2.1	1.5	0	2	2.4	1.1	2.2	1	1.5	-4.6	-1.7	2.1	2.2	1.8	0.9	-3.4	1.3	-3
MGM	9.1	-0.3	0.6	-0.4	0	-4.2	1.5	-3.4	1.5	0	0	0.2	-0.2	-3.7	-6.2	-3.2	-3.2	-3.2	-5.1
MGRC	5.6	-0.5	1.9	0	0	7.7	3.3	3.2	3.9	0	2.9	3.4	4.3	2.4	4.6	36.8	3.5	2.5	4
MIDD	-6.4	-6.3	-0.6	-1.6	-0	-0.9	-4	-0.4	-0.5	2.1	-0.1	-1.7	-5.2	-1.6	-2.3	-0.9	-1.1	-0.6	-1.3
MRO	-5.2	-2.8	-4.5	-1.6	-3.7	-4.3	8	0.3	0.3	-0.9	-0.4	-2.9	-3.5	-4.5	-0.4	-4.8	-5.1	-1	-0.3
MSA	6	4.2	0.5	0	0	3.3	0.6	1.6	0	0	1.8	0	0.7	0	7.1	-3.3	3.3	1.1	1.9
MT	-7.9	-4.5	0.1	-3.7	-1.6	-3.9	0	-3.9	0	-1.9	-1.9	-2.2	-3.1	0.5	-4.3	-5.3	0	-2.7	0
MTZ	6.7	6.6	-0.5	0	0	1.9	2	1.7	2.4	1.6	2.4	2	1.1	1.5	1.5	5	1.4	3.9	2.6
MYGN	8.9	-0.8	-1.3	-2.9	1.7	2.2	-6.8	2	-1	-2.3	41.3	-1.8	-2.1	1.1	1.6	0.6	0.7	1.4	2.3
NBIX	5.9	-0.6	0.8	2	2	1.6	1.8	3.7	1.9	2.1	2.1	2.1	2	2.9	2.9	2.9	2	5.5	3.5
NEOG	13.1	3.2	3.8	2.1	2.1	1.3	-1.9	-0.2	1.6	-0.4	-118.4	-14.7	1.1	3.3	2.6	7.4	1.6	-1.2	-0.6
NFLX	2.6	7.1	2.9	0.6	0.6	1.1	1.5	0.9	0.9	1.5	3.5	2.4	1	1.3	1.3	1.2	-0.5	3.3	0.9
NG	1.9	-0.8	4.8	2.6	2.6	1.8	1.5	3.1	3.7	0	0	1.9	1.7	2.2	0	2.9	-0.4	2.3	2.5
NGD	7.2	-9.9	-6.8	-0.7	-7.6	-2.6	-2.4	-3.7	-6	-6.1	-3.5	-6.3	-3.3	-4.7	-2.8	0	-3	-4.6	-5.7
NGG	1.4	1.2	3.2	3.1	3.9	0.6	0.4	0.3	0.9	1	0.7	0.1	3	3.6	3.2	1.7	-0.2	1.8	2.5
NICE	16	7.1	5.8	2.8	5.3	1.9	2.2	4	2.8	4.1	2.8	0	0	2.7	2	3.6	4.4	3.4	6
NNI	5.9	2.5	1.3	0	0	0	0	2.9	1.9	4.3	0	0	2.9	0	1.7	-2.4	2.8	3.5	2.3
NNN	13.2	3.2	1.8	-0.8	2.5	1	2.9	2.5	1.9	3.1	3.5	2.4	2.6	3.1	0	3.1	1.9	2.5	2.7
NOG	6.8	1.7	-0.9	-0	-0	2.8	0.8	0.8	-0.1	-3.5	-0.5	-1.5	-0.8	1.8	1.5	-0	3.1	3.1	-0.9
NRG	11.2	-2	-1.9	-1.6	-2.2	2.9	2	0	3.5	0	2.3	1.7	3.7	0.9	1.9	3.8	3	2.7	3.3
NVMI	-1.4	0	-5.7	4	2.1	3.4	2.9	2.1	3.7	1.3	1.1	2	0	1.8	1.4	2.5	3	2.9	3.5
NVS	1.4	3.3	0.6	-4.8	-0.4	1.5	0.8	-1	2.6	2.3	1.9	3.7	1.4	1.7	1.5	-0.8	0.6	-0.8	-2.9
NWBI	0.3	-1.6	-1.6	-2.5	-0.3	-2.1	2	-2.6	-2.8	-3.7	-1.6	1.5	2	-3.4	7.9	1.5	-2.3	1.2	9.3
OGE	7.7	-1.2	-3.9	2	2.8	4	2.3	1.2	2.3	2.7	2.5	2.6	2.5	3.3	3.3	1.6	2.5	2	2.5
OMCL	5.4	-1.7	0.1	1.2	1.3	1.7	2.2	-0.9	-1.8	3.2	1.8	2.3	2.8	3.1	2.8	3.1	2.2	0.4	2.1
PAYX	4.6	0.8	2.2	2.1	2.4	1.5	2.2	2	1.9	2.4	2.1	1.1	-9.5	1.6	1.8	3.2	2.8	-5	-4.4
PB	6.8	-3.9	1.9	-1.1	0	0.5	-3.1	-2.1	-2.6	-0.5	1.1	2.1	-6.2	2	-0.2	-5	0.2	-0.1	5.1
PCH	-1.2	-2	-5.1	-2.7	-3.7	-3.1	-4.9	-5.1	0.8	-0.6	0.8	-4.5	-3.5	2	1.9	0.6	-2.4	-13.1	1.6
PDCE	2.9	-3.1	-3.8	-1.8	-2.5	0.7	-1.8	-2.1	-1.5	-0.6	-1.5	-1.2	-2.6	-2.4	-2	-2.1	-1.8	-1.8	8
PDFS	4.8	-1.3	2.4	1	0.9	0.5	0.3	0.7	1.5	1.2	2	2.3	1.6	1	-5.3	-3.5	-2.7	-6.6	1.4
PDS	11.1	-1.8	-0.2	-1.5	-5.9	-17.5	-9.6	-5.1	-2.2	2	-2.3	-2.7	-1.9	-3.3	-2	-2.7	-5.1	-5.5	-1.7
PERI	10.2	-1.2	-3.5	1.8	-5.8	2.3	3.1	2.1	2.8	1.6	0.9	1.4	2.2	3.5	2.3	3.4	3.2	-8.5	-2.1
PHG	7.1	-2	-5.2	0	4.9	-1.1	4.9	3.9	0	1.8	3.6	1.5	-1.9	0	3.9	2.8	0.4	-0	12.1
PNM	0.9	3.1	1.9	0.5	2.4	1.3	1.3	1.4	1.3	1.2	1.3	1.1	1.5	1.9	1.6	3.2	0.5	1.5	0.9
POR	10	0	-3.7	1.2	1.2	2	2	2.8	2	1.6	1.8	1.7	2	0.3	1.5	1.9	1.7	1.9	2
PRGS	5.3	2.5	0.5	-1.1	-0.5	0	-5	-0.6	-0.7	-0.7	0.4	-7.8	-4.8	-1.2	-0.6	0.1	-4.7	-3.4	-0.4
QCOM	6.1	2.3	-5.3	4.2	2.5	-2.4	0.8	-3.8	-1.5	0.5	0.3	-0.3	0.2	3.4	3.6	-0.5	-2.6	-1.7	1.3
RAMP	10.1	-0.6	3.8	5.5	4.6	9.3	4.4	1.8	3.4	1.6	-0.4	-2	-2.2	1.2	2.2	1.3	4	3.1	2.7
RGR	3.1	2	1	-0.1	-32.2	-2.5	-6.1	-6.9	0.4	-2.5	-4.6	-2.4	0	-1.9	-1.3	-1.2	-0.2	-3.8	-2.2
RHI	6.6	2.1	-1.6	-0.9	-1.1	4.2	3.3	-3.3	3.5	0.5	-6.4	-1.5	2.1	0.8	-2.1	0.3	-2	3.3	-1.8
RJF	3.1	-0.1	1	0.6	-2.7	-1.3	-5.4	-3.9	-4.9	0.8	0.8	-2.4	-0.6	0.6	-1.4	-2.6	-0.3	-7.5	-2
RL	11.4	-0.5	-0.1	1.9	0.9	-0.4	-1.5	-0.4	-3.9	-2.2	1.4	-0	-4.1	-2.3	-1.5	-0.7	1.7	-0.4	-0.2
ROG	9	-0.4	1.6	-5.6	-1.3	0	-2.3	-7	-2.6	-0.3	-1.6	0.2	1.9	-5.9	-1.8	-0.6	2.3	-5	-0.8
ROIC	5.1	-0.6	-2.9	0.2	1.6	0.1	0.3	-9.1	0.2	1.1	0.8	0.5	-5.1	-0.8	-4.1	2.1	-0.2	0	-13.3
RPM	9.7	-7.6	-1.1	2.4	0.7	3.4	2.9	1.4	-2.1	-6.1	3.3	-2.6	-6.7	-4.5	1.9	3.5	3.3	4.7	2
RPT	2.9	1.5	-0.8	0.7	0.7	1.1	2	1.8	1.6	-6	-6.2	-9.8	0	-4.6	-1.4	-8.9	1.4	0.2	-1.6
RTX	2	2.5	1.5	2	1.3	-0.3	1.7	0.3	-3.4	0.3	1	-3.9	1	1.2	2.3	0	-0.1	-2.4	-10.2
RUSHA	6.5	1	-2.6	-29.7	-54.7	-4	-3.7	-4.2	-2.1	-1.1	-0.3	-0.4	0.2	-5	-10.7	-0.4	-3.2	-3.2	-0.4

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Label	MST	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
RY	6	-3	-4.1	0	-7.6	0.5	0.4	0.3	0	-2.8	-0.1	0.6	0.7	0	0.4	0.6	0.3	0.5	0
SAH	9.8	3.3	2	3.6	3.8	3.3	0.3	2.6	0.5	2.2	2.1	0.9	1.7	2.3	-2.9	-0.3	3.4	2.5	2.9
SAIA	3.9	-0.5	-0.3	1.5	1.5	1.4	2.4	3.6	-2.4	0.2	-3	0.8	-0.6	1.2	-1.7	2.5	1.2	1.8	0.5
SASR	-6.1	-2.4	-5.2	0	0	-1	0.1	-0.4	-3.2	-0.7	1.2	2.2	-1.9	-0.3	-4.3	-5	0.2	-2.9	1.3
SBH	3.3	-0.9	-3.9	2.2	1.4	3.7	7.8	1	1.7	-0.6	0.7	4.9	3.3	0.8	1.5	1.2	3	-1.8	0.9
SBRA	4.1	1.2	1.6	3.1	3.5	-26.2	2.3	1.8	1.9	-0.1	2.9	2.7	1.4	4.9	1.4	3.4	3.5	2	3.7
SBS	11	1.1	3.1	0.7	-2	-3.5	-3.8	2.2	3.6	3	3.4	2.1	2.2	2	-4.4	2	-2.6	-3.6	-0.4
SCI	-1	1.6	2.5	0	0	1.4	26.9	1.5	2	1.6	1.4	1.5	1.8	0	1.8	0.1	2.3	2.7	1.9
SCVL	8.4	2.7	-5.3	2.2	1.8	2.2	1.7	1.7	-1.5	1.9	1.4	1.6	3.3	2	1.9	2.1	1.2	1.6	1.2
SEIC	-1.5	-3	-1.5	-1.4	-2.1	-4	-0.2	-6.9	-2.7	-2	-1.6	-9.4	-26.3	-1.2	-2.5	-2.5	-1.5	-1.8	-8.1
SIEGY	2.9	-4.6	0.1	0.3	1.9	1.3	1.8	-1.6	0	-3.1	0	0	-2.2	-2.7	5.2	-7.2	-3.8	4.4	-1.7
SITC	6.4	-1.8	-1.1	0.6	1.6	5.7	1.9	1.3	1.7	-0.3	2.6	1.7	-1.1	1.2	-1.9	-0.1	1.8	3.2	1.5
SKYW	3.7	-0	-0.9	2.3	3.1	1.4	4.6	0	0	0	-5.9	3.7	3.3	-3.9	-2	1.4	5.4	3	1.5
SNX	-2.8	-3.1	-8.9	-3.2	-3	0.3	-0.7	-4.6	-4.5	-1.9	-1.7	-3.5	-66.9	0.7	-12.4	-1.2	-9.1	-2.1	-3.3
SO	4.2	2.2	-5.9	-2.6	-3.2	-3.8	-4.5	1.7	1.8	1.6	1.6	1.7	1.6	-4.9	-2.3	-4	-6.7	-6.7	2.3
SRPT	5.4	1.5	5.6	2.7	2	2.4	0.9	0	-0.3	-1.2	-1.2	2.5	3.2	2.1	2.1	2.3	3.4	5.3	5.5
STC	2.8	2.1	2.5	0.6	0.5	-5.5	-0.9	-4.6	2.2	0	-34.7	0	-2.4	-5.3	-0.3	0.9	-6.3	-2.1	0
STLD	-0.7	-0.4	-2.9	-2.5	-10	-2.1	-2	-1.8	-1.7	-0.9	-3.1	-3.2	-2.5	-0.5	-1.6	-0.3	-2.1	-4.4	1
STM	5.7	-6.5	-1.2	-1.8	0	-0.2	-1.9	-0.4	2	2	3.9	-0.1	2.6	-3.1	-1.3	2.2	0	1.5	-2.4
STT	6.7	-4.3	-7.6	-6.8	-5.7	-3.8	-5.1	-5.5	-31.3	-10.3	-53.9	-83	-5.7	-3.9	-5.7	-4.9	-1.2	-5.1	-2.8
STX	16.6	1.2	-0.1	-2	-2.5	-7.9	-2.9	2.5	2.5	4.7	1.1	1.8	4.4	2.8	-1.6	2.7	-2.5	5.9	4.2
SYNA	4.9	-0.1	2.2	0.3	1.3	3.1	-1	2.5	1.9	4	4	-5.6	2.2	1	-0.1	1.1	1.3	2.2	2.6
TDC	-3.1	-0.1	1.1	0.3	0	-7.4	-6.2	-1.3	0.9	0.5	-3.6	-3.5	4.9	0	0	-3.3	-1.6	-1.1	1.6
TEX	10.8	-3.8	-5.2	0.9	1.8	0.7	0	-1.1	1.9	0.4	0	0	-3.3	-1.8	-1.1	0	0	-2.5	-2.7
THG	1.1	0.8	-0.5	4.2	0.6	2.7	1.7	0	1.6	5.1	4.2	2.2	1.4	3.2	3.7	3.8	1.9	3.8	0.9
TITN	1.6	2.2	-2	-5.9	-3.1	0.2	-0.2	5.3	-3.3	4.9	-6.1	-2	-0.8	-4.8	-2.2	0.9	-1.5	-3	-3.9
TLK	4	-0.1	-1.2	0.6	-0.5	-2.1	-2.8	-3	-2.9	-0.2	0.4	-0.1	0	-1.5	-0.1	-0.2	-3	-7.3	-1.5
TREE	0.8	0.8	5.4	1.2	1.1	0.7	-1.9	-0.4	-3	-0.9	-0.7	-4	-3	0.2	-0	0.4	2.3	-2.2	0.4
TREX	15.5	0.8	2.8	2.6	2.2	-3.5	-3.5	-4.6	-5.6	2.4	2.9	2.7	-3.4	0.3	0.3	0.4	-3.7	1.1	0.9
TRMK	-0.4	0.4	1.6	0.8	-3.4	-7.3	1.1	0.7	-3.2	2.2	1.3	1.6	-1.8	-3.1	-3.8	-1.4	-3.4	-8.6	6.9
TSM	2.4	-0.8	2.2	1.5	-1.6	-1.9	2.2	-4.5	-3.2	1.3	1.9	1.5	-6	-1.5	-2.1	2.4	-2.1	1.2	-1.1
TTC	5.6	4.4	-2.3	-1.9	-5.6	-5.3	1.8	1.2	-1.7	1.6	2.1	1.2	-0.9	-5.2	2	2.3	2.1	2.6	-1
TU	11.3	4.1	0	1.8	1.3	-0.9	-5	-11.6	-0.4	-3.2	0.4	1	1.7	2	2.6	-1.8	-2.3	-0.3	-2.4
TXN	8.6	2.4	0.2	2.1	2.9	3.8	2.7	2.7	-0.6	0.7	1.8	1.5	1.3	0.6	1	6.5	2.8	2.6	2.8
TXRH	6.2	-0	0	0.3	1.1	-0.6	0.4	-2.4	-0.2	-0.8	-1.7	0.5	-1.1	0.5	-0.7	-0.3	-1.1	-2.9	0
UBSI	10.6	0.9	-9.5	1.7	-0.7	2.9	3.8	2.3	1.8	4.2	1.4	2.9	2.1	0	-0.3	2.5	2.1	1.9	4.3
UGP	0	-3.4	-5.3	-9.7	-7.3	-3.2	-10.4	-9.2	-13.1	-5.7	-5.3	-4.2	-1.5	-1.3	-10	-10.5	-10.1	-3.9	-7.3
UHS	7.1	4.3	-0.8	6.6	2.7	2.8	3.3	4	1.3	1.5	1.4	2.3	1.7	2.6	0.1	4.1	4.5	1.8	4.3
UHT	5.6	-1.6	1.5	2.9	2.6	2.7	3.1	3.1	3.2	2.3	2.6	2.1	2.7	4	4.1	0.6	-2.5	3.7	2.4
UNF	5.5	-0.2	1.9	1.4	3	1.8	2.1	1.5	3.1	3.7	1.3	1.4	1.6	2.1	1.5	1.6	-1.8	2.8	1.4
WEC	5.3	1	1	2.6	1.9	2.9	2.3	2.1	2.1	1.7	1.9	2	2.3	2.4	3	3.2	2.7	2.5	1.9
WELL	4.3	-1.4	-0.8	-0.4	3.7	2.1	2.7	2.2	2.6	2.1	2.7	2.4	2.7	1.4	1.7	2.5	2.3	3.5	3.1
WEN	9.3	3.3	3.8	2.1	4.5	3.4	2.9	2.3	2.2	-0.8	2	2.9	2.4	0.3	1.4	3.6	0.4	0.1	5.4
WIRE	1.9	4.5	-1	0.7	0.8	0.8	3.6	1	2.2	1.3	0	0	1.9	2	1.1	1.2	0.7	0.6	1.6
WLK	-1.3	-5.2	0.4	-4.3	-3.5	-3.2	-3.5	3.1	-2.8	-2.3	-3.5	-0.1	-2	-4.1	-4.9	-6.9	-3.8	-3.8	-4.3
WMK	17.8	3.5	0.8	0.9	0.1	-2.6	-1.5	-1.3	-1.9	0.3	6.1	0.6	1.8	1.3	1.3	-2	-2.3	0.9	-1.1
WMT	7.4	-1.4	-0.2	-1.2	-34	-1.2	-0.9	0	-1.9	-2.2	0	-3.4	-2.6	-5.3	-8.5	-1.5	-4.4	-4.1	-0.8
WOR	8.5	-6.4	0.4	-2.9	-2.8	-6.7	-4.9	0.6	-5.9	-2.3	-2.2	-1.9	-4.5	-2.7	-1.8	-6.9	-5.1	-8	-1.1
WPC	5.3	-1.1	-0.2	2.3	1.8	1.4	2.2	1.6	0	2.2	2.3	1.9	1.8	2.1	1.9	2.4	2.2	0.3	2.7
WSM	14.9	2.7	2.4	4.4	3.1	4.6	3.3	4	4.6	3.2	3.2	3.5	1.4	5.1	4.7	2.5	5.1	3.4	5.2
WTI	7.8	0.3	4.2	0.5	0.6	0.6	2.7	-3.1	1.8	0.8	1.8	1.8	0.9	-0.5	-0.9	-0.1	5.7	-0.7	0.8
WW	-5	2.9	0.6	11	6.5	-1.6	5.5	5.1	8	-3.6	-3	-2.8	4.5	5	8.6	-1	-2.8	-0.3	-1
XPO	4.7	4.7	3.4	-2.1	-0.4	-1.4	-1	-1.4	0.1	-1.5	13.3	-6.4	-0.4	0	0.7	2	0.9	0.4	-0.4

Table B.7: Sharpe Ratio Results for MSTGAM (MST) versus sub-strategy for St3θ8, ⋯ S5θ3 experimented in Chapter 6, where cardinal numbers denote specific sub-strategies (e.g., 38 = St3θ8, 53 = St5θ3) as described in Section 6.4

Label	MST	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53
AAON	7.7	-10.1	1.7	-3.4	0.3	4.5	-0.9	0.4	-0.2	0.8	1.6	0.2	1	5.7	-3.6	5.3	4.4	-3.6
AAPL	7.2	-0.3	-2	1.2	1.4	4	4.8	1.5	3.2	-4.2	-2.9	-1.4	-1.9	-0.1	0	5.2	5.7	1.1
ACM	12	-3.8	0	-7.5	-6.9	1.5	2.4	4.3	1.5	-2.9	0.3	-1.7	2.2	-2.8	-2	-1.6	0.3	2.7
AG	5.9	6.4	6.6	2.2	3.1	4.9	2.6	-7.3	3.3	-6	3.7	0.6	1.1	-3.5	2	3	0.2	-0
AGEN	2.1	1.8	1.2	2	2	-4.8	-4.8	2.1	1.4	1.9	0.9	-1.4	-0.2	-3	1.7	2.8	2.8	-4.6
ANDE	11.5	2.6	4.4	-2.9	2.6	-5.1	2.7	2.8	-7.2	-1	-3.4	-5.8	4.3	2.7	-5.8	-1.2	-4.7	2.6
ASGN	12.3	-1.1	-1.4	-1	-0.4	0.4	4.4	-1.2	2.2	-1.7	1.2	-4	-2.8	-2.8	-3.7	-1.7	-4.2	5.2
AWI	10	-1.2	-0.1	-2.2	2.2	3.2	3.1	6.4	-2.3	0.3	-4.5	-2	-5.1	-2.6	-1.2	3.6	0.5	10.7
BANR	5.1	-4	0.3	1.3	-1	-1.2	-5.2	-2.3	-1.1	-7	-2.3	-2.9	1.4	-0.9	-7.5	0.7	-2.4	5.7
BCPC	3.3	4.4	2.1	2.6	2.4	6	-1.7	1	1.3	4.2	0.1	0.3	-2.8	-3.2	-2.5	0	3.9	1.8
BG	8.3	-3.6	0	-3	2.2	0.4	-10.3	-0.3	-1.4	-5.1	-0.2	1	1.8	0.7	-10.3	-0.9	-2.1	-5.5
BHLB	-5.6	-0.8	0.5	-0	-2.8	0.5	-4.7	-2.8	1.3	-0.6	1.5	0	0.4	-4.9	-2.5	-1.3	-5.6	5.7
BHP	7.2	7.3	2.7	-2.4	4	-2	2.5	4.3	0.2	3.1	3	-1.1	-4.9	-1.6	-2.3	-2.1	-2.4	3.9
BKR	-6.8	4.9	-2	-1.6	-0.5	1.1	0.2	1.1	-0.8	2.4	-1.1	-4.2	6.1	-2.9	-3.3	-8	-1.7	-4.5
BMI	12.7	-1.9	4.3	2.4	1.6	2.4	0.2	6	0.2	-1.7	1.6	2.3	1.2	5.3	1.4	5.1	6.7	-4
BMY	5.4	-9.2	-3.2	-1.4	11.5	1.9	-0.8	-1.4	2.4	2.2	-1.3	-1.9	-1.9	-0.3	-4.3	-2.2	-2.4	-0.8
BSAC	-2.7	-2.3	-2	-3.3	-1.8	-2.2	-3.9	-2.7	-4.6	-7.2	-4.9	-3.8	-2.3	-5.3	-2.8	-5.5	-2.9	-3
BSBR	22.4	0	0.9	2.5	3.4	-0.1	-0.5	-2.4	-1	0.6	-2	-0.5	0.4	-4.7	-5	-5.5	2	1.2
BSX	11.3	2.5	5.2	0	-1.8	-0.3	3.9	3.2	8.5	1.9	2.2	0.5	-2.5	-0.2	-1.7	4.9	0.9	6.1
BX	8.6	2.2	4.6	-0.4	0.7	3.1	4.1	1.5	-0.4	-3.4	-0.4	0.9	2	2.7	1.8	-2	4.6	4
BYD	1.1	-3.2	0.5	0.6	-2.6	-2.5	-1.9	-2.6	-3.3	-0.8	-3.4	-7.7	-5.4	-3.5	-3.1	4.4	1.2	1.1
CBZ	19.9	4.1	1.8	2.4	0	2.8	2.4	3.2	2.5	-0.5	-1.6	2.4	2.6	0	0.2	3.7	5.3	3.8
CCEP	16.6	2.7	3.1	-0.2	-2.6	1.6	1.6	2.1	0.8	1.2	-1	-0.8	-2.6	-3.4	-3.7	8.4	-0.3	3.5
CCI	5.2	2.1	1.9	1.7	3.3	-2.5	-2.1	-7.6	-8.8	-5.1	-2.4	5.1	0.2	3.5	79.1	5.3	4.9	0.7
CCL	-11.7	-2.8	-2.7	-4.6	2.5	-3.8	-3.4	-1.6	-3	-1.2	-2.2	-5.2	-5.5	-9.6	-9.8	-4.4	0.1	1.2
CHH	7.1	3.3	2.5	2.6	2.4	0.1	6.9	-0.3	0.7	-4.4	-4.5	-0.7	-0.8	1.8	-0.5	0.3	-4.4	3.5
CMP	3.1	-3.7	-2.4	-2.2	-2.6	-6.8	-2.3	-1.8	6.1	-3.5	-4.3	-2	-3.9	-2.3	-6.1	-3	-0.5	-4.8
CNK	2.8	-1.1	2.4	0.5	1.3	-3.8	-2	-3	-4.5	0.9	-4.1	-8.4	-4.4	-7	-0.7	-1.5	-1.5	4.2
CNXN	7.6	1	2.5	3.7	2.2	3.7	4.1	6.5	0.5	2.1	-1.1	-4.6	2.7	2.8	0.7	-0.7	5.2	0.9
COST	8.9	5.4	3.1	3	2.7	5.4	3.9	6.7	2.5	1.9	4.6	9.8	-0.9	0.9	0	6.3	4.1	2.7
CRK	1.4	-3.2	0	-3.2	0.1	-1.4	-5.2	-1.3	-1.1	-2.3	0.2	4.8	-4.9	0.3	-1.3	2	-5.5	0.5
CSV	7.8	-0.2	-9	-7.5	-4	0.4	-5.3	1.4	0.8	0.4	0.6	-1.1	1	-2	-4.4	1.8	2.5	0.7
CUBE	3.5	2.3	2.4	1.2	1.1	5	0.2	1.5	5.1	-2.7	0.7	-0.8	-13.8	-4.2	-4.5	8.6	1.2	2
D	4.5	1.8	0	0	-4.8	0.3	-1.9	-1.2	-2.5	-2.4	-2.1	-9.5	-0.7	-1.4	-1.3	3.6	1.3	-2.6
DCOM	0.6	-0.4	0.7	1.1	-3.4	-4.6	-3.4	1.1	0.7	-3.3	-2.7	-6.7	-5.7	-2.4	-5.5	2.3	0.7	-1.6
DDS	4.8	-1.3	0.9	-0.4	3.6	1.1	8	1.4	0.7	-1	0	1	-3	-0.3	1.2	-2.8	6.2	3.7
DENN	15.2	2.4	2.2	6.5	-2	0.7	6.3	1.3	2.7	1.2	7.3	1.8	-1.6	-2.3	-0.3	-2.6	3.7	8.1
DIOD	4.7	1.6	4.1	2.8	4.5	4.8	3.4	1.4	2.9	0.3	2.6	0.6	0.2	1.8	4.2	6.2	4.4	-0.3
DIS	17.2	-10	-11.3	-0.4	-1.5	-2.1	3.6	5.5	2.8	1.5	2	-0.2	1.7	-0.3	0.3	1.2	2.5	6.8
DRQ	-3.3	1.1	-2.9	-5.6	0.2	-9.3	1.5	2.2	-0.7	-4.4	1	-1	-4.8	-1.5	4.5	2.4	-2	-3.3
EAT	21	1.2	-3.6	4.2	2.1	2.4	6.9	7.6	2	4.3	4.4	-4.2	-5.4	-2.6	-0.1	2.1	3.3	4
EBR	8.2	4.1	3.2	4.4	3.1	-3.1	4.6	8.8	1.8	4.4	4.2	8.1	0.2	1.9	2.6	-0.9	4.3	2.5
EC	7.2	4.3	2.7	3.1	6.9	7.4	-3.8	-1.3	-2.3	0.3	-0.2	-7.1	-6.1	-5.3	-5.8	4.5	3.9	-0.6
EFSC	-1.4	3.1	3.6	4.4	2.2	-4.5	1.1	1.7	0	-3.9	-4.2	-3	-2.9	-4.6	-2.2	-7.5	2.7	-6
EGHT	6.2	-2.6	1.3	6.1	4.1	3.7	5.9	-0.6	-0.9	-0.5	2.4	2.4	1	-0.6	-2.7	13.3	7.3	6.1
EGO	6.9	-1.4	-1.4	-7.3	-1.9	-1.1	-1.1	-3.1	-4.9	0.6	1.1	2.1	1.3	1.6	-1.1	1.5	-1.9	2
EMN	-5.3	-5	-4	-2.2	-3.4	-0.5	-1.9	-7.2	-9.9	-9.3	-8.3	-2.1	-4.6	-2.7	-3	-4.8	-4.2	3.9
EQR	8	2.9	2.5	-2.2	-5.2	2	1.4	-0.5	0	-3.1	-2	-1.5	0	0	0	2	-0.8	3.2
ERII	10.9	-1.7	-0.7	-1.2	-2.9	-0.1	1.5	-1.3	-2.4	-0.3	-3.7	-2.3	-2.7	-0.7	-2.8	0.3	0.8	-3.2
ERJ	-5.2	-1.4	-1.3	-1	-3.4	2.5	2.2	-0.3	-1.9	0.3	-2.9	3.3	3.5	5.7	3.8	1.7	3.1	2.2
ET	5.2	-1.1	-1.1	-2.2	-2.2	0.3	2.2	-0.1	-3.2	-2.3	-5.5	-5.7	-3.1	-5.6	-2.7	-5.5	-0.9	2.6
EVR	7.4	-0.8	-0.7	-0.5	-0.5	3.2	2.4	0.5	-2.4	-0.7	-0.4	-6.7	-5.1	-2.5	-3.3	2.9	0.1	0.3
FARO	8.6	2	1.2	0.1	3.8	-0.1	1.5	-0.6	-1.4	1.7	1.9	-4.8	-5.5	-1.8	-2.4	0.8	-5.8	3
FBNC	4.4	-3.2	-4	1.1	-0.3	2.1	2.9	1	2.2	-1.9	-4.7	-2	-3.6	-0.3	-1.2	-6.6	-0.8	-0.2
FELE	10.7	-0.3	1.2	4	-5.3	0.4	2.1	4.1	8	1.5	2	1.6	-0.4	-0.5	-5.3	3	-1.5	1.7
FFIN	8.4	1.5	4.1	3.1	1.7	6	2.7	8	5.9	2.9	0.7	2.3	7	2.4	2.5	-0.1	4.3	7.2

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Table B.7 continued from previous page

Label	MST	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53
FISI	-3	2.1	1.3	2.2	2.7	-1	-2.4	0.4	0.7	-3.1	1	-3.9	-2.9	-2.7	-1.3	3.9	4	1
FIX	13.6	2.1	1.4	1.7	-2.5	3.1	3.2	-4.6	-2.1	3.2	2.2	-3	3.4	-3.3	-1.1	3.5	5.1	4.2
FLO	4.2	8	3.2	4	1.4	3	1.4	2.2	-0.1	-2.7	1.9	-1.3	-1.6	-2.4	-0	-1.5	-1.4	1.5
GCO	16.5	2.8	3.6	-2.6	-1.4	-2.1	-0.1	-3.2	-0.7	2.9	0.5	-1.4	-1.5	-5.5	-8.1	1.3	13.3	18.9
GD	8.6	-1.5	-0.4	-0.9	1	-2.7	3.3	1.5	1.9	-1.9	-5.5	-0.4	-3.7	-0.7	-2.9	-2.1	-2.1	-0.7
GE	-7.2	-5.6	-4.7	-6.7	-4	-4.2	-1	-1.8	-1.8	-1.2	-5.6	-4.5	-4.5	-4.3	-3.5	-4.3	-9.1	-10
GSAT	7.1	-3.6	-1	-4.7	-3.2	-4.4	-4.4	-4.4	-4.4	-3.2	-3.2	-2.6	-2.6	-6.8	-3.8	-9.5	-9.5	-9.5
GTE	14.6	2.7	3.4	-2.1	1.9	-2.4	-2.4	-4	3.5	-3.8	-2.4	-3	-3.4	-0.9	-4.1	4.3	4.3	-0.4
GTLS	2.9	0.6	-2.3	1.5	2.2	-4	-12.6	3.7	-1.2	-1.1	0.4	1.4	2.4	-4.1	-7.5	-2.6	5.7	0.2
GTN	3.1	1.5	1.3	1.9	1.9	2.5	2.9	3	-2.3	-0.6	0.8	-1.1	-1.2	-0.9	-3.6	-2.3	-1.6	-3.4
HA	7	0.5	-2.5	0.4	-3.7	-0.4	-2.3	-1.2	-1.7	-2.4	-4.2	-1.5	-1.5	-3.2	-4.6	1.4	-0.2	6.9
HELE	14.1	2.6	3.3	2.4	-2.6	-2.7	0.6	0.2	5.5	-0.5	-3.1	0.1	0.3	-5.1	-1.2	-0	3.3	4.8
HIW	5.6	1.3	-0.3	-68.2	-2.3	0.1	-0.7	0.4	-1.1	-1.2	-1.3	-0.5	-9.7	-4.6	-7.4	-2	-0.8	-0.9
HLX	8.5	2.9	1.9	4.2	3.1	2.3	2.9	2.7	-1.4	-0.9	1.2	5.5	6.2	-0.9	-0.9	8.1	8.3	2.1
HMY	3.7	-3.4	1.3	2.5	1.9	-3.2	-3.2	-2	1.7	1.5	2.4	2.1	2	3.5	7.3	-3.9	-3.9	-7.5
HOPE	3.6	-3.8	-6.5	-20	-3	-9.1	-1.5	-5.1	-0.9	2.2	0.4	-2.7	-0.2	-3.7	-1.9	-4.6	-6.1	-4.7
HRI	9.7	-5.2	-4.8	-3.4	-1.8	2.8	5	4.4	5.7	-2.1	-3.5	-1.5	-3.1	-9.5	-3.6	3.9	4	-3.9
HWC	-2.2	-3.4	5.1	-0.1	-2.6	0.6	-2.9	-1	-4.9	-8.7	-4.2	-1.5	-3.8	-5.2	-4.3	-0.6	-0.5	-3.4
IART	10.7	3.3	2.5	0.2	2.3	6	-2.2	5.4	6.8	-0.3	-0.9	-3.3	-1.2	-3.1	-2.2	5.3	0.8	-5.5
IDT	8.9	-3	-6.2	-2.7	-0.4	0.1	-5.9	0.7	1.1	-0.3	-0.4	-0.1	0.2	0.7	-2.1	-1.3	-3.3	-4.3
IMAX	-4.3	-4.3	-1.4	-1.8	1	-1.1	-1.9	-5.7	-3.9	-2.8	-3.7	-6.7	-2.1	-4.1	-6.3	3.2	-1.2	-4.1
IMGN	-6.5	-1.1	-1.1	-4	1.7	2.1	-2.1	2.4	2.4	0.4	3.2	-5.5	-0.4	-5.7	0.7	-5.4	-4.9	-4.4
INSM	7.1	1.5	-2.5	-0.1	-1.9	-5.1	-3.5	0.8	-2.2	2.3	2	1.8	-3.3	0.6	-8.4	-3.4	-0.8	-2.5
IOSP	3.4	5.2	1.9	3.4	2.8	3.3	4.4	12.3	-5.7	0.2	-0.6	-3.6	-0.9	-5.4	-6	3.2	5.3	-2.3
IP	-0.9	-2.2	-2	-115.1	-0.5	-3.8	-1.2	-3.4	-1.5	-3.3	-5.3	-6.5	-8.7	-5.8	-3.3	-1.3	1.1	-1.4
IPAR	9.7	1.4	4	4.5	6.5	4.4	4.7	1.7	5.2	2.4	-4.4	-3.2	0.8	-3.9	-0.7	7	7.1	4.9
IRBT	-8.3	-3.4	-2.5	-1.9	-2.4	-2	-1.6	-3.4	-0.7	-0.2	-1.6	-2	-4.5	-1.8	-10.4	-1.2	-3.4	-2.5
IT	3.6	-2.2	-0.2	1.8	1.4	-0.7	2.7	2.2	-2.4	-2.5	-1.1	-2.2	-3.3	-2.3	-1.6	-0.6	3.7	-0.4
ITGR	4	5.7	4.6	5.6	1.9	2.8	2	3.4	-0.8	1.5	3.1	1.8	-1.5	4.5	5	5.5	10.5	5.7
ITT	12.2	1.6	-0	1.9	-1.6	-7.6	0.8	3.9	6.3	-1.1	-0.1	-0.5	0.2	-1.7	-0.7	0.5	2.4	-0.3
JKHY	13.2	2	3.8	2.5	1.3	2.1	2.8	-1.8	-3.7	-2.2	-1.5	-2.5	-2.1	-2.1	0.6	0.9	4.6	0.5
KAI	5.9	-2.2	-4.8	2.9	1	-1.9	0.8	-0.7	3.8	-3.1	5.8	-4.7	-3.1	-7.5	-3	0.3	-4.2	-4.3
KBR	4.6	-3.1	-1.7	-7	3.7	4.5	4.3	9.3	-1.4	0.7	-3.7	-1.7	-2.6	1.8	5.2	3.2	4.2	3.6
KFRC	4.9	4.5	2.5	0.2	2.7	0.5	3.4	4.9	7.2	1.9	5.2	1.1	0.9	-1.4	-1.5	0.9	-1.7	8.3
KLIC	5.8	1.6	0.8	2.8	-1	3.8	1.7	-2.5	-10.3	3.4	5.9	-1.1	-1.5	-4.9	-5.4	-2.3	1.5	-0.1
LANC	18.2	3.8	3.7	4.2	3	-0.4	3.2	2.7	0.9	1.6	1.4	-1.9	-0.4	0.6	0.8	-0.2	2.8	2.9
LBAI	-5	-5.5	-4	-2.1	-3.3	-5.7	-8.6	-3.6	-3.2	-4.2	-4.1	-3.1	-2.5	-0.2	-2.8	-9.6	-3.9	-3.3
LMAT	8	7.4	0.5	1.8	1.1	-1.1	3.8	2.3	-0.3	-1.9	1.3	-2.8	-1.4	-3.3	-1.9	4.9	-4.7	-6.6
LOW	19.2	3.1	2.1	1.7	4	1.5	-0.2	0.9	0.3	-1.3	-5.2	-0.8	-1.9	-0.2	-2.3	2.4	5.6	-1.2
LRN	7	1.9	1.4	1.7	1.2	5.5	0.4	1.7	1.8	0.2	-3.3	-4.6	-4.9	-4.5	-3.8	0.2	-2.4	2.9
LSI	1.7	1.6	3.5	-5.4	-3.3	2.8	1.4	1.7	-1.3	-1.4	-2	0.3	-4.3	-4.7	-1	5.9	4.2	0.8
LYG	4.6	-3.7	0.1	-1.2	-2.7	-0.3	-0.3	-2.7	0.1	-1.3	0.6	1.2	-3	-4.2	-2.8	-0.8	-3.4	-2.5
MCY	1.4	0.3	-1.7	2.4	2.6	-0	1.1	3.5	2.7	0.8	-8.2	-3.7	-3.3	-0.6	-3.3	-5.6	1.4	0.9
MDC	1.2	1.7	-15.6	0	2	-3.5	-3.5	3.3	2.2	4.2	1.1	3	3.2	3.6	3.6	-1.3	0	-1.3
MGM	9.1	0	2.9	-1.2	-1	2.5	4.9	-2.8	2	0.7	-3.7	-0.3	-0.8	-3.6	-2.8	-5.6	-7	-1.8
MGRC	5.6	4.2	3.1	3.4	3.4	3.5	2.4	2.3	0.1	-1.5	-1.3	-1.7	-2.1	-1.6	-1.2	4.5	4.9	0.1
MIDD	-6.4	4.3	-1	0.3	-0.8	0.3	4	0.8	-1.5	-4.2	-5.7	-6	-4.9	-3.7	-6.3	-3.1	-4.8	-0.9
MRO	-5.2	-0.7	-2	6.5	-2	2.6	3.5	-2.1	2.1	2.1	-1.1	-0.7	-1.6	-1.7	-0.5	-3.4	-1.4	-3.1
MSA	6	-0.8	2.8	1.2	2.4	-0	2.6	-3.7	1.2	-0.9	0.9	0.6	1	5	1.3	6	4.2	0
MT	-7.9	-1.8	-1.8	-2.1	-3.2	-4.5	-3.8	-4.1	-9.1	0.5	-4.8	-6.2	-3.1	-2.8	-3.1	-5.7	-3.6	-6.7
MTZ	6.7	2.5	3	-4.1	0	3.6	2.7	3.6	5.7	3	0.6	2	0.5	-2.9	-1	-8.1	-2.5	-3.1
MYGN	8.9	-0.4	0.9	0.6	2.1	6.3	4.6	-1.3	-2.8	2.4	2.1	-2.1	1	0.9	-3.7	-4	-0.4	6.7
NBIX	5.9	1.3	4.3	3.9	2.7	0.7	5.6	-0.8	-1.5	-0.8	2.6	0.7	-0.9	-1.4	-1.5	8.5	4	-2.8
NEOG	13.1	2.2	6.8	-2.8	3.2	4.8	-2.3	2.7	3.9	0.2	-2.4	-2.6	-3.1	-3.8	-2.3	-0.7	-2.6	0.7
NFLX	2.6	2.5	6.6	7.7	1.8	4.1	-1	-1.6	0.2	10.4	4.6	-5.7	-4.7	-3.1	-5.8	3	4.7	7.5
NG	1.9	2.5	2.5	4	1.8	9.3	6.8	10	3.7	2.9	2.3	4.3	-0.3	2.3	1	-2	-2.9	4
NGD	7.2	-2.9	-8.2	-4.8	-3.4	-5.5	-5.5	-10.9	-10.9	-8.3	-9.5	-9.4	-6	-2.7	-2.1	-3.8	-3.8	-5
NGG	1.4	0.8	1.2	2.3	1.5	4.9	-2.7	5.7	3.4	3.3	-0.5	-0.8	-0.3	-4.3	-4.7	5.3	-4.7	-1.2
NICE	16	0	-2.5	-10.8	-11.8	3.4	4.4	1	4.3	0.4	3.2	0.6	-2.9	-2	5.8	7	-1.8	0.4

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Table B.7 continued from previous page

Label	MST	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53
NNI	5.9	2.2	4.1	2.3	0.2	3.7	-4	1.5	2.3	-0.3	0.5	-3.5	-3.3	-1.7	2.7	2.1	-2.8	-2.2
NNN	13.2	2	4	4.8	2.1	7.6	4.4	4.8	2.9	3.5	2.3	0.8	0.8	1.8	5	7.6	4.2	0.3
NOG	6.8	-2.1	0.6	-4.5	0.9	5.1	5.1	2.4	1.4	6.4	6.2	5	0.3	3	-0.3	1	1	2.1
NRG	11.2	3.8	-4.5	3.4	-3.5	3.6	4.3	4.4	-0.2	3.5	-2	2.8	8.7	-3.3	-1.3	5.6	8	-4.1
NVMI	-1.4	3.4	2.6	3.3	3.7	3.2	3.5	2.4	5.4	2.8	1.3	0.4	-2.1	-1.5	-4.2	3.6	5.3	-4.4
NVS	1.4	0.1	2.3	2.2	2.8	-1.2	0.6	1.3	-2.6	-2.7	-2.3	-1.2	-0.2	-0.8	-2.5	-1.2	1.1	3.8
NWBI	0.3	-4.2	0.3	1.1	1.2	1.1	9.4	5.1	0.4	4.5	1.5	-0.7	1	-0.8	-2.9	-3	2.7	0.3
OGE	7.7	1.7	2.8	2.7	1.9	0.4	-0.1	-2	0.8	-1.7	-0.4	-1.8	-1.8	-1.3	-2.5	1.1	3.9	3
OMCL	5.4	0.7	2.4	-3.2	2.5	4.4	1.8	1.6	0.1	0.9	0.6	-2.3	-4.4	-4.4	-3	-1	-6.6	-0.6
PAYX	4.6	1.3	2.5	-4.7	-3.6	2.6	6.4	-1.1	0.1	-3.9	-20.4	-1.4	-0.7	0	0	8.2	2.7	-5.6
PB	6.8	1.9	3.4	-0.7	-8.2	-2.1	5.6	-0.3	4.2	2	-0.5	-3.9	-3.6	-4.7	-5.5	0.9	2.5	-2.1
PCH	-1.2	-3.3	-9.7	-1.4	-1.3	-4.5	-1.8	0.7	-1.3	-2.8	-2.5	-1.5	-1.5	-2.7	-3	-1.2	-2.9	-1.3
PDCE	2.9	-0	-2	-2.1	-2.1	-2.1	-1.8	-5.3	-2.2	-1.6	-1.8	-0.8	-5.1	-7.4	-6	-4.2	-4.7	-2.6
PDFS	4.8	1.9	-0.1	0.5	1.1	2.4	2.9	1.4	1	0.4	-5.6	1.5	0.1	-0.3	-5.7	2.5	-1.5	-5.7
PDS	11.1	-0.7	-2.9	-1.8	-2.2	-1.1	-1.1	-5.7	-2.1	-5.2	-6.4	-1.1	-3.2	-4.8	-3	-3.7	-3.7	-2.8
PERI	10.2	-2.1	2.6	1.7	1	0.3	0.3	-1.3	0.8	0.4	2.7	-0.3	-3.6	-5.8	0.8	0	0	2.1
PHG	7.1	1.6	1.6	0	1.1	-1	2.3	2.4	4.1	5.2	4.4	1.4	0.8	3.6	4.6	-0.4	7	1.6
PNM	0.9	2.2	2.7	2.2	1.9	0.4	0.4	-0.2	2.5	1.1	-3.3	-1.3	2	2.3	2	0.6	-1.5	-3
POR	10	1.4	1.9	2.2	-28.8	-4.5	-0.5	2.1	-1.8	-4	-1.1	-2.9	-3.7	-1.7	-1.2	3.1	3.3	4.1
PRGS	5.3	-1.6	-0.7	1	-2.2	2.2	1.3	-3.5	-2.9	-0.4	-1.2	-4.1	-7.5	-5.9	-2.7	5	7.9	3.6
QCOM	6.1	-2.7	-5.1	-6.8	-2.2	3.8	3.4	1.7	2.6	4.6	-5.9	-9.2	-7.5	-7	-4.9	5.1	-0.3	5.8
RAMP	10.1	-6	0.6	-1.3	-1.1	2.3	5.5	0.5	3.1	4.4	2.3	0.9	1.7	-9.6	-32.8	4.6	8.3	0.8
RGR	3.1	0.5	1.4	2.4	0	-1.2	-4	-0.3	-2.4	-1.3	-0.8	-1.7	-1.7	-6.8	-7.9	-2	1.3	0.3
RHI	6.6	6.1	0.6	2.3	0.1	-3.4	-0.7	-0	1.5	0.1	-7.3	-8.3	-0	-15.5	-6.6	-4.7	7.8	3.9
RJF	3.1	-2.1	2.2	-4.8	0.6	-3.8	-0.8	-1.8	4.9	1.2	0.9	0.4	-1.9	-0.5	-1.6	2.9	0.1	2.2
RL	11.4	0.7	0.9	0.2	-3.7	1.3	-2.8	3.8	-7.3	3.2	3	-8.7	-7.3	-5.6	-5.2	-2.9	2.2	-0.2
ROG	9	-3.8	-0.7	0.1	0.7	-1.7	-0	4.7	1.1	-9.1	4.1	-8.2	-8.6	-9	-6.5	5	-0.7	-8.4
ROIC	5.1	1.8	0.3	1.4	-4.2	5.6	3.5	-0.7	3.2	-0.9	-2.5	-1.8	0	1.2	0.1	1.3	-4.7	6.6
RPM	9.7	-1.1	1.1	2.3	-0.9	0.6	4.7	3.7	3.5	0.8	-3.6	-2.7	-3.9	0.4	-1.4	1.7	2.6	2.9
RPT	2.9	-11.2	-17.6	2.8	1.8	2.5	1.5	2.2	1.8	0	-1.2	-1.2	-1	2.3	0.4	-1.2	5	-2.9
RTX	2	0.2	-0.6	2	2.1	-2.9	-1.5	-2.4	-1.7	-0.5	0.2	-8.5	-7.3	-3.7	-2.6	3.7	1.2	-0.2
RUSHA	6.5	-3.4	-1.2	-0	-0.9	-2.5	1.4	0.8	-5.5	-3.4	-3.2	-4.3	-3.5	-0.7	-1.6	3.7	-6	-0.5
RY	6	0.3	0.1	0.7	0	3.1	0.2	-2.4	-1.5	-8.3	-4.8	-3.6	-2.5	0	0	1.5	4.7	-1.9
SAH	9.8	0.2	-0.6	-4.4	1.5	3.1	3.1	4.2	2.6	-2.3	0.4	-0.8	2.4	3.2	1.6	3.8	3.2	-7.4
SAIA	3.9	1.7	3.4	1.4	1.3	4.4	4.4	4.5	2.3	2.3	3.4	-0.1	-0.8	-1.2	-6.1	5.1	4.8	-4.6
SASR	-6.1	1.3	0.4	2	-2.5	4.9	3.9	6.1	-1.8	-8.1	-3.4	-2.2	-2.6	-3.4	-3	-6	-4.3	-3.7
SBH	3.3	-2.1	1.2	2.6	0.8	2.2	-2.6	0.3	-0.6	0.9	2.2	-1.1	-0.4	-2.8	-1.7	-1.9	-3.9	-1.6
SBRA	4.1	3.7	0.6	0.4	0.9	5.3	0.9	5.7	1.2	1.7	2.2	-1.5	-2	-1.9	-1.9	2.2	-0.6	3.5
SBS	11	-6.5	0.9	2.6	5.4	0.5	-0.2	0.8	0.4	-3.2	-4.1	0.1	-4.3	-0.6	1.5	1.6	1.7	-0.8
SCI	-1	3.2	1.8	4.3	2.1	5.9	0.7	5.5	-4	-1.6	-0.7	-3.7	-6.7	-3	-5.4	-1.8	2.5	-0.8
SCVL	8.4	1.7	0.1	3	0.8	3.2	1.3	-0.2	2.9	-3.8	-2	1.1	2.2	-2.8	-2.2	2.9	4.7	4.8
SEIC	-1.5	-3.4	-3.5	-1	-3.7	-3.9	-0.6	-3.2	-6.9	-3.4	-1.8	-4.1	-3.5	-5.1	-2.3	-4	-3.2	-5.8
SIEGY	2.9	-1.3	-5.8	-3.6	0.5	2.8	-3	-4.4	-2.7	-1	-0.4	-2.8	-4.3	-2.7	-2	-2.8	-4.4	-4.9
SITC	6.4	2.4	3.2	0.2	3.4	-0.1	1.3	1.5	1.7	0.4	3	0.8	0.6	-1.6	-1.1	-0.2	-0.5	4.8
SKYW	3.7	5	5.6	-0.3	1.3	-0.1	0.1	2.1	7.4	0.4	2.2	0.4	5.4	4.9	-3.3	6.7	5.1	0.5
SNX	-2.8	-2.9	-2.9	-2.2	-3	-3.5	-4.2	0.6	-2.5	-2.9	-5.7	-5	-3.9	-3.2	-5.6	2.2	-1	1.3
SO	4.2	3	3.1	3.1	-10	-3.7	-1.4	-1.1	0.1	-0.1	2.6	0.1	-9	-25.8	2	3.6	4.3	3.9
SRPT	5.4	3	4.9	8.1	3.9	2.4	2	3.7	1.9	5.6	1.7	4.1	8.2	-0.1	1.2	5.2	3.2	2.6
STC	2.8	0.1	-0.3	-0.1	0.7	2.2	0.5	-2.7	-0.7	-8.3	-6.1	-2.8	-2.6	-2.9	-0.3	5.3	5	1.5
STLD	-0.7	-0.8	-1.3	-1.8	-3.7	2.7	-2.1	0.1	-3.4	2.9	-3.7	-4	-5.5	-7.3	-3.5	-0.8	-1.3	-7
STM	5.7	-3.3	0.9	-1.7	-0.3	0.2	-3.5	1.8	1.2	-12.8	-2.3	-10.7	3	-1.7	-2.3	4.4	4.4	2.4
STT	6.7	-2.1	-5.5	-8.4	-2.9	-13.6	-8.3	-2.7	-8.1	0.2	-10.3	-12.9	-8.4	-8.9	-3.9	-3.3	0.5	-2.9
STX	16.6	2.1	2.1	1.9	1.9	2.9	3	3	1.6	-2.8	-4.2	-2.2	0.9	-1.1	-1.4	0.1	-6.3	3.5
SYNA	4.9	2.9	2.8	1.8	1.9	2.6	-3.1	-0.6	2.6	3.2	1.1	1.9	-2.5	-4.5	-4.7	8.3	4.5	4.6
TDC	-3.1	-2.5	2.5	-0.2	-2.5	1.3	0.4	6	1.7	-5.7	-6.1	-6.1	-7.4	-3.9	0	4.4	7.4	7.1
TEX	10.8	-5.7	-5.3	-6	-6.1	-8.4	-5.7	-0.8	-3.5	-6	-4.1	-9.1	-10.2	-2.2	-6.6	-2.3	-0.6	0.3
THG	1.1	5.5	3.9	4	1.8	2.7	-3.8	-0.9	3.7	3.5	8.5	0.6	-0.9	-1	0	3.5	2.6	4.6
TITN	1.6	-4.6	-5.5	-3.2	-2	0.2	-14.1	-2.2	-4.6	-2.3	-1.2	-1.9	-0.2	2.7	-4.5	-2.4	-2.8	-6.2
TLK	4	-0.3	-4.5	-1.7	0.3	-8.8	-2.8	2.6	-1	-0.9	1.5	-3.1	1.4	0.7	-2.2	0.7	-1.9	-0.7

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Table B.7 continued from previous page

Label	MST	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53
TREE	0.8	0.4	1.1	-1.5	-1.1	2.8	3.6	2	1.4	2.3	-0	4.2	-1.9	4.3	-2.6	1.8	5.5	-10.9
TREX	15.5	1.6	-6.1	7.5	1.8	3.8	3.5	-3.9	-1	1.5	4.4	3.2	2.2	-2.2	-0.3	4.3	3.8	4
TRMK	-0.4	-1.7	-2.8	-1.4	3.2	1.3	-1.8	3.1	-0.2	-2.1	-0.4	-1.9	-1.7	-4.1	-1.6	-1.5	-11.3	-1.8
TSM	2.4	-1.1	-5	-5.9	-3.6	-2.6	5.3	1.1	1.8	3	2.6	-6.9	-4.4	-5.2	-2.6	5.4	4.9	5.3
TTC	5.6	-2.9	-4.3	-4.3	-2.9	-2.4	2.2	5.4	2	-5.9	-1.5	-5.1	-1.9	-3	-5.2	4.3	-9.4	-1.7
TU	11.3	-4.8	-2.2	1.1	-3.4	1.9	-3.1	1.8	1.2	5.9	3.3	-1	-0.9	0.2	0	-3.4	-1	-5.2
TXN	8.6	2.6	4.6	3.1	4.6	2.6	0.6	3	-0.4	2.7	-7.1	-3.3	-1.4	-1	-2.4	5.4	-7.2	2.9
TXRH	6.2	-1.3	2.1	0.7	3	-7.1	-9.4	-3.2	1.9	1.6	2.8	-0.9	-2.1	1.2	-3	0.8	2.6	0.8
UBSI	10.6	3.1	0.7	3	2.4	1.1	-0.5	3.3	0.4	5	3.5	-8.7	6.7	-4.3	-0.2	-1.4	3.9	-1.1
UGP	0	-5.9	-3.1	-3.1	5.5	-8	-3.2	-1.9	-2.3	-1	-2.3	-5.7	-2.5	-2	-3.5	-1.5	-2.1	-8.3
UHS	7.1	0.7	-0.1	0	1.7	0.6	5.3	0.1	3.4	2.5	-5.2	-4.1	-0.3	-11.4	-8.8	3.1	-1	3.4
UHT	5.6	2.2	-4.2	2.5	2.9	-1	-0.4	4.6	3.4	1.8	0.3	-0.4	-1	0.1	-3.3	3.1	-4.3	3.1
UNF	5.5	0	1.6	-3.6	1.6	4.1	-5.9	-3.9	0	0.6	1.9	-0.1	-1.1	-1.1	-3.1	-8	1.9	2.3
WEC	5.3	3.3	2.4	2.1	2.3	1.8	-5.6	-2	-3.5	-3.4	-3.3	-1.2	-2.3	0.3	-6.1	-5.2	-5.7	4.4
WELL	4.3	2.5	3.1	-1.6	2.9	-3.3	1.3	6.3	3.3	-2.4	-0.7	-1.1	-0.7	-0.1	0	3.1	2.4	4.2
WEN	9.3	3	2.4	3.9	2.9	4.4	3.7	7.3	1.4	-0	5	6.5	5.2	2.1	0.2	6.6	0.5	0.4
WIRE	1.9	2.6	0.5	3.2	2.9	3.4	-3.2	3.3	4.4	1.6	-0.5	-3.3	-4.5	-5.6	-5.5	6.5	5.3	2.4
WLK	-1.3	-3	-2.2	-2.3	-2.6	-3	-2.8	-3.7	-0.4	-1.7	-7	-1	-3.7	-3.8	-2.9	2.8	-1.1	-1.6
WMK	17.8	-3.3	-2.6	0.3	1.4	0.6	-1.2	2.2	4.6	0.4	1.2	-5.4	-4.1	-6.1	-5.1	-0.3	-3.2	-4
WMT	7.4	-9.5	-2.2	-1.9	2.6	-3.7	0.2	-0.9	-3.9	-3.6	-2.7	-2.5	3	-0.8	2	4.7	2.8	6.3
WOR	8.5	-2.7	-0.4	-7	-2.5	0.6	-3.2	-5.3	-3.6	2.1	1.4	0.2	0	-5.7	-5.5	1.3	6.7	-1.6
WPC	5.3	2.2	-4.1	2.2	2.4	1.9	-0.3	1.1	0.1	0.5	-2.1	-2.2	-2.9	0	3.2	1.9	-3.8	10.6
WSM	14.9	4.7	3.7	2.9	4.1	3.5	4.3	3.1	3.9	6.8	8.9	-7.4	-4.2	-2.1	2.5	5	-0.3	3.2
WTI	7.8	-1.9	-0.8	-0.1	0.7	-0.2	3.6	4.1	3.9	1.6	1.7	-1.5	-2	-1.8	-2	-3.7	-4	0.1
WW	-5	-0.1	0.4	3.5	1.8	1.1	-0.9	1.1	-7.5	-5.6	-3.5	-1.1	-2.3	-1.9	-2.2	-0.1	-2.7	0.9
XPO	4.7	-6.3	-4.5	-1.9	-0.4	-4.8	3.4	-3.4	-0.8	-4.2	0.5	-3.7	-2.8	2.2	-3	3	9.9	1.8

Table B.8: Sharpe Ratio Results for MSTGAM (MST) versus sub-strategy for St5θ4, $\cdots$ St8θ5 experimented in Chapter 6, where cardinal numbers denote specific sub-strategies (e.g., 54 = St5θ4, 70 = St8θ5) as described in Section 6.4

Label	MST	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70
AAON	7.7	1.6	6.1	7.4	4.1	0.6	3.2	1.7	0.5	0.5	0.9	1.5	1.8	-2.2	-1.5	-0.6	-1.5	-2.4
AAPL	7.2	3.8	2.6	2.5	3.3	-3.2	-3.9	1.6	4.6	5.3	4.7	3.4	4.1	0.8	1.5	5.7	2	0
ACM	12	-0.4	-8.4	-3.8	-1.9	-1.2	-1.7	-5.5	2.1	1.2	0.2	-2.2	0	1.5	0.7	0.4	2.3	5.4
AG	5.9	0	-5.8	4.1	4	3	2.4	2.7	1	2.5	2.5	1.4	4.5	3.8	0.2	0.2	0.2	4
AGEN	2.1	1.9	3.7	2.2	-2.2	0.4	-0.5	3.6	4.7	4.7	0	0	0	5.2	5.2	4.6	10.4	6.7
ANDE	11.5	1.3	5.2	1.2	7.8	-0.7	3.8	-1.5	0.9	1.7	0.2	0.5	-1.8	4.1	4	12.1	7.9	2.9
ASGN	12.3	2.6	-3.5	8.2	2.7	-6	5.6	5.4	0.9	1.1	0.8	0.4	1	-0.7	-1	-2.2	-1.7	0
AWI	10	3.9	3.3	4.7	1.5	1.9	3.9	3.3	1.9	1.4	0.4	3.1	0.3	0.3	0.9	0.6	-4.4	-4
BANR	5.1	0.8	2.5	-2.3	-0.6	1.9	-1	-2.6	4.4	4.6	5.5	2.2	-1.2	4.6	1.3	-0.8	-0.8	0
BCPC	3.3	2.3	3	4.8	1.4	4.9	1	-7.7	0.8	4.2	5.3	4.9	2	-3.1	-3.1	-1.9	-1.4	-0
BG	8.3	2.8	3.9	-0.4	4.5	-1.6	-2.8	2.1	4.7	4.8	6.6	1.3	0.4	4.3	1.7	-14.1	0	-0.5
BHLB	-5.6	-2.3	-2.5	4.8	0.9	7.5	-0.7	-0.5	0.8	0.7	-1.5	-0.1	3.2	-0.1	0.5	1.7	0	0
BHP	7.2	-0.4	2.9	2.8	6	0.9	2.1	-4.3	3.1	1.7	-0.8	0.6	-0.8	3.9	3	4.6	2	1.6
BKR	-6.8	1.4	-1.6	2	-0.3	-2.6	-0.6	-0.7	5.1	4.7	1.8	1.9	-0.6	5.9	-1.1	-1.9	-1.1	0.2
BMI	12.7	7.8	6.5	-5.2	5.5	3.3	-2.2	3.3	1.9	0.1	-0.8	-0.4	-7.4	6.4	3.7	2.3	-3.8	1.9
BMY	5.4	-2.7	2.7	-0.4	4	-1	-0.2	4.7	1.7	1.2	1.5	1.5	-2.1	-1.2	-0.5	-2.7	-2.3	-1.8
BSAC	-2.7	-2.6	-0.8	-1.6	-2.3	-0.6	1.8	-1	4.8	3.4	1.9	-2.2	0	-5.3	0	-3.5	-7.1	-2
BSBR	22.4	6.5	1.6	-2.6	-0.6	-1.6	4.2	4.4	5	5	7.4	7.3	5.8	2.3	-2	-3.7	10.7	10.7
BSX	11.3	5.4	0.7	10.8	5.6	3.9	10	3.3	-2.1	-0.8	1.6	-0.2	-5.4	1.7	1	1	0	0
BX	8.6	5.4	0.3	5.8	6.1	0.3	0.7	8.6	4.8	4.1	4.4	1.8	0.5	-1.5	1.5	1.8	0	0
BYD	1.1	2.6	0.1	1.1	-0.1	4.3	-2.7	0.2	3.4	3.4	3.9	3.3	7.1	11.9	11.9	0.5	-2.2	-0.2
CBZ	19.9	-1.8	3.2	1	5.2	5.9	7.7	4.3	13.9	13.5	2.7	2.8	0	-0.1	1.3	0.6	1.2	0.6
CCEP	16.6	5.2	-2.3	6.6	2.6	0.8	1.8	3.4	12.7	6.3	4.4	1.6	0	3.7	1	0	0	0
CCI	5.2	4.6	2.4	8.8	3.6	3	3.9	4.1	3.9	5.6	3	4.2	3.3	-5	-4.4	-1.9	0	0

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Table B.8 continued from previous page

Label	MST	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70
CCL	-11.7	-8.4	1.8	-1.6	2	-6.9	-3.7	1.7	4.1	5.5	3.7	39.9	0	-0.4	1.5	2.4	2.1	1.6
CHH	7.1	1.1	-0.1	-4.5	-1	5	3.1	2.8	5.6	5.1	4.9	2.2	1.4	5.1	1.3	-3	-2.9	0
CMP	3.1	-2.6	-3.9	-1.6	-3.1	-3	0.1	-3.9	-0.1	-0.6	-1.3	5.2	4.4	4.1	2.5	0.7	0.6	0
CNK	2.8	2.3	-4	0.4	2.1	2.9	0.9	0.9	3	3.5	-4.1	-3.9	-4	-2	0.7	1.2	-0.7	-1.2
CNXN	7.6	6.9	5.9	6.7	6.6	1.5	-1	2.3	5.9	4.4	3.5	3.4	1	-3.2	-3.1	0.8	0.6	1.7
COST	8.9	7.7	4.9	4.4	4.3	4	0	3.6	7.8	10.5	7.2	4.4	4	0.8	0.8	0	0	0
CRK	1.4	0.2	3.7	-9.6	2.7	-2.7	-4.9	1	3.4	3.4	3.2	3	3.7	2	2.5	2.6	4.1	2.4
CSV	7.8	0.1	-1.3	-4.3	0.9	1.1	1.6	2.5	4.9	3.6	3	1.3	1.6	4.5	9.5	2.9	2.8	2.2
CUBE	3.5	2.3	1.6	-0.6	3.2	2.9	1.8	0	-4	5.1	1.3	0.7	1.9	0.5	-1.5	7.5	-1.4	-0.7
D	4.5	-5.7	-4.4	-5.6	-1.3	-5.2	-5.3	-0.5	0.9	0.2	0.2	0.5	-1.8	1.3	-15.5	1.2	1.2	0
DCOM	0.6	-3.9	-11.7	-1.7	-4.7	-2.6	-1.4	1.3	8.5	5.3	4.3	3.7	1.5	-0.7	-2.1	-1.1	-1.1	-3.5
DDS	4.8	-7.1	2.1	4.1	3.7	3.1	5.5	-12	0.6	0.8	2.2	3.5	4	-0.1	0.3	0	-1.1	-1.4
DENN	15.2	3.3	3.5	3.1	0.9	0.6	2.1	4.8	0.1	-0.5	-0.2	-10.9	-6	2.9	1.6	0.9	4.4	-61.7
DIOD	4.7	0.9	1.3	3	9	0.8	4.2	6.9	3.6	3.5	1.9	1.4	1	2.2	-1.7	2.1	3	5.4
DIS	17.2	-1.7	-1.6	3.4	1.1	1.8	6.5	3.7	1.4	3.4	2.7	-3.3	-37.1	11.2	11.8	3.4	1.5	9.4
DRQ	-3.3	-3.8	0.9	-5.8	-13.1	2.5	0.5	4.5	3.6	3.6	4.4	0.1	1.1	3.2	5.2	6.5	0.7	2
EAT	21	-0.6	4.2	3.6	4.8	-0	2.4	0.6	2	5.1	2.4	3	0.9	3.1	5.4	3.8	3.5	2.7
EBR	8.2	-1.1	2.2	5.6	0.1	1.1	-0.7	1.6	6.2	6.2	3.1	2.8	2.3	0.1	-0.1	-1.3	-1.4	-0.4
EC	7.2	3.6	3	3.3	-4.4	-0.7	0.6	1.9	3.4	-1.4	-2.3	-8.4	-2.7	1.7	1.7	2	1.5	2.5
EFSC	-1.4	0.7	0.5	-1	0.8	-1.6	2.5	-1.7	2.8	2.5	1.6	1.4	2.4	1.4	0	-0.6	3.8	0.1
EGHT	6.2	-2.2	3	2.2	1.6	1.3	4.7	10.7	-1.4	-0.1	-0.5	1.2	-0.9	2.1	-3.1	-1.1	-1.8	-0.8
EGO	6.9	0.1	-1.4	1.3	-0.5	-6.4	-4.2	-0.8	4.3	4.6	4.6	6.6	3.1	-3.2	-3.2	-2.4	1.7	-1
EMN	-5.3	-2.7	4.5	1.2	-2.6	-0.1	3.7	-3.1	1.3	2.6	1.8	0	0	3.3	2.5	1.5	-0.2	0.4
EQR	8	2.5	2.5	-0.2	-2.3	1.5	0	2.5	9.4	7.9	3.6	2.7	3.9	-16.3	-2.6	-2.6	0.9	0
ERII	10.9	-4.4	-2.5	-5.3	-6	0.9	-0.8	-1.2	-3.5	-0.9	0	0	0	6.3	5.7	5.8	10	6.9
ERJ	-5.2	2.3	-1.9	-0.2	4.9	-0.4	4.2	1.5	3.5	3.5	3.9	2.3	2.6	5.9	7.1	11.3	7.5	5.4
ET	5.2	-0.5	0.5	2	5.3	-1.5	0.1	-0.2	3.3	3.3	3.4	4.4	0.7	5.4	7.6	2.9	4.8	2.6
EVR	7.4	-0.2	1.5	2.8	-2.6	-2.2	4.2	2.4	6.5	4.6	5.2	1	-83.7	6.2	5	1.2	1.8	1.8
FARO	8.6	-1.1	1.1	1.1	3.2	3.6	5.7	0.7	5.2	3.1	4.2	3.8	1.5	2.2	3.8	4.5	3.1	4.2
FBNC	4.4	0.9	1	4.6	1	2.1	-2	2.3	1.3	0.6	1.8	2.1	3	6.1	7.7	3.8	0.6	0
FELE	10.7	-4	-3	-1.4	4.5	-0.7	-0.1	1.6	1.7	2.2	0	2.6	2.5	12.2	13.7	11.7	-0.1	4.1
FFIN	8.4	0.7	4.9	7.7	0.5	6.4	7.1	0.8	4.7	4.7	3.8	2.2	-0.2	0.7	1.1	0.9	-0.3	-0.6
FISI	-3	-1.5	2.3	-3.1	-3	-5.8	-2.6	-1.9	0	-0.9	1.2	1.3	-3.4	2.6	-0.4	-3.1	-2.2	-7.5
FIX	13.6	6.6	1.7	1.3	5.3	2	2.1	4.4	3.8	4.1	2	0	1.5	0.5	1.9	-1.4	-1.1	-2.1
FLO	4.2	4.2	3.8	-0.2	-1.1	-0.6	-0.5	-1	-3.3	-3.6	-3.3	0	0	-2.8	-1.9	-2.8	-9.6	-0.9
GCO	16.5	9.6	3.6	7.1	1.3	-0.4	-1.9	2.8	-1.1	-1.1	2.7	2.7	-1.7	1.8	1.3	-4.2	0	0
GD	8.6	0.4	4.5	-1.5	-2.2	-3.9	-1.3	-0.3	6.8	8.7	6.6	4.7	2.3	2.3	0.3	0.8	1.4	0
GE	-7.2	-8.7	-2.6	-0.2	-3.9	-3.1	-4.1	1.4	-0.9	-1.3	0.5	0.9	1.8	6.9	7.7	4.9	4.9	2.9
GSAT	7.1	-9.5	-7.1	-7.1	-10.7	-9.5	-7	-10.1	2.3	2.3	2.3	2.3	2.3	0.7	0.7	0.7	0.7	3.5
GTE	14.6	3.1	-1.8	0.3	2.3	0.2	0.7	3.4	0	0	0	0	0	6.7	6.7	5.8	8.2	13.1
GTLS	2.9	3.7	-1.1	2.4	1.3	4	-0.2	-0.7	5.6	3.2	4	1.3	3.1	7.5	7.5	3.7	4.5	3.6
GTN	3.1	-5	1.8	3.2	-1.6	-1.2	2.3	2.1	5	5	4.8	2.7	2.2	3.8	3.8	2.7	1.4	2.4
HA	7	-7.3	-6.1	-3.4	0.7	-1.3	-5.6	-1.5	0.1	-0.8	-0.6	0.4	-1	-0.5	-0.5	-1.2	-0.5	-0.5
HELE	14.1	2.7	-3.7	1	2.5	7.4	1.4	3.7	6.7	5.6	1.6	1.7	-44	0.3	1.2	0.3	0	0
HIW	5.6	-0.2	0.5	0.9	-1.6	-0.4	1.6	0.4	5.8	2.7	3.3	2	1.6	-1.1	-3.9	-2.5	4.4	5.3
HLX	8.5	2.8	1.1	2.5	0.5	-1	-4.1	1.9	2.5	2	3.2	4.5	3.9	3.2	6.5	1.4	0.7	0
HMY	3.7	-5.3	-8	-0.7	0.2	-3.9	-1.2	-0.2	-0.5	-0.5	0.9	-0.9	-0.6	-0.2	-0.2	-1.1	-2.5	-4
HOPE	3.6	-3.4	-1.6	2.9	2.1	-1.5	1.2	-3.9	1.9	0.5	0.7	-0.6	-1.9	4.5	3.2	1.1	0	0
HRI	9.7	-9.1	-7.3	-1.2	-4.5	-1.3	-4.4	-0.8	-2.1	-0.3	-2	-2	1.5	-2.1	-2.1	1.3	1	0.3
HWC	-2.2	-1.8	-5.9	-3.4	0.6	-5.4	-3.5	-2.8	4.8	3.6	1.9	-0.8	-5.8	1.4	3	7	3.9	0
IART	10.7	9.8	0.4	-4.3	2.7	6.2	1.4	3.3	4.2	3.8	-0.7	0.3	0.7	1.9	1.9	0	0	0
IDT	8.9	-3	-5.7	-3.8	-2.4	-4.2	-2	-1.1	4.8	4.7	3.4	3.1	1.8	4.8	2.6	2.8	0.8	0.5
IMAX	-4.3	-6.7	-5	3.6	-2.3	-6.1	-0.9	4.9	3.5	3.5	-0.9	-2.1	-3.6	-3.2	1.7	-40.2	-2.3	-1.3
IMGN	-6.5	1.4	-9.8	0.1	-0.3	-1.2	0.4	-2.6	-4.4	1.7	3.2	4	2.6	-2.9	-2.9	-3.7	-3.5	-4.2
INSM	7.1	7.7	-6.2	-6.5	-13.3	3.3	4.2	3	-2.8	-2.8	-1.6	inf	3.7	6.5	8.6	7.4	6	0
IOSP	3.4	2.5	5.3	3.1	0.9	1.9	6.5	3.8	2.4	2.1	2.4	-39.4	-1.1	8.7	8.1	9.3	1	-1.5
IP	-0.9	1.7	-0.7	-7	3	-8.2	5.5	-0.2	0.8	-0.2	3.2	3.6	1.6	5.4	1.9	3.1	-0.2	-1.3
IPAR	9.7	-2.1	4.5	7.8	1.4	2.6	4.1	-0.8	6.4	5.9	2.7	1	0.1	-27.9	0.1	-2	0.7	-0.8
IRBT	-8.3	-3.2	8.9	-3.4	3	5.6	1.4	4.3	1.1	2.2	4.4	3.4	-0.8	-20.6	1.7	2.8	1.7	0

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Table B.8 continued from previous page

Label	MST	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70
IT	3.6	4.8	13.9	-4.9	1.1	-0.7	1.4	-0.9	12.2	8.6	6.6	6.5	6	-2.2	-16.3	0.8	0.3	8.8
ITGR	4	2.8	3.6	4.1	3.6	8	2.9	4.2	0.5	0.7	0.5	1.1	0.5	8.5	6.2	7.3	3.9	3.9
ITT	12.2	0.7	8.2	2.8	2.5	3.4	1.9	7.2	7.1	5.7	3.3	3.3	2.8	2.7	2.2	2.2	2.3	0
JKHY	13.2	5.8	1.8	-2.4	8.6	5.9	0.4	2.4	2.4	2.9	-2.7	-3.1	-1.9	0.7	-3.2	0	-0.5	7.9
KAI	5.9	-3.6	-0.2	-1.2	3.1	6.2	-5.2	5.7	0.2	2.6	2	1.1	2.1	3.1	2.1	0.8	-0.1	1.7
KBR	4.6	0.7	4.9	-2.2	-2.8	-1.7	2.1	7.3	15.5	11	8.6	6.1	3	-6	-3.2	-1.5	-1.5	0
KFRC	4.9	-1.9	2.3	1	2.4	3.2	0.2	4.6	1.5	1.4	1.2	2.7	3.7	13.5	9.4	11.3	5.9	1.9
KLIC	5.8	2.7	1.2	-2.9	-1.2	2.3	3.3	0.3	4.5	5.1	2.3	2.5	3.9	1.8	1.8	3	4.5	4.4
LANC	18.2	1.2	0.5	0	1	3.3	1.4	4.5	0.3	0.6	2.1	2	-16.2	1.5	-0.9	-2.4	-3.2	-1.3
LBAI	-5	-1.7	-1	-3.9	0.4	-5.5	-1.2	-2.2	1.1	3.9	0	0	0	5.5	4.8	3.2	2.3	-0.7
LMAT	8	-5.1	-3.9	3.5	5.1	1.1	-0.1	-2	5.2	2.9	5.6	5.3	5.6	1.2	1.2	-0.7	0	-1.2
LOW	19.2	5.5	5	3.9	4	0.4	2.1	1.9	12.3	11.6	7	5.2	3.7	1.3	8.2	5.4	2.8	2.8
LRN	7	6.3	4.9	0.7	-5.8	-1.4	-4.4	-2.4	1.5	0.9	-4.4	-3.6	-0.7	5.2	7.7	8	2.1	2.4
LSI	1.7	3.8	3.6	6.8	1.2	1.2	0.1	1.8	0.9	0.2	-0.9	-2	-2.2	-1.5	0.9	3.9	3.1	1.6
LYG	4.6	-3.7	-5.8	-5.6	-4.4	2.8	0.3	-2.8	3.5	3.5	3.4	3.7	0	0.3	-0.3	1	3.5	7
MCY	1.4	-4.5	1.7	0.1	2.4	1.9	-5.2	-3.5	5.4	6.7	4.2	0.7	2.4	-3	-3.1	-1.7	-5.1	3.2
MDC	1.2	7	3.7	2	2.5	-1.7	0.5	-0.4	1.9	2.3	-0	-5.3	-6.7	2.4	0.5	-1	0	0
MGM	9.1	-1.8	-0	-2.5	1.3	0.7	-3.3	-3.3	5.3	2.6	-1	-2	1.7	1.7	2.6	-0.1	-0.4	0.5
MGRC	5.6	4.6	-4.2	3.9	-3.6	2.1	1.8	1.3	2.6	9.3	-0.2	1.4	2.4	2.1	6.1	2.9	1.6	0.7
MIDD	-6.4	3.9	0.1	6.1	-3.1	-2	-1.7	-5.9	3.8	3.2	3.1	3.8	2.2	-0	-0.6	0	0	0
MRO	-5.2	-2.9	-4.2	-3.9	1.1	0.1	1.6	-0.6	-1.9	-3.5	-1.3	0.6	0	4.9	4.9	2.9	4.4	2.9
MSA	6	2.7	2.7	-1	-0.5	-1.2	4.2	3.3	-0.5	-1.5	-0.1	-0.8	1.8	0.1	-0.2	-6.3	4.5	0
MT	-7.9	-1.9	-5.6	-4.1	-2.8	-4	-5	-1.7	7.5	7.5	9.1	9.1	3.2	3.6	3.6	3.3	1.4	2.2
MTZ	6.7	6.6	2.5	6.8	6.5	-1.6	1.5	-2	1.3	0.4	0	0	0	4.8	8.8	7.1	6.2	5.6
MYGN	8.9	-0.2	-1.8	-2.3	-0.1	2.1	3.5	-0.8	1.5	2.9	6.3	3.3	4.9	-1.3	0.1	5.6	3.9	3.9
NBIX	5.9	-0.8	1.9	3.8	5.1	1.2	5.3	2.5	5.7	2.3	6.6	2.1	0.6	4.1	4.1	2	2	2.6
NEOG	13.1	0	3.6	6.5	4.5	-0.7	-2.1	0.9	2.8	2.7	3.9	4.3	4.4	-1.3	1	1.8	-0.2	0
NFLX	2.6	6.4	-1.4	2.2	-0.8	2.8	7.1	0.2	3.6	3.6	1.8	1.6	1.6	2.4	5	4	4	4.7
NG	1.9	-0	1.7	-2.3	0.4	-5	-0.8	2.8	3.9	2.7	0.6	-0.2	-16.6	6	6	2.7	4.3	3
NGD	7.2	-5	-3.6	-7.7	-4.6	-6.1	-6.9	-6.1	2.5	2.5	2.5	2.5	2.5	11	11	9.7	9.7	8
NGG	1.4	-3.2	-1.3	6.8	-0.2	-1.1	-2.8	1.1	0.7	0.1	-1.9	-1.6	-0.8	4.1	0.2	-0.2	-0.4	0
NICE	16	7.2	3.3	7.5	4.8	2.1	5.2	6.5	1.1	1	0.5	-0	-3.4	1.9	0.1	4.4	3.3	0
NNI	5.9	-4.3	0.5	-2.3	-0.7	1.1	4.5	2.9	2.4	1	-3	-3	-3	-0.2	5.6	1.6	-2.1	0
NNN	13.2	3.1	4.2	5.6	2.9	4	0	-2.4	3.2	1.9	3.6	2.4	-1.9	0.3	0.5	16.1	0	0
NOG	6.8	-1.6	3.7	2.1	2.9	5.7	-0.7	4.4	2.6	2.6	0.4	0.5	0.5	1.2	1.2	1.1	0.7	1.2
NRG	11.2	-2.4	8.3	-0.7	3.3	-2.2	4.3	3.3	0	-0.6	2	-0.7	-31.2	6.3	4.9	4.7	0.3	-0.7
NVMI	-1.4	2.3	-7	0.6	1.2	-1.9	7.1	-1.2	2.4	1.8	3.3	1.4	-2.6	1.8	9.1	-4.3	-3.3	-7
NVS	1.4	-6.2	-4.6	-3.8	2.2	1.9	1.3	2.9	2	6	3.9	2.6	-8.5	-3.2	-1.8	-2.5	3.7	0
NWBI	0.3	1.7	3.9	-5.6	-1.4	-4.6	0.6	2.6	-1	0.9	2	0.6	-2.3	-2.7	-2.7	0	0	0
OGE	7.7	0.4	-0.1	1.4	0.6	-0.1	-1.5	1.5	-1.8	1.4	-0.9	1	2	2.7	2.7	2	1.1	-1.3
OMCL	5.4	3.6	2.8	2.7	1.9	-1	1.6	4.9	3.5	3	1	0.8	0	3.9	6.1	6.9	3.6	3.6
PAYX	4.6	0.9	9	0.8	2.4	0.6	0.4	-1.9	8.9	10.4	5.3	5	-0.7	-2.1	-2.1	0	0	0
PB	6.8	6	0.3	0.6	3.6	-1	-5.8	-2	9.4	10.5	3.3	3	-1.7	1.7	1.7	0	0	0
PCH	-1.2	-0.8	-3.1	3.4	0.9	-0.1	-6.2	2.3	7.4	2.3	1.6	-2.4	-0.4	-7.4	6.9	-1.8	-1.6	-1.8
PDCE	2.9	1.7	-5.7	-3.3	-8.2	-8.2	-2	-0.7	3.8	5	4.7	0	0	-0.5	4.5	1.5	1.5	1.6
PDFS	4.8	-7.2	1.4	0.7	-5.7	-1.4	0.3	-1.4	3.1	5.3	5.6	6.5	4.7	-0.3	-0.7	-2.5	0.4	2.7
PDS	11.1	1.7	3.9	1.4	0.3	-7.7	-2.9	-6.2	5.9	5.9	8.2	5.4	2.8	5	5	5.8	12.2	9.2
PERI	10.2	-1.2	1.6	0.8	-0.3	-1.9	-0	-2.2	4.5	4.5	3.6	3	2.1	-1.4	-1.4	-3	-4.5	-2.6
PHG	7.1	-2.1	5.8	0.7	-3.3	-3.4	0.5	1.1	0.9	2.7	0.8	-0	1.6	-0.9	-0.9	0	0	0
PNM	0.9	-0.9	-0.2	-4.6	-2.1	0.2	-1.8	-0.7	-0.5	1.8	0.9	-2	-2.2	0	0	1.2	0.2	-2.8
POR	10	0.1	2.4	-6.9	-1.8	-0.9	-0.7	-1.5	4	3.1	5.9	-1.8	-5.3	-3.4	0	0.6	0	0.8
PRGS	5.3	4.7	-1	-3.3	3.2	3	-4	-2.2	4.9	4.9	0.6	4	2.3	0.9	3.8	5.9	4.8	7.5
QCOM	6.1	1.7	3	5.3	5	-2.2	0.3	-0.9	9.3	10.4	5	2.6	2.6	4.2	6.2	3.3	-1.2	-2
RAMP	10.1	3.8	-0	7.9	1.8	5.8	5.8	1.7	6.6	3.5	2.8	1.6	-2.3	1.5	-1.2	-1.7	-1.3	-1.6
RGR	3.1	-0	1.8	5.7	0.2	-4.4	-2.8	-0.1	1.2	-0.6	1.7	0	2.2	-1.4	-2.2	-0.1	-0.1	0
RHI	6.6	-1.3	5.8	0.2	4.4	0.3	2.1	2.3	1.2	0.6	2.2	-1.9	-3.8	2.9	0.8	1.2	3.2	-0.9
RJF	3.1	-2	-3.8	1.2	-6.4	0.4	4.5	-0.2	6.2	4.9	-2.6	-2.9	-1.2	8.6	6.3	7.2	1.7	5.7
RL	11.4	3.4	0.3	6.2	4.9	4.9	1.5	4.3	5.5	3.2	1.4	0.9	0	1	0.4	5.6	5.9	4
ROG	9	3.1	3.9	-1.7	3.8	2.8	-1.1	-4.1	5.1	7.8	5	3.3	2.5	10	5.8	6.8	8	5

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Table B.8 continued from previous page

Label	MST	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70
ROIC	5.1	1.8	5	0.6	2.2	1.7	0.6	3	5.3	4.3	2	0	5.7	10.9	-3	0.3	-0.7	1.5
RPM	9.7	3.3	-0	4.3	-1.5	-2.2	0.5	3.8	14.6	9.5	3.7	0	0	0	-0.2	5.9	0.3	2.4
RPT	2.9	-1.1	-2.2	2.9	-0	-0.7	2.2	-1.2	0.2	0	-2.4	0.7	-2	3.2	0.5	1.1	0	2.1
RTX	2	0.6	5.8	3.3	-3.8	-2.8	-2.4	-1.1	6.7	6.8	8.6	5.2	-0.3	-2.9	-2.9	-4.4	0	-2.1
RUSHA	6.5	0.2	-3.3	-5.5	-1.2	1.9	-4.5	-2.7	7.5	7.9	3.1	0.3	0.8	0.8	3.4	0.8	1.9	1
RY	6	1.4	1.9	2.1	1.8	0.3	1.9	-1.9	4.2	2.6	-2.1	-5.6	-4.2	-2.5	-0.6	10.2	5.3	0
SAH	9.8	4	-1.9	-9.6	5.2	1.6	-0.4	-3.2	-1.9	-3.1	-10.5	2.5	0.7	3.3	5.7	7.1	0.8	0
SAIA	3.9	-3.8	0.1	2.7	5.4	4.2	-1.1	0.3	8.1	0.6	-0.6	3.1	2.3	-2.2	-2.3	-0.4	-2.8	1
SASR	-6.1	-2.1	-1.2	1.6	-3.8	3	-0.8	-1.5	0.7	0.9	3.6	1.6	0.3	-0.1	-0.1	-2.9	-2	0
SBH	3.3	1.1	5.6	2.5	4.3	-1.1	-0.5	-3.4	6.6	6.1	5.3	5.5	2.1	-2.7	-2.7	1.7	4.8	7.3
SBRA	4.1	3.3	2.9	-1.4	0.4	3.6	0.5	5.2	5	3.9	1.9	1	-2.7	-2.7	-1.9	0	0	0
SBS	11	4.4	6.6	2.8	0.6	7.2	4.2	-2.8	5	4.9	4.9	3	2.3	0.7	-0.6	5.2	2	2
SCI	-1	3.6	-2.4	3	-5.3	3.3	6.6	6.2	2.5	1.9	0.3	1.8	2.1	-3.1	-3	-0.3	0	0
SCVL	8.4	7	5.4	0.4	-1.4	6.4	-1.8	3.7	4.5	4.4	4.1	5	4.3	-0.4	59.2	-0	-0.2	-1.4
SEIC	-1.5	-4.5	-5.4	0.1	-6.5	-4.3	-1.2	0.3	-2.6	-3.2	1.5	-3.4	-3.1	3.3	4.5	1.6	0	0
SIEGY	2.9	1.7	-3	4.6	2.5	0.2	1.7	-8.3	4.8	3.9	6.6	4	9.7	2.6	-0.5	-1.1	2.9	13.8
SITC	6.4	2	1.1	4	3.2	2.1	1.2	3	2.1	0.2	0.2	-0.7	0	7	6	13.7	5.1	0.5
SKYW	3.7	7.3	5.6	8.1	1	-0.8	5.6	4.8	6.5	5.2	2.9	0.6	-7.1	3.1	1.4	0.9	1.9	3.8
SNX	-2.8	-3.5	-4.8	0.7	-0.3	0.2	3.1	-4.5	4.1	4.7	2.6	2	-6.8	3.4	7	1.8	0.3	1
SO	4.2	2.9	2.3	0.8	5.2	-0.7	-3.9	-0.7	3.3	2.6	1.5	0.1	-2	2.1	2.7	0.6	0	0
SRPT	5.4	4.3	10.1	3.2	6.1	5.9	0.3	4.8	-4	-2.9	-3	-1.2	-5.1	-1.2	-0.6	-1.2	-0.6	-1.4
STC	2.8	-3.4	2.1	0.2	1.8	2.1	1.8	-3.9	1.3	1.3	0.6	1.5	0	5	6.8	0.6	-0.3	0
STLD	-0.7	-2.5	1.5	-0.5	-4	-10.8	-0.3	-2	3.6	3.4	3.8	4.5	2.3	8.9	2.2	4.7	1.2	0.4
STM	5.7	-7.9	-2.8	-0.5	-2.5	-2	6.9	0.5	1.5	-0.1	0.6	2.6	1.9	0.3	2.5	0.7	0	5
STT	6.7	-2.2	-5.3	-1.9	4.6	-3.9	-4.6	0.6	3.9	4.7	1.5	1.1	2.9	-2.6	1.2	3.5	3.8	8.2
STX	16.6	2.9	4.2	0.8	3.1	-1.2	0.5	-0.1	8.5	6.3	2.6	3.6	2.4	5.7	5.7	3.9	0	0
SYNA	4.9	2	0.4	2.1	2.4	5.3	-5.1	-3.9	3.8	0.2	-2.2	-0.1	-2.2	0.3	0.3	0.8	2.9	1.5
TDC	-3.1	4.2	3.6	-3.4	1.4	0	8.8	4.3	3.9	3.9	1.8	0.2	0	3.2	1.2	8.6	2.3	0
TEX	10.8	-7.8	3.3	-3.6	-3.9	-6	-3.2	-2.4	2.6	2.7	3	3	-1.8	1.9	1.2	0.4	1.3	-0.6
THG	1.1	6.1	3.4	4	2.1	3.1	1.2	2.2	-2.4	2.6	0.1	-0.6	-3.3	3.6	6.7	-1.4	0	0
TITN	1.6	-2.1	0	1.3	-7.7	2.9	-2.9	0.7	0.3	-0.7	-0.6	-0.1	-2.6	1.5	-2.1	-2.2	-2.2	-0.2
TLK	4	-5.8	2.6	-0.6	8.3	2.2	-1.2	-1.2	4.2	4.3	6.8	2.7	0.7	-1.1	0.4	4.5	5.3	0.6
TREE	0.8	-1.9	4.4	2	1	2.1	-0	6.1	8.2	7.7	4.8	5.1	6	3.8	2.7	7	3.1	3.1
TREX	15.5	2.8	3.4	1.7	2.7	0.4	3.8	-0.5	-0.6	-2.1	-2.5	3.4	4.8	-2.3	-1.1	-0.1	-2.4	1
TRMK	-0.4	3	-0.3	0.2	-5.8	2.8	4.1	-0.3	3	4	0.5	2.2	0	8.4	9.3	-3.4	-3.4	2.2
TSM	2.4	-0.5	0.9	2.2	-4.3	-2.9	-0.5	0.4	12.7	10.9	4.7	2.2	1.7	4.7	4.2	2.2	1.2	4
TTC	5.6	-1.3	-0.1	6	1.9	-1	-4.9	-6.2	8.3	6.3	2.5	3.6	3.1	-0.7	4.3	0.1	-1.4	0
TU	11.3	-0.9	0.2	5.2	0.3	0.4	-2.3	-1.9	5	-1.5	0.5	1.2	0	4.6	8.2	-0.5	0	0
TXN	8.6	-1.9	4	-7.8	-1.5	-0.8	-1.8	1.5	3.3	3.3	-0	0.5	-0.8	1.5	5	-0.2	-0.9	0.5
TXRH	6.2	-3.4	3.6	-3	0.6	0.5	-1.7	1.4	5.5	4.7	0.3	2.1	1.8	-1.4	-1.4	-0.7	0.3	4.8
UBSI	10.6	0.1	0.7	5.2	-4.7	-1.3	3.7	-1.1	1.1	1.6	0.3	-0.1	0.8	9.9	5.5	3.9	2.7	2.2
UGP	0	-7.1	-8.3	-4.9	-3.1	-2.3	-4	-6	0	-0.9	-0.9	0.1	-1.9	13.2	12.1	5.3	3.9	5.4
UHS	7.1	3.3	8.3	1.3	3.6	4.9	2.9	3.3	3.6	3.4	4.7	-0.8	1.2	-5.4	-0.1	9.3	-1.7	0
UHT	5.6	0.7	-1.4	-1.6	-2.3	3.4	-1.4	3.1	5.4	4.2	3.3	6.9	5.9	5.7	8.1	1.6	1.7	0.6
UNF	5.5	-2.9	2.1	2.6	4.1	1.6	0.9	-1	4.5	4.3	1.1	1.6	-1.9	2.7	-0.2	-1.1	0	0
WEC	5.3	1.8	-0.1	-6.3	-1.3	3.5	-0.5	2.5	1.8	2.8	-0.4	0	0	-3.6	-252.1	7.7	-6.4	0
WELL	4.3	4.9	-7.5	0.6	-0.2	1.2	0.8	1.2	5	4.5	4.4	4.9	4.2	1.6	1.6	1.3	4.7	2.4
WEN	9.3	0.5	-0.3	-1.6	0.6	-1.9	1	1	4.2	4.1	2.2	1	2.9	1.4	2	4.6	2.3	0.9
WIRE	1.9	-1.8	-2.8	4.4	1.1	-1	0.3	-1.1	6.7	4.4	2	1.7	-2	-0.7	-0.7	0.7	0.8	-1.1
WLK	-1.3	-4.8	-0.5	-2.4	-1.8	-6.6	-2.5	-3.7	2.9	2.5	0.1	-0.8	-4.8	2.7	1.9	1.2	1.4	10
WMK	17.8	-0.2	-2.7	-2.9	1.5	-1.5	1.5	1	2.9	1.9	1.1	3	7.8	-0.8	3.4	1.2	1.7	0
WMT	7.4	3.7	0.5	-0.4	-5.3	3.5	-2.8	0.1	2.8	1.9	-2.2	-4	-1.9	2.5	1.1	0	0	1.8
WOR	8.5	-1	-0.8	-1.7	1.6	1.9	-4.1	-8.7	6.3	3.5	3.8	4.5	4.6	2.2	2.7	2.2	2.2	4.2
WPC	5.3	2.9	2	-1.6	2	-2.2	0.5	0.5	0.3	1.3	2	3	1.7	2	-0	0	0	-0.1
WSM	14.9	0.1	5.2	5.7	-11.6	-1.1	3.2	1.9	0.6	0.1	0.4	2.1	0.6	1.6	2	1.2	-0.2	0
WTI	7.8	5.6	4.5	0.4	1.7	-1.4	-2.1	-7.7	7.4	7.1	5.8	3.4	3.1	3.8	3.6	3.6	3.8	2.3
WW	-5	4.7	1.1	-0.2	3	-3.6	2.8	-3.2	9.2	7.6	5.8	7.6	6.7	2.7	2.7	2.7	3.2	3.2
XPO	4.7	2.5	0.5	-2	1.5	5.3	2.9	1.7	4.5	2.8	1.7	-0.3	-1.2	-1.4	0.8	0.3	-0.6	2.3

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