DEVELOPING TRADING STRATEGIES UNDER THE DIRECTIONAL CHANGES FRAMEWORK

With application in the FX Market

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Abstract

Directional Changes (DC) is a framework for studying price movements. Many studies have reported that the DC framework is useful in analysing financial markets. Other studies have suggested that, theoretically, a trading strategy that exploits the full promise of the DC framework could be astonishingly profitable. However, such a strategy is yet to be discovered. In this thesis, we explore, and consequently provide proof of, the usefulness of the DC framework as the basis of a profitable trading strategy.

Existing trading strategies can be categorised into two groups: the first comprising those that rely on forecasting models; the second comprising all other strategies. In line with existing research, this thesis develops two trading strategies: the first relies on forecasting Directional Changes in order to decide when to trade; whereas the second strategy, whilst based on the DC framework, uses no forecasting models at all.

This thesis comprises three original research elements:

1. We formalize the problem of forecasting the change of a trend’s direction under the DC framework. We propose a solution for the defined forecasting problem. Our solution includes discovering a novel indicator, which is based on the DC framework.
2. We develop the first trading strategy that relies on the forecasting approach established above (Point 1) to decide when to trade.
3. We develop a second trading strategy which does not rely on any forecasting model. This is trading strategy employs a DC-based procedure to examine historical prices in order to discover profitable trading rules.

We examine the performance of these two trading strategies in the foreign exchange market. The results indicate that both can be profitable and that both outperform other DC-based trading strategies. The results additionally suggest that none of these two trading strategies outperforms the other in terms of profitability and risk simultaneously.

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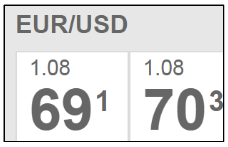
Glossary

Base and Counter Currency: For a given currency pair (e.g. EUR/USD in the figure below), the first listed currency of a currency pair (i.e. EUR) is called the base currency, and the second currency (i.e. USD) is called the counter currency. The currency pair indicates how much of the counter currency is needed to purchase one unit of the base currency. The counter currency is also referred to as the *quoted* currency.



Bid and Ask price: The term ‘bid and ask’ refers to a two-way price quotation that indicates the price at which a currency can be sold and bought at a given point in time. The bid price represents the price that a buyer (usually a trader) needs to pay for a currency. The ask price represents the price that a seller (usually a market maker) wants to receive. For example, in the figure above the bid price of EUR/USD is 1.08691; while the ask price is 1.08703.

Bull and Bear market: The opposite of a bull market is a bear market, which is characterized by falling prices and typically shrouded in pessimism. These notions are used to express the movement of a market. If the trend is up, it is a bull market. If the trend is down, it is a bear market.

Buy and Hold: Buy and hold is a passive trading strategy in which a trader buys stocks (or currencies) and holds them for a relatively long period, regardless of fluctuations in the market. The basic idea is that the trader buys a given stock or currency and holds it throughout the trading period. The basic assumption is that, in the long run, values of stocks (or currencies) will eventually increase.

Contrarian trading strategy: Contrarian trading is an investment style that goes against prevailing market trends. A contrarian trader buys a specific stock or currency when the market exhibits a downtrend and sells when the market exhibits an uptrend.

Foreign exchange (Forex): Forex (FX) is the market in which currencies are traded. The forex market is the largest, most liquid market in the world, with average traded values that can be trillions of dollars per day. It includes all of the currencies in the world.

G10: The G10 consists of eleven industrialized nations that meet on an annual basis (or more frequently, as necessary) to consult, debate and cooperate on international financial matters (see http://www.investopedia.com/terms/g/groupoften.asp).

Intra-day trader: An intra-day trader is a particular type of trader that both opens and closes a new position in a stock in the same trading day. Usually, they do not hold over-night positions.

Margin call: A margin call occurs when the account value falls below the broker's required minimum value. Simply put, this is the edge at which the market maker typically decides that a trader does not have sufficient capital to continue trading.

Market maker: A market maker is a "market participant" or member firm of an exchange that also buys and sells currencies at prices it displays in an exchange’s trading system for its own account. Using these systems, a market maker can enter and adjust quotes to buy or sell, enter and execute orders, and clear those orders.

Risk-adjusted return: Risk-adjusted return refines an investment's return by measuring how much risk is involved in producing that return, which is generally expressed as a number or rating. Risk-adjusted returns are applied to individual securities, investment funds and portfolios.

Risk-free rate: The risk-free rate of return is the theoretical rate of return of an investment with zero risk. The risk-free rate represents the interest an investor would expect from an absolutely risk-free investment over a specified period of time.

Transaction cost: Transaction costs are expenses incurred when buying or selling goods or services. Transaction costs represent the labor required to bring these goods or services to market, giving rise to entire industries dedicated to facilitating exchanges. In a financial sense, transaction costs include brokers' commissions and spreads, which are the differences between the price the dealer paid for a security and the price the buyer pays.

Transaction: In the context of this thesis, we define “transaction” as an agreement between two parties (usually a trader and market maker) to buy one currency against selling another currency at an agreed price (e.g. bid or ask).

List of Acronyms

ANN: Artificial Neural Network

ARIMA: Auto-Regressive Integrated Moving Average

B&H: buy and hold

BIS: bank of international settlement

CT: contrarian trader

DC: Directional Changes

GA: Genetic Algorithm

NN: Neural Network

OS: Overshoot

OSV: Overshoot Value

MDD: maximum drawdown

RR: rate of return

TF: trend's follower

TTR: technical trading rule

List of Publications

- A. Bakhach, E. P. K. Tsang and H. Jalalian, "Forecasting directional changes in the FX markets," *2016 IEEE Symposium on Computational Intelligence for Financial Engineer & Economic (CIFEr' 2016)*, Athens, Greece, 2016, pp. 1-8. doi: 10.1109/SSCI.2016.7850020.

- A. Bakhach, E. P. K. Tsang, Wing Lon Ng and V. L. R. Chinthalapati, "Backlash Agent: A trading strategy based on Directional Change," *2016 IEEE Symposium on Computational Intelligence for Financial Engineer & Economic (CIFEr' 2016)*, Athens, Greece, 2016, pp. 1-9. doi: 10.1109/SSCI.2016.7850004.

- A. Bakhach, E. P. K. Tsang and V. L. R. Chinthalapati, "TSFDC: A Trading Strategy Based on Forecasting Directional Changes", Journal of “Intelligent Systems in Accounting, Finance and Management” volume 25; pp. 105–123, 2018 https://doi.org/10.1002/isaf.1425

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Part I

Introduction, Background and Literature Review

1 Introduction

In this introductory chapter, we describe the adopted rationale which was utilized to conduct this research. Firstly, we outline two concepts, namely: the Foreign Exchange (FX) market and the Directional Change (DC) framework. We then discuss the thesis' motivations and objectives, before ending with a succinct description of the thesis structure.

1.1 The foreign exchange market and the Directional Changes framework

Currency trading is the act of buying and selling different world currencies. The foreign exchange (FX) market is the market on which these currencies are traded. The importance of the FX markets has developed due to increased global trade, capital flows and investment. The main participants in the FX market are central banks, commercial banks, institutional investors, traders, hedge funds, corporations and retail investors [1] [2]. The objectives pursued by these participants range from pure profit generation (hedge funds, financial institutions) to hedging cash flows; from business core activities (corporations) to implementing macroeconomic and monetary policy objectives (central banks). The analysis of the FX market is a common objective of all market participants. Institutional and retail investors are particularly interested in discovering moneymaking trading strategies for currency trading (i.e. the devising of a set of rules to indicate when to buy or sell a given currency). Many studies have been published with this goal in mind (e.g. [3] [4] [5] [6] [7] [8]).

Directional Changes (DC) is a technique that summarizes market prices [9] [10]. Under the DC framework the market is cast into alternating upward and downward trends. A DC trend is identified as a change in market price larger than, or equal to, a given threshold. This threshold, named *theta*, is set by the observer and usually expressed as a percentage. A DC trend ends whenever a price change of the same threshold *theta* is observed in the opposite direction. For example, a market downtrend ends when we observe a price rise of magnitude $theta$; in which case we say that the market changes its direction to an uptrend. Similarly, a market's uptrend ends when we observe a price decline of magnitude $theta$; in which case we say that the market changes its direction to a downtrend. Many studies have proven the DC framework to be useful for analysing the FX market (e.g. [11] [12] [13] [14]). A DC-based trading strategy is a model that employs the DC framework to analyse, and sometimes to forecast, price movements in order to establish profitable trading rules as to when to buy or to sell a given asset. Some studies have tried to develop profitable DC-based trading strategies (e.g. [15] [16] [17]). However, the full promise of the DC framework as the basis of a trading strategy has not yet been completely exploited [16].

1.2 Thesis motivations and objectives

A very important, and also very attractive, research area is trading strategy design. This thesis is motivated by the following factors:

a. Studies (e.g. [18] [19]) have suggested that the profits produced by an idealistic DC-based trading strategy could be of up to 1600% per year, assuming perfect foresight of market trends under the DC context. Even though perfect forecasting is not practically feasible, this estimated profit is still attractive from a trader's viewpoint.
b. In 2017, Golub at al., [16] suggested that the full promise of the DC framework as the basis of a trading strategy is yet to be exploited [16].

Thus, the objective of this thesis is to explore, and subsequently to prove, the usefulness of the DC framework as the basis of a profitable trading strategy. To this end, we aim to develop trading strategies based on the DC framework.

Most existing trading strategies can be classified into two groups: 1) strategies that do rely on forecasting models, and 2) strategies that do not. In keeping with the existing research, this thesis proposes two trading strategies, both of which are based on the DC framework. The first one comprises a forecasting model that aims to predict the change of direction of a market trend under the DC context. The proposed trading strategy, then, uses this forecasting model to decide when to initiate a buy or sell order. Our second intended DC-based trading strategy employs no forecasting model. It examines historical prices, using a DC-based computational approach, to unveil profitable conditions of when to buy or sell a given asset.

In order to reach our stated goal certain steps must be taken, the first of which being to provide answers to the following questions.

A. Are Directional Changes predictable?

A common objective for traders is to predict the direction of a market trend (either up or down). Based on this forecasting, the trader makes the decision to buy or sell a particular asset. In this thesis, we address the following questions: how does one formulate the problem of forecasting a trend’s direction under the DC framework?; how would one solve this problem?; and, how accurate is the proposed forecasting model when compared to other existing forecasting techniques?

We answer these questions in Chapter 5. We consider the problem of whether the current trend will continue for a specific threshold of price change before the trend changes. We also propose a solution for this problem. We compare the accuracy of our approach to the traditional forecasting technique called ARIMA [20].

B. How to develop a successful trading strategy based on forecasting DC?

Even an accurate forecasting model does not necessarily guarantee profit in trading. To translate accurate forecasting into profit, a trader needs a trading strategy that can utilize the forecasting effectively [21]. Therefore, we need to answer the question of how to develop a successful trading strategy based on forecasting the change of a trend's direction, i.e. Directional Changes of a given price series?

In Chapter 6, we present a DC-based trading strategy which relies on the forecasting approach from question A, above, to decide when to initiate a trade. We will examine the performance of the proposed trading strategy and compare it to other DC-based trading strategies.

C. What would be a useful DC-based analysis of historical prices to establish a profitable trading strategy?

Some trading strategies do not employ any forecasting models. A common approach is to examine historical price movements to discover lucrative conditions of when to buy or sell a particular asset. In this part of the thesis, we address the question of what a useful DC-based approach might be to examine historical market price movements in order to develop a profitable trading strategy?

In Chapter 7, we introduce a new DC-based trading strategy that does not rely on any forecasting model. Instead, it examines the historical prices of a given asset, using a DC-based approach, to discover profitable trading rules. We will examine the performance of this second proposed trading strategy and compare it to other DC-based trading strategies.

Naturally, one might ask why we introduce two trading strategies if one of them is better than the other? We answer this question in Chapter 8, where we compare the performances of the two proposed trading strategies and argue that either of them could be more attractive to different types of traders.

1.3 Thesis outline

The organization of this thesis is as follows:

Chapter 2 provides a general overview of the FX market and looks at the basic terminology of FX trading. Chapter 3 reviews some existing trading strategies in the financial markets. We also list and explain some evaluation metrics that are utilized to evaluate the performance of a given trading strategy. In Chapter 4, we explain in detail the Directional Changes concept and clarify how market price movements are sampled under the DC framework. We list some studies that provide evidence as to the importance of the DC framework in analysing the FX market. We also review some trading strategies that are based on the DC concept.

In Chapter 5 we propose a formalism of the problem of forecasting the change of a trend's direction based on the DC framework. We also offer a solution to the established forecasting problem. We prove that our approach provides better accuracy than the ARIMA model. In Chapter 6 we introduce a trading strategy, named TSFDC. TSFDC relies on the forecasting model, developed in Chapter 5, to decide when to trade. We apply TSFDC to eight currency pairs. We evaluate the performance of TSFDC using a rolling window approach. We measure the profitability, risk and risk-adjusted return of TSFDC. We compare TSFDC with other DC-based trading strategies.

In Chapter 7 we present a second trading strategy, named Dynamic Backlash Agent (DBA). We clarify how DBA uses a DC-based procedure to discover profitable trading rules. The performance of DBA will be evaluated the same way as TSFDC in Chapter 6. We compare TSFDC with other DC-based trading strategies.

In Chapter 8 we compare the performances of TSFDC and DBA. The objective of Chapter 8 is to answer the question as to whether either TSFDC or DBA can simultaneously provide greater profit and less risk than the other. Finally Chapter 9 presents our conclusions, which will wrap up this thesis and propose possible future works.

2 The Foreign Exchange Market

In this chapter we provide a brief introduction to the Foreign Exchange (FX) market. We list essential vocabularies related to FX trading. Finally, we review some studies that have examined the profitability of FX trading.

2.1 Introduction

The foreign exchange (FX) market is the market on which currencies are traded. This includes all aspects of buying, selling and exchanging currencies at determined prices. In terms of volume of trading, it is by far the largest market in the world with an average daily turnover of 5.1 trillion US dollars as of April 2016 [1]. The FX market determines the exchange rates for global trade. Thus, it is critical to the support of imports and exports around the world.

The FX market is largely organized as an over-the-counter (OTC) market. In other words, there is no centralized exchange. In centralized exchange-based markets, there is a single price obtaining at any point in time – the market price. However, the FX market is a global decentralized market for the trading of currencies. In decentralized markets, by default, there is no visible common price. The FX market is the largest market of this kind. Unlike stock markets, FX trading is not dealt across a trading floor during a fixed period of several hours a day. Instead, trading is done online (e.g. via computer networks) between dealers in different trading centres around the world.

In the last decade, the study of the FX market has gained increasing interest in the literature. Some studies have focused on the relationship between the FX market and international economics (e.g. [22]), or the relationship between capital flows and trade balance (e.g. [23]). Other studies have focused on the impact of the intervention of the central banks on the FX market (e.g. the case of the Bank of Japan [24] [25] [26], the case of the Czech National Bank [27], the case of the Bank of Canada [28]). In addition, many studies have concentrated on the discovery of statistical properties (e.g. scaling laws and seasonality statistics in the FX market [14] [29] [30]). Further studies (e.g. [3] [4] [5] [6]) have focused on developing profitable trading strategies that specify when to buy or sell a given currency (i.e. FX trading).

The foreign exchange market is unique because of the following characteristics [1] [2]:

- *Market Size*: The FX market is by far the most liquid market in the world. This high liquidity has pushed transaction costs to very low levels.
- *Market Participants*: A very heterogeneous set of actors participates in the FX market (e.g. central banks, commercial banks, institutional investors, traders, corporations and retail

investors). These market participants, often, do not share the same interests when trading currencies.

- *Global Decentralized Market*: There is no specific physical centre to exchange currencies.

This chapter continues as follows: we list and explain some essential terminologies related to FX trading in Section 2.2. In Section 2.3 we review some studies those have examined how profitable the FX trading could be.

2.2 Essential terminologies for FX trading

In this section we describe some essential vocabularies related to FX trading [31]:

- *Exchange Rate*: In a typical foreign exchange transaction, a party purchases a quantity of one currency by paying with a quantity of another currency. The exchange rate represents the number of units of one currency that can be exchanged for a unit of another.
- *Currency Pair*: A currency pair is the quotation and pricing structure of currencies traded in the FX market. The value of a currency is known as a 'rate' and is determined by its comparison to another currency. For example, the currency pair quoted as 'EUR/USD' represents the number of US dollars that can be bought with one euro (see Fig. 2.1 for example).

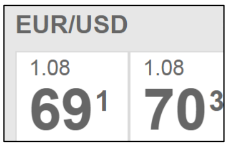

Fig. 2.1. A typical quote of the EUR/USD currency pair. The bid price is 1.08691, the ask price is 1.08703.

- *Base and Counter Currency*: For a given currency pair (e.g. EUR/USD in Fig. 2.1), the first listed currency of a currency pair (i.e. EUR) is called the base currency, and the second currency (i.e. USD) is called the counter currency. The currency pair indicates how much of the counter currency is needed to purchase one unit of the base currency. The counter currency is also referred to as the *quoted* currency.
- *Bid, Ask, and Mid-price*: The bid price represents how much of the counter currency you need in order to purchase one unit of the base currency. The ask price for the currency pair represents how much you will acquire of the counter currency for selling one unit of base currency. For example, in Fig. 2.1 above the bid price of EUR/USD is 1.08691; while the ask price is 1.08703. The mid-price is defined as the average of the bid and ask prices being quoted. For example, in Fig. 2.1 the mid-price would be: (1.08691 + 1.08703) / 2 =

1.08697. Usually, the mid-price is utilized to illustrate the historical exchange rates of a given currency pair over a specific period (see Fig. 2.2 for example).

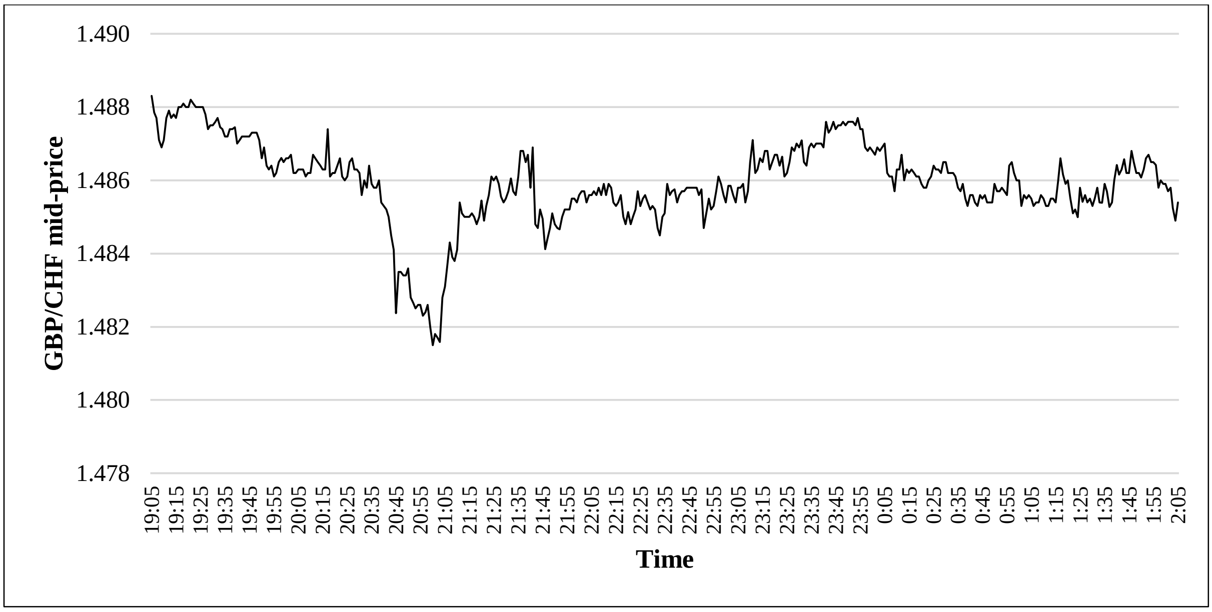

Fig. 2.2. GBP/CHF mid-prices sampled minute by minute from 1/1/2013 19:05 to 1/2/2013 02:05 (UK).

- *FX Market Maker*: A financial institution whose primary business is entering into transactions on both sides of the market, seeking profits by taking risks in these markets. Market makers set both the bid and the ask prices on their systems and display them publicly on their quote screens. The market maker buys from and sells to its investors, as well as other market-makers, and accordingly makes earnings from the differences between the bid and the ask prices. Their systems are prepared to make transactions at these prices with their customers, who range from small banks to retail FX traders.
- *Individuals and Retail FX Traders*: A retail investor is an individual investor who buys and sells securities for their personal account, and not for another company or organization. Also known as an ‘individual investor’ or ‘small investor’. An individual trader is expected to deal (i.e. buy and sell) with a market maker.
- *Transaction costs*: Transaction costs are expenses incurred when buying or selling an asset. In a financial sense, transaction costs include the market maker’s commission.
- *Transaction data*: The transaction data denote the details of one single trade (a buy or sell agreement between a buyer and a seller). These details include: a time-stamp (the time at which the trade has occurred), price (either bid or ask), order size (i.e. quantity of share/volume that was sold or bought). It is worth noting that several trades (buy or sell

orders) may occur within one second. Data gathered at the transaction level are usually referred to as ‘high frequency data’.

2.3 About the profitability of FX trading

In this section we review those studies that have researched the profitability of FX trading. tMost of these studies focus on a specific trading style named ‘technical trading’. Typically, a technical trader tries to discover patterns in the historical price movements of a security using *technical indicators*. Technical indicators are statistics used to measure current conditions, as well as to forecast financial trends. Technical indicators are used to predict changes in market trends or price patterns in any traded asset [32] [33]. Eventually, a technical trader establishes a trading strategy (i.e. buy and sell rules) based on the discovered pattern(s). A Technical Trading Rule (TTR) is an instruction that is based on technical indicators and indicates whether the security displays a suitable behaviour to buy or to sell.

In 2013, Neely and Weller [34] studied the convenience of technical trading in the FX market. They reported that technical trading can produce profit in the FX market, especially when applied to emerging markets’ currencies (e.g. Latin America). They reported that technical trading on the FX market can produce better returns in comparison to risk than it does in the S&P500. Their results suggested that it would be better not to embrace fixed technical trading rules or fixed portfolios of these rules, but rather to employ a strategy that switches between different rules and currency pairs according to past performance. Finally, they reported that technical trading in the FX market could generate profits even during financial crisis.

In 2016, Coakley, et al. [35] provided an empirical investigation of the profitability of more than 100,000 technical trading rules (TTR) in the FX market for 22 currency pairs. They reported that technical trading can achieve annualised returns of up to 30%.

In 2016, Hsu et al. [36] carried out an investigation of more than 20,000 technical trading rules (TTR) in the foreign exchange market, using daily data sampled over 45 years for 30 developed and emerging market currencies. They reported that technical trading can generate attractive returns. Moreover, they concluded that these returns are not, in general, wiped out when realistic allowance is made for transaction costs; which confirms the findings of other studies (e.g. [3] [36] [37]).

In 2017, Zarrabi et al. [3] examined the profitability of technical trading rules (TTR) in the foreign exchange market, taking into account transaction costs. They considered a universe of

7,650 trading rules and six currencies: SEK, CHF, GBP, NOK, JPY and CAD. The findings indicated that technical trading could generate positive returns even during financial crisis (e.g. between January 2007 and December 2009). In addition, their results suggested that, rather than sticking to a specific set of TTRs, investors should update their portfolios frequently in order to adapt to changes in the economy; thus confirming the findings of Neely and Weller [34]. They also reported that technical trading can still achieve an attractive level of risk-adjusted return after taking into account transaction costs; which conforms to the deduction of Hsu et al., [36].

In 2016, Davison [38] examined the profitability of retail traders in the FX market. He considered the quarterly data collected from 19 US market makers and aggregated by the on-line website Finance Magnates (Finance Magnates [39]) during the period 1/10/2010 to 31/3/2014. He reported that, on average, 20% of the retail traders ended up with profitable accounts, which concurs with the results of Heimer and Simon [40]. Davison [38] concluded that around 40% of the remaining retail traders might have expected their accounts to be subject to a margin call[a]. He also reported that there was no conclusive evidence that the success of the profitable retail traders was due to their knowledge or skills edge.

So, the studies conducted in [3] [35] [36] examined the profitability of thousands of technical trading rules (TTRs). They concluded that many TTRs can generate profits in the FX market. However, Davison [38] reported that, on average, only 20% of retail traders do, in reality, make a profit. A possible reason for the inconsistency of these conclusions could be that it is not easy for most retail traders to examine several thousands of TTRs, to examine the profitability of certain trading rules, before starting trading with real money. Besides, some studies (e.g. [34] [3]) reported that, in order to make consistent profits using TTRs, traders must update their TTRs often to adjust to the variations in the market, rather than sticking to a particular set of TTRs. This necessity to update TTRs continuously makes FX trading harder for retail traders.

2.4 Summary

The FX market is the market on which currencies are traded. It comprises a wide range of heterogeneous participants (e.g. central banks, retail investors). In Section 2.2, we described some essential terminologies related to FX trading (e.g. base and counter currencies, mid-price rate). We also reviewed the studies (e.g. [3] [35] [36]) that highlighted the profitability of FX trading (Section

[a] A margin call occurs when the account value falls below the broker's required minimum value. Simply put, this is the edge at which the market maker decides that a trader does not have sufficient capital to continue trading.

2.3). Some studies (e.g. [3] [36]) concluded that FX trading can be attractively profitable even after taking into account the transaction costs. However, other studies (e.g. [38]) warned that, in reality, most retail traders do not make the profits they might have expected.

3 Trading Strategies for Financial Markets

In this chapter, we review some of the existing trading strategies and list selected evaluation metrics to assess the performance of a trading strategy.

3.1 Introduction

A trading strategy is a set of objective 'trading rules'. Trading rules are the conditions that must be met to initiate a *buy* or *sell* order. In this chapter we review previous research into existing trading strategies. In general, these trading strategies can be classified into two categories:

1. The first consists of strategies that aim, firstly, to forecast market prices or changes in a trend's direction and, secondly, to create trading strategies based on the established forecasting model. The trading strategies in this category usually employ machine learning models to predict market prices or a trend's direction. They then employ these forecasting models to decide when to initiate buy or sell orders.
2. The second category embraces trading models that do not rely on any forecasting model.

We want to highlight that in this chapter we review those studies *not* based on the directional changes framework [10] and therefore, provide only a brief review for each study. This chapter continues as follows: we review trading strategies from the first and second categories outlined in Sections 3.2 and 3.3 respectively. In Section 3.4 we list and explain essential evaluation metrics that aim to measure the performance of a given trading strategy. We conclude with Section 3.5.

3.2 The first category: Trading strategies based on forecasting models

As stated, this section considers trading strategies that are not based on the DC framework. Instead of providing an extensive literature review, our objective is, rather, to provide general examples as to the approaches currently prevailing for the development of trading strategies. Strategies that are based on the DC framework will be revised in Chapter 4.

Generally, trading strategies based on forecasting models try to forecast the prices or the direction of a financial market's trend before then building trading strategies upon the established forecasting model. The following outlines some trading strategies belonging to this category:

In 2009, Li et al. [41] proposed a framework for predicting turning points. The proposed model combined chaotic dynamic analysis with an Ensemble Artificial Neural Network (EANN) model. The sought objective was to capture the non-linear and chaotic behaviour of the financial market in order to forecast potential turning points. A Genetic Algorithm (GA) module was then added to optimize predefined trading parameters to maximize the produced profit of the proposed trading strategy. They applied their forecasting, and trading, strategy to the Dow Jones Industrial Average (DJIA) index time series and TESCO stock (UK). Experimental results suggested that applying the proposed trading strategy to the TESCO stock (UK) could produce an annualized return of 69.78%.

In 2012, Huang et al. [42] proposed a methodology for stock selection using Support Vector Regression (SVR) and a Genetic Algorithm (GA). They used an SVR model to predict, and classify, the profitability of stocks. This classification process included the usage of fundamental stock criteria (e.g. share price rationality, growth, profitability, liquidity). The stocks classified as 'most profitable' were then employed to form a portfolio. On top of this model, a GA was employed for the optimization of the trading model's parameters. The reported experiment consisted of building a portfolio using 30 stocks. Experimental results suggested that, in the best case, the proposed trading system could produce an annualized return of 17.57%.

In 2013, Evans et al., [6] introduced a prediction and decision making model based on Artificial Neural Networks (ANN) and Genetic Algorithms (GA) to predict the changes in a market's trend direction. The dataset utilized for this research comprised 70 weeks of historical exchange rates of GBP/USD, EUR/GBP, and EUR/USD currency pairs. They reported that the proposed trading strategy could produce an annualized return of 23.3%.

In 2015, Giacomel et al. [43] proposed an ANN model to predict the direction of price movements. They actually proposed two ANN models: the first one trained to predict the expected opening and closing values for the next period; whereas the second was trained to predict the stock direction in the next period. These two ANN models were combined to form a trading strategy. The proposed model was tested using 18 stocks selected from the North American and the Brazilian stock markets. Experimental results suggested that the proposed trading strategy could yield an annualized return of up to 76%.

In 2016, Chourmouziadis and Chatzoglou [44] presented a trading fuzzy system. They used a mixture of four technical indicators to predict stock prices. Two of these indicators are very rarely used in research papers, namely Parabolic SAR and GANN-HiLo. They presented 16 fuzzy rules in total, based on these four technical indicators. The fuzzy system assigned a weight to each rule based on its profitability during the training (in-sample) period. The experiments were conducted using daily data from the Athens Stock Exchange over a period of more than 15 years. This data was divided into bull and bear market periods. The results suggested that the proposed system produced fewer losses during bear market periods and smaller gains during bull market periods compared with the buy and hold[b] strategy.

In 2016, Chen and Chen [45] proposed an intelligent pattern recognition model to predict the turning point of an upwards trend (i.e. the bullish turning point). The proposed model used nine technical indicators as pattern recognition factors for recognizing stock pattern. They employed the rough sets theory and genetic algorithms for forecasting the bullish turning point. Then, the authors established a trading strategy based on the proposed forecasting model. In the model verification, they evaluated the proposed model in two stock databases (TAIEX and NASDAQ). They reported that the proposed trading strategy could generate on average an annualized return of 57%.

In 2016, Göçken et al. [46] presented a model to predict stock prices on the Istanbul Stock Exchange. The proposed model employed a hybrid Artificial Neural Network where the inputs were technical indicators chosen via a model that combined Harmony Search (HS) and Genetic Algorithm (GA). They established a trading strategy based on the proposed forecasting model and applied the proposed trading strategy to Turkey's stock index BIST 100. They reported a positive return of 6.04% during 160 trading days.

Finally, we should note that in spite of the fact that forecasting financial time series has proven a very attractive objective, many studies (e.g. [47] [48] [49] [50] [51]) have not supported their forecasting model with any trading strategy. The establishment of a trading strategy is important in order to give some empirical guarantee that the proposed forecasting method can be used in a real-world situation [21] [52].

3.3 The second category: Trading strategies with no embedded forecasting models

This category encompasses a variety of trading styles that do not rely on any forecasting model. In this section we provide three examples of trading styles that fall under this category, namely: technical trading, momentum strategy and carry trade. Keep in mind that a detailed review of these trading styles is out of the scope of this thesis as they are not based on the DC framework.

[b] Buy and hold is an investment strategy in which an investor buys stocks and holds them for a long period of time (a month or years), regardless of fluctuations in the market. The principle of this strategy is based on the view that in the long run financial markets give a good rate of return to investors.

3.3.1 Technical trading

The first trading style we consider is ‘technical trading’. Typically, a technical trader analyses price charts to develop theories as to what direction the market is likely to move. This sort of analysis employs a large set of *technical indicators.* Technical indicators look to predict future price levels, or simply the general price direction, of a security by looking at past patterns. Eventually, the discovery of such pattern(s) can help in establishing trading strategies (i.e. buy and sell rules). Examples of traditional technical indicators include: Moving Average Convergence Divergence; Average Directional Index; Relative Strength Index; Stochastic Oscillator; and Bollinger Bands [32] [33]. Developing trading strategies based on technical indicators is very common in the literature (e.g. [53] [54] [55] [56]). In this section we outline some technical trading strategies.

In 2009, Watson [57] established a new approach to studying the profitability of two technical indicators, namely: *head and shoulders* and *point and figure*. He applied his approach to daily data of 4,983 stocks traded on the London Stock Exchange sampled from January 1st 1980 to December 31st 2003. He concluded that the head and shoulders pattern generated a mean excess return of 5.5% on an annual basis. He also concluded that point and figure was particularly suited to the intra-day trader[c].

In 2009, Schulmeister [54] examined the profitability of 2,580 technical trading rules (TTR). He reported that the profitability of these TTRs has steadily declined since 1960, and has been unprofitable since the early 1990s when using daily data. However, when based on 30-minute-data the same TTRs produce an average return of 7.2% per year. He reported that technical trading can be particularly profitable for intra-day trading.

In 2015, Cervelló-Royo at al. [58] proposed a risk-adjusted technical trading rule. They proposed a modified version of a technical indicator named ‘flag pattern’ that aims to “*strengthen the robustness of the flag pattern and its use in the design of the trading rule*” [58]. They generated 96 different configurations of trading rules and applied these trading rules to three indexes: the US Dow Jones (DJIA), the German DAX and the British FTSE. Experimental results suggest that the trading rules were able to produce returns of up to 94.9% in the period from November 26th 2004 to February 27th 2007.

[c] The name “intra-day trader” refers to a trader who opens and closes a position in a security in the same trading day.

3.3.2 Momentum strategy

The second considered trading style, which does not depend on any trading model, is 'Momentum strategy'. In general terms, a momentum strategy consists of buying assets with high recent returns and selling assets with low recent returns.

In 2011, a study by the Monetary and Economic Department at the Bank of International Settlement (BIS) [7] provided a broad empirical investigation concerning the profitability of momentum strategies in the FX market. The authors found that momentum portfolios are significantly skewed towards minor currencies (i.e. currencies that are not actively traded in the FX markets) that have relatively high transaction costs (sometimes these transactions are estimated as high as 50% of momentum returns). They also argued that momentum strategies may deliver higher returns in the FX markets than in stock markets.

In 2013, Daryl et al. [59] proposed a momentum strategy that embedded a security selection approach based on a new risk-return ratio criterion. They sought to create portfolios based on the introduced risk-return ratio criterion. They applied their model to the stock market index of South Korea (KOSPI 200) over the period June 2006 to June 2012. They reported that the proposed momentum strategy did produce attractive positive returns.

3.3.3 Carry trade

The carry trade is a strategy in which traders borrow a currency that has a low interest rate and use the funds to buy a different currency that is paying a higher interest rate. The FX carry trade is of major practical relevance since it represents an important investment style implemented by FX managers [60].

In 2011, Bertolini [8] examined the profitability of several carry portfolio strategies. He analysed whether different asset allocation, market-timing and money management methodologies had the potential to improve the performance of a simple carry portfolio. The experiments were directed using datasets from the G10 currency universe[d] in the period 1st January 1999 to 5th March 2010. He considered various FX carry portfolio strategies and found that the best performance was achieved by ranking the currencies according to the yields with the shortest maturity (i.e. 1-week yields).

In 2014, Laborda et al., [61] proposed an asset allocation strategy that aimed to improve the performance of the currency carry trade, where currencies were selected from the G10 currency

[d] For more information about G10, see http://www.investopedia.com/terms/g/groupoften.asp.

universe. The proposed model assigned weights dynamically for long and short positions in a carry trade portfolio. These weights were determined by a combination of financial variables that reflected variations in macroeconomic conditions, as well as the likelihood of crash risk across periods. They reported that the proposed asset allocation strategy produced markedly more returns than a naive currency carry trade during the out-of-sample period between January 2009 and February 2012.

3.4 Evaluating the performance of a trading strategy

A trading strategy can be analysed on historical data to project the future performance of the strategy. This process is known as 'backtesting'. Backtesting is accomplished by reconstructing, with historical data, trades that would have occurred in the past using the rules defined by a given strategy. The result of backtesting offers statistics that can be utilized to gauge the effectiveness of the strategy. Using a rule-based trading strategy has some benefits:

- It helps remove human emotion from decision making.
- Models can be easily backtested on historical data to check their worth before taking the risk with real money.

There exist many metrics that attempt to evaluate the performance of a given trading strategy. In this thesis, we choose the following metrics to measure the performance of our planned trading strategies. These metrics have been reported as appropriate for a decent assessment ([52] [62]).

- Rates of return: The rate of return (*RR*) symbolizes the bottom line for a trading system over a definite period of time. Total Profit (*TP*) represents the profitability of total trades. *TP* is computed by removing the sum of all losing trades from the sum of all winning trades (3.1). *TP* can be negative when the loss is greater than the gain. We denote by *RR* (3.2) the gain or loss on an investment over a given evaluation period expressed as a percentage of the amount invested. In (3.2) *INV* denote the initial capital employed in investment.

$$TP = \text{sum of all profits} - \text{sum of all losses} \tag{3.1}$$

$$RR = \frac{TP}{INV} \times 100 \tag{3.2}$$

- Profit factor [62]: The profit factor is defined as the sum of profits of all profitable trades divided by the sum of losses of all losing trades for the entire trading period. This metric measures the amount of profit per unit of risk, with values greater than one signifying a profitable system.

$$Profit\ factor = \frac{\text{sum of all profits}}{\text{sum of all losses}} \tag{3.3}$$

- Max drawdown (%) [63]: The drawdown (3.4) is defined as the difference, in percentage, between the highest profit (or capital), previous to the current time point, and the current profit (or capital) value. The Maximum Drawdown (*MDD*) is the largest drawdown observed during a specific trading period. *MDD* measures the risk as the ‘worst case scenario’ for a trading period. This metric can help measure the amount of risk incurred by a system and determine if a system is practical. In (3.4) and (3.5), t_i denote the time-index (i.e. time-stamp). *capital*(t_i) denote the value of capital at time t_i. The *maximum capital*(t_i) refers to the peak capital’s value that has been reached since the beginning of trading up to time t_i. Thus, $drawdown\ (t_i)$ (3.4), is interpreted as the peak-to-trough decline from the start of the trading period up to time t_i. The *MDD* (3.5) is the maximum value among all computed $drawdown\ (t_i)$. Many studies (e.g. [4] [16] [17]) have used *MDD* to measure the risk of a trading strategy. If the largest amount of money that a trader is willing to risk is greater than the maximum drawdown, the trading system is not suitable for the trader.

$$drawdown\ (t_i) = \left| \frac{capital\ (t_i) - maximum\ capital(t_i)}{maximum\ capital(t_i)} \right| \tag{3.4}$$

$$MDD = Max\left(drawdown\ (t_i)\right), \qquad \forall\ time\ t_i \in trading\ period \tag{3.5}$$

- Win ratio [62]: The win ratio is calculated by dividing the number of winning trades by the total number of trades for a specified trading period. It expresses the probability that a trade will have a positive return.

$$Win\ ratio = \frac{number\ of\ winning\ trades}{total\ number\ of\ all\ trades} \tag{3.6}$$

- Sortino ratio [63]: the Sortino ratio represents the average return earned in excess of the risk-free rate per unit of volatility or total risk. The downside risk (3.7) is defined as the standard deviation of negative asset returns. The Sortino ratio (3.8) uses the downside risk to measure the risk associated with a given investment. In (3.8), the ‘$return$’’ represents the profits generated by a given trading strategy and the ‘$target\ return$’ is the minimum acceptable return (MAR).

$$Downside\ risk = \sqrt{\frac{\sum_{i=1}^{m}(return_i - target\ return_i)^2 f(i)}{m}}; \tag{3.7}$$

$$\text{Where } f(i) = \begin{cases} 1 & if\ return_i < \ target\ return_i \\ 0 & if\ return_i \geq target\ return_i \end{cases}$$

$$Sortino\ ratio = (return - target\ return) \div Downside\ risk \tag{3.8}$$

where $return = \ \sum_{i=1}^{m} return_i$; $target\ return = \ \sum_{i=1}^{m} target\ return_i$

In (3.8): 1) m denote the number of trading sub-periods[e] which could be measured in weeks, months, ..etc; and 2) $return_i$ and $target\ return_i$ denote, respectively, the returns of the trading strategy and the risk-free return at the i^{th} sub-period.

- Sharpe ratio [64]: The Sharpe ratio (3.9) is a measure for calculating risk-adjusted return. The basic purpose of the Sharpe ratio is to allow an investor to analyse how much greater a return he or she is obtaining in relation to the level of additional risk taken to generate that return. The Sharpe ratio can be seen as the average return earned in excess of the risk-free rate per unit of volatility or total risk. To date, it remains one of the most popular risk-adjusted performance measures due to its practical use. Some studies (e.g. [65] [66]) have reported that, despite its shortcomings, the Sharpe ratio indicates similar performance rankings to the more sophisticated performance risk-adjusted ratios (e.g. Treynor ratio [67]).

$$Sharpe\ ratio = \frac{R_p - R_f}{\sigma_p} \tag{3.9}$$

Where: R_p denote the expected portfolio returns over the entire trading period; R_f is the risk-free rate. Assuming that the trading period is divided into m sub-period, let $return_i$ denote the returns of the trading strategy at the i^{th} sub-period. Thus, in total we will have m returns (one return for each sub-period). In (3.9), σ_p denote the standard deviation of the m returns, of the m sub-periods, computed as in (3.10). The $average\ return$ in (3.10) denote the mathematical average of the m returns and $return_i$ denote the return of the trading strategy return at the i^{th} sub-period. One intuition of the Sharpe ratio calculation (3.9) is that a portfolio engaging in 'zero risk' investment, such as the purchase of U.S. Treasury bills (for which the expected return is the risk-free rate), has a Sharpe ratio of exactly zero.

$$\sigma_p = \sqrt{\frac{\sum_{i=1}^{m}(return_i - average\ return)^2}{m}} \tag{3.10}$$

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[e] Dividing the trading period into sub-periods is a common practice [52]. There are different options to split a trading period into sub-periods. For example, a trading period of 12 months could be divided into: a) 12 sub-periods the length of each is one month, or b) 6 sub-periods the length of each is two months.

- Beta [68]: Beta is a measure of the volatility, or systematic risk, of a security or a portfolio, in comparison to a benchmark. Beta measures how the strategy responds to a benchmark. A Beta of greater than 1 indicates that the security's price will be more volatile than the considered benchmark. For example, if an asset’s Beta is 1.3, then it is theoretically 30% more volatile than the benchmark. Essentially, Beta denote the vital trade-off between reducing risk and maximizing return. Ruppert [69] reports that (3.11) gives the estimated value of Beta (see equations (7.9) and (7.10), p. 230-231 [69]). Let m denote the number of sub-trading periods.

$$Beta_{p,b} = \frac{\sum_{i=1}^{m}\left(R_b^i - \bar{R}_b\right)\left(R_p^i - \bar{R}_p\right)}{\sum\left(R_b^i - \bar{R}_b\right)^2} \tag{3.11}$$

  Where, $Beta_{p,b}$ is the Beta of the portfolio p computed with reference to a benchmark b. R_p^i and R_b^i denote, respectively, the return of the portfolio and the benchmark over the i^{th} sub-trading periods. $\bar{R}_p$ and $\bar{R}_b$ are the average of the returns over the m sub-periods of the portfolio and the selected benchmark respectively.

- Jensen’s Alpha [70]: Jensen’s Alpha is a measure of an investment's performance on a risk-adjusted basis. Jensen’s Alpha (3.12) measures the trading return in excess of a security, or portfolio of securities, over the theoretical expected return. For example, a positive Jensen’s Alpha of 1.0 means the fund has outperformed its benchmark index by 1%. The Jensen’s Alpha is computed as:

$$Jensen's\ Alpha = R_p - R_f - Beta_{p,b} \times (R_b - R_f) \tag{3.12}$$

  Where, R_p is the total return of the portfolio, R_f is the risk free rate, R_b denote the return of the selected benchmark, and $Beta_{p,b}$ is computed as in (3.11).

All of these evaluation metrics will be used later in this thesis to evaluate the performance of our proposed trading strategies as we shall describe in Chapters 6 and 7.

3.5 Summary

In this chapter, we briefly reviewed some of the existing trading strategies from the literature. We identified two categories of trading strategies. The first category contains trading strategies that employ forecasting models. Strategies under this category, usually, embed a machine learning, or artificial intelligence, model to predict market prices or a trend’s direction (Section 3.2). The second category consists of those strategies that do not rely on any forecasting model. Under this category, we reviewed three trading styles, namely: technical trading, momentum strategy, and carry trade (Section 3.3). None of the trading strategies reviewed in this chapter is based on the directional changes framework.

In Section 3.4, we listed and explained selected evaluation metrics usually employed to evaluate the performance of a given trading strategy. All of these metrics will be used later to assess the performance of our intended trading strategies.

4 The Directional Changes Framework

Directional Changes (DC) is a framework for summarizing price movements. In this chapter, we provide a detailed explanation of the concept of DC. We review several studies that have concluded that the DC framework is useful in analysing the foreign exchange (FX) market. We also review some existing trading strategies that are based on the DC framework. To conclude, we clarify the difference between the DC concept and other similar notions.

4.1 Introduction

A common way to summarize raw data in the financial markets is to first choose a time interval, and then sample raw data at fixed time points based on the chosen interval; for example, hourly, daily or monthly. We call data summarized this way 'interval-based summary'. Naturally, an interval-based summary becomes a time series. A time series is a sequence of numerical data observations recorded sequentially in time [71].

The Foreign Exchange (FX) market is open 24 hours a day. Trading activities in the FX market can be affected by many factors. For instance, on the announcement of political or economic news, there tends to be a sharp rise in market trading activity in response to the news. Similarly, during weekends, trading activity has a tendency to decline [12]. Due to these fluctuations, an interval-based summary may not appropriately capture irregularity in traders' activities. This raises an essential need to come up with a time-framework that, adequately, captures significant price movements in financial time series beyond the notion of the interval-based summary. This need is particularly important for the analysis of high-frequency data [72].

The concept of 'intrinsic time' is an approach to studying financial time series [73]. Intrinsic time is defined by events. In this context, events are price movements considered as vital by the observer. The objective of using the event-based approach to summarize a time series is to eliminate irrelevant details of price evolution. Although there are many ways of defining events, in this thesis, we consider a specific type of event named Directional Change (or DC for short) which was established by Guillaume et al., [9].

This chapter continues as follows: in Section 4.2, we provide a detailed explanation of how the DC concept summarizes a market's activities (as explained in Guillaume et al., [9]; Ao and Tsang [10]). In Section 4.3 we discuss those studies that have examined the DC framework's usefulness in analyzing the FX market. We review some existing DC-based trading strategies in Section 4.4.

In Section 4.5, we clarify the difference between the concept of the Directional Changes framework, adopted in this thesis, and other similar notions. We conclude with Section 4.6.

4.2 Directional Changes

4.2.1 The basic concept

In this section, we explain how market prices are summarized based on the DC concept. Directional changes (DC) is an approach to summarizing price changes. Under the DC framework, the market is represented as alternating uptrends and downtrends. The basic idea is that the magnitude of price change during an uptrend, or a downtrend, must be at least equal to a specific threshold $theta$. Here, $theta$ is a percentage that the observer considers substantial (usually expressed as a percentage). For example, Fig. 4.1, shown below, depicts a price's drop between points A and $A^{0.1}$. This price drop is equal to the selected, hypothetical, threshold of 0.1%. In this case, we say that we have a DC downtrend that starts at point A. Any price change less than the identified threshold, $theta$, will not be considered as a trend when summarizing price movements [9] [10].

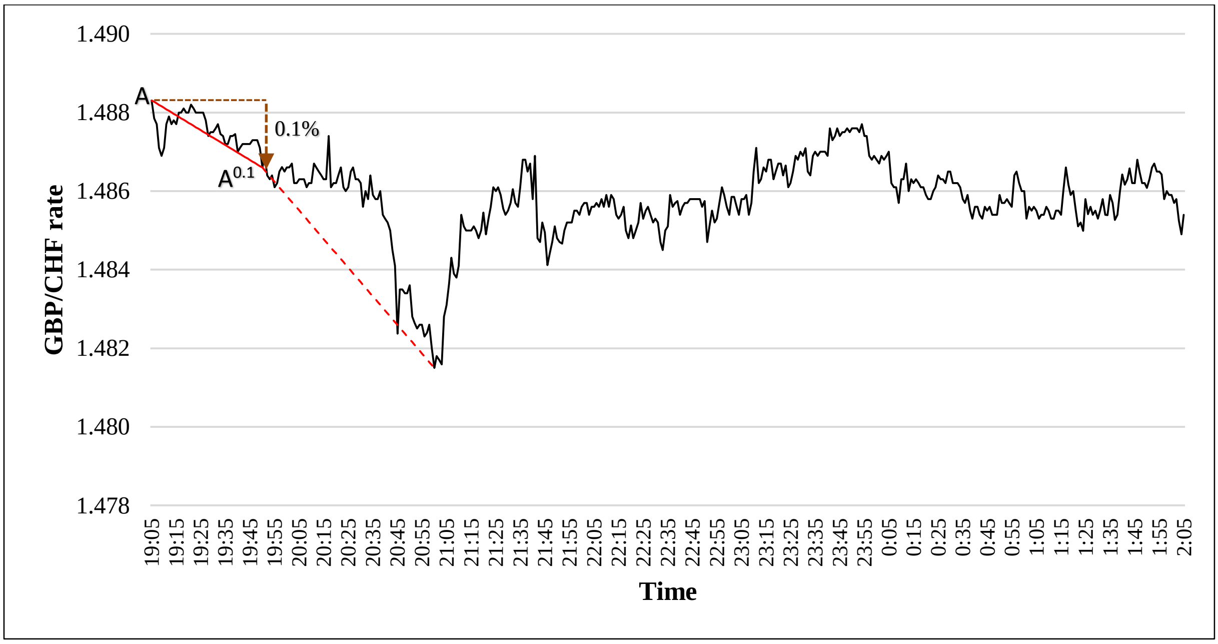

Fig. 4.1. The black line indicates GBP/CHF mid-prices sampled minute by minute from 1/1/2013 19:05:00 to 1/2/2013 02:05:00 (UK). The red line exemplifies what is a DC downtrend looks like.

Under the DC framework, each uptrend is followed by a downtrend and vice versa. The detection of a new uptrend, or downtrend, is a crucial task. The detection of a new downtrend, or uptrend, is a two-steps algorithmic approach:

Step 1:

If the market is currently in a downtrend, let P_{EXT}^{next} denote the lowest price in this downtrend. Note that the value of P_{EXT}^{next} may probably change as the price movement continues. We use Table 4.1, shown below, to exemplify this note. For example, at time 20:54:00, in Table 4.1, the mid-price is 1. 48260. The lowest price observed between time 20:54:00 and 20:58:00 is 1.48230 which was observed at time 20:56:00. Therefore, the value of P_{EXT}^{next}, at time 20:58:00 is 1.48230. However, as the price's movement continues, at time 21:01:00 the mid-price becomes 1.48180. In this case, the lowest price observed between point time 20:54:00 and time 21:01:00 becomes $P_{EXT}^{next} = 1.48150$ (which was observed at time 21:00:00). Similarly, if the market is currently in uptrend, then P_{EXT}^{next} would refer to the highest price in this uptrend.

Table 4.1: The progress of the value of P_{EXT}^{next} during the period from 20:54:00 and 21:05:00. According to Fig. 4.1 this period refer to a downtrend. In such a case, P_{EXT}^{next} refer to the lowest price observed so far during this downtrend.

Time	**Mid-price (P_c)**	P_{EXT}^{next}	**Point**
20:54:00	1.48260	1.48260	
20:55:00	1.48260	1.48260	
20:56:00	1.48230	1.48230	
20:57:00	1.48240	1.48230	
20:58:00	1.48260	1.48230	
20:59:00	1.48200	1.48200	
21:00:00	1.48150	1.48150	B (Extreme point)
21:01:00	1.48180	1.48150	
21:02:00	1.48170	1.48150	
21:03:00	1.48159	1.48150	
21:04:00	1.48280	1.48150	
21:05:00	1.48310	1.48150	$B^{0.1}$ (DCC point)

$$\left|\frac{P_c - P_{EXT}^{next}}{P_{EXT}^{next}}\right| \geq theta \tag{4.1}$$

Step 2:

Let P_c be the current price (e.g. mid-price as in Table 4.1). We say that the market switches its direction from a downtrend to an uptrend if P_c becomes greater than P_{EXT}^{next} by at least $theta$ (where $theta$ is the threshold predetermined by the observer). Similarly, we say that the market switches its direction from an uptrend to a downtrend if P_c becomes less than P_{EXT}^{next} by at least $theta$. The detection of a new DC uptrend or a new DC downtrend is a formalized inequality, as shown in (4.1). For example, in Table 4.1, at time 21:05:00, the current price, P_c, is 1.48310. At time 21:05:00, the P_{EXT}^{next} is 1.48150 (which was observed at time 21:00:00). In this case, the magnitude of price's change between P_c and P_{EXT}^{next} is ≥ 0.1%. Thus, the inequality (4.1) holds and we can confirm the observation of a new DC uptrend. In other words, at time 21:05:00, we can confirm the observation of a new DC uptrend which has started at time 21:00:00. If the inequality (4.1) holds, then the time at which the market traded at P_{EXT}^{next} is called an 'extreme point' (e.g. point B in Table 4.1) and the time at which the market trades at P_c is called a DC confirmation point, or DCC point for short point' (e.g. point $B^{0.1}$ in Table 4.1). By definition, the extreme point of an uptrend has the lowest price amongst all points of current uptrend and the immediately preceding downtrend. Similarly, the extreme point of a downtrend has the highest price amongst all points of current downtrend and the immediately preceding uptrend.

Fig. 4.2 shown below illustrates the identification of extreme and DCC points. In Fig. 4.2, points A, B, C, D, E, F and G are the 'extreme points'. Whereas, points $A^{0.1}$, $B^{0.1}$, $C^{0.1}$, $D^{0.1}$, $E^{0.1}$, $F^{0.1}$, and $G^{0.1}$ are the 'DCC points'. An extreme point can be seen as a local minima (e.g. point D in Fig. 4.2) or a local maxima (e.g. point C in Fig. 4.2). An extreme point is only recognized in hindsight; precisely at the DCC point (i.e. when the inequality (4.1) becomes true). For example, in Fig. 4.2, at point $A^{0.1}$ we confirm that point A is an extreme point. Similarly, in Fig. 4.2, at point $D^{0.1}$ we confirm that point D is an extreme point. We denote by 'price extreme' (P_{EXT}) the price at which a trend starts. Eventually, when (4.1) holds, i.e. when a new DC trend is recognized (either uptrend or downtrend), the P_{EXT}^{next} becomes the P_{EXT} of this new DC trend.

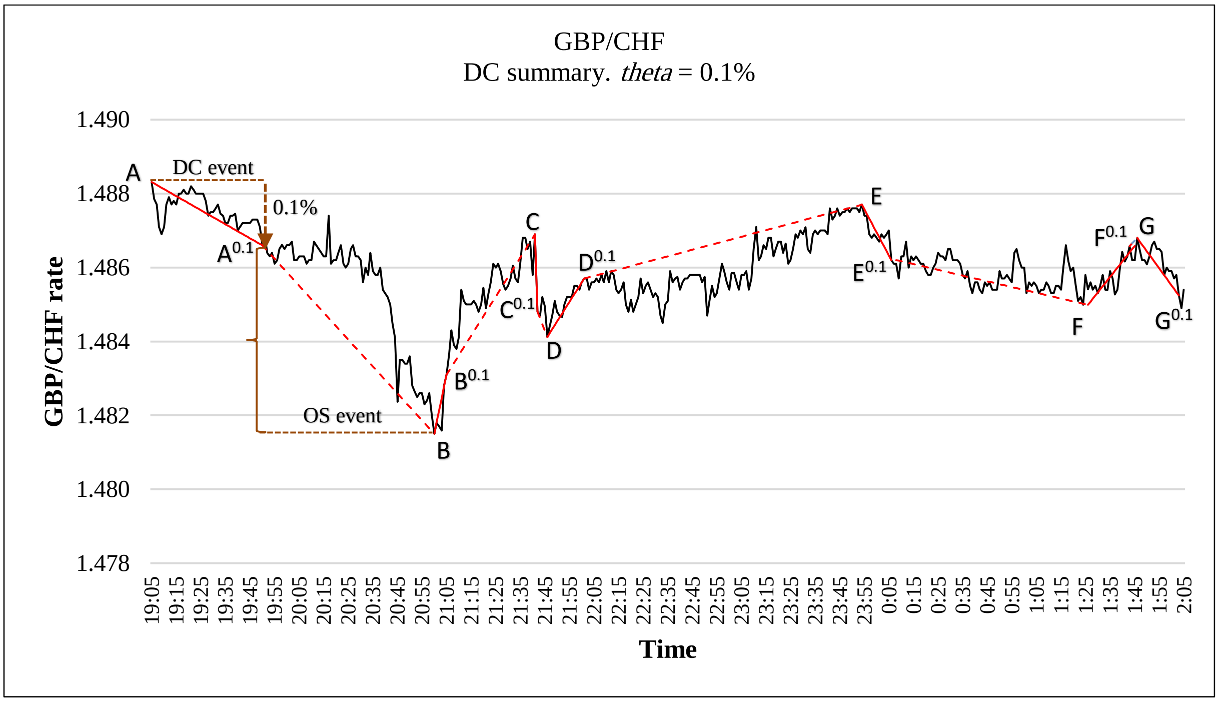

Fig. 4.2. An example of a DC-based summary of the price series shown in Fig. 4.1. Threshold $theta = 0.1\%$. The black line indicates GBP/CHF mid-prices sampled minute by minute. Solid red lines represent DC events. Dashed red lines represent OS events. Each of the points A, B, C, D, E, F, and G is an extreme point. Each of the points $A^{0.1}$, $B^{0.1}$, $C^{0.1}$, $D^{0.1}$, $E^{0.1}$, $F^{0.1}$, and $G^{0.1}$ is a DC confirmation point (DCC point).

Under the DC framework, a trend is dissected into a DC event and an overshoot (OS) event. A DC event starts with an extreme point and ends with a DCC point. We refer to a specific DC event by its starting point, i.e. extreme point, and its DCC point. For example, in Fig. 4.2 the DC event which starts at point A and ends at point $A^{0.1}$ is denoted as $[AA^{0.1}]$. An OS event starts at the DCC point and ends at the next extreme point.

4.2.2 The DC summary

The DC summary of a given market is the identification of the DC and OS events, governed by the threshold $theta$. Fig. 4.2 shows an example of a DC summary with $theta = 0.1\%$. Note that we can produce multiple DC summaries for the same considered price series by selecting multiple thresholds. For example, Fig. 4.2 and Fig. 4.3 illustrate two distinct DC summaries for the same price series using two thresholds: 0.1% for Fig. 4.2 and 0.2% for Fig. 4.3.

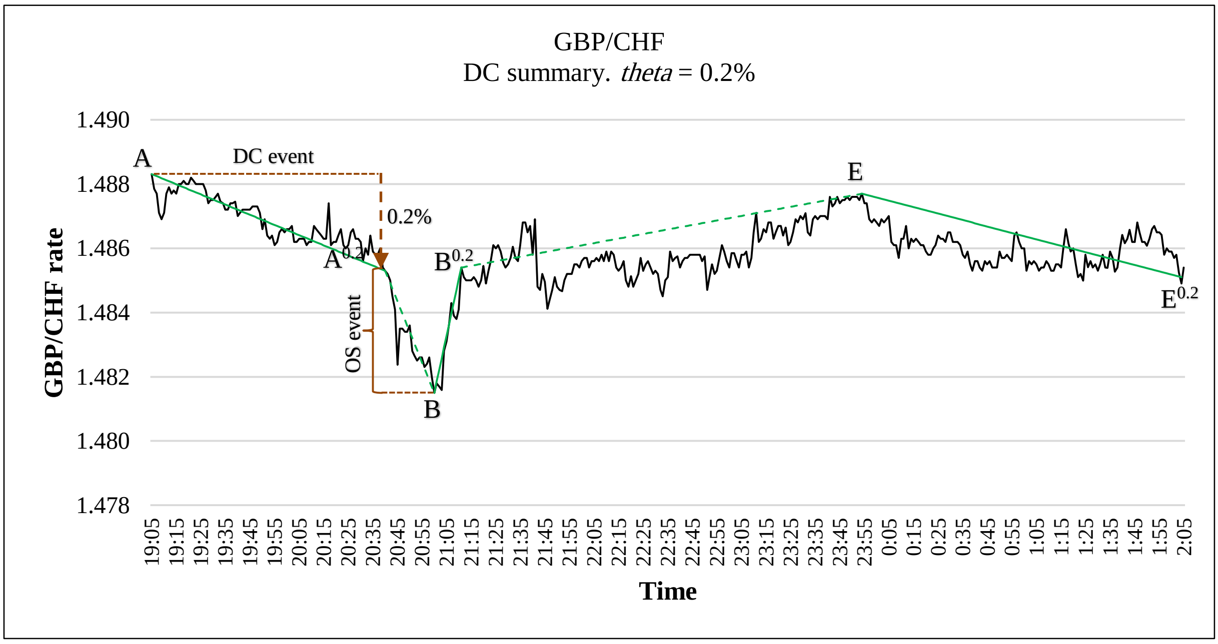

Fig. 4.3. An example of a DC-based summary of the price series shown in Fig. 4.1. $theta = 0.2\%$. The black line indicates GBP/CHF mid-prices. Solid green lines represent DC events. Dashed green lines represent OS events. Each of the points A, B, E is an extreme point. Each of the points $A^{0.2}$, $B^{0.2}$, $E^{0.2}$ is a DC confirmation point.

Keep in mind that the observer should specify the value of the DC threshold $theta$. One observer may consider 0.10% to be an important change, while another observer may consider 0.20% as important. The chosen threshold determines what constitutes a directional change [12] [10]. If a greater threshold had been chosen, then fewer directional changes would have been concluded between the points. For instance, in Fig. 4.2 the DC summary of threshold 0.10% uncovers 4 downtrends and 3 uptrends. Whereas, in Fig. 4.3 the DC summary of threshold 0.20% uncovers 2 downtrends and 1 uptrend.

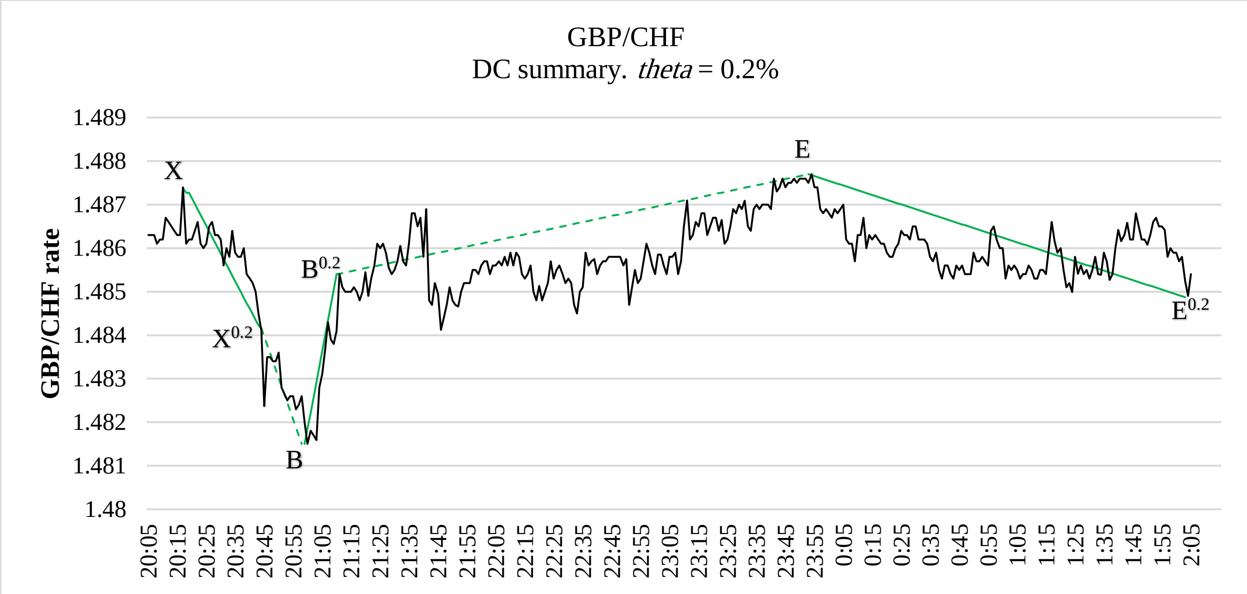

Fig. 4.4.a. An example of a DC-based summary of the price series shown in Fig. 4.3. *theta* = 0.2%. The black line indicates GBP/CHF mid-prices sampled minute by minute from 1/1/2013 20:05 to 1/2/2013 02:05 (UK).

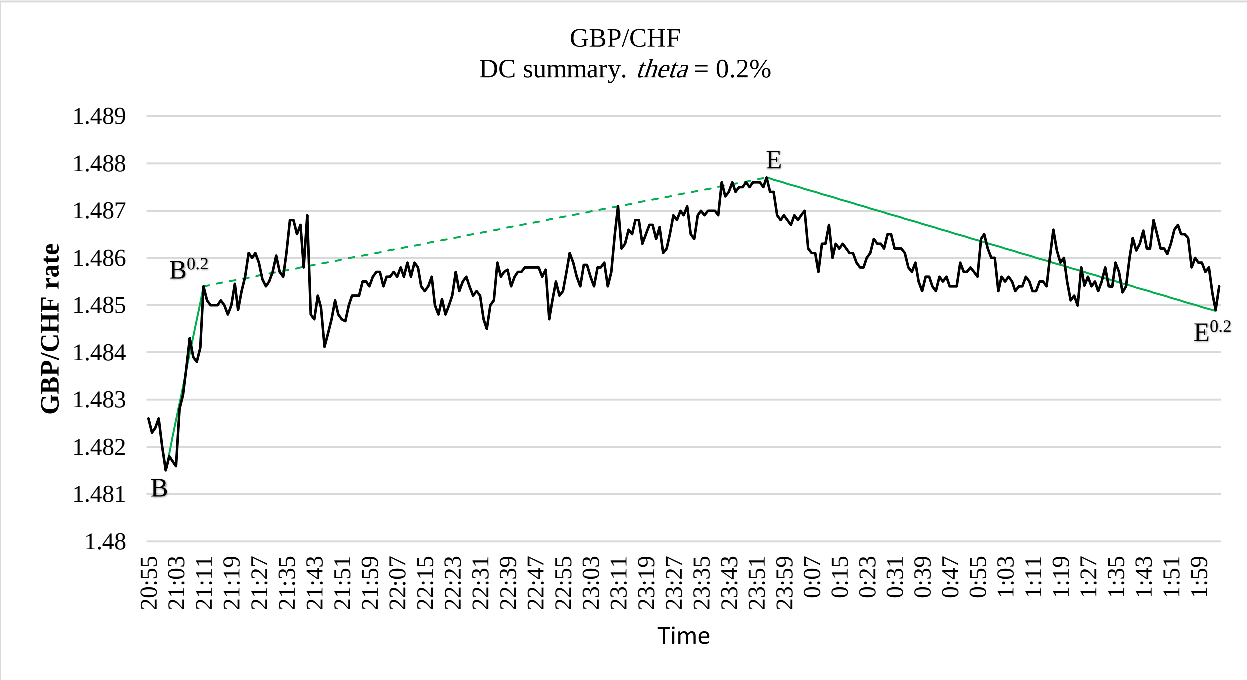

Fig. 4.4.b. An example of a DC-based summary of the price series shown in Fig. 4.1. *theta* = 0.2%. The black line indicates GBP/CHF mid-prices sampled minute by minute from 1/1/2013 20:55 to 1/2/2013 02:05 (UK).

We can obtain different DC summaries if we change: 1) time, or date, of the beginning of the DC analysis; or 2) the selected value of the threshold $theta$. For example, Fig. 4.4.a, shown above, illustrates the DC summary of the GBP/CHF mid-prices sampled minute by minute from 1/1/2013 20:05 to 1/2/2013 02:05 (UK) with $theta = 0.2\%$. This is the same price series and threshold (0.2%) employed in Fig. 4.3, but with a different starting time: The DC summary in Fig. 4.4.a starts 60 minutes later than the DC summary shown in Fig. 4.3. In Fig 4.4.a, we can see that, in this case, the first confirmed DC event is [XX$^{0.2}$] (and not [AA$^{0.2}$] anymore). The new extreme point 'X' is observed at time 20:17 and the new DCC point, X$^{0.2}$, is confirmed at time 20:45.

Fig. 4.4.b, shown above, provides another example of how the DC summary may differ if we select a different starting time-point. In this case, we can see that the first confirmed DC event is [BB$^{0.2}$] which is an uptrend. In Fig. 4.4.b, the DC events [AA$^{0.2}$] (observed in Fig. 4.3) and [XX$^{0.2}$] (observed in Fig. 4.4.a) cannot be recognized anymore.

4.2.3 DC notations

In this section, we introduce some DC-based notations that will help in clarifying our forecasting and trading models later in this thesis:

- P_c: Denote the current price.
- P_{EXT}: Is the price at an extreme point. This is the price at which a trend starts; i.e. a local minima or local maxima. In the case of a downtrend, P_{EXT} will refer to the highest price in this downtrend. In the case of an uptrend, P_{EXT} will refer to the lowest price in this uptrend.
- P_{EXT}^{next}: If the market exhibits a downtrend, then P_{EXT}^{next} would refer to the lowest price observed so far in this particular downtrend. Similarly, if the market exhibits an uptrend, then P_{EXT}^{next} would refer to the highest price observed in this uptrend.
- $P_{DCC\downarrow}$ and $P_{DCC\uparrow}$: We associate two variables to each DC trend— namely $P_{DCC\downarrow}$ and $P_{DCC\uparrow}$. However, the interpretation of these two variables depend on whether the market is in uptrend or downtrend:
    - If the market is in uptrend then, $P_{DCC\uparrow}$ would denote the minimum price required to confirm the current uptrend. It is computed based on the extreme point of the current uptrend as in equation (4.2.a). For example, in the case of the upward DC event [BB$^{0.2}$] in Fig. 4.4.b shown above, $P_{DCC\uparrow}$ is computed by replacing P_{EXT}, in equation (4.2.a) below, with the price at point B, namely 'P_B' (see 4.2.b). Whereas $P_{DCC\downarrow}$ (equation 4.3.a) would denote the price required to confirm the next DC downtrend (i.e. a price drop of threshold $theta$). It is computed as a function of P_{EXT}^{next}. In Fig. 4.4.b, assume that point E is observed at time 23:54. For any price recorded after the observation of point E (i.e. after 23:54), $P_{DCC\downarrow}$ is computed by replacing P_{EXT}^{next} (see equation 4.3.a), with the price at point E, namely P_E (see equation 4.3.b). If the market is in uptrend and if $P_c \leq P_{DCC\downarrow}$ then we can confirm the observance of a new downward DC event (i.e. we say that the market has changed its direction to downtrend).

$$P_{DCC\uparrow} = P_{EXT} \times (1 + theta) \tag{4.2.a}$$

$$P_{DCC\uparrow} = P_B \times (1 + 0.002) \tag{4.2.b}$$

$$P_{DCC\downarrow} = P_{EXT}^{next} \times (1 - theta) \tag{4.3.a}$$

$$P_{DCC\downarrow} = P_E \times (1 - 0.002) \tag{4.3.b}$$

- On the other hand, if the market is in downtrend then, $P_{DCC\downarrow}$ would denote the highest price required to confirm the current downtrend (see equation 4.4.a). It is computed based on the extreme point of the current downtrend. For example, in the case of the downward DC event [XX$^{0.2}$] in Fig. 4.4.a shown above, we replace P_{EXT} by the price at the extreme point X 'P_X' (see equation 4.4.b). Whereas $P_{DCC\uparrow}$ would denote the price required to confirm a price rise of threshold $theta$ (see equation 4.5). It is computed as a function of P_{EXT}^{next}. If the market is in downtrend and if $P_c \geq P_{DCC\uparrow}$ then we can confirm the observance of a new upward DC event (i.e. we say that the market has changed its direction to uptrend).

$$P_{DCC\downarrow} = P_{EXT} \times (1 - theta) \tag{4.4.a}$$

$$P_{DCC\downarrow} = P_X \times (1 - 0.002) \tag{4.4.b}$$

$$P_{DCC\uparrow} = P_{EXT}^{next} \times (1 + theta) \tag{4.5}$$

4.3 Applying DC to analyse financial markets

The DC framework is relatively new approach to analyse financial markets comparing to time series. So far, no study has focused on the drawbacks of the DC framework. In this section, we review some studies that have concluded the DC framework to be helpful in analysing the FX markets. In 2011, Glattfelder et al. [12] revealed new scaling laws (i.e. stylized facts), based on the DC concept, which uncover innovative facts in the FX market. The authors consider five years of tick-by-tick data for 13 currency pairs. In detail, 11 out of the 18 novel scaling-law relations relate to DC and OS events. Two examples of these scaling laws are:

1) The average of the magnitude of price changes during all OS events is equal to the selected threshold $theta$ (see Fig. 4.5 below).

2) Let t denote the average time lengths for all DC events and let T denote the average of time lengths of all OS events. The second scaling law reported in [12] states that we shall have $T \approx 2 \times t$ (see Fig. 4.5).

The authors reported that these scaling laws hold true among all of the considered 13 currency pairs and for different values of threshold $theta$. Later on, these findings were used as the foundation of various trading strategies (e.g. Kampouridis and Otero [17], Golub at al., [16]).

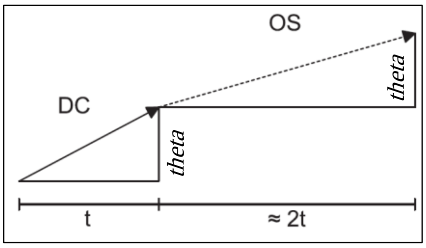

Fig. 4.5. An illustration of two scaling laws related to the DC and OS events reported in [12].

In 2012, Bisig et al. [74] presented the so-called Scale of Market Quakes (SMQ) based on the DC concept. SMQ aimed to quantify FX market activity during noteworthy economic and political events. To this end, SMQ analyses the magnitude of price movements during OS events. The authors suggested that the SMQ model can be used in different ways. For instance, an investor can use SMQ as a tool to filter the significance of market events. The authors also suggested that SMQ can be used as an input to forecasting or trading models to identify regime shifts. They applied the SMQ model to monitor the behaviour of EUR/USD on the occasion of eight releases of non-farm employment numbers from the Bureau of Labour Statistics (https://www.bls.gov/). They recognized a wide variety of market responses (e.g. little reaction from the market, a volatile market or a drop immediately followed by a recovery [74]).

In 2013, Aloud et al. [11] analysed the statistical properties of the transactions data in the FX market using a DC-based approach. They reported the discovery of four new scaling laws holding across EUR/USD and EUR/CHF transactions. In contrast to the scaling laws presented by Glattfelder et al., [12] which focused on price movements, these new scaling laws focused on transactions data. For instance, the authors found that, on average, an OS event contains roughly twice as many transactions as a DC event.

Also in 2013, Masry [13] presented a study that deciphers FX market activity during an overshoot (OS) event based on the DC concept. She provided empirical evidence of diminishing market liquidity at the end of the overshoot period for all studied currency pairs. She found that a price overshoot stops due to more participants placing counter trend trades, a finding that is valid across all magnitudes of price movement events. She also found that small imbalances of market activity in large overshoots can modify the price trend. Masry additionally identified when the market would be vulnerable to the placement of large orders, and the impact of opening a counter trend or a trend follower positions on price overshoots.

In 2014, Golub et al., [75] proposed a new way to measure liquidity in the FX market based on the DC framework. Their new approach sought to model market dynamics to predict stress in financial markets. They defined an information theoretic measurement termed liquidity that characterises the instability of price curves during an overshoot event and argued that the new metric could forecast stress in financial markets. They proposed that their model to quantify liquidity in the FX market could be used as an early warning system [75].

In 2017, Aloud and Fasli [76] presented an agent-based model which aimed to reproduce, to a certain extent, the stylized facts (e.g. seasonality, scaling laws) previously discovered in FX market transactions data by Aloud et al. [11]. The presented study examined the existence of a relation between the functionality of a DC-based trading strategy and a discovered stylized fact in the FX market. They suggested that the proposed model could be utilized to help in the design of agent trading strategies and decision support systems for the FX market.

In 2017, Tsang et al., [77] presented a new approach to profiling companies and financial markets. They proposed several DC-based indicators to characterize the high-frequency price movements of a given market. They suggested that these indicators helped to compare markets in terms of volatility and potential profit. They concluded that information obtained through DC-based analysis and from time series complement each other.

4.4 DC-based trading strategies

Recently, some studies have tried to develop trading strategies based on the DC framework (i.e. DC-based trading strategies). In this section, we review four of these studies.

4.4.1 The 'DCT1'

In 2012, Aloud et al., [14] presented a DC-based trading strategy named Zero Intelligence Directional Change Trading (ZI-DCT0). ZI-DCT0 runs a DC summary with a threshold named 'Δ_{xDC}'. ZI-DCT0 has two trading rules:

a. It initiates a trade at the DC confirmation point of a DC event. The type of trade can be either: counter trend (CT) or trend follow (TF)[f]. In the case of CT, ZI-DCT0 opens a position against the market's trend. TF does the opposite. The user must specify the type of trade: either CT or TF.

[f] A CT (contrarian) trader opens a position (i.e. makes a buy or sell order) with the expectation that the current trend will reverse. A TF (trend follower) trader opens their position with the expectation that the current trend will continue.

b. ZI-DCT0 closes the position at the DC confirmation point of the succeeding DC event.

When trading with ZI-DCT0, the trader must determine two parameters:

- The type of trade: CT or TF.
- The threshold Δ_{xDC} to be used for conducting the DC summary.

In 2015, Aloud [15] presented a trading strategy called 'DCT1'. The DCT1 was presented as an updated version of ZI-DCT0. The trading rules of DCT1 are the same as ZI-DCT0 (i.e. rules a. and b. shown above); however DCT1 is designed to automatically compute the two parameters: the DC threshold Δ_{xDC} and the type of trade (CT or TF). Firstly, the trader defines a range of thresholds. Secondly, DCT1 automatically examines the profitability of each threshold, included in the specified range, using historical price data (as the training set). To this end, for each threshold value, the DCT1 applies the trading rules of ZI-DCT0 from two points of view: counter trend (CT) and trend follow (TF). In other words, during the training period, the DCT1 examines the profitability of all possible combinations of: 1) threshold, included in the range, and 2) the trade type (CT or TF). DCT1 returns the threshold Δ_{xDC} and the type of trade (CT or TF) corresponding to the highest produced returns during the training period. It then uses these values to trade over the trading period.

DCT1 was tested using high frequency data of the EUR/USD currency pair. The author reported that DCT1 was able to produce a rate of return of 6.2% during a testing period of one year (with bid-ask spread being taken into concern). The author did not report any: a) comparison to a benchmark, b) measurement of risk (e.g. *MDD*), or c) evaluation of risk-adjusted metrics (e.g. Sharpe ratio).

4.4.2 A DC-based trading strategy

In 2015, Gypteau et al., [78] presented a DC-based trading strategy. The proposed approach follows the standard tree-based Genetic Programming (GP) configuration. Each individual GP tree comprises internal and terminal nodes. The internal nodes are Boolean functions {AND, OR, NOR, XOR, NOT}.

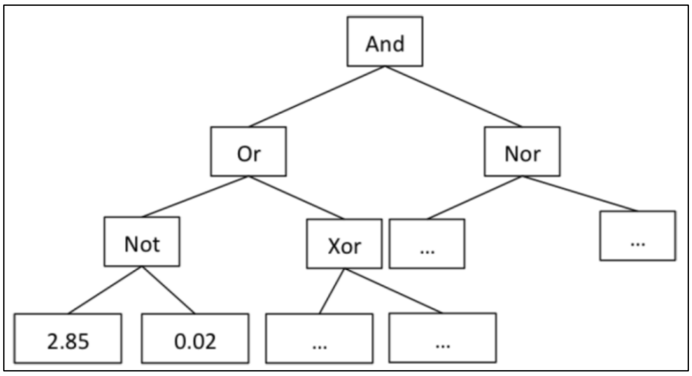

Fig. 4.6. A sample individual GP tree: internal nodes are represented by Boolean functions, while terminal nodes correspond to different DC thresholds. Given a price, terminal nodes output a Boolean value according to the DC or OS events detected. For example, if we detect a downtrend (uptrend) DC event of a DC summary of threshold 2.85%, then the left-most terminal node will be replaced with 'False' ('True'). Source Gypteau et al., [78].

The terminal nodes represent the output of DC thresholds as Boolean values: 'True' if the detected event is an upward DC event; 'False' if the detected event is a downward DC event. For example, Fig. 4.6, shown above, illustrates a sample individual GP tree. In this example, if we detect an upward (downward) DC event of threshold 2.85%, then the left-most terminal node would be set as 'True' ('False'). So that, for a given price, all of the terminal nodes of the GP-tree will be replaced with either 'True' or 'False'.

Each GP tree can be interpreted as a Boolean expression; the output of which is either 'True' or 'False'. In summary, given a GP tree, the strategy consists of iterating over the training (in-sample) dataset and, based on the output of the individual GP tree, taking the action of selling or buying a stock. At each iteration, the current price information (data point) is used as an input for each DC threshold node. Based on the detected event, the expression represented by a GP tree culminates in a Boolean value that indicates the action to be taken: buy at the current price (True); sell at the current price (False).

In order to evaluate the output of a GP tree, the algorithm provides a price value to the terminal nodes, which enables the different thresholds to detect DC events. Based on these detected events, each terminal node is replaced by a Boolean value ('True' or 'False'). Consequently, the overall Boolean expression, represented by the GP tree, returns a 'True' or 'False', which is then translated into trading rules; with 'True' triggering a buy signal and 'False' triggering a sell signal. Thus, each GP tree institutes a trading strategy.

The values of the thresholds, in the terminal nodes, are randomly chosen at the start of the algorithm. The evolution of GP consists in finding the best GP tree (i.e. the thresholds of the terminal nodes and Boolean functions of the internal nodes) which has succeeded in producing the highest profit during the training period.

With respect to the evaluation of the proposed DC-based strategy, the authors applied their trading model to four markets: two stocks from the UK FTSE100 market (Barclays and Marks & Spencer) and two indices (NASDAQ and the NYSE), sampled using daily closing price or index. For each market, they considered a training period of 1000 days in length to train their GP model. Then, they considered a testing (out-of-sample) period of 500 days in length for evaluation. However, the authors did not report the dates of the training and testing periods!

The authors reported only the returns of the proposed trading strategy [78]. These were less than 10% over a trading period of 500 days for each of the four considered markets. Furthermore, they did not report any: a) measurement of risk (e.g. *MDD*), b) comparison to a benchmark, or c) evaluation of risk-adjusted metrics (e.g. Sharpe ratio).

4.4.3 The 'DC + GA'

In 2017, Kampouridis and Otero [17] proposed a DC-based trading strategy named 'DC+GA'. DC+GA runs multiple DC summaries concurrently (using multiple thresholds). For each threshold, DC+GA calculates the average time length of each DC and OS event for every DC trend during a training (in-sample) period. DC+GA employs two variables to express the average ratio of the OS event length over the DC event length. These two variables are r_u and r_d, where r_u is the average ratio of the upwards OS event and r_d is the average ratio of the downwards OS event. Thus, DC+GA analyses uptrends and downtrends separately. The objective is to be able to anticipate the end of an uptrend, or downtrend (approximately) and, as a result, make trading decisions (buy or sell) once an OS event has reached the average ratio of r_u or r_d. Theoretically, DC+GA initiates a trade when the length of an OS event exceeds r_u or r_d.

Based on the established scaling laws in [12] r_u and r_d are both equal to 1; which was confirmed by Kampouridis and Otero [17]. However, in reality, it is generally expected that the OS event might last longer, or be over earlier, than the estimated average values r_u and r_d (which are both 1). To address this issue, the authors created two parameters, namely b_1 and b_2, that define a range of time within the OS period in which trading is allowed. For instance, if a trader expects the OS event to last for 2 hours (this expectation is based on the calculus of r_u and r_d) and assuming that the range of $[b_1, b_2]$ is [0.9, 1.0], then this means that DC+GA is going to trade (buy or sell) in the last 10% of 1 hour's duration, i.e. in the last 6 minutes.

Recall that DC+GA runs multiple DC summaries simultaneously (using multiple thresholds) for a given currency pair. Let N_{theta} be the number of employed DC thresholds. The user/trader should choose the values of the N_{theta} thresholds. DC+GA assigns a weight to each DC threshold.

For a given price observation, each threshold provides a recommendation (buy, sell or hold) based on the values of b_1, b_2, r_u and r_d. At a given time, the N_{theta} thresholds provide N_{theta} recommendations. These N_{theta} recommendations are grouped into two groups based on the produced recommendation: the first group contains the DC thresholds recommending to buy; the second group contains the DC thresholds with sell recommendations. In order to decide which recommendation (buy, sell, or hold) to adopt, DC+GA sums the weights of the thresholds of the two groups: if the sum of the weights for all thresholds recommending a buy (sell) action is greater than the sum of the weights for all thresholds recommending a sell (buy) action, then the strategy's action will be to buy (sell).

To optimize the weights of these N_{theta} thresholds and the associated trading parameters, DC+GA employs a Genetic Algorithm (GA). DC+GA symbolizes a trading strategy as a GA gene. In this context, a GA's gene comprises: the weights of the N_{theta} thresholds, b_1, b_2, and Q, with Q being the order size (i.e. how much to buy or to sell). During the in-sample (training) period, the evolution of GA consists in discovering the best GA gene. The best GA gene is the one that returns the maximum profit during the training period. This best gene will be used for trading during the out-of-sample (trading) period. DC+GA employs a fitness function that aims to minimize the maximum drawdown (*MDD*) and maximize returns at the same time.

To evaluate the performance of DC+GA, the authors considered five currency pairs sampled within a 10-minute interval over one year. They adopted a daily-basis rolling window approach, with the training period being 1 day. When examining the reported monthly returns (in Tables 5 and A1, pages 156 and 158 respectively, Kampouridis and Otero [17]) one can easily note that the proposed trading models incur losses in about 50% of the cases! The authors concluded that the proposed model "…*could not consistently return profitable strategies and thus their mean returns were negative.*" Kampouridis and Otero [17] reported the average monthly returns of applying DC+GA to five currency pairs (shown in Table 6, page 158 [17]). We note that DC+GA incurs overall losses in two out of the five cases.

As for the risk-adjusted performance, the authors did not provide any risk-adjusted measurement explicitly. However, based on the reported monthly returns (Table 5, page 158, [17]), we can compute the Sharpe ratio. If we consider a risk-free rate of 0.5% per annum, then we find that DC+GA produced a positive Sharpe ratio in only two out of the five considered currency pairs as follow:

- In the case of EUR/GBP: 0.00

- In the case of EUR/JPY: 0.25
- In the case of EUR/USD: – 0.35
- In the case of GBP/CHF: – 0.30
- In the case of GBP/USD: 0.10

The authors adopted the buy and hold approach as a benchmark. They reported that the proposed trading strategy " *…return a similar average return with BH*" . We should finally note that the reported *MDD* of DC+GA was less than 0.15% (measured on a daily basis) in all considered cases (Table 8, [17]). We consider this value to be an attractive level of drawdown risk.

4.4.4 The 'Alpha Engine'

In 2017, Golub at al., [16] presented a DC-based trading strategy called 'Alpha Engine'. The Alpha Engine is a contrarian trading strategy. The mechanism of initialization of new positions and the management of existing positions in the market works as follows:

Initially, the Alpha Engine opens a new position against the market trend during an OS event in which the price's change exceeds a certain threshold named 'ω'. ω is a function of the predetermined DC threshold $theta$ and a parameter named α (4.4). The value of α is governed by a money management module that we shall describe next.

$$\omega = \alpha \times theta \tag{4.6}$$

The Alpha Engine does not have an explicit stop-loss rule. Instead, it employs a sophisticated money management approach. Each time the Alpha Engine opens a new position, it names this position a 'trading agent'. The Alpha Engine is capable of opening and managing multiple positions (i.e. multiple trading agents) concurrently. When Alpha Engine opens a new position (i.e. initiates a new trading agent), it keeps managing the size of this position until it closes in a profit. The Alpha Engine increases and decreases the size of the position (i.e. the quantity of inventory held by a trading agent) as the price progresses. The basic idea is that an existing position is increased by some increment in case of a loss, bringing the average closer to the current price. For a de-cascading event, an existing position is decreased, realizing a profit.

When triggering a new trade, a trading agent must decide the '*time*' and the '*size*' of that trade. For this purpose, the Alpha Engine takes into concern two main factors:

a. *The accumulation of inventory sizes as the market price moves up and down*: the threshold ω is essentially utilized to control the time at which a trading agent should initiate a new order. More particularly, the Alpha Engine manages a parameter α to control the value of

ω (4.3). The value of α is a function of the inventory size. Let I denote the overall inventory size held by all generated trading agents altogether. The authors considered I as a proxy for the market. The Alpha Engine uses the value of I to manage the parameter α; and, consequently, the threshold ω.

b. *A probability indicator, denoted as '$\mathcal{L}$'*: The value of $\mathcal{L}$ is interpreted as the probability that the trend will go up or down given the current state. More specifically, $\mathcal{L}$ is computed using a transition network which has two states: ω and $theta$. This transition network is designed so that, in the case of an unlikely price trajectory (i.e. abnormal market behavior), $\mathcal{L} \approx 0$. On the other hand, if the markets show normal behavior, i.e. no strong trend can be recognized, then $\mathcal{L} \approx 1$. The Alpha Engine uses $\mathcal{L}$ to control the size of a new order. The size of a new order increases (decreases) as $\mathcal{L}$ approaches 1 (0). It follows from the previous description that $\mathcal{L}$ helps the trading agents not to build up large positions that they cannot unload. Besides, by slowing down the increase of the inventory of a trading agent during market overshoots, the overall trading model experiences smaller drawdowns and better risk-adjusted performance. The concept of $\mathcal{L}$ was introduced by Golub et al. [75] to discover if a market exhibits normal, or abnormal, behavior.

Moreover, the Alpha Engine uses asymmetric thresholds for uptrends and downtrends. The authors found that the market is most likely to exhibit different behaviors during uptrends and downtrends. To cover this dilemma, the Alpha Engine employs two different DC thresholds (instead of just one: '$theta$); one for uptrends ($theta_{up}$) and another for downtrends ($theta_{down}$). Similarly, the Alpha Engine has two different ω thresholds — the so-called ω_{up} and ω_{down}, with $\omega_{up} = \alpha_{up} \times theta_{up}$ and $\omega_{down} = \alpha_{down} \times theta_{down}$. α_{up} and α_{down} are two trading parameters, the values of which rely on the inventory I as explained in point a. above.

The details of this money management mechanism are quite complicated, so for.more information on it, we would recommend Golub et al., [16]. Overall, we would note that this money management approach is an integrated module of the Alpha Engine.

The Alpha Engine was extensively back-tested using a portfolio of 23 currency rates sampled tick-by-tick over a period of eight years, from the beginning of 2006 until the beginning of 2014. Alpha Engine produced a return of 21.34% over eight years (they used the bid and ask prices), with a maximum drawdown of 0.71% (calculated on a daily basis). The authors reported an annual Sharpe ratio (4.6) of 3.06. However, they did not specify the used risk-free rate! The authors made the code of the Alpha Engine available online at Github [79].

4.5 Notions and concepts similar to DC

In this section, we distinguish the DC concept adopted in this thesis from other similar notions. Despite the similarity in the names, the DC concept as described in this thesis is completely different from both the 'Change Direction' [80] and 'Direction– of– Change' [81]concepts. In both studies, [80] and [81] the authors used interval– based datasets (daily close value); neither a threshold $theta$ was used, nor a DC event defined. Instead, they tried to forecast when a given stock index would switch its trend direction (upward or downward) at the daily closing price without measuring the magnitude of the price change. Their models aimed to answer the question: "will today's close price extend yesterday's trend?"

The DC concept is similar to the zigzag indicator, however. The zigzag approach models price movement as alternating uptrend and downtrend [82] [83] [84]. The price change during an uptrend or a downtrend must be at least equal to a specific threshold. The literature comprises another similar notion: the 'turning points'. In general, price movement can be symbolized as alternating uptrends and downtrends, separated by 'turning points'. Turning points are essentially local minimum and maximum points in a time series, or in practical terms, the peaks and troughs [41]. Turning points are the points at which the trend's direction reverses, usually for a magnitude predetermined by the observer. Turning points can be interpreted as the extreme points under the DC context.

The zigzag indicator and turning points concepts are pretty similar to the DC framework with the main difference being that a trend, under the DC methodology, is dissected into: 1) a DC event of fixed percentage equal to the selected threshold and 2) an OS event represented by the remaining part of the trend before it reverses. Such partitioning is not part of the zigzag indicator nor of the turning point model. Keep in mind that the dissection of a trend into DC and OS events, under the DC framework, has been reported to be helpful in analysing and characterizing the financial markets in many studies (e.g. [11] [12] [77] [74] [85]).

4.6 Summary

In this chapter, we have explained the concept of Directional Changes (DC). The DC framework is an approach to summarizing prices in the financial markets. A directional change is defined by a threshold that the observer considers significant, e.g. 5%. A $theta$ % directional change is basically a price change of $theta$ % from the last peak or bottom price. Under the DC framework the market is seen as a series of alternating uptrends and downtrends. A trend is dissected into a DC event (of fixed threshold $theta$) and an OS event (consisting of the remaining part of the trend).

In Section 4.2.3, we listed some important DC-based notations that will be used later in this thesis (e.g. $P_{DCC\downarrow}$, $P_{DCC\uparrow}$, P_{EXT}).

Reviewing the literature in Section 4.3, we found that many studies have concluded that the DC framework is helpful in gaining more insight into the analysis of the FX market. This comprised the discovery of new scaling laws, understanding the impact of new trades on a market's trend, and measuring the impact of political and economic events on the market. We also noticed that only recently, some studies have tried to develop trading strategies based on the DC framework. We reviewed four of these studies in Section 4.4. Later in this thesis, we will compare these four DC-based trading strategies with our planned trading strategies in Chapters 6 and 7.

In this thesis we aim to explore, and consequently to provide a proof of, the usefulness of the DC framework as a foundation for successful trading strategies. It is important to note that our planned DC-based trading strategies in this thesis are not based on any other DC-based strategy. However, some similar features may exist, as we shall discuss in Chapters 6 and 7.

Part II

Thesis Contributions

5 Forecasting Directional Changes: Problem Formulation and Solution

Many studies have tried to forecast the change in direction of a market trend. To the best of our knowledge, no study has considered this problem within the DC context. In this chapter, we study this problem under the DC framework. The central research question which we pose here is whether the current trend will continue for a specific percentage before the direction of the trend reverses.

In this chapter, we formalize this forecasting problem from the DC perspective and propose a solution. We evaluate the accuracy of our approach using eight currency pairs from the FX market. The experimental results suggest that the accuracy of the proposed forecasting model is very good; in some cases, prediction accuracy is over 80%.

5.1 Introduction

Forecasting financial time series is a common objective for financial institutions and traders. This task has proven to be very challenging [86]. Many studies have focused on the issue of next-value prediction, which entails forecasting the future value of time series at the oncoming time step, given the historical observations up to the current time. There may, however, be advantages in predicting the change of a market trend's direction directly (i.e. without explicitly predicting the future value of the series). For example, traders may take decisions based on their estimation of whether the price of a particular market will rise or fall [81].

Many studies have tried to predict when a given market would switch its trend direction. These studies usually aim to answer the question: will today's close price extend yesterday's trend? In other words, these studies consider the market prediction problem as a classification problem, where the question is whether the market goes up or down. Usually this problem is referred to as forecasting the change of direction. For instance, Park et al. [80] proposed a continuous Hidden Markov Model (HMM) to predict the change of direction of a financial time series. They proposed to split the data, consisting of daily closing prices, into two classes based on direction changes in the next day's closing price, and to train two HMMs (one for each class). The two formed HMM models would then beemployed to forecast changes in direction of the next day's closing price. Skabar [81] presented a Bayesian multilayer perceptron model to predict the direction of the daily close value of the Australian financial index. Skabar [87] proposed another forecasting model in which he used a similarity-based classification model to predict the trend direction of tomorrow's close price. He admitted that both models, introduced in [81] and [87], have almost equal accuracy. Giacomel et al. [43] proposed an ensemble of two ANNs to predict the direction of price movement. The proposed model was tested using two cases: the North American and the Brazilian stock markets for a total of 18 stocks. Evans et al. [6] introduced a model which combined Artificial Neural Networks (ANN) and Genetic Algorithms (GA) to predict intra-day market price direction. They employed a GA module to search the best network topology of a multiple layer perceptron (MLP) in order to improve forecasting accuracy. It is important to note that the objective of these studies is to forecast whether the next price observation will be greater, or smaller, than the last recorded price. In this chapter we consider a different forecasting problem that we shall describe next.

Price movements can be symbolized as alternating uptrends and downtrends, separated by ‘turning points’. Turning points are essentially local minimum and maximum points on a time series or, in practical terms, the peaks and troughs [41]. Turning points are the points at which the trend’s direction reverses, usually for a magnitude predetermined by the observer. An investor who can trade exactly at the turning points (e.g. buying at minima and selling at maxima) would gain the maximum possible profit. Therefore, a common objective for traders in the financial markets is to forecast turning points. Predicting turning points has long been a tough task in the field of time series analysis. Many machine learning models have been developed for this purpose, with the majority of cases focusing on stock markets.

For instance, Azzini et al. [83] tried to predict a turning point in the S&P500 index. Their objective was to predict the magnitude of the price change of the entire trend (i.e. between two consecutive turning points) before the trend reversed. They used two models for this purpose: fuzzy logic and neural networks. Li et al. [41] proposed a framework for turning point prediction that combines chaotic dynamic analysis with a neural network. Their proposed model tries to predict whether the next time step in the time series is a peak, a trough or none. El-Yaniv and Faynburd [88] proposed a model for the prediction of turning points based on support vector regression.

Many studies have concluded that the directional change (DC) framework is useful in analysing the FX market (e.g. [11] [12] [14] [74]). In this chapter, we consider the problem of forecasting the change of a trend’s direction from the DC perspective. The task is to forecast whether the current trend, either uptrend or downtrend, will continue in the same direction for a specific percentage before it reverses (i.e. before the occurrence of the next extreme point). Answering this question can be useful for investment decisions. For example, it could help a trader to make a buy or a sell decision (as we shall argue in Chapter 6).

Forecasting crucially depends on the variables used. As a first attempt to tackle the proposed forecasting problem, we introduce an original DC-based independent variable. We prove that it is useful for the proposed forecasting problem. Our forecasting model, in this chapter, is novel because:

- *In terms of problem formulation*: We consider the problem of 'forecasting whether the current trend will continue in the same direction for a specific percentage before it reverses' from the DC perspective. To the best of our knowledge, no previous study has considered this problem from the DC perspective.
- *In terms of the proposed solution*: We will introduce an original DC-based indicator and prove that it is helpful in predicting the change of a trend's direction with very good accuracy. Most of the existing forecasting approaches use traditional technical indicators [21].

The rest of this chapter is organized as follows: we introduce a new concept named Big-Theta, which is based on the DC concept, in Section 5.2. Then we provide the formal definition of our proposed forecasting problem in Section 5.3. In Section 5.4, we present our approach to solving the introduced forecasting problem. We describe a set of experiments in Section 5.5, designed to examine the accuracy of our forecasting model. The experimental results are reported and discussed in Section 5.6. We conclude with Section 5.7.

5.2 The concept of Big-Theta

5.2.1 Big-Theta

In this section, we introduce a new concept named Big-Theta. The notion of Big-Theta refers to the situation at which the price movements of a DC event of threshold *STheta* may possibly continue in the same direction (either upward or downward) so that the magnitude of price change, during this particular DC trend, reaches another threshold named *BTheta* (with *STheta* < *BTheta*). To clarify the notion of Big-Theta[g], we provide the following examples: Fig. 5.1, shown below, illustrates a downward DC event, named [AA^{STheta}], of an unknown threshold *STheta*. At the time of the observation of point A^{STheta}, we can confirm a price drop of magnitude *STheta* from point A. The total magnitude of price change, for this particular DC trend, increases as the price's movement continues in the same downward direction. Later on, at point A^{BTheta} this magnitude

[g] An alternative, and more rigorous, definition of the concept of Big-Theta would be: "Each DC event of threshold *BTheta* will embrace another DC event of threshold *STheta* such that they both have the same extreme point". We provide more in-depth discussion and proof for this alternative definition in Appendix B.

becomes equal to *BTheta*. Thus, it becomes possible, at point A^{BTheta}, to confirm the observation of another downward DC event, named [AA^{BTheta}], of a threshold *BTheta* (with *STheta* < *BTheta*). The observation of this new DC event [AA^{BTheta}] can be confirmed only when the price change between the points A and A^{BTheta} becomes larger than or equal to *BTheta* (see Fig. 5.1 below); but not before that.

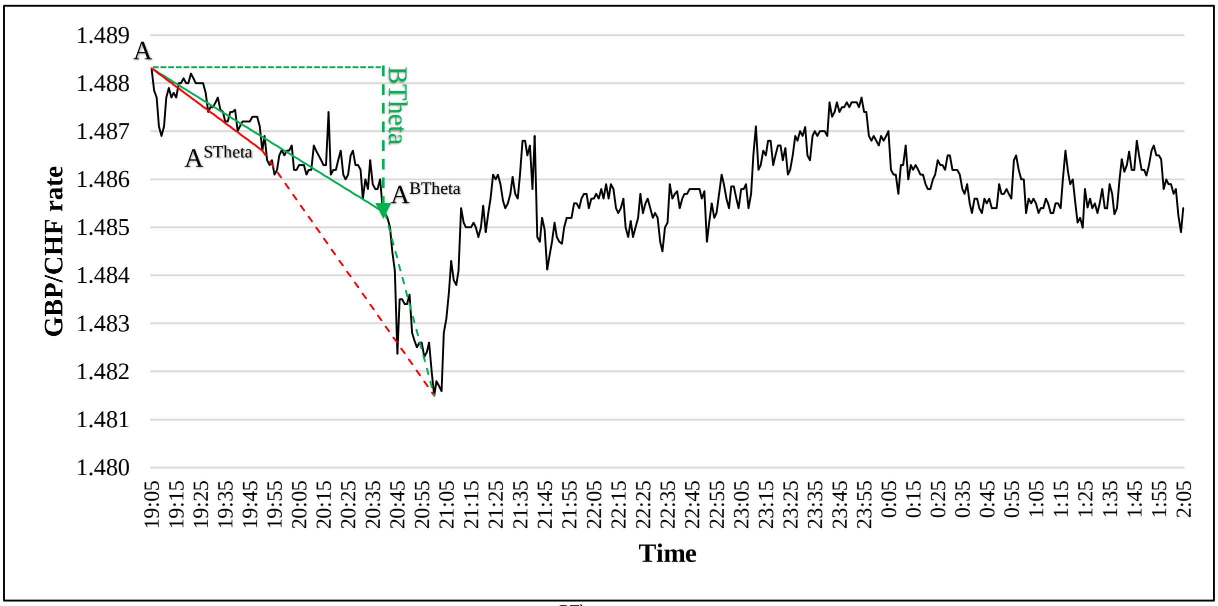

Fig. 5.1. An example of a downward DC event [AA^{BTheta}] of threshold *BTheta* which embraces another downward DC event of a smaller threshold *STheta* [AA^{STheta}].

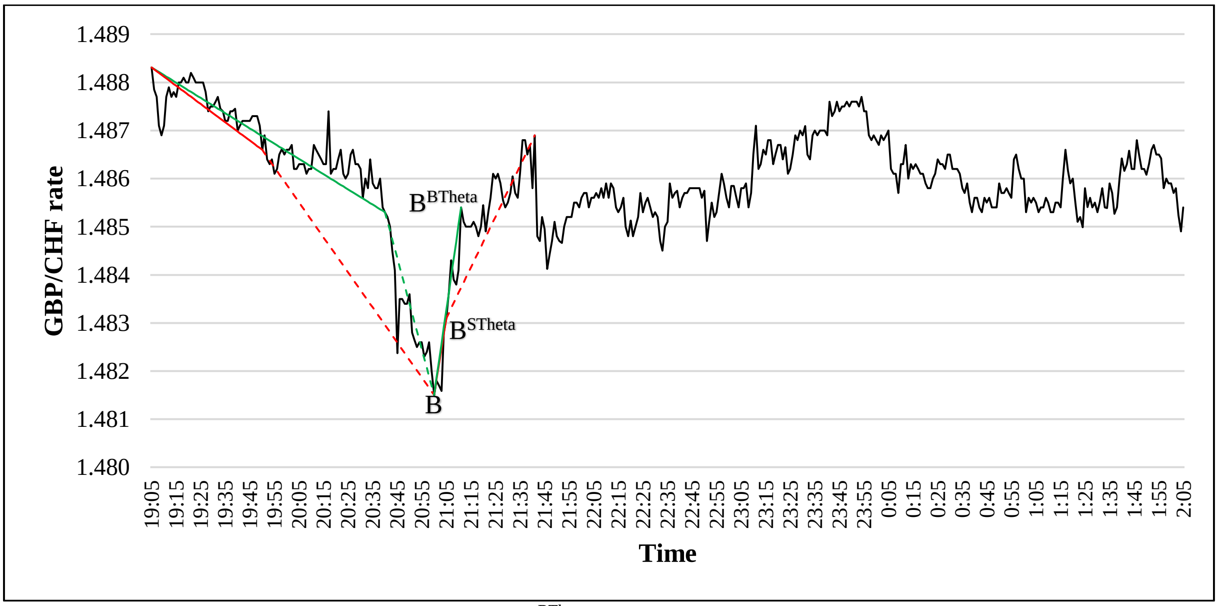

Fig. 5.2. An example of an upward DC event [BB^{BTheta}] of threshold *BTheta* which embraces another upward DC event of a smaller threshold *STheta* [BB^{STheta}].

Similarly, let us consider the upward DC event, named [BB^{STheta}], of threshold *STheta* exposed in Fig. 5.2, shown above. At the time of when the point B^{STheta} is observed we can confirm a price rise of threshold *STheta*. As the price movements continues in the same upward direction, the total magnitude of price change, for this particular DC trend, increases. At point B^{BTheta}, this total magnitude becomes equal to *BTheta*. Thus, at point B^{BTheta} we are able to confirm the observation of another upward DC event, named [BB^{BTheta}], of threshold *BTheta*.

Fig. 5.3, shown below, illustrates two DC summaries of a GBP/CHF price series using two thresholds: *STheta* (0.1%) and *BTheta* (0.2%). We will use Fig. 5.3 to illustrate the notion of Big-Theta. As explained in Chapter 4, for the same price series, we may produce several DC summaries by using multiple thresholds [10] [12]. In Fig. 5.3 we consider the two DC events of threshold *STheta* (0.1%); namely [$AA^{0.1}$] and [$BB^{0.1}$] (shown in solid red lines). We can see that the price movements of each of these two DC events was prolonged so that later on, as the price movements continues, we can confirm another DC event of threshold *BTheta* namely [$AA^{0.2}$] and [$BB^{0.2}$].

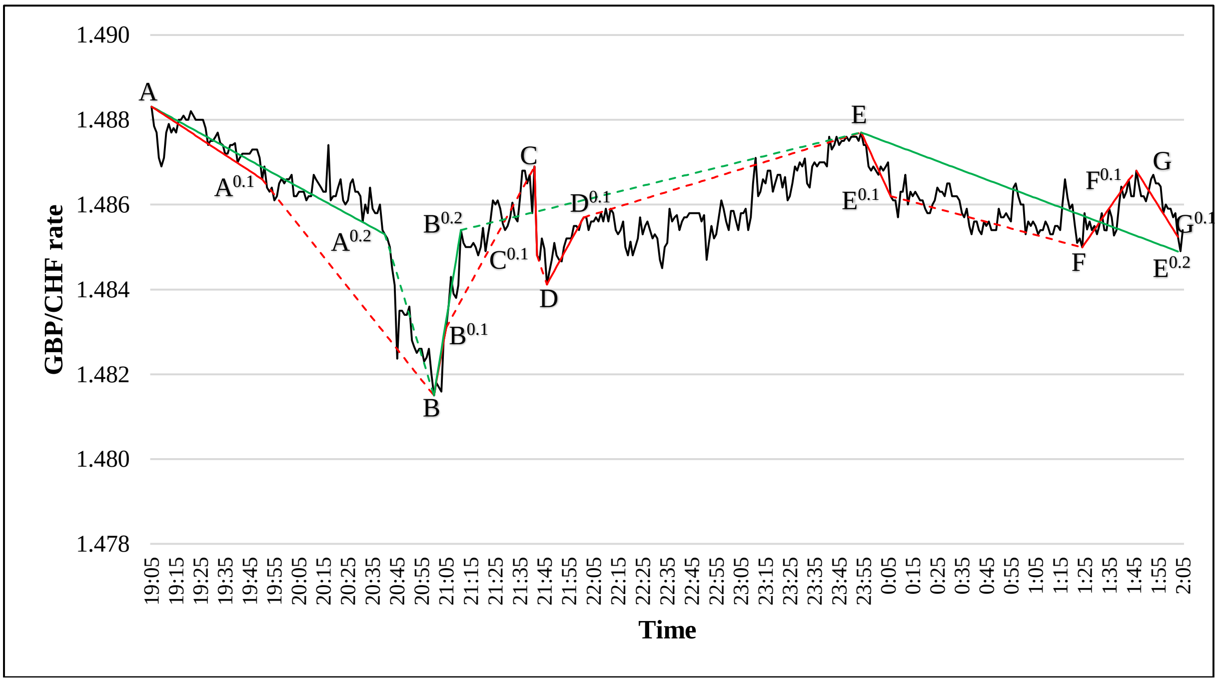

Fig. 5.3. The synchronization of the two DC summaries using two thresholds: *STheta* (0.1%) and *BTheta* (0.2%). The black line indicates GBP/CHF mid-prices sampled minute by minute from 1/1/2013 19:05 to 1/2/2013 02:05. Solid red lines represent DC events. Dashed red lines represent OS events for threshold *STheta*. Solid red lines represent DC events. Dashed red lines represent OS events for threshold *BTheta*.

5.2.2 The Boolean variable BBTheta

In this section, we use the concept of ‘Big-Theta’ to introduce a new Boolean variable named *BBTheta*. Fig. 5.3, shown above, illustrates the synchronization of two DC summaries of same price series using two threshold 0.1% and 0.2%. For each DC event of threshold *STheta*, we associate a value of the Boolean variable *BBTheta*. For example, let $BBTheta^{1}$ denote the value of *BBTheta* associated to the first DC event of threshold *STheta*, which is [$AA^{0.1}$] in this case (see

Fig. 5.3). In general, let *BBTheta*^{i} be the value of *BBTheta* associated with the i^{th} DC event of the DC summary of threshold *STheta*. *BBTheta*^{i} can be only *True* or *False*. The value of *BBTheta*^{i} is defined as follows:

If the total price change during the i^{th} *DC trend, of the DC summary of threshold STheta, is at least equal to BTheta, then BBTheta*^{i} *= True; otherwise BBTheta*^{i} *= False. In other words, BBTheta*^{i} *is 'True' only if the price change between the* i^{th} *and* $(i+1)^{th}$ *extreme points is larger than or equal to BTheta.*

We use Table 5.1, shown below, to clarify this definition. The first column from the left in Table 5.1 represents the index of the DC events observed under threshold *STheta* (i.e. 1st, 2nd, etc.) in Fig. 5.3. The column 'Extreme point' contains the extreme points resulting from the DC summary of threshold *STheta* (according to Fig. 5.3 shown above). The column 'Mid-price at extreme point' shows the market's price at the indicated extreme point. We can catch the value of *BBTheta*^{i} by calculating the magnitude of price changes between the i^{th} and $(i+1)^{th}$ extreme points detected under the threshold *STheta*.

Table 5.1: Example of DC events of threshold *STheta* and the computation of corresponding *BBTheta*^{i} based on Fig. 5.3.

DC event index (*STheta*)	**Extreme point**	**Mid-price at extreme point**	**DCC point**	**BBTheta**
1	A	1.48831	$A^{0.1}$	*BBTheta*^{1}= *True*
2	B	1.48150	$B^{0.1}$	*BBTheta*^{2}= *True*
3	C	1.48690	$C^{0.1}$	*BBTheta*^{3}= *False*
4	D	1.48412	$D^{0.1}$	*BBTheta*^{4}= *False*
5	E	1.48770	$E^{0.1}$	*BBTheta*^{5}= *True*
6	F	1.48499	$F^{0.1}$	*BBTheta*^{6}= *False*
7	G	1.48680	$G^{0.1}$	*BBTheta*^{7}= *False*

For example, to compute *BBTheta*^{1} we calculate the price change between the prices of the 1st and 2nd extreme points shown in column 'Extreme point' (i.e. points A and B). In this example, the price change is:

$$(P_A - P_B)/\, P_A = (1.48831 - 1.48150)/\, 1.48831 = 0.00458 \tag{5.1}$$

The value of (5.1), i.e. 0.00458, is larger than *BTheta* (0.2%). Thus, *BBTheta*^{1}= *True* as shown in column 'BBTheta'. Similarly, to compute *BBTheta*^{3} we calculate the price change between the prices of the 3rd and 4th extreme points shown in column 'Extreme point' (i.e. points C and D). In this case, the price change is:

$$(P_C - P_D)/\ P_C = (1.48690 - 1.48412)/\ 1.48690 = 0.00187 \tag{5.2}$$

The value of (5.2), i.e. 0.00187, is less than *BTheta* (0.2%). Thus, $BBTheta^3 = False$ as shown in column 'FBBTheta'. The column 'BBTheta' embraces the set of all instances of $BBTheta^i$. We refer to this set as *BBTheta.* Given two DC summaries of the same price series, corresponding to two different thresholds, *STheta* and *BTheta*, we compute $BBTheta^i$ for each DC event of threshold *STheta* as exemplified in Table 5.1.

5.3 Formulation of the forecasting problem

In this chapter, our task is to forecast the value of *BBTheta.* In other words, we are looking to forecast, at the DCC point of a DC event of threshold *STheta* (e.g. points $A^{0.1}$, $B^{0.1}$ from Table 5.1), whether the associated instance of *BBTheta* (shown in the column 'BBTheta' Table 5.1) is *True* or *False.* In this section, we introduce our proposed forecasting problem.

Table 5.2, shown below, simplifies the synchronization of the two DC summaries. We use Table 5.2 to provide an example of the proposed forecasting problem. Based on Table 5.2, we consider two uptrend DC events:

1. The DC event [$BB^{0.1}$] of threshold 0.1%. [$BB^{0.1}$] starts at time 21:00:00 and ends at time 21:05:00.
2. The DC event [$BB^{0.2}$] of threshold 0.2%. [$BB^{0.2}$] starts at time 21:00:00 and ends at time 21:10:00.

In the column 'Point', $B^{0.1}$ denote the DCC point of the DC event [$BB^{0.1}$], and $B^{0.2}$ denote the DCC point of the DC event [$BB^{0.2}$]. We also note two facts:

1. Both DC events, [$BB^{0.1}$] and [$BB^{0.2}$], start at the same point B.
2. Point $B^{0.1}$ (which is observed at time 21:05:00, column 'Time') occurred before we observed point $B^{0.2}$ (at time 21:10:00).

Note that at point $B^{0.1}$ (i.e. at time 21:05:00) we can confirm that point B is the extreme point of an uptrend DC event of threshold *STheta* = 0.1%. In this example, [$BB^{0.1}$] is the second DC event of threshold *STheta* (see Table 5.1). Therefore, our objective is to forecast whether $BBTheta^2$ is *True*. In other words, we want to predict at point $B^{0.1}$, whether the current uptrend will continue so that its total magnitude will reach a threshold of 0.2% (i.e. *BTheta*). Note that at point $B^{0.1}$ we cannot confirm yet whether *BBTheta*^{2} is *True* or *False*). At point B$^{0.2}$ (i.e. at time 21:10:00) we can confirm that *BBTheta*^{2} is *True* (i.e. point B is an extreme point of a DC event of threshold *BTheta*), but not before that. In general, for the i^{th} DC event of threshold *STheta*, we want to predict whether the corresponding *BBTheta*^{i} is *True.*

Table 5.2: The synchronization of two DC summaries of GBP/CHF mid-prices sampled between 19:05:00 1/1/2013 and 00:06:00 2/1/2013. The two thresholds are: *STheta* = 0.1% and *BTheta* = 0.2%. Unnecessary minutes and prices are omitted.

Time	**Mid-price**	**DC Summary (0.1%)**	**DC Summary (0.2%)**	**Point**
19:05:00	1.48831	start DC event (DOWNTREND)	start DC event (DOWNTREND)	A
………..				
19:50:00	1.48660	start OS event (DOWNTREND)		A$^{0.1}$
………..				
20:40:00	1.48530		start OS event (DOWNTREND)	A$^{0.2}$
………..				
21:00:00	1.48150	start DC event (UPTREND)	start DC event (UPTREND)	B
21:01:00	1.48180			
21:02:00	1.48170			
21:03:00	1.48159			
21:04:00	1.48280			
21:05:00	1.48310	start OS event (UPTREND)		B$^{0.1}$
21:06:00	1.48365			
21:07:00	1.48430			
21:08:00	1.48390			
21:09:00	1.48380			
21:10:00	1.48541		start OS event (UPTREND)	B$^{0.2}$
………..				
21:41:00	1.48690	start DC event (DOWNTREND)		C
21:42:00	1.48480	start OS event (DOWNTREND)		C$^{0.1}$
21:43:00	1.48470			
21:44:00	1.48520			
21:45:00	1.48495			
21:46:00	1.48412	start DC event (UPTREND)		D
………..				
22:01:00	1.48570	start OS event (UPTREND)		D$^{0.1}$
………..				
23:45:00	1.48770	start DC event (DOWNTREND)		E
………..				
00:06:00	1.48620	start OS event (DOWNTREND)		E$^{0.1}$

To recap, in this chapter we propose to tackle the following forecasting problem: ‘to forecast whether the current DC trend of threshold *STheta* will continue so that the total price change of this particular DC trend will be at least equal to *BTheta*’. This forecasting objective is shortened to predict the Boolean variable *BBTheta*. To the best of our knowledge, no previous study has provided a similar formalization of this forecasting problem under the DC context. We believe that solving such a forecasting problem under the DC framework could be the basis of a successful trading strategy (as we shall argue in Chapter 6).

5.4 Our approach to forecasting the end of a trend

In this section, we propose an approach to solving the forecasting problem presented in Section 5.3. The objective is to forecast for the i^{th} DC event of threshold *STheta* whether the corresponding $BBTheta^i$ is *True*. To this end, we introduce a novel DC-based indicator, which is also based on the concept of Big-Theta. We use the J48 procedure to make the forecast. Firstly, we introduce the novel DC-based indicator which will be used as the independent variable. Then, we briefly describe the adopted machine learning procedure, J48, which we will use to forecast *BBTheta*.

5.4.1 The independent variable

The accuracy of a forecasting model depends on the independent variable(s) used. Many forecasting models rely on technical indicators to make a forecast (e.g. [6] [44] [46]). Our task is particularly difficult because, so far, no published work has provided a formal method as to how to apply existing technical indicators (e.g. Ehler Leading Indicator [89], Aroon indicator [32], RSI or ADX [90]) can be applied under the DC framework. Recently, Kampouridis and Otero [17] suggested that more research should be undertaken into defining new indicators emerging from the DC concept, in a manner similar to how technical indicators exist within traditional time series. Tsang et al., [77] introduced several DC-based indicators with the aim of profiling the financial markets. However, they did not examine the usefulness of these indicators for forecasting purposes.

In this section, we introduce a novel DC-based indicator named OSV_{BTheta}^{STheta}. The abbreviation OSV stands for Over Shoot Value. The OSV is intended to measure the magnitude of price movements during the overshoot event. Keep in mind that a large DC trend embraces smaller DC trend(s) ([10] [12]). We introduce the variable OSV_{BTheta}^{STheta} in order to unveil the possible relation which may exist between the overshoot event of a large DC trend (as observed under *BTheta*) and a smaller DC trend (as observed under *STheta*). We believe that such a relation could be helpful to predict smaller DC trends. OSV_{BTheta}^{STheta} is the single independent variable which we will use to forecast *BBTheta*.

By definition, we associate an instance of the variable OSV_{BTheta}^{STheta} to each DC event of threshold *STheta*. Let $OSV_{BTheta}^{STheta\_i}$ be the instance of OSV_{BTheta}^{STheta} corresponding to the i^{th} DC event as observed under threshold *STheta*. The objective of the variable $OSV_{BTheta}^{STheta\_i}$ is to help in predicting $BBTheta^i$. Next, we will state the general formula and then will provide two examples of how to calculate $OSV_{BTheta}^{STheta\_i}$. In general, we define $OSV_{BTheta}^{STheta\_i}$ as:

$$OSV_{BTheta}^{STheta\_i} = \; ((P_i^{STheta} - PDCC^{BTheta}) / \; PDCC^{BTheta}) / \; BTheta \tag{5.3}$$

where P_i^{STheta} is the price at the extreme point of the i^{th} DC event of threshold *STheta*. $PDCC^{BTheta}$ is the price required to confirm a price change of threshold *BTheta* computed with reference to the most recent DC event observed under the DC summary of threshold *BTheta*. Note that the computation of $PDCC^{BTheta}$ depends on the type of the most recent trend (whether it is an uptrend or a downtrend) confirmed under threshold *BTheta*. *Example 1* and *Example 2*, shown next, clarify how $OSV_{BTheta}^{STheta\_i}$ is computed with reference to Fig. 5.4 shown below.

Example 1:

Consider Table 5.2, [B $B^{0.1}$] is the second DC event of threshold 0.1%. Thus, take the objective of predicting whether $BBTheta^2$ is *True*, at point $B^{0.1}$, we compute $OSV_{0.2}^{0.1\_2}$ as follows:

$$OSV_{0.2}^{0.1\_2} = ((P_B - PDCC^{0.2}) \; / \; PDCC^{0.2})/0.002 \tag{5.4}$$

where P_B is the price at point B. $PDCC^{0.2}$ is the price required to confirm a price change of threshold 0.2% computed based on the most recent extreme point observed by the DC summary of threshold 0.2%, which is, in this case, point A (see Fig. 5.4 shown below). Point A is an extreme point of a downward DC event of threhsold 0.2% (see Table 5.2). Hence, in this example:

$$PDCC^{0.2} = P_A \times (1 - 0.002) \tag{5.5}$$

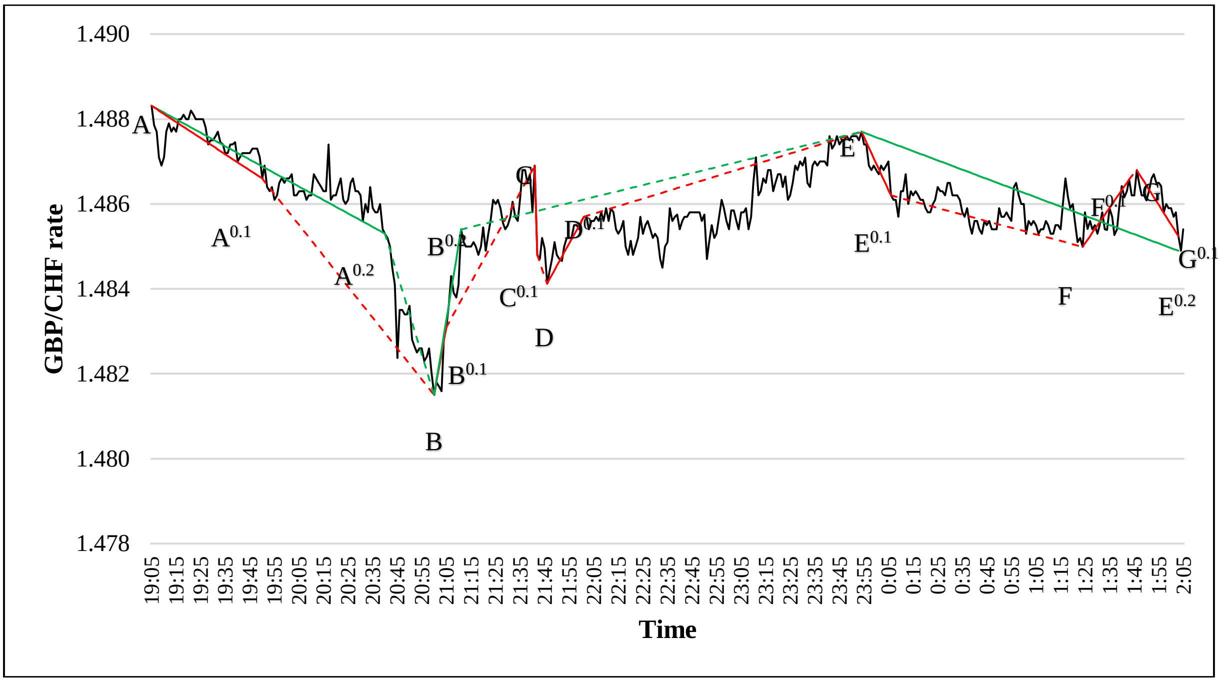

Fig. 5.4. The synchronization of the two DC summaries with two thresholds: *STheta* = 0.1% and *BTheta* = 0.2%.

where P_A is the price at point A. Here, P_A =1.48831 and P_B =1.48150 (see Table 5.2, Section 5.3). Thus, (5.5) can be re-written as:

$$PDCC^{0.2} = 1.48831 \times (1 - 0.002) = 1.48533338 \tag{5.6}$$

Substituting $PDCC^{0.2}$ by its value in (5.4), we get:

$$OSV_{0.2}^{0.1\_2} = ((1.48150 - 1.48533338) \,/\, 1.48533338)/0.002 = -1.29041 \tag{5.7}$$

Example 2:

We provide a second example as to how to compute $OSV_{BTheta}^{STheta\_i}$. [EE$^{0.1}$] is the fifth DC event of threshold 0.1%. Thus, the objective is to predict whether $BBTheta^5$ is *True*. In this case, we should compute $OSV_{0.2}^{0.1\_5}$ as:

$$OSV_{0.2}^{0.1\_5} = ((P_E - PDCC^{0.2}) \,/\, PDCC^{0.2}) \,/\, 0.002 \tag{5.8}$$

where P_E is the price at point E. $PDCC^{0.2}$ is the price required to confirm a price change of threshold 0.2%, computed with reference to the most recent confirmed extreme point of the DC summary of threshold 0.2%, which is, in this case B (see Fig. 5.4). Note that [BB$^{0.2}$] is an uptrend DC event. Hence, in this case:

$$PDCC^{0.2} = P_B \times (1 + 0.002) \tag{5.9}$$

where P_B is the price at point B. Here, P_E =1.48770 and P_B =1.48150 (see Table 5.2 above). Thus, (5.6) can be re-written as:

$$PDCC^{0.2} = 1.48150 \times (1 + 0.002) = 1.484463 \tag{5.10}$$

Replacing $PDCC^{0.2}$ by its value in (5.8), we obtain:

$$OSV_{0.2}^{0.1\_5} = ((1.48770 - 1.484463) \ / \ 1.484463)/0.002 = 1.09029 \tag{5.11}$$

5.4.2 The decision tree procedure J48

In this chapter, we employ the decision tree procedure, J48, to find the relation between the two variables *BBTheta* and OSV_{BTheta}^{STheta}. J48 is the open-source Java implementation of the C4.5 algorithm [91]. J48 has three main steps. First, for each attribute λ it computes the normalized information gain ratio from splitting on λ. Let *λ_best* be the attribute with the highest normalized information gain. Second, it creates a decision node *nd* that splits on *λ_best*. Third, it recurs on the sub-lists obtained by splitting on *λ_best* and adds those nodes as children of node *nd*. The three steps are repeated until a base case is reached.

5.5 Evaluation of our approach to forecasting DC: Experiments

In Section 5.4, we explained our approach to forecasting the change of a market trend's direction under the DC context. In this section, we aim to examine the accuracy of our proposed forecasting approach. We test this approach in the FX market using eight currency pairs. We provide two sets of experiments: 1) the objective of the first set is to evaluate the accuracy of our forecasting approach, 2) the objective of the second set is to evaluate the impact of the value of *BTheta* on the accuracy of our forecasting approach. We firstly introduce a variable, named α, which we will use to measure the *True-False* imbalance in *BBTheta.*

5.5.1 Measuring the True-False imbalance

In Section 5.3 we introduced *BBTheta* as the Boolean dependent variable to be predicted. Some studies (e.g. [92]) have reported that the performance of some machine learning algorithms can be affected by the *True-False* imbalance in the dependent variable. In this section, we introduce a new variable named α. The objective of α is to measure the levels of *True-False* imbalance in the dependent variable *BBTheta*. α is measured as the fraction of *True* instances of *BBTheta.*

Let $nbTrends\_BTheta$ be the number of all trends obtained by directing a DC summary with threshold *BTheta* on a particular currency pair. Similarly, let $nbTrends\_STheta$ be the number of all trends obtained by running a DC summary with threshold *STheta*. We compute α as:

$$\alpha = \frac{nbTrends\_BTheta}{nbTrends\_STheta} \tag{5.12}$$

The value of α is interpreted as follows: if $\alpha = 0.70$, then 70% of the instances of *BBTheta* are *True* and 30% are *False*. Note that, as explained in Section 4.2, the number of DC trends as observed under threshold *BTheta* is greater than the number of DC trends as observed under threshold *STheta* because *STheta* < *BTheta* (i.e. $nbTrends\_BTheta > nbTrends\_BTheta$).

5.5.2 Experiment 5.1: Evaluating the accuracy of our forecasting approach

In order to evaluate the accuracy of our forecasting approach, we apply it to eight currency pairs: EUR/CHF, GBP/CHF, EUR/USD, GBP/AUD, GBP/JPY, NZD/JPY, AUD/JPY and EUR/NZD. Each currency pair is sampled minute-by-minute for a period of 31 months: from 1/1/2013 to 31/7/2015 and split into (training) in-sample and testing (out-of-sample) datasets (see Fig. 5.5). For each currency pair, we composed this period into training and testing periods. For each currency pair, we use the training set (in-sample) to run two DC summaries: a) based on threshold *STheta*, and b) based on threshold *BTheta*. We employ these two DC summaries to compute the *BBTheta* and OSV_{BTheta}^{STheta}. Then, we use the J48 decision tree to find the relation between OSV_{BTheta}^{STheta} (as input) and *BBTheta* (as output). The obtained decision tree will be then employed to do the forecast over the testing (out-of-sample) set. The lengths of the in-sample and out-of-sample datasets are selected arbitrarily. The value of *STheta* and *BTheta* are chosen arbitrarily.

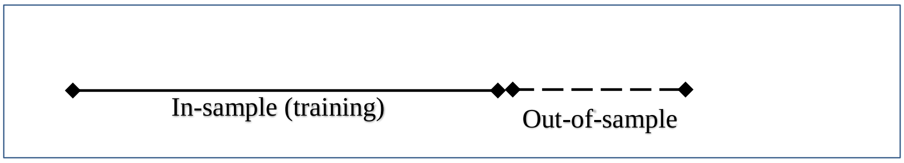

Fig. 5.5. Illustration of one in-sample (training) and the corresponding out-of-sample sets.

In preliminary experiments, we found that it would be better to forecast the uptrends and downtrends of threshold *STheta* separately. This practice — of splitting upward and downward trends for forecasting purposes — has also been adopted by other studies (e.g. [80]). In this experiment, we consider, and save, the uptrends and downtrends as two independent datasets. Then, we divide each of the downtrends and uptrends into training (i.e. in-sample) and testing (i.e. out-of-sample) sets. As a benchmark, we chose to compare the accuracy of our forecasting model with the ARIMA model. The Autoregressive Integrated Moving Average model (ARIMA) has been reported in some studies (e.g. [20] [93]) as a good forecasting technique for time series. The ARIMA model has been used as a benchmark for forecasting models in many studies (e.g. [47] [94]).

5.5.3 Experiment 5.2: The impact of BTheta on the accuracy of our forecasting model

In this experiment, we aim to examine whether the accuracy of our approach can be affected by the value of *BTheta*. To this end, we consider the eight currency pairs listed in Experiment 5.1. In this experiment, *STheta* is fixed to 0.10% for each of the eight currency pairs. For each of these eight currency pairs, we apply our forecasting approach using ten different values of *BTheta* (from 0.13% to 0.22% with a step size of 0.01). For each currency pair, the training and testing periods are set to be the same as in Experiment 5.1.

We use the linear regression model to examine the impact of *BTheta* on the accuracy of our forecasting approach, setting *BTheta* as the independent variable and the accuracy of our approach as the dependent variable. By analysing the *p*-value of *BTheta*, resulting from the linear regression, we can answer the question of whether *BTheta* has a significant linear impact on the accuracy of our approach.

In Section 5.5.1, we defined as 'α' the fraction of '*True*' instances in *BBTheta*. α is employed to express the *True-False* imbalance in the dependent variable *BBTheta*. Note that the value of α depends on the value of *BTheta*. Consequently, in this experiment, by choosing ten different values of *BTheta,* we obtain ten different levels of *True-False* imbalance in the dependent variable *BBTheta* (i.e. ten different values of α). Thus, we can use the results of this experiment to study the accuracy of our forecasting approach under different levels of *True-False* imbalance.

For this purpose, we employ a dummy-prediction approach as a benchmark. In the case of predicting a Boolean variable, e.g. *BBTheta*, the dummy prediction refers to the act of predicting '*True*' or '*False'*. The accuracy of dummy prediction can be high if the *True-False* imbalance in the dependent variable is high. For example, if we know that 85% of the instances of the Boolean dependent variable, e.g. *BBTheta*, are '*True'* then we can achieve an accuracy of 85% by just continuing to predict '*True'*. Fig. 5.6, shown below, illustrates the accuracy of dummy prediction as a function of such a *True-False* imbalance. We consider two dummy predictions: one that continually predicts '*True*' and a second which continually predicts '*False*'. Usually, the superiority of a dummy tree, in comparison to another forecasting approach, could be explained by the fact that the performance of many machine learning algorithms could be affected by such a *True-False* imbalance in the dependent variable [95] [92]. In cases of extreme imbalance, e.g. 95%

of instances are '*True*', the dummy prediction, which keeps predicting True, will have an accuracy of 95%. Similarly, if 95% of the instances of the dependent variable are '*False*' then a dummy prediction, which keeps predicting *False*, will have an accuracy of 95%. This example illustrates the importance of employing the dummy prediction as a benchmark in the case of *True-False* imbalance. In the context of *BTheta* and *STheta*, if *BTheta* = *STheta* then we will have 100% of the instances of *BBTheta* being 'True'. In which case, the accuracy of a dummy prediction that keeps predicting '*True'* would be 100%. Therefore, dummy prediction is considered as a good benchmark in the cases of extreme *True-False* imbalance in the dependent variable.

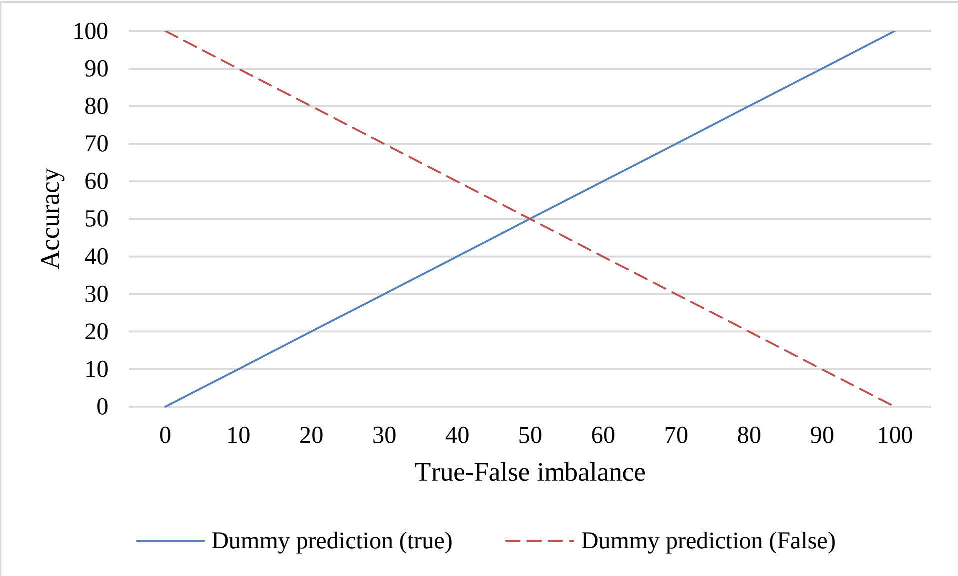

Fig. 5.6. The illustration of the accuracy of dummy prediction as function of *True-False* imbalance. In the x-axis, the value '10' indicates that 10% of instances are '*True'* and 90% are '*False'*.

5.6 Evaluation of our approach to forecasting DC: Results and discussion

5.6.1 Experiment 5.1: Evaluating accuracy of our forecasting approach

5.6.1.1 Experiment 5.1: Results

The objective of this experiment is to evaluate the accuracy of our approach to forecasting the change of a trend's direction, within the DC context, in the FX market. To this end, we apply our approach to eight currency pairs sampled minute-by-minute. For each currency pair, we consider the uptrends and downtrends separately. The values of the thresholds *STheta* and *BTheta* are chosen arbitrarily.

The experimental results and parameters' values are reported in Table 5.3. In Table 5.3, the column 'Currency Pair' specifies the considered currency pair. The columns 'STheta (%)' and 'BTheta (%)'denote the values of *STheta* and *BTheta* respectively. The column 'α' denote the *True-False* imbalance resulting from the values of *STheta* and *BTheta* corresponding to the out-of-sample testing set. We should note that the difference between the values of α corresponding to the in-sample training and those corresponding to the out-of-sample is no larger than 3% for any currency pair. The column ‘Type of Trend’ specifies whether the set of uptrends or downtrends, corresponding to the DC analysis of *STheta*, is in question. The columns ‘Training period’ and ‘Testing Period’ indicate the periods of the in-sample (training) and out-of-sample (testing) for each currency pair. We should note that the difference between the values of α corresponding to the in-sample and those corresponding to the out-of-sample is less than 2% for all considered currency pairs. That is, for all considered currency pairs, we have:

$$\alpha_{in-sample} = \alpha_{out-of-sample} \pm 2\% \tag{5.13}$$

Table 5.3: The settings and results of applying our forecasting approach, and ARIMA model, to the eight currency pairs. All reported accuracies correspond to the out-of-sample testing periods.

Currency Pair	**STheta (%)**	**BTheta (%)**	**α**	**Training Period**	**Testing Period**	**Type of Trend**	**Accuracy of our approach**	**ARIMA**
EUR/CHF	0.10	0.13	0.63	From 1/1/2013 to 30/6/2015	From 1/7/2015 to 31/7/2015	Uptrends	0.82	0.59
						Downtrends	0.82	0.54
GBP/CHF	0.20	0.25	0.65	From 1/1/2013 to 30/4/2015	From 1/5/2015 to 31/7/2015	Uptrends	0.80	0.59
						Downtrends	0.82	0.58
EUR/USD	0.30	0.35	0.76	From 1/1/2013 to 31/12/2014	From 1/1/2015 to 31/7/2015	Uptrends	0.83	0.68
						Downtrends	0.85	0.70
GBP/AUD	0.10	0.13	0.51	From 1/1/2013 to 31/12/2014	From 1/1/2015 to 31/7/2015	Uptrends	0.81	0.72
						Downtrends	0.82	0.73
GBP/JPY	0.10	0.13	0.64	From 1/1/2013 to 31/12/2014	From 1/1/2015 to 31/7/2015	Uptrends	0.81	0.65
						Downtrends	0.82	0.62
NZD/JPY	0.10	0.13	0.63	From 1/1/2013 to 31/12/2014	From 1/1/2015 to 31/7/2015	Uptrends	0.82	0.59
						Downtrends	0.82	0.60
AUD/JPY	0.10	0.13	0.56	From 1/1/2013 to 31/12/2014	From 1/1/2015 to 31/7/2015	Uptrends	0.79	0.57
						Downtrends	0.79	0.58
EUR/NZD	0.10	0.13	0.63	From 1/1/2013 to 31/12/2014	From 1/1/2015 to 31/7/2015	Uptrends	0.82	0.59
						Downtrends	0.82	0.61

The column ‘Accuracy’ shows the accuracy of our approach, computed as:

$$\text{Accuracy} = \frac{TP+TN}{N} \tag{5.14}$$

where *N* is either the total number of upward or downward DC events (see the column ‘Type of Trend’ to know) obtained from running the DC summary of threshold *STheta*. *TP* is the number of correctly forecasted *True* instances of *BBTheta*. *TN* is the number of correctly forecasted *False* instances of *BBTheta*. All reported accuracies in Table 5.3 are measured for the out-of-sample period of each currency pair. We then compare the accuracy of our approach with the ARIMA forecasting technique. For this purpose, we symbolize the ‘*True’* and ‘*False’* instances of *BBTheta* as ‘1’ and ‘0’ respectively. Then we apply ARIMA to the composed sequence of ‘1’ and ‘0’. We use the function auto.arima() from the package ‘forecast’ of the statistical software R to predict *BBTheta*. The forecasting accuracy of the ARIMA model is reported in column ‘ARIMA’ in Table 5.3.

5.6.1.2 *Experiment 5.1: Results’ discussion*

The objective of this experiment is to examine the accuracy of our forecasting approach. As can be seen in Table 5.3, for different testing periods and different selected values of *STheta* and *BTheta*, each of the obtained accuracies of our forecasting approach is above 0.78 (i.e. 78%). These results indicate that the proposed independent variable, OSV_{BTheta}^{STheta}, is very useful for forecasting *BBTheta*. The column ‘ARIMA’ in Table 5.3 shows the accuracy obtained by forecasting *BBTheta* using the ARIMA model. By comparing the accuracies of our approach (reported in column ‘Accuracy of our approach’) and the accuracy of the ARIMA technique (reported in column ‘ARIMA’) we notice that our approach outperforms ARIMA in all cases.

5.6.2 *Experiment 5.2: The impact of BTheta on forecasting accuracy*

The objective of this experiment is to examine whether the value of *BTheta* may affect the accuracy of the forecasting approach proposed in this chapter. To this end, we apply our forecasting approach to each of the considered eight currency pairs using ten different values of *BTheta*. For each value of *BTheta*, we measure the corresponding accuracy for downtrends and uptrends separately. To avoid tedious results we report the results of four currency pairs in this section. The results of the remaining four currency pairs are reported in Appendix C.

5.6.2.1 *Experiment 5.2: Results*

The results of this experiment relating to the currency pairs EUR/CHF, GBP/CHF, EUR/USD and GBP/AUD are reported in Tables 5.4, 5.5, 5.6 and 5.7 respectively. Each table, with selfexplanatory column headings, reports the results of applying our forecasting approach to the uptrends and downtrends of one currency pair. We will also use the results of this experiment to evaluate the performance of our forecasting approach under different levels of *True-False* imbalance in the dependent variable *BBTheta*.

Table 5.4: Analyzing the impact of *BTheta* on the accuracy of our forecasting approach on the currency pair EUR/CHF. *STheta* is fixed to 0.10%. The testing period is 4 weeks in length. The reported accuracy corresponds to the testing (out-of-sample) period. The number of DC events of threshold *STheta* (0.1%) is 327 (i.e. number of instances of *BBTheta* is 327).

Uptrends of DC summary with *STheta* = 0.10%				Downtrends of DC summary with *STheta* = 0.10%		
BTheta (%)	**Accuracy**	**α**		**BTheta (%)**	**Accuracy**	**α**
0.13	0.82	0.63		0.13	0.82	0.63
0.14	0.78	0.54		0.14	0.78	0.54
0.15	0.74	0.48		0.15	0.75	0.48
0.16	0.72	0.42		0.16	0.72	0.42
0.17	0.70	0.37		0.17	0.70	0.37
0.18	0.67	0.33		0.18	0.67	0.33
0.19	0.65	0.30		0.19	0.66	0.30
0.20	0.64	0.27		0.20	0.64	0.27
0.21	0.63	0.25		0.21	0.64	0.25
0.22	0.62	0.22		0.22	0.62	0.22

Table 5.5: Analysing the impact of BTheta on the accuracy of our forecasting approach on the currency pair GBP/CHF: STheta is fixed to 0.10%. The testing period is 3 months. The reported accuracy corresponds to the testing (out-of-sample) period. The number of DC events of threshold 0.1% is 1245 (i.e. number of instances of BBTheta is 1245).

Uptrends of DC summary with *STheta* = 0.10%				Downtrends of DC summary with *STheta* = 0.10%		
BTheta (%)	**Accuracy**	**α**		**BTheta (%)**	**Accuracy**	**α**
0.13	0.82	0.64		0.13	0.81	0.64
0.14	0.79	0.55		0.14	0.77	0.55
0.15	0.75	0.49		0.15	0.75	0.49
0.16	0.73	0.42		0.16	0.71	0.42
0.17	0.71	0.37		0.17	0.70	0.37
0.18	0.69	0.33		0.18	0.68	0.33
0.19	0.67	0.30		0.19	0.66	0.30
0.20	0.64	0.27		0.20	0.64	0.27
0.21	0.64	0.25		0.21	0.64	0.25
0.22	0.62	0.23		0.22	0.63	0.23

Table 5.6: Analysing the impact of BTheta on the accuracy of our forecasting approach on the currency pair EUR/USD: STheta is fixed to 0.10%. The testing period is 7 months and 2 weeks. The reported accuracy corresponds to the testing (out-of-sample) period. The number of DC events of threshold 0.1% is 1962 (i.e. number of instances of *BBTheta* is 1962).

Uptrends of DC summary with *STheta* = 0.10%				Downtrends of DC summary with *STheta* = 0.10%		
BTheta (%)	**Accuracy**	**α**		**BTheta (%)**	**Accuracy**	**α**
0.13	0.82	0.64		0.13	0.80	0.64
0.14	0.80	0.56		0.14	0.77	0.56
0.15	0.77	0.50		0.15	0.74	0.50
0.16	0.74	0.45		0.16	0.72	0.45
0.17	0.71	0.40		0.17	0.70	0.40
0.18	0.70	0.36		0.18	0.67	0.36
0.19	0.68	0.33		0.19	0.65	0.33
0.20	0.64	0.30		0.20	0.66	0.30
0.21	0.65	0.28		0.21	0.63	0.28
0.22	0.64	0.26		0.22	0.62	0.26

Table 5.7: Analysing the impact of BTheta on the accuracy of our forecasting approach on the currency pair GBP/AUD: STheta is fixed to 0.10%. The testing period is 7 months. The reported accuracy corresponds to the testing (out-of-sample) period. The number of DC events of threshold 0.1% is 3682 (i.e. number of instances of *BBTheta* is 3682).

Uptrends of DC summary with *STheta* = 0.10%				Downtrends of DC summary with *STheta* = 0.10%		
BTheta (%)	**Accuracy**	**α**		**BTheta (%)**	**Accuracy**	**α**
0.13	0.81	0.51		0.13	0.82	0.51
0.14	0.78	0.49		0.14	0.78	0.49
0.15	0.75	0.47		0.15	0.75	0.47
0.16	0.72	0.45		0.16	0.72	0.45
0.17	0.70	0.41		0.17	0.70	0.41
0.18	0.68	0.37		0.18	0.68	0.37
0.19	0.67	0.34		0.19	0.67	0.34
0.20	0.66	0.30		0.20	0.65	0.30
0.21	0.65	0.28		0.21	0.64	0.28
0.22	0.63	0.26		0.22	0.63	0.26

5.6.2.2 Experiment 5.2: Results' discussion

The objective of this experiment was to ascertain whether the value of *BTheta* affects the accuracy of our approach. In each of the Tables 5.4 through 5.7, we note that the values in column 'Accuracy' increase as 'BTheta (%)' decreases. To statistically validate this observation, we apply a linear regression model in which the column 'BTheta (%)' symbolises the independent variable and the column 'Accuracy' represents the dependent variable. We apply the linear regression model to each of these four tables, separately evaluating the uptrends and downtrends. We examine the *p*-value corresponding to *BTheta* for each linear regression analysis. The resulted *p*-value of the explanatory variable, 'BTheta (%)', is less than 0.01 in all cases. This is less than the common level of 0.05, which indicates that the value of *BTheta* can significantly impact the accuracy of our forecasting approach. Moreover, the R-square[h] (R^2), associated to the linear regression model, is greater than 0.90 in all four currency pairs (see for example Fig. 5.4 below). These results, of *p*-value and R^2, show that changes in *BTheta* are associated with changes in accuracy.

Furthermore, as stated in Section 5.5.3, the results, shown in Tables 5.4 through 5.7, also allow us to examine the performance of our proposed forecasting model under different levels of *True-False* imbalance in the dependent variable. These results highlight two points:

- The accuracy of our approach is quite good for most levels of *True-False* imbalance in the dependent variable *BBTheta*. For example, in the case of Table 5.4, we note that α ranges between 0.22 (i.e. 22% of *BBTheta* instances are *True*) and 0.63 (i.e. 63% of *BBTheta* instances are *True*). The corresponding accuracies range between 0.62 and 0.82. As for the results corresponding to GBP/CHF, shown in Table 5.5, we note that α ranges between 0.23 and 0.64. The corresponding accuracies range between 0.62 and 0.82. The results obtained based on EUR/USD are reported in Table 5.7, from which we can see the range of α is between 0.26 and 0.64. The range of accuracy is between 0.62 and 0.82. The results of GBP/AUD, shown in Table 5.8, match with the results reported in Tables 5.4 through 5.6. We consider this range of accuracy (between 0.62 and 0.82) to be fairly good.
- These results also suggest that the accuracy of our forecasting approach is reasonably consistent across the four considered currency pairs. In each table, the accuracies range between 0.62 and 0.82.

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[h] R-squared is a statistical measure of how close the accuracies are to the fitted regression line (see Fig. 5.4 below). See https://en.wikipedia.org/wiki/Coefficient_of_determination.

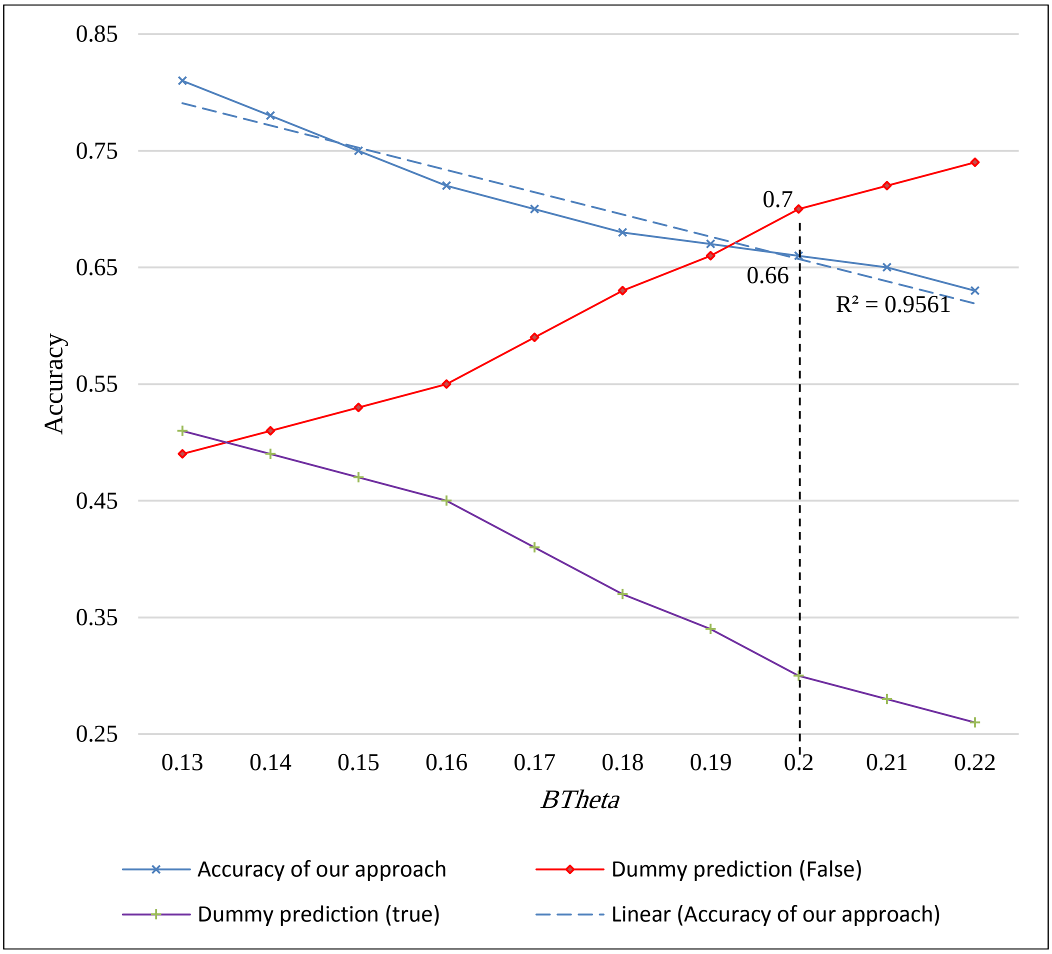

Fig. 5.7. The illustration of the variation in accuracy of forecasting the uptrends of GBP/AUD as a function of *BTheta* (see Table 5.7). The solid blue line denote the curve of the accuracy of our approach. The purple and red lines and the dummy prediction corresponding to continually predicting 'True' and 'False' respectively. The blue dashed line symbolizes the linear regression that most fitted the 'Accuracy of our approach'.

Fig. 5.7, shown above, analyzes the performance of our approach in comparison to dummy prediction based on the case of GBP/AUD. By examining Fig. 5.7, we can see that by starting a specific level of *True-False* imbalance, our proposed forecasting approach becomes outperformed by dummy-prediction (which keeps predicting *False*). For instance, for *BTheta* ≥ 0.2%, the accuracy of dummy prediction that keeps predicting '*False*' is ≥ 70%; whereas the accuracy of our approach is ≤ 66%. Fig. 5.6 considers the case of GBP/AUD. Similarly, the results of the other cases, shown in Tables 5.5 thru 5.7, support this conclusion. These results also indicate that for extreme *True-False* imbalance, the accuracy of our approach could be useless. This indicates that our approach cannot be used to predict small trends based on very large trends. To conclude, in this section, we reported and analysed the results of applying our forecasting approach to four currency pairs. The results of the linear regression analysis show that *BTheta* does have a significant impact on the accuracy of our approach. We want to highlight that the analysis of the remaining four currency pairs, reported in Appendix C, supports this conclusion. The analysis of the same results also suggest that our forecasting model can be outperformed by dummy prediction under specific conditions.

5.7 Summary and conclusion

In this chapter, we addressed the problem of forecasting the change of a trend's direction within the DC framework. Our first objective was to formalize the considered forecasting problem under the DC context. The second objective was to provide a solution for this problem.

The first contribution of this chapter was in formulating the prediction of the change of direction of a market's trend under the DC framework. For this purpose we proposed tracking price movements using 2 concurrent DC thresholds: *STheta* and *BTheta*. Our task was to forecast whether a DC trend, as observed under threshold *STheta*, would continue so that its total magnitude could be at least equal to *BTheta*. We introduced a new concept named Big-Theta that originates from the DC framework. The notion of Big-Theta states that a DC event of threshold *BTheta* will embrace at least one DC event of a smaller threshold *STheta* (with *BTheta* > *STheta*). We used the concept of Big-Theta to introduce the Boolean variable named *BBTheta* (Section 5.2.1). The value of *BBTheta* expresses whether the total price change of a DC trend, as observed under the threshold *STheta*, reaches *BTheta* (Section 5.3). Thus, our objective was to forecast *BBTheta*.

Our second contribution was in identifying one novel DC-based indicator as the independent variable and in proving that it is relevant to our prediction problem. This DC-based indicator, also based on the concept of Big-Theta, is OSV_{BTheta}^{STheta}(Section 5.4). We used the machine learning procedure J48 to detect the relation between OSV_{BTheta}^{STheta} and *BBTheta*.

We examined the performance of our forecasting approach using eight currency pairs sampled minute-by-minute (Section 5.5). The results demonstrated that our approach outperforms the traditional forecasting technique ARIMA (Table 5.4, Section 5.6.1), with the accuracy of our approach ranging between 62% and 80% (Section 5.6.2). We consider this range as pretty good. However, the results also suggested that the accuracy of our approach decreases as the difference between *STheta* and *BTheta* increases. When this difference reaches a specific level, our approach is outperformed by a dummy prediction, which keeps predicting *False* (Section 5.6.2).

To conclude, we believe that this is the first attempt to forecast the change of a trend's direction under the DC-framework. Our contribution is in formulating the forecasting problem and proposing a solution. We shortened the formalization of this problem in order to forecast one Boolean variable named *BBTheta*. The proposed solution comprises the discovery of a novel DC-based indicator named OSV_{BTheta}^{STheta}. We demonstrated that OSV_{BTheta}^{STheta} is helpful in forecasting *BBTheta*. We argued that our forecasting approach is more accurate than the ARIMA model and that the change of a trend's direction is predictable under the DC framework with pretty good accuracy.

6 TSFDC: A Trading Strategy Based on Forecasting Directional Changes

The previous chapter introduced an approach to forecasting the change in direction of a market's trend under the Directional Changes (DC) framework. Based on our findings in Chapter 5, this chapter aims to develop a successful trading strategy founded on the established forecasting model. In order to examine the success of this proposed trading strategy, called TSFDC, we provide several experiments using eight currency pairs from the FX market. The results suggest that, after deducting the bid and ask spread (but not the transaction costs), TSFDC can generate returns of more than 40% within seven months. We argue that TSFDC outperforms another DC-based trading strategy.

6.1 Introduction

The objective of this thesis is to explore, and consequently to provide a proof of, the usefulness of the DC framework as the basis of a profitable trading strategy. In Chapter 3, we suggested that existing trading strategies can mostly be categorised into two groups (see Sections 3.2 and 3.3). The first group contains trading strategies that are based on forecasting models (e.g. [6] [41] [42] [43] [44] [45]). The second group consists of trading strategies that do not rely on any forecasting model (e.g. [3] [57] [58] [59] [96]). In line with the literature, in this thesis we aim to develop two DC-based trading strategies – one strategy belongs to the first identified group of trading strategies and the second strategy belongs to the second group.

In Chapter 5, we formalized the problem of forecasting the change of a trend's direction under the DC framework. In this chapter, we develop a trading strategy named 'Trading Strategy based on Forecasting DC', henceforth TSFDC. TSFDC relies on the forecasting model developed in Chapter 5 to decide when to start a trade. We provide a set of experiments to examine the performance of TSFDC using eight currency pairs from the FX market.

The chapter continues as follows: Section 6.2 provides a brief summary of the forecasting model introduced in Chapter 5. We present TSFDC and its trading rules in Section 6.3. We discuss the selection and preparation of the used datasets in Section 6.4. The details of the experiments, conducted to evaluate the performance of TSFDC, are provided in Section 6.5. Section 6.6 reports and discusses the results of these experiments. We compare our trading strategy with other DC-based strategies in Section 6.7. Finally, we summarize the major findings of this chapter in Section 6.8.

6.2 Forecasting DC: A brief overview

In Chapter 5 we formalized a new forecasting problem under the DC framework. To formalize this objective, we tracked price changes with two thresholds simultaneously: *BTheta* and *STheta* (with *BTheta* > *STheta*; as in Fig. 6.1 below). The objective of this was to forecast whether the total price change of a DC trend, as observed under the threshold *STheta*, reaches the selected threshold of *BTheta*.

We defined a Boolean variable named *BBTheta* (Section 5.2.2). Each DC trend of threshold *STheta* is associated with a value of *BBTheta* which is *True* if, and only if, the magnitude of total price change of this trend is at least equal to *BTheta*. Our aim was to predict *BBTheta* at the DC confirmation point (DCC point) of a DC event of threshold *STheta*. For example, in Fig. 6.1 [$AA^{0.1}$] denote the first DC event observed under threshold *STheta* (0.1%). Let *BBTheta*^{1} denote the value of *BBTheta* corresponding to [$AA^{0.1}$]. Point $A^{0.1}$ is the DCC point of the DC event [$AA^{0.1}$]. At $A^{0.1}$ we don't know yet whether *BBTheta*^{1} is *True*. In this example, we want to forecast *BBTheta*^{1} at $A^{0.1}$. Note that, in this case, at point $A^{0.2}$ we are able to confirm that *BBTheta*^{1} is *True*; but not before.

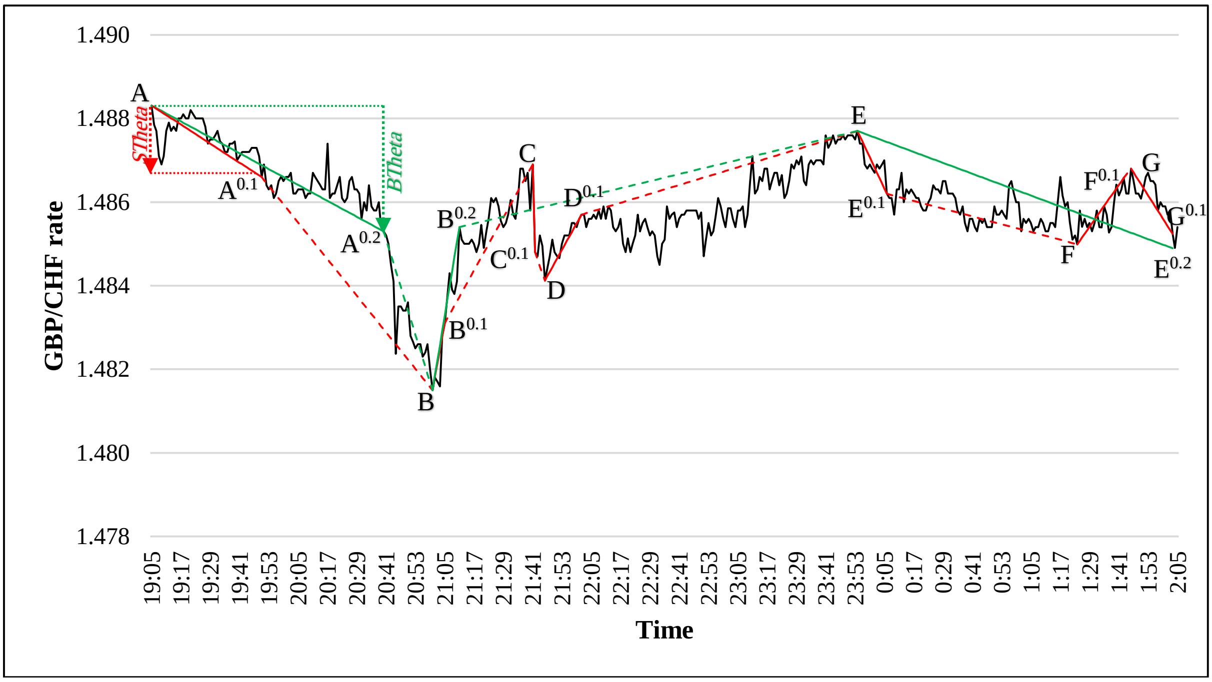

Fig. 6.1. The synchronization of two DC summaries with two thresholds: *STheta* = 0.1% (in red lines) and *BTheta* = 0.2% (in green) for GBP/CHF rate sampled minute by minute from 1/1/2013 19:05:00 to 1/2/2013 02:05:00.

Generally, for each DC event, of threshold *STheta*, we associate a value of *BBTheta*. In Chapter 5, we provided an approach to forecasting the value of *BBTheta* associated to each DC event of threshold *STheta* (Section 5.4). In many cases, the accuracy of our forecasting model was over 80%

(see Table 5.4, Section 5.6.1). In this chapter, our objective is to develop a successful trading strategy based on this forecasting model.

6.3 Introducing the trading strategy TSFDC

In this section we introduce a DC based trading strategy named 'Trading Strategy based on Forecasting DC' (TSFDC). TSFDC is designed as a contrarian trading strategy (i.e. TSFDC generates buy and sell signals against the market's trend) and is based on the forecasting model established in Chapter 5. We present two versions of TSFDC: TSFDC-down and TSFDC-up. The former is to be applied if the market exhibits a downward trend under the DC context, with the latter employed in the opposite case. We want to highlight that TSFDC-down and TSFDC-up are two different and independent strategies. They will be trained and tested separately. The following explains how TSFDC-down and TSFDC-up operate.

6.3.1 TSFDC-down

TSFDC-down is only applicable when the market is in a downtrend. TSFDC-down relies on the forecasting approach presented in Chapter 5 to decide when to trigger a buy signal. Let $BBTheta^i$ be the value of *BBTheta* associated with the i^{th} DC event of threshold *STheta* (Section 5.2.2). Let $FBBTheta^i$ denote the forecasted value of $BBTheta^i$. The value of $FBBTheta^i$ is determined based on the forecasting model described in Chapter 5. Note that we compute the value of $FBBTheta^i$ at the DCC point of the i^{th} DC event of threshold *STheta* (e.g. $FBBTheta^1$ is calculated at point $A^{0.1}$ in Fig. 6.1 above). If $FBBTheta^i$ is *True*, then we anticipate that the total price change of the i^{th} DC trend, observed under threshold *STheta*, will be at least equal to *BTheta*. TSFDC-down relies on $FBBTheta^i$ to decide when to trigger a buy signal. More particularly, there are two conditions under which TSFDC-down generates a buy signal (depending on whether $FBBTheta^i$ is *True* or *False*):

At the DCC point for the i^{th} DC trend (STheta), we predict $FBBTheta^i$:

- *Rule TSFDC-down.1 (generate buy signal):*

  If $FBBTheta^i = False$ then generate buy signal.

- *Rule TSFDC-down.2 (generate buy signal):*

  If ($FBBTheta^i = True$) and (we confirm a new DC event of threshold *BTheta*) then generate buy signal.

- *Rule TSFDC-down.3 (generate sell signal):*

  If ($P_c \geq P_{DCC\uparrow}$) and (a buy order has been fulfilled) then generate sell signal.

with P_c denoting the current price and $P_{DCC\uparrow}$ denoting the minimum prices required to confirm the occurrence of the succeeding uptrend DC event of threshold *STheta* (see Section 4.2.3). If the condition of *Rule TSFDC-down.1* is satisfied, then TSFDC-down generates a buy signal at the DCC point as observed under the threshold *STheta*. On the other hand, if both conditions of *Rule TSFDC-down.2* are fulfilled then TSFDC-down generates a buy signal at the DCC point as observed under the threshold *BTheta*. The first condition of *Rule TSFDC-down.3*, i.e. $P_c \geq P_{DCC\uparrow}$, denote the case under which we confirm the DCC point of a new uptrend DC event of threshold *STheta*. It is important to note that *Rule TSFDC-down.3* is not a stand-alone rule in the sense that it does not open any short position. *Rule TSFDC-down.3* initiates a sell signal only if a buy order has been previously triggered and executed (either by *TSFDC-down.1* or *TSFDC-down.2*). *TSFDC-down.3* plays two simultaneous roles: *take-profit* and *stop-loss*. When *TSFC-down.3* triggers a sell signal, it may incur losses (hence, functioning as *stop-loss*) or generates profit (thus, working as *take-profit*). In our experiments we will consider the bid and ask prices. When TSFDC-down triggers a buy (sell) signal we use the ask (bid) price as quoted by the market maker. Appendix D provides a pseudo-code that clarifies how TSFDC-down uses the forecasting model established in Chapter 5 and the three trading rules to trade.

Table 6.1, shown below, exemplifies two DC summaries with two different thresholds: 0.10% (*STheta*) and 0.20% (*BTheta*). We use Table 6.1 to provide two trading scenarios that demonstrate the function of TSFDC-down's trading rules. *Scenario 1:* Consider the DC event [AA$^{0.1}$] (of threshold *STheta* = 0.10%) which starts at point A (see column 'Point', Table 6.1).

a) [AA$^{0.1}$] refers to a downward DC event of threshold 0.10% which starts at time 19:05:00 (shown in column 'Time', Table 6.1). Point A$^{0.1}$ is the DCC point of [AA$^{0.1}$] as observed at time at time 19:50:00. At point A$^{0.1}$, assume that we predict[i] *FBBTheta^1* is *True* (as shown in column 'FBBTheta').
b) [AA$^{0.2}$] refers to a downward DC event of threshold 0.20% which starts at time 19:05:00. Point A$^{0.2}$ is the DCC point of [AA$^{0.2}$] as observed at time 20:40:00.
c) Based on a) and b), the conditions of *Rule TSFDC-down.2* are fulfilled at point A$^{0.2}$. Thus, TSFDC-down initiates a buy signal at point A$^{0.2}$ (i.e. at time 20:40:00).
d) [BB$^{0.1}$] refers to the uptrend DC event, of the threshold 0.10%, that directly follows [AA$^{0.1}$]. At time 21:05:00, we confirm the DCC point of [BB$^{0.1}$], which is B$^{0.1}$. Following *Rule TSFDC-down.3*, TSFDC-down will trigger a sell signal at point B$^{0.1}$.

[i] As [AA$^{0.1}$] is the first DC event in Table 6.1, our objective is to forecast the value of *BBTheta^1*. Here, we denote by *FBBTheta^1* the forecasted value of *BBTheta^1*.

Table 6.1: The synchronization of two DC summaries of GBP/CHF mid-prices sampled between 19:05:00 1/1/2013 and 00:06:00 2/1/2013. The two thresholds are: *STheta* = 0.10% and *BTheta* = 0.20%. Unnecessary minutes and prices are omitted. The '*True*' and '*False*' shown in column 'FBBTheta' are hypothetical (for explanation purpose only).

Time	**Mid-price**	**DC Summary (*STheta* = 0.1%)**	**DC Summary (*BTheta* = 0.2%)**	**Point**	**FBBTheta**
19:05:00	1.48831	start DC event (DOWNTREND)	start DC event (DOWNTREND)	A	
…………					
19:50:00	1.48660	start OS event (DOWNTREND)		$A^{0.1}$	*True*
…………					
20:40:00	1.48530		start OS event (DOWNTREND)	$A^{0.2}$	
…………					
21:00:00	1.48150	start DC event (UPTREND)	start DC event (UPTREND)	B	
21:01:00	1.48180				
21:02:00	1.48170				
21:03:00	1.48159				
21:04:00	1.48280				
21:05:00	1.48310	start OS event (UPTREND)		$B^{0.1}$	*True*
21:06:00	1.48365				
21:07:00	1.48430				
21:08:00	1.48390				
21:09:00	1.48380				
21:10:00	1.48541		start OS event (UPTREND)	$B^{0.2}$	
…………					
21:41:00	1.48690	start DC event (DOWNTREND)		C	
21:42:00	1.48480	start OS event (DOWNTREND)		$C^{0.1}$	*False*
21:43:00	1.48470				
21:44:00	1.48520				
21:45:00	1.48495				
21:46:00	1.48412	start DC event (UPTREND)		D	
…………					
22:01:00	1.48570	start OS event (UPTREND)		$D^{0.1}$	*False*
…………					
23:45:00	1.48770	start DC event (DOWNTREND)		E	
…………					
00:06:00	1.48620	start OS event (DOWNTREND)		$E^{0.1}$	

Scenario 2: Consider the downward DC event [$CC^{0.1}$] which starts at time 21:41:00.

a) [$CC^{0.1}$] refers to a downward DC event of threshold 0.10% which starts at time 21:41:00. [$CC^{0.1}$] is the third DC event in Table 6.1. At point $C^{0.1}$ (at time 21:42:00) assume that we predict *FBBTheta*^{3} is *False* (as shown in column 'FBBTheta').
b) Based on a), the condition of *Rule TSFDC-down.1* holds at point $C^{0.1}$. Thus, TSFDC-down initiates a buy signal at point $C^{0.1}$.
c) [$DD^{0.1}$] refers to the upward DC event of threshold 0.10% which directly follow [$CC^{0.1}$]. At time 22:01:00, we confirm the DCC point of [$DD^{0.1}$], which is $D^{0.1}$. Following *Rule TSFDC-down.3*, TSFDC-down will trigger a sell signal at point $D^{0.1}$.

6.3.2 TSFDC-up

Firstly, we want to highlight that TSFDC-up is completely independent from TSFDC-down. The two versions of TSFDC are not run concurrently. They are two different strategies that are trained, applied and evaluated separately. TSFDC-up could be considered as the mirror of TSFDC-down in that it is only applicable when the market exhibits an upward trend. TSFDC-up uses *FBBTheta*^{i} (i.e. the forecasted value of *BBTheta*^{i}) to decide when to open a position. TSFDC-up relies on *FBBTheta*^{i} to decide when to trigger a sell signal. More particularly, there are two conditions under which TSFDC-up generates a sell signal[j] (depending on whether *FBBTheta*^{i} is *True* or *False*):

At the DCC point for the ith DC trend (STheta), we predict FBBTheta^i:

- *Rule TSFDC-up.1 (generate sell signal):*

  If *FBBTheta*^{i} $=$ *False* then generate sell signal.

- *Rule TSFDC-up.2 (generate sell signal):*

  If (*FBBTheta*^{i} $=$ *True*) and (we confirm a new DCC point of DC event of threshold *BTheta*) then generate sell signal.

- *Rule TSFDC-up.3 (generate buy signal):*

  If ($P_c \leq P_{DCC\downarrow}$) and (a sell order has been fulfilled) then generate buy signal.

Note that if the condition of *Rule TSFDC-up.1* is *True* then TSFDC-up generates a sell signal at the DCC point observed under threshold *STheta*. On the other hand, if the conditions of *Rule TSFDC-up.2* are both *True* then TSFDC-up triggers a sell signal at the DCC point observed under

[j] We want to highlight that no short selling is allowed. In case of a sell signal, we assume that we use the counter currency to buy base currency.

threshold *BTheta*. In this context, a 'sell' signal means that TSFDC-up sells the base currency in exchange for the counter currency, whereas a 'buy' signal means that TSFDC-up buys the base currency using the counter currency (see Section 2.2 for more detail about base and counter currencies).

The first condition of *Rule TSFDC-up.3*, i.e. $P_c \leq P_{DCC\downarrow}$, denote the case under which we confirm the DCC point for a new DC downtrend of threshold *STheta*. $P_{DCC\downarrow}$ denote the price required to confirm the right-next downtrend (see Section 4.2.3). *Rule TSFDC-up.3* is applicable only if a sell signal has been triggered and executed (either by *TSFDC-up.1* or *TSFDC-up.2*). When TSFDC-up triggers a buy signal, it may generate profits or losses. Rule *TSFDC-up.3* has the same role as *Rule TSFDC-down.3: to take-profits* and *stop-loss*.

We use Table 6.1, shown above, to provide two trading scenarios in demonstration of how TSFDC-up's rules are applied. *Scenario 1*: Consider the uptrend DC event [$BB^{0.1}$] (of threshold *STheta* = 0.10%):

a) [$BB^{0.1}$] refers to an upward DC event of threshold 0.10% that starts at time 21:00:00 (shown in column 'Time', Table 6.1). Point $B^{0.1}$ is the DCC point of [$BB^{0.1}$] as observed at time at time 21:05:00. At point $B^{0.1}$, assume that we predict *FBBTheta*[2] is *True* (as shown in column 'FBBTheta').
b) [$BB^{0.2}$] refers to an upward DC event of threshold 0.20% that starts at time 21:00:00. Point $B^{0.2}$ is the DCC point of [$BB^{0.2}$] as observed at time 21:10:00.
c) Based on a) and b), the conditions of *Rule TSFDC-up.2* are fulfilled at point $B^{0.2}$. Thus, TSFDC-up initiates a sell signal at point $B^{0.2}$ (i.e. at time 21:10:00).
d) [$CC^{0.1}$] refers to the uptrend DC event, of the threshold 0.10%, that directly follows [$BB^{0.1}$]. At time 21:42:00, we confirm the DCC point of [$CC^{0.1}$], which is $C^{0.1}$. Following *Rule TSFDC-up.3*, TSFDC-up will trigger a buy signal at point $C^{0.1}$.

Scenario 2: Consider the upward DC event [$DD^{0.1}$] (of threshold *STheta* = 0.10%).

a) At time 22:01:00, at point $D^{0.1}$, assume that we predict *FBBTheta*[4] is *False* (as shown in column 'FBBTheta').
b) Based on a), the condition of *Rule TSFDC-up.1* holds at point $D^{0.1}$. Thus, TSFDC-up initiates a sell signal at point $D^{0.1}$.
c) [$EE^{0.1}$] refers to the downward DC event of threshold 0.10% that directly follows [$DD^{0.1}$]. At time 00:06:00, we confirm the DCC point [$EE^{0.1}$], which is $E^{0.1}$. Following *Rule TSFDC-up.3*, TSFDC-up will trigger a buy signal at point $E^{0.1}$.

6.4 Preparation of the datasets and other considerations

This section provides essential notes regarding the selection and preparation of the datasets used in our experiments. When designing our experiment approach, we paid attention to important concerns put forward by other studies (e.g. [52] [97]) that highlight serious experimental flaws presented in several published papers. In the context of our experiments, we consider the following points:

6.4.1 Data selection

Pardo [52] emphasizes the importance of backtesting (see Section 3.4 for the definition of backtesting) using a set of assets with different trends. Such variation in the selected dataset will help to test the performance of the trading strategy under different market scenarios. This broadening helps in avoiding any bias towards particular patterns. In this chapter, we consider eight currency pairs, namely: EUR/CHF, GBP/CHF, EUR/USD, GBP/AUD, GBP/JPY, NZD/JPY, AUD/JPY, and EUR/NZD. The mid-prices of these currency pairs are sampled minute-by-minute during a period of 31 months between 01/01/2013 and 31/07/2015. Our focus, in this section, is to examine the variation of the trends of these currency pairs during the (out-of-sample) trading period which lasts from 1/1/2015 to 31/7/2015. The training (in-sample) period took place between 1/1/2013 and 31/12/2014. Holidays and weekends are not included in our datasets.

In this section, we investigate the variation of the trends of the selected currency pairs. Variation is important because some studies (e.g. [52]) have shown that trend changes can have a large and often negative impact on trading performance. Fig. 6.2, shown below, depicts the normalized daily exchange rates of the selected eight currency pairs throughout the considered trading period of seven months (from 1/1/2015 to 31/7/2015). It provides a visual indication as to the existence of a variety of trends in our dataset over the considered trading period. The variation of the trends, as visualized in Fig. 6.2, indicate that we avoid possible bias in our experiment, which would have occurred had we only picked currency pairs with similar trends during the selected trading period.

Fig. 6.2 indicates that the selected currency pairs exhibit different trends during the trading period. The trends of the training period, considered from 1/1/2013 to 31/12/2014, were not studied as this data is not specifically related to the evaluation of the performance of TSFDC during the out-of-sample period. Note that although our initial datasets in this experiment (i.e. the eight currency pairs) are sampled as a time series (with a time interval of one minute), the TSFDC's trading rules (presented in Section 6.3) are based on variables (e.g. *FBBTheta*) that originate from the DC concept.

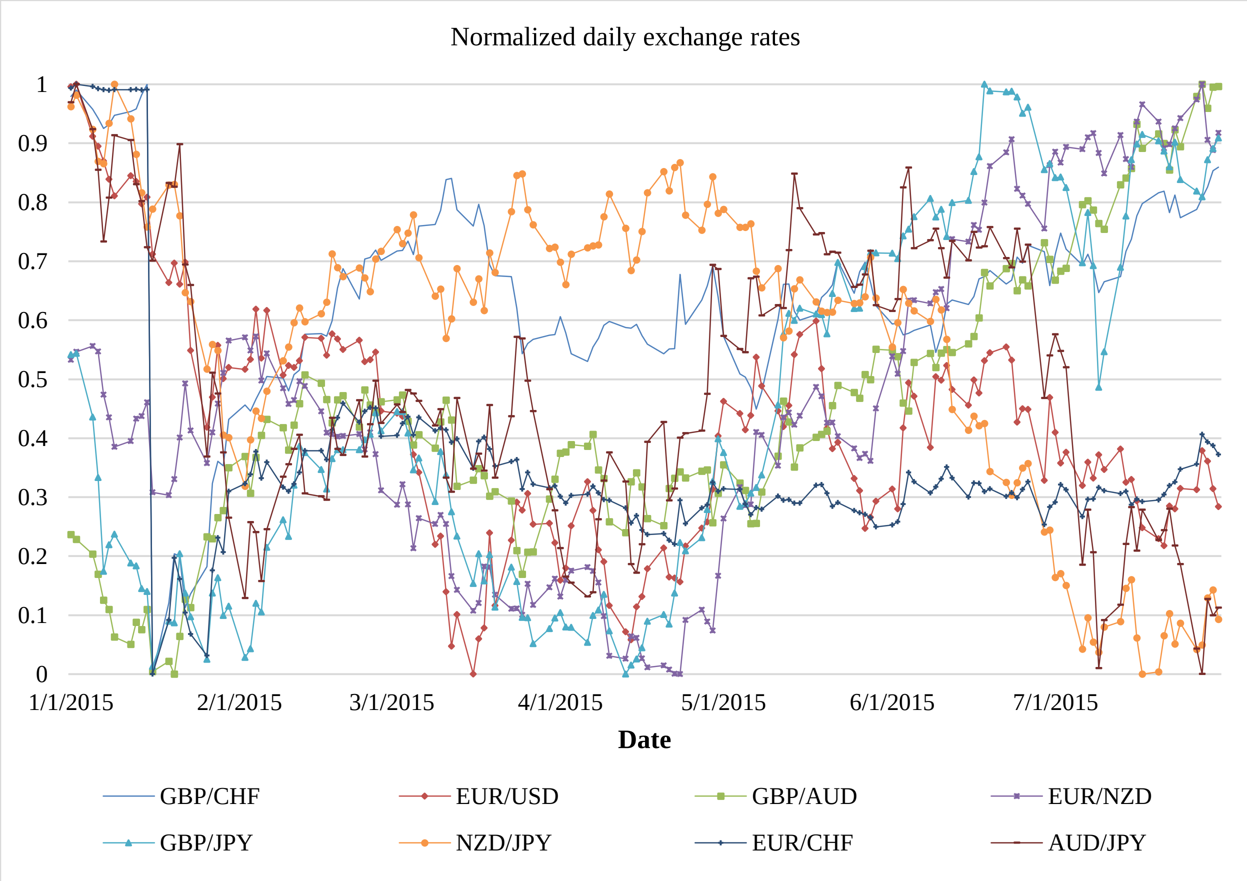

Fig. 6.2 Normalized daily exchanges rate, using mid-prices, of the 8 selected currency pairs between 1/1/2015 and 31/7/2015. This figure aims to illustrate the divergence of trends within selected currency pairs. In order to avoid excessive points, we use a daily exchange rate instead of a minute-based exchange rates.

6.4.2 *Evaluating the performance of a trading strategy*

Many studies define success solely on the grounds of forecasting accuracy and win ratios, which, practically, has little value [98] [99]. In practice, an investor might be interested in other metrics that evaluate the risk and risk-adjusted performance of a given trading strategy [62] [100]. In this chapter, we evaluate the performance of TSFDC using a range of evaluation metrics such as: profit factor, maximum drawdown, Sharpe ratio, Jensen's Alpha, Beta and others (see Section 3.4). These metrics are marked as adequate for a decent evaluation of the performance of a given trading strategy [62] [52].

6.4.3 *Bid and ask prices*

In reality the market makers quote two rates in the forex market: the ask or offer, and the bid or sell rate (see Section 2.2 for more detail about bid and ask prices). In this thesis, we will consider the real instant bid and ask prices in all of our experiments. When any version of TSFDC triggers a buy (sell) signal we use the ask (bid) price as quoted by the market maker. For each trade (either buy or sell) we use the actual instantaneous bid or ask prices as provided by the data provider kibot.com. This last note applies for all experiments. The mean and standard deviation of the bid-ask spread of each of the eight currency pairs during the aforementioned trading period, sampled minute-by-minute, are shown in Table 6.2 below. In Table 6.2, the column ‘Quantile 25’ indicates that 25% of the spreads are below the reported number. The same interpretation holds for the column ‘Quantile 75’.

Table 6.2: The mean and standard deviation of the bid-ask spread of the selected currency pairs during the trading period (1/1/2015 to 31/7/2015).

	Mean	**Standard deviation**	**Quantile 25**	**Quantile 75**
EUR/USD	0.00014	0.00012	0.00006	0.00025
GBP/JPY	0.04320	0.01026	0.03904	0.04500
EUR/CHF	0.00037	0.00015	0.00030	0.00051
GBP/CHF	0.00060	0.00024	0.00042	0.00077
AUD/JPY	0.01815	0.00962	0.01105	0.02270
EUR/NZD	0.00073	0.00049	0.00037	0.00110
NZD/JPY	0.03458	0.01989	0.02104	0.04900
GBP/AUD	0.00061	0.00034	0.00031	0.00092

6.4.4 Model training and testing process

Pardo [52] suggests the adoption of a rolling window approach as being more reliable to test a trading strategy. This approach is usually used for evaluating trading systems and establishes a more rigorous and convincing methodology. This method involves splitting the data into overlapping training-applied sets and, on each cycle, moving each set forward through the time series. This methodology tends to result in more robust models due to more frequent retraining and large out-of-sample data sets (increasing training processing requirements but also resulting in models which adapt more quickly to changing market conditions). In our experiments, we train and test TSFDC using a monthly-basis rolling window as we will explain next.

6.4.5 Preparing the rolling windows

Our experiments examine eight currency pairs: EUR/CHF, GBP/CHF, EUR/USD, GBP/AUD, GBP/JPY, NZD/JPY, AUD/JPY, and EUR/NZD and consider the minute-by-minute mid-prices of these currency pairs for 31 months: from 1/1/2013 to 31/7/2015. Given that the preparation process of the rolling windows for each currency pair is the same, we will use a two-step preparation of the rolling windows, explained below, for the currency pairing GBP/CHF as an example to detail our method.

6.4.5.1 Step 1: Producing DC summary for the dataset

We run the Directional Change (DC) summary on the initial dataset of GBP/CHF sampled minute-by-minute over 31 months. Section 4.2 provides a detailed description of the DC summary.

In simple terms, given a threshold *STheta*, we achieve, through DC summary, the identification of all DC and OS events in the initial dataset (see Table 6.3 below). Arbitrarily, we set $STheta = 0.10\%$ and produce the DC summary to the initial dataset of GBP/CHF. Let *GBPCHF_DC0.1* be the output of this DC summary. Part of *GBPCHF_DC0.1* is illustrated in Table 6.3. *GBPCHF_DC0.1* comprises the date, time and the price of each observation of the initial dataset. In Table 6.3, the column 'Event Type' marks the occurrence of any DC or OS event that starts at the specified date and time (see Section 4.2 for more information on DC summary).

Table 6.3: An example of a DC summary using GBP/CHF mid-prices sampled minute-by-minute from 21:41:00 to 22:01:00 (UK time).

Date	Time	Mid-price	Event Type
1/1/2013	21:41:00	1.48690	start DC event (DOWNTREND)
1/1/2013	21:42:00	1.48480	start OS event (DOWNTREND)
1/1/2013	21:43:00	1.48470	
1/1/2013	21:44:00	1.48520	
1/1/2013	21:45:00	1.48495	
1/1/2013	21:46:00	1.48412	start DC event (UPTREND)
1/1/2013	21:47:00	1.48440	
1/1/2013	21:48:00	1.48470	
1/1/2013	21:49:00	1.48510	
1/1/2013	21:50:00	1.48480	
1/1/2013	21:51:00	1.48470	
1/1/2013	21:52:00	1.48466	
1/1/2013	21:53:00	1.48500	
1/1/2013	21:54:00	1.48520	
1/1/2013	21:55:00	1.48520	
1/1/2013	21:56:00	1.48520	
1/1/2013	21:57:00	1.48550	
1/1/2013	21:58:00	1.48550	
1/1/2013	21:59:00	1.48540	
1/1/2013	22:00:00	1.48560	
1/1/2013	22:01:00	1.48570	start OS event (UPTREND)

6.4.5.2 Step 2: Composing the rolling windows

Motivated by the recommendation of Pardo [52], we use a rolling window approach (see Fig. 6.3 below) to evaluate the performance of our proposed trading strategy. As the dataset *GBPCHF_DC0.1* covers 31 months, we compose seven rolling windows — each of which comprises a training window (24 months in length) and an applied window (1 month in length). This means that the overall trading period, throughout the seven rolling windows, is seven months. The lengths of the training and applied windows are set arbitrarily. Note that we measure the length of the training and applied windows as a function of months, not as a fixed number of days. For example, the training period of the second rolling window lasts from 1/2/2013 to 31/1/2015 (i.e. 24 months). The associated applied window lasts from 1/2/2015 00:01:00 to 28/2/2015 23:59:00 (i.e. the month of February 2015). The start and end dates of the training and ending period of each rolling window are reported in Table 6.4 (shown below). Let *GBPCHF_RWDC0.1* represent the set of these seven rolling windows. Similarly, we construct seven sets of rolling windows (one for each of the remaining currency pairs). For example, let *EURCHF_RWDC0.1* be the set of the seven rolling windows corresponding to EUR/CHF and let *EURUSD_RWDC0.1* be the set of the seven rolling windows corresponding to EUR/USD and so on. These sets are compiled in the same two steps as *GBPCHF_RWDC0.1* with a threshold $STheta = 0.10\%$. Finally, we get the following eight sets of rolling windows: *EURCHF_RWDC0.1*, *GBPCHF_RWDC0.1*, *EURUSD_RWDC0.1*, *GBPAUD_RWDC0.1*, *GBPJPY_RWDC0.1*, *NZDJPY_RWDC0.1*, *AUDJPY_RWDC0.1*, and *EURNZD_RWDC0.1*.

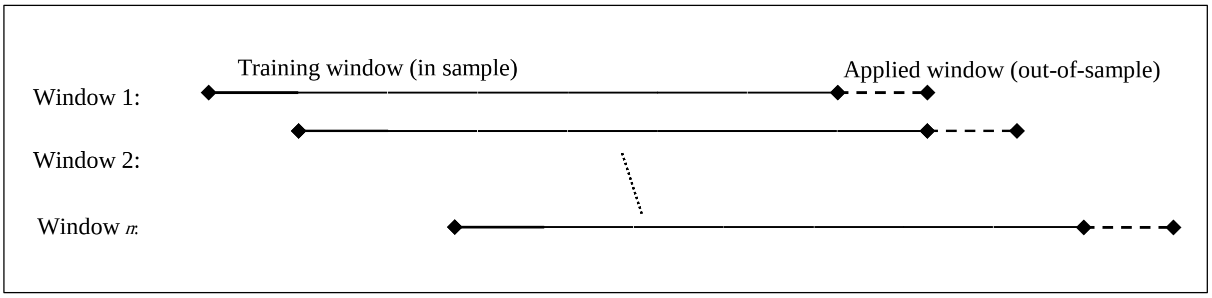

Fig. 6.3. Illustration of one set composed of *n* rolling windows. The dashed lines represent the applied windows.

Table 6.4: The starting and end dates of each (in-sample) training period and (out-of-sample) applied period for each composed window.

Rolling window	Training period (24 months)		Applied period (1 month)	
	From	To	From	To
1	1/1/2013	31/12/2014	1/1/2015	31/1/2015
2	1/2/2013	31/1/2015	1/2/2015	28/2/2015
3	1/3/2013	28/2/2015	1/3/2015	31/3/2015
4	1/4/2013	31/3/2015	1/4/2015	30/4/2015
5	1/5/2013	30/4/2015	1/5/2015	31/5/2015
6	1/6/2013	31/5/2015	1/6/2015	30/6/2015
7	1/7/2013	30/6/2015	1/7/2015	31/7/2015

6.5 Evaluation of TSFDC: The experiments

In this section, we examine the performance of TSFDC. The objective is to evaluate the profitability and risk of both versions of TSFDC (i.e. TSFDC-down and TSFDC-up) using the rolling windows previously composed in Section 6.4.4. We provide the details of the experiments after describing the adopted money management approach.

6.5.1 Money management approach

We apply the money management approach to both TSFDC-down and TSFDC-up as follows. When TSFDC-down initiates a buy signal, we convert the entire capital from the counter currency to the base currency[k] (more details about counter and base currencies were provided in Section 2.2). When TSFDC-down generates a sell signal we convert the entire capital from the base currency to the counter currency. Likewise in the case of TSFDC-up. Although this sounds like a naïve approach to money management, our main objective is to prove that TSFDC is a successful trading strategy. Future works may address the development of a better money management approach.

When we operate any version of TSFDC, we make sure that no position is left open at the end of the trading period. Should we encounter an open position at the end of the trading period, then the last trades will not be considered when computing the evaluation metrics — instead, we roll back to the previous transaction. In other words, we do not count this last trade when measuring any of the evaluation metrics (previously introduced in Section 3.4). Thus, as a result of this

[k] For a given currency pairs 'X/Y', 'X' denote the 'base currency' and 'Y' denote the 'counter currency' (see Section 2.2 for more details about base and counter currencies). In this thesis, a 'sell' signal means that we are selling the base currency in exchange for the counter currency; whereas a 'buy' signal means that we are buying the base currency using the counter currency.

approach, if TSFDC opens a position it will not be able to open any other positions until the current position is closed.

In Section 4.4 we reviewed four DC-based trading strategies ([15] [16] [17] [78]). None of the authors of these trading strategies considered transaction costs in their experiments. Therefore, in our experiments, we do not account for the transaction costs either. This helps to provide a fairer comparison between our planned trading strategies and the four DC-based trading strategies we reviewed earlier. Generally speaking, the impact of transaction costs on the performance of trading strategy is controversial. Some studies (e.g. [97] [101] [102] [103]) have concluded that, in general, transaction costs can have a tremendous impact on a strategy's profitability and that the impact of transaction costs should not be neglected when backtesting a trading strategy. However, by contrast, other studies (e.g. [3] [36] [37] [104]) have concluded that transaction costs are not expected to have a substantial negative impact on the profitability of FX trading. In this thesis, while there is no direct transaction fee, we consider the bid–ask spread as a kind of indirect charge as in ([6] [15] [16]).

We should also point out that we ignore the effect of 'slippage' in our trading simulations. In trading, 'slippage' refers to the difference between what a trader expects to pay for a trade and the actual price at which the trade is executed. Normally, slippage happens because there might be a slight time delay between the trader initiating the trade and the time the broker receives the order. During this time delay, the price may have changed. It can either work in favour of, or against, the trader [105].

6.5.2 Experiment 6.1: Evaluation of the performance of TSFDC

The objective of this experiment is to evaluate the performance of TSFDC-down and TSFDC-up. Each of TSFDC-down and TSFDC-up run independently from the other. For this purpose, we apply each version to the eight sets of rolling windows: *EURCHF_RWDC0.1*, *GBPCHF_RWDC0.1*, *EURUSD_RWDC0.1…*etc. (previously composed in Section 6.4.4). For each of these eight sets, the training period of each rolling window (24 months) is utilized to train the forecasting model (developed in Chapter 5). Next, the forecasting model is employed to compute the value of *FBBTheta* (i.e. to forecast *BBTheta*) for each DC event, of threshold *STheta*, during the trading period (i.e. the associated applied window of 1 month). TSFDC uses *FBBTheta* to decide when to initiate a trade, as described in Section 6.3, during the trading period. The overall trading period of each set is seven months in length: from 1/1/2015 to 31/7/2015. For each of the eight sets, *BTheta* is fixed, arbitrarily, to 0.13%. We measure the evaluation metrics previously listed in Section 3.4 to evaluate the performance of TSFDC.

The evaluation metrics, Jensen's Alpha and Beta, serve to evaluate, respectively, the profitability and risk of a given trading strategy, with reference to a benchmark (Section 3.4). In this thesis, we consider the buy and hold approach as our benchmark. Thus, we apply the buy and hold approach to each considered currency pair (buying at the opening price on a monthly basis; holding it over the course of the trading month, and selling at the closing price). For each currency pair, we compute the monthly returns resulting from applying the buy and hold to the specified trading periods (from 1st January 2015 to 31st July 2015). We then use these monthly returns to compute Jensen's Alpha and Beta of TSFDC.

Furthermore, as we consider the buy and hold (B&H) as a benchmark, we compare the Sharpe ratios of both versions of TSFDC with the Sharpe ratio obtained by the buy and hold approach. To validate this comparison statistically, we employ the Wilcoxon rank sum test (sometimes called Mann Whitney U Test) [106] twice. Firstly, we apply the Wilcoxon test with the null hypothesis being that 'the median difference between the Sharpe ratio produced by TSFDC-Down and B&H is zero'. Secondly, we apply the Wilcoxon test with the null hypothesis being that 'the median difference between the Sharpe ratio produced by TSFDC-Up and B&H is zero'.

Likewise, we apply the Wilcoxon test to compare the win ratio of TSFDC-down and TSFDC-up to that of dummy prediction. The dummy prediction of a Boolean variable (e.g. *BBTheta*) refers to the act of continuously predicting *True* or *False* (Section 5.6.2). The win ratio of a trading strategy, which is based on dummy prediction, is estimated as the accuracy of the dummy prediction[1]. In the context of our experiment, the win ratio of dummy prediction for a given currency pair is the level of *True-False* imbalance of *BBTheta* (Section 5.6.2).

We apply the Wilcoxon rank sum test to compare the win ratio of TSFDC-down and TSFDC-up with the expected win ratio of a trading strategy which is based on dummy prediction. We therefore employ the Wilcoxon test twice: a) The first time with the null hypothesis being that 'the median difference between the win ratio of TSFDC-Up and dummy prediction is zero'; and b) The second time we examine the null hypothesis of 'the median difference between the win ratio of TSFDC-Down and dummy prediction is zero'.

[1] This is only from a theoretical perspective. In reality, the actual win ratio will depend also on the trading rules established based on the dummy prediction.

6.5.3 Experiment 6.2: Compare the return and risk of both versions of TSFDC

The objective of this experiment is to test whether TSFDC-down and TSFDC-up have similar performance. More particularly, we want to compare the return and risk of both versions of TSFDC. For simplicity, we consider the maximum drawdown (*MDD*) as a measure of risk (similarly to [4], [17] and [18]). We use the rate of returns (*RR*) and maximum drawdown (*MDD*) resulting from applying both versions of TSFDC to the eight currency pairs from Experiment 6.1 (Section 6.5.2). In details, in this experiment, we want to find out whether TSFDC-down and TSFDC-up provide similar *RR* and *MDD*.

In order to validate our test statistically, we apply the non-parametric Wilcoxon rank sum test twice [106]. Firstly, we apply the Wilcoxon test with the null hypothesis that the median difference between the two sets of *RR* of TSFDC-down and TSFDC-up is zero. In this instance, based on Experiment 6.1, we consider the *RR* generated by applying TSFDC-down to the eight currency rates as the first set (Section 6.5.2). Similarly, the second set comprises the *RR* generated by applying TSFDC-up to the eight currency rates. Each of these set consists of 8 observations (8 currency rates with 1 *RR* for each currency rate).

Secondly, we seek to compare the risk of both versions of TSFDC. Based on Experiment 6.1, Taking the maximum drawdown as an indicator of risk (as in [16] [17]), we compose a first set by applying TSFDC-down to the eight currency rates. This set comprises 8 observations (8 currency rates with 1 *MDD* for each currency rate). We compose a second set of *MDD* by trading with TSFDC-up over the eight currency rates. We apply the Wilcoxon Rank Sum test with the null hypothesis that the median difference between these two sets of *MDD*, of TSFDC-down and TSFDC-up, is zero.

6.6 Evaluation of TSFDC: Results and discussion

6.6.1 Experiment 6.1: Evaluation of the performance of TSFDC

The objective of this experiment is to evaluate the performance of TSFDC-down and TSFDC-up using eight currency pairs sampled minute-by-minute. To this end, we applied the two versions of TSFDC to the eight sets of rolling windows composed in Section 6.4.4. We followed the money management approach outlined in Section 6.5.1 and measured the evaluation metrics listed in Section 3.4. These evaluation metrics are:

- Rate of returns (RR): *RR* is interpreted as the gain or loss on an investment over a given evaluation period expressed as a percentage of the amount invested.

- Profit factor: This is calculated by dividing the sum of profits produced by all profitable trades by the sum of losses incurred by all losing trades. This metric measures the amount of profit per unit of risk.
- Max drawdown: This is the largest difference, in percentage, between the maximum amount (i.e. peak) and the minimum amount (i.e. through) of capital during a trading period. It measures the risk as the worst peak-to-trough decline in capital.
- Win ratio: This is the probability that a trade produces a positive return.
- Sharpe ratio: This measures the risk-adjusted return. It represents the average return earned in excess of the risk-free rate per unit of volatility.
- Sortino ratio: Denote the excess return over the risk-free rate divided by the downside semi-variance, and so measures the return to ‘bad’ volatility.
- Jensen’s Alpha: Indicates whether a trading strategy is earning the proper return for its level of risk.
- Beta: Serves to measure the volatility, or systematic risk, of a security or a portfolio, in comparison to a benchmark.

In order to avoid tedious detail, this section reports TSFDC’s general trading performance during the overall trading period for the eight currency pairs. Keep in mind that we consider the bid and ask prices in our experiments. While there is no direct transaction fee, the instantaneous actual bid–ask spread is a kind of indirect charge.

6.6.1.1 Experiment 6.1: The results

For each currency pair, we use the same values of *STheta* (0.10%) and *BTheta* (0.13%). These values are chosen arbitrarily. Bear in mind that, for each currency pair, we compose seven rolling windows. Each window comprises a trading period of one month. At the beginning of the first trading period, i.e. January 2015, both TSFDC-down and TSFDC-up start with a capital of 1,000,000 monetary units[m]; this represents the initial, hypothetically, invested amount of money. We consider the instantaneous actual bid and ask spread for each made trade; but not the transaction costs.

Table 6.5, shown below, reports the general performance of both versions of TSFDC during the overall trading period of seven months. Keep in mind that TSFDC-down and TSFDC-up are not

[m] In the case of trading with TSFDC-down, for each currency pair, we assume that we start trading with 1,000,000 monetary units of the counter currency. For example: in the case of EUR/CHF, we start trading with 1,000,000 CHF. Whereas in the case of NZD/JPY, we start with 1,000,000 JPY. However, in the case of TSFDC-up we assume that we start trading with 1,000,000 monetary units of the base currency.

run concurrently. They are evaluated separately. In Table 6.5, the column ‘Currency Pair’ denote the considered currency pair. The column ‘Trading Strategy’ indicates which version of TSFDC is applied. The columns ‘RR’, ‘Profit Factor’, ‘Max Drawdown (%)’, and ‘Win Ratio’ refer to the chosen evaluation metrics. The last row in Table 6.5 is interpreted as follows: applying TSFDC-up to EUR/NZD generates a total return of 41.22% during the trading period of seven months (from 1/1/2015 to 31/7/2015). In this case, TSFDC-up executes 4218 trades with an overall Win Ratio of 0.70. The maximum drawdown in capital is – 7.2%. The details of monthly Rates of Return (*RR*) of applying TSFDC-down and TSFDC-up to these currency pairs are shown in Tables 6.6 and 6.7 respectively. The annualized returns are reported in Appendix E.

Table 6.5: Trading performance of TSFDC-down and TSFDC-up models following the seven months out-of-sample period (from 1/1/2015 to 31/7/2015) of the eight currency pairs.

Currency Pair	**Trading Strategy**	**RR**	**Profit Factor**	**Total Number of Trades**	**Max Drawdown (%)**	**Win Ratio**
EUR/CHF	**TSFDC-down**	9.13	1.66	2056	– 19.4	0.66
	TSFDC -up	4.83	1.72	2009	– 21.1	0.64
GBP/CHF	**TSFDC-down**	10.82	1.58	2489	– 14.0	0.66
	TSFDC -up	12.07	1.61	2531	– 13.8	0.67
EUR/USD	**TSFDC-down**	– 1.46	0.96	1431	– 10.5	0.56
	TSFDC-up	0.67	1.09	1453	– 9.1	0.60
GBP/AUD	**TSFDC-down**	9.02	1.60	3021	– 6.4	0.64
	TSFDC-up	4.59	1.32	2960	– 6.5	0.63
GBP/JPY	**TSFDC-down**	– 2.72	0.91	1585	– 7.8	0.60
	TSFDC-up	– 4.93	0.85	1601	– 7.7	0.59
NZD/JPY	**TSFDC-down**	26.98	1.85	3046	– 5.9	0.65
	TSFDC-up	26.37	1.78	3010	– 6.5	0.66
AUD/JPY	**TSFDC-down**	12.09	1.56	2885	– 6.9	0.67
	TSFDC-up	15.4	1.62	2860	– 7.2	0.67
EUR/NZD	**TSFDC-down**	41.87	2.14	3961	– 7.0	0.69
	TSFDC-up	41.22	2.16	4218	– 7.2	0.69

Table 6.6: Monthly *RR* of applying TSFDC-down to the eight currency pairs shown in Table 6.5.

Trading period	EUR/ CHF	GBP/ CHF	EUR/ USD	GBP/ AUD	GBP/ JPY	NZD/ JPY	AUD/ JPY	EUR/ NZD
Jan 2015	0.39	2.22	– 0.29	1.47	1.04	2.95	1.80	2.59
Feb 2015	0.94	1.59	0.86	1.39	0.52	2.73	1.15	2.70
Mar 2015	2.49	1.44	– 3.1	0.51	– 0.02	1.69	0.66	3.28
Apr 2015	0.41	0.31	0.13	1.93	0.56	5.28	2.34	5.75
May 2015	1.77	0.58	0.19	2.21	0.51	3.87	4.09	5.45
Jun 2015	1.86	2.38	1.07	0.77	– 0.33	1.91	1.28	7.89
Jul 2015	1.27	2.30	– 0.32	0.74	– 5.00	8.55	0.77	14.21
Sum	**9.13**	**10.82**	**– 1.46**	**9.02**	**– 2.72**	**26.98**	**12.09**	**41.87**

Table 6.7: Monthly *RR* of applying TSFDC-up to the eight currency pairs shown in Table 6.5.

Trading period	EUR/ CHF	GBP/ CHF	EUR/ USD	GBP/ AUD	GBP/ JPY	NZD/ JPY	AUD/ JPY	EUR/ NZD
Jan 2015	0.27	5.18	0.18	1.23	1.32	4.89	2.51	1.28
Feb 2015	0.57	1.13	0.43	1.41	– 0.06	2.75	1.73	4.24
Mar 2015	1.69	1.88	– 0.25	0.41	0.16	3.11	2.27	4.35
Apr 2015	0.64	1.47	– 0.33	0.42	0.08	3.64	1.95	7.47
May 2015	0.57	0.71	0.56	0.64	– 0.09	3.24	2.67	6.95
Jun 2015	0.72	0.91	0.42	0.10	– 0.04	4.73	2.62	9.50
Jul 2015	0.37	0.78	– 0.35	0.37	– 6.30	4.02	1.65	7.43
Sum	**4.83**	**12.07**	**0.67**	**4.59**	**– 4.93**	**26.37**	**15.40**	**41.22**

The monthly *RR*, reported in Tables 6.6 and 6.7, will be utilized to compute the Sharpe and Sortino ratios, as well as Jensen's Alpha and Beta. The computation of these evaluation metrics take into consideration the minimum acceptable return (MAR) and risk-free rates (see Section 3.4 for more details). In this thesis we consider the interest rate for each currency to be both the MAR and risk-free rates. Table 6.8, shown below, reports the interest rate of each currency as determined by the corresponding central banks during the considered trading period. To determine the MAR and the risk free rates for each currency pair, we consider the higher interest rate between the base and counter currencies. For example, in the case of EUR/CHF (the first column in Table 6.9): the yearly interest rate of EUR was 0.05% whereas the interest rate of CHF was – 0.75% (Table 6.8). Therefore, we consider 0.50% as the MAR and risk-free rate of EUR/CHF (the first column in Table 6.9). Table 6.9, shown below, displays the employed values of MAR and risk-free rates for each currency pair. These values, shown in Table 6.9, will be used as the MAR and risk-free rates to compute the Sharpe and Sortino ratios and Jensen's Alpha and Beta. The Sharpe and Sortino ratios are shown in Table 6.10.

Table 6.8: The interest rates of the 7 currencies (in %) considered as the risk-free rate for each currency pair (source: World Bank's data bank http://databank.worldbank.org/data/home.aspx)

EUR	**USD**	**AUD**	**JPY**	**NZD**	**GBP**	**CHF**
0.05	0.25	2.50	0.00	3.50	0.50	– 0.75

Table 6.9: The employed values of MAR and risk-free rate for each considered currency pair.

EUR/ CHF	**GBP/ CHF**	**EUR/ USD**	**GBP/ AUD**	**GBP/ JPY**	**NZD/ JPY**	**AUD/ JPY**	**EUR/ NZD**
0.05	0.50	0.25	2.50	0.50	3.50	2.50	3.50

Table 6.10: The Sortino and Sharpe ratio of the two versions of TSFDC. The mathematic symbol ∞ denote positive infinity.

Currency pair	**TSFDC-down**		**TSFDC-up**	
	Sortino ratio	**Sharpe ratio**	**Sortino ratio**	**Sharpe ratio**
EUR/CHF	∞	1.79	∞	1.58
GBP/CHF	∞	1.94	∞	1.15
EUR/USD	– 1.37	– 0.18	2.23	0.19
GBP/AUD	∞	1.81	74.43	1.0
GBP/JPY	– 1.58	– 0.22	– 2.17	– 0.32
NZD/JPY	∞	1.60	∞	4.59
AUD/JPY	∞	1.37	∞	5.08
EUR/NZD	∞	1.50	∞	2.20

Additionally, the computation of Jensen's Alpha and Beta consists of comparing TSFDC to a particular benchmark. In this thesis, we adopt the buy and hold approach as a benchmark. The buy and hold (B&H) approach has been used as a benchmark for trading strategies' performance in many studies (e.g. [4] [43]). For each currency pair, we apply the B&H approach on a monthly basis over the considered trading period from 1/1/2015 to 31/7/2015 (seven months). Table 6.11, shown below, summarizes the monthly *RR* of applying the B&H approach to the eight currency pairs. The row 'Sum', in Table 6.11, shows the sum of all *RR* generated by applying B&H to the seven months for each considered currency pair. We use the monthly *RR* of the buy and hold method to calculate Jensen's Alpha and Beta of TSFDC. The values of Jensen's Alpha and Beta are reported in Table 6.12.

Table 6.11: Summary of the monthly RR (%) obtained by applying the buy and hold (B&H) approach to each of the eight considered currency pairs. The trading period is from 1/1/2015 to 31/7/2015.

Trading period	**EUR/ CHF**	**GBP/ CHF**	**EUR/ USD**	**GBP/ AUD**	**GBP/ JPY**	**NZD/ JPY**	**AUD/ JPY**	**EUR/ NZD**
Jan 2015	– 12.88	– 9.68	– 6.48	2.07	5.43	– 9.04	– 7.28	0.54
Feb 2015	1.75	5.17	– 1.07	1.45	4.59	6.6	3.02	– 5.08
Mar 2015	– 1.95	– 2.01	– 3.66	– 1.42	– 3.73	– 1.14	– 2.26	– 2.54
Apr 2015	0.10	– 0.60	3.96	– 0.45	3.34	1.60	3.49	2.38
May 2015	– 1.41	0.57	– 2.31	2.32	3.32	– 2.93	0.49	4.43
Jun 2015	0.99	1.92	1.72	1.59	1.34	– 5.41	0.27	6.12
Jul 2015	1.77	2.69	– 1.38	3.18	0.81	– 1.84	4.48	1.79
Sum	**– 11.63**	**– 1.94**	**– 9.22**	**8.74**	**15.10**	**–12.16**	**2.21**	**7.64**

Table 6.12: The values of Jensen's Alpha and Beta of TSFDC with reference to the buy and hold as benchmark. The values are rounded to one decimal digit.

Currency pair	**TSFDC-down**		**TSFDC-up**	
	Jensen's Alpha	**Beta**	**Jensen's Alpha**	**Beta**
EUR/CHF	1.21	0.05	0.65	0.02
GBP/CHF	1.51	– 0.02	1.78	– 0.31
EUR/USD	– 0.48	0.18	0.09	– 0.01
GBP/AUD	1.14	0.06	0.51	0.06
GBP/JPY	0.06	0.23	– 0.31	0.21
NZD/JPY	3.46	0.05	3.75	– 0.14
AUD/JPY	1.52	0.01	1.98	– 0.07
EUR/NZD	6.09	0.5	5.97	0.48

Furthermore, as we consider the B&H as a benchmark, we compare the Sharpe ratio produced by the B&H to that of TSFDC. Table 6.13, shown below, we summarize the Sharpe ratio produced by B&H (named SR_BH), TSFDC-down (named SR_TSFDC_Down) and TSFDC-up (named SR_TSFDC_Up). The values of SR_TSFDC_Down and SR_TSFDC_Up are extracted from Table 6.10 shown above. The values of SR_BH are computed based on the monthly RR of B&H previously reported in Table 6.11. To validate the comparison between the Sharpe ratios of TSFDC and B&H statistically, we applied the Wilcoxon test with the null hypothesis being that the median difference between the Sharpe ratio of TSFDC and the buy and hold approach is null. The results of test statistics[n] of the Wilcoxon tests are reported in Table 6.14, symbolized as '**W**', along with their level of significance.

[n] For more details regarding the Wilcoxon test statistics 'W', readers may refer to http://sphweb.bumc.bu.edu/otlt/mph-modules/bs/bs704_nonparametric/BS704_Nonparametric4.html

Table 6.13: The Sharpe ratio values corresponding to the buy and hold (SR_BH), TSFDC-down (SR_TSFDC_Down), and TSFDC-up (SR_TSFDC_Up).

	EUR/ CHF	GBP/ CHF	EUR/ USD	GBP/ AUD	GBP/ JPY	NZD/ JPY	AUD/ JPY	EUR/ NZD
SR_BH	– 0.35	– 0.07	– 0.42	0.69	0.74	– 0.44	0.03	0.22
SR_TSFDC_Down	1.79	1.94	– 0.18	1.81	– 0.22	1.60	1.37	1.50
SR_TSFDC_Up	1.58	1.15	0.19	1.00	– 0.32	4.59	5.08	2.20

Table 6.14: The test statistics '**W**' of the conducted Wilcoxon tests of comparing the Sharpe ratios of B&H with TSFDC-down and TSFDC-up based on the numbers reported in Table 6.13. The levels of significance are denoted as: ****=1% and **=5%.*

	SR_TSFDC_Down	SR_TSFDC_Up
W	10**	8**

Similarly, we apply the Wilcoxon test to compare the win ratio of dummy prediction and the two versions of TSFDC. The win ratio of dummy prediction, TSFDC-down, and TSFDC-up are summarized in Table 6.15, shown below. The values shown in the rows named DP_WR, TSFDC_Down_WR, and TSFDC_Up_WR denote the sets of win ratios of trading with dummy prediction, TSFDC-down and TSFDC-up respectively. The value of DP_WR can be interpreted as the expected win ratio of a trading strategy, which is equal to the accuracy of dummy prediction, for each currency pair. The values of TSFDC_Down_WR, and TSFDC_Up_WR are extracted from Table 6.5, whereas the values of DP_WR are computed as the *True-False* imbalance for the variable *BBTheta* for each currency pair (see Section 5.5.3). We consider the null hypothesis that the median difference between the of win ratios of dummy prediction and TSFDC is zero. The results of test statistics of these Wilcoxon tests are reported in Table 6.16, symbolized as '**W**', along with their level of significance.

Table 6.15: The win ratio of dummy prediction, TSFDC-down, and TSFDC-up.

	EUR/ CHF	GBP/ CHF	EUR/ USD	GBP/ AUD	GBP/ JPY	NZD/ JPY	AUD/ JPY	EUR/ NZD
DP_WR	0.63	0.64	0.64	0.51	0.64	0.63	0.56	0.63
TSFDC_Down_WR	0.66	0.66	0.56	0.64	0.60	0.65	0.67	0.69
TSFDC_Up_WR	0.64	0.67	0.60	0.63	0.59	0.66	0.67	0.69

Table 6.16: The test statistics '**W**' of the conducted Wilcoxon tests of comparing the win ratio of dummy prediction with TSFDC-down and TSFDC-up based on the numbers reported in Table 6.15. The levels of significance are denoted as: ****=1% and **=5%.*

	TSFDC_Down_WR	TSFDC_Up_WR
W	14	18

6.6.1.2 Experiment 6.1: Results' Discussion

We begin with an examination of the results obtained from the B&H (shown in Table 6.11). For each currency pair (i.e. each column), we note that the B&H approach does generate profit in some months, but incurs losses in others. This observation indicates that none of the selected currency pairs exhibit a monotonic trend during the trading period. Besides, the numbers shown in the last row in Table 6.11 (named 'Sum') demonstrate that, overall, the B&H method generates profit in four cases: GBP/AUD, GBP/JPY, AUD/JPY, and EUR/NZD (with a total rate of return, *RR*, of up to 15.10% in the case of GBP/JPY). The same row also shows that the buy and hold method incurs losses in the other four cases (with total *RR* equal to –12.16% in the case of NZD/JPY). These observations support our claim regarding the variation of the trends of the selected currency rates in Section 6.4.1.

We then examine the profitability of both versions of TSFDC. The monthly rates of return (*RR*) reported in Tables 6.6 and 6.7 suggest that both versions of TSFDC are mostly profitable (except in a few cases; e.g. trading with TSFDC-down on EUR/USD in March 2015 when it incurred losses of – 3.1%, Table 6.6). The results in column (RR), shown in Table 6.5, suggest that TSFDC can be highly profitable (with *RR* of up to 41.22 %, as in the case of applying TSFDC-up to EUR/NZD, the last row in Table 6.5). However, the profitability of TSFDC is not guaranteed for all currency pairs. For example, in Table 6.7 one can easily observe an important difference between the produced total *RR* (from – 4.93% for GBP/JPY, compared to 41.22% for EUR/NZD). This indicates that, whilst TSFDC may generate profits in most cases, its performance may vary substantially from one currency rate to another. It follows then that a trader may want to consider other currency pairs as TSFDC may, possibly, perform better on these currencies than on those reported in this chapter. Moreover, we want to declare that 41.22% is the highest *RR* that we have ever obtained in our preliminary experiments. Thus, EUR/NZD could be possibly the currency for which TSFDC performs best. We also want to point out that, if we had considered only the mid-price instead of bid/ask prices, the *RR* in the case of EUR/NZD would raise to 500%. Therefore, we also believe that if we had considered the transaction costs, it would be a good chance that the reported *RR* in Table 6.6 could have decreased.

Furthermore, when comparing the win ratio of TSFDC-down and TSFDC-up, shown in Table 6.5, to the accuracy of your forecasting model reported in Table 5.3 (Chapter 5), one can easily note a remarkable difference. For example, according to Table 6.5 the accuracy of our forecasting approach introduced in Chapter 5, range between 0.75 and 0.82; whereas the win ratio of both versions of TSFDC ranges between 0.56 and 0.69 as reported in Table 6.5. This observation indicates that the win ratio measure would me more challenging than the accuracy of the founded forecasting model to examine the performance of a given trading strategy.

When we inspect the risk of TSFDC, in Table 6.3, we notice that, in most cases, the maximum drawdown (*MDD*) is worse than –7.5% — values that we consider to be relatively high. However, the values of the Sortino ratio, reported in Table 6.10, are, in many cases, at positive infinity (∞). This reflects the fact that the downside risk (see equation (3.5) in Section 3.4) of TSFDC is null in most of these experiments. Also, in all cases, the values of the figures in the column 'Beta' (indicated in Table 6.12) range between –1.0 and 1.0. This range demonstrates that TSFDC is less volatile than the buy and hold approach. Keep in mind that the volatility of returns is usually used as an indicator of the risk of a trading strategy [62].

We examine the risk-adjusted performance of TSFDC. For this purpose, we consider the values of the Sharpe ratio and Jensen's Alpha shown in Tables 6.10 and 6.12 respectively. The Sharpe ratio is, in most cases, positive (Table 6.10). A positive Sharpe ratio indicates that the TSFDC has surpassed the risk-free rate of interest rate, demonstrating that TSFDC generates worthy excess returns for each additional unit of risk it takes. The Jensen's Alpha results are, generally, consistent with the Sharpe ratio scores (Table 6.12). We conclude that, in general, TSFDC earns more than enough return to compensate for the risks it took over the trading period.

Furthermore, as part of evaluating the risk-adjusted performance of TSFDC, we compare the Sharpe ratio of buy and hold to that of TSFDC. To validate this comparison statistically, we employ the Wilcoxon test to find out whether there is any difference between the Sharpe ratio produced by TSFDC and the buy and hold approach. The test statistics 'W' of these tests, reported in Table 6.14, are both marked with (**), leading us to reject the null hypothesis at the 5% level of significance. In other words, the Wilcoxon test suggests that the median of the Sharpe ratios of B&H is not equal to that provided by TSFDC-down or TSFDC-up.

Similarly, we used the Wilcoxon test to examine whether the median difference between the win ratio of TSFDC and dummy prediction is null. The test statistics 'W' returned by the Wilcoxon test, reported in Table 6.16, are not statistically significant, at the level of 5%, to show that the two populations of win ratios are not equal. In other words, the Wilcoxon test could not reject the hypothesis that the win ratio medians of TSFDC and dummy prediction are equal. A possible reason for that could be that despite that the sample data, reported in Table 6.15, suggest a difference, however the sample size could be too small to conclude that there is a statistical significant difference.

We conclude from the above analysis that TSFDC-down and TSFDC-up provide better Sharpe ratios and less risk than the buy and hold method. Additionally, both versions of TSFDC can be highly profitable, with *RR* of more than 41% (Table 6.5). However, TSFDC may incur losses in a few cases. We also argue that TSFDC can, in most cases, deliver a positive Sharpe ratio. Finally, the established variety of the selected currency pairs in the initial dataset (Section 6.4.1) suggest that TSFDC can be profitably applied to a wide range of currency rates.

6.6.2 Experiment 6.2: Compare the return and risk of both versions of TSFDC

The objective of this experiment is to compare the return and risk of TSFDC-up and TSFDC-down. We consider the rates of return (*RR*) and maximum drawdown (*MDD*) resulting from applying both versions of TSFDC to the eight currency pairs in the previous experiment (Section 6.6.1). These values of *RR* and *MDD* of TSFDC-down and TSFDC-up are summarized in Table 6.17 shown below. These values are extracted from Table 6.5 in Section 6.6.1. Firstly, we apply the Wilcoxon test with the null hypothesis that the median difference between the two sets of *RR* (shown in the column named *RR* in Table 6.17) of TSFDC-down and TSFDC-up is zero. Secondly, we apply the Wilcoxon test with the null hypothesis being that the median difference between the two sets of *MDD* (shown in the column named *MDD* in Table 6.17) of TSFDC-down and TSFDC-up is zero. The values of the test statistics 'W' are reported in Table 6.18 below.

Table 6.17: The summaries of *RR* and *MDD* rustled from trading with TSFDC-down and TSFDC-up

Currency Pair	***RR***		***MDD***	
	TSFDC-down	**TSFDC-up**	**TSFDC-down**	**TSFDC-up**
EUR/CHF	9.13	4.83	– 19.4	– 21.1
GBP/CHF	10.82	12.07	– 14.0	– 13.8
EUR/USD	0.67	– 1.46	– 10.5	– 9.1
GBP/AUD	9.02	4.59	– 6.4	– 6.5
GBP/JPY	– 2.72	– 4.93	– 7.8	– 7.7
NZD/JPY	26.98	26.37	– 5.9	– 6.5
AUD/JPY	12.09	15.4	– 6.9	– 7.2
EUR/NZD	41.87	41.22	– 7.0	– 7.2

Table 6.18: The test statistics '**W**' of the conducted Wilcoxon tests of comparing the *RR* and *MDD* of TSFDC-down and TSFDC-up based on the numbers reported in Table 6.17. The levels of significance are denoted as: ****=1% and **=5%*. The table of critical value of '**W**' can be found at http://sphweb.bumc.bu.edu/otlt/mph-modules/bs/bs704_nonparametric/BS704_Nonparametric4.html

	RR	**MDD**
W	35	35

The test statistics 'W' returned by the Wilcoxon test, reported in Table 6.18, are not statistically significant, at the level of 5%. In other words, the Wilcoxon test could not reject the hypothesis that the medians of *RR* of TSFDC-down and TSFDC-up are equal. Similarly, the Wilcoxon test could not reject the hypothesis that the medians of *MDD* of TSFDC-down and TSFDC-up are equal. We consider these results as sensible; because both versions of TSFDC, TSFDC-down and TSFDC-up, are based on the same forecasting model (established in Chapter 5) and have, basically, mirrored trading rules (as described in Section 6.3).

6.7 Comparing TSFDC to other DC-based strategies

In Section 4.4, we reviewed some existing trading strategies that are based on the DC framework. In this section, we compare TSFDC with two other DC-based trading strategies: (a) the one presented by Gypteau et al., [78] and (b) the trading strategy named 'DC+GA' by Kampouridis and Otero [17]. The details of these two strategies can be found in Section 4.4.

6.7.1 The DC-based trading strategy by Gypteau et al.

In this section, we highlight the differences between TSFDC and the DC-based trading strategy presented by Gypteau et al., [78] which was reviewed in detail in Section 4.4.2. We will start with a brief recap on the functionality of this DC-based trading strategy before comparing it to TSFDC.

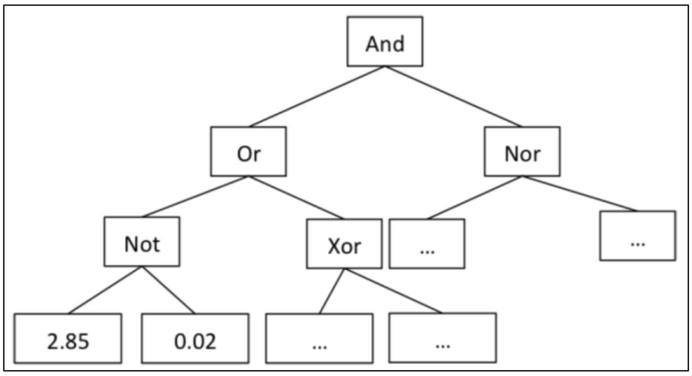

Fig. 6.4. A sample individual GP tree: internal nodes are represented by Boolean functions, while terminal nodes correspond to different DC thresholds. Given a price, terminal nodes output a Boolean value according to the DC or OS events detected. For example, if we detect a downtrend (uptrend) DC event of a DC summary of threshold 2.85%, then the left- most terminal node will be evaluated as 'False' ('True'). Source Gypteau et al., [78].

The proposed approach follows the standard tree-based Genetic Programming (GP) configuration. It runs multiple DC summaries, using different DC thresholds, concurrently. For example, Fig. 6.4, shown above, illustrates a sample individual GP tree. Each GP individual tree comprises internal and terminal nodes. The internal nodes are Boolean functions and the terminal nodes are DC thresholds. In Fig. 6.4 each threshold, shown in terminal nodes, is replaced with a 'True' or 'False' value, depending whether an uptrend or downtrend DC event of the stated threshold is detected. For example, in Fig. 6.4, if we detect an upward (downward) DC event of threshold 2.85% the left-most terminal node would be set to 'True' ('False').

These 'True' and 'False' values at the terminal nodes are, then, combined together using the Boolean functions (e.g. AND, Nor, Xor) presented in the internal nodes to form a GP-tree (see Fig. 6.4). As such, a GP tree can be interpreted as a Boolean expression; the output of which can be only True or False. This output is translated into trading rules with 'True' triggering a buy signal and 'False' triggering a sell signal. Consequently, each GP tree represents a trading strategy. The profitability of the GP tree (i.e. trading strategy) is measured based on the returns resulting from the triggered buy and sell orders over an in-sample dataset. The evolution of the objective function of the Genetic Programming (GP) aims to find the best GP-tree that yields the highest returns.

The authors applied their trading strategy to four markets: two stocks from the UK FTSE100 market (Barclays Bank and Marks & Spencer), and two international indices (NASDAQ and the NYSE). For each market, they used a training period of 1000 days to train their GP model. Then followed a testing period of 500 days for evaluation. Unfortunately, the authors did not report the dates of the training or testing periods! (For more detail on this trading model, see Section 4.4.2).

We provide the following two comments on the study of Gypteau et al. [78]:

1. The authors stated that: "*... the proposed approach aims to find an optimal trading strategy to forecast the future price moves of a financial market*" [78]. However, having investigated the study [78], we could not find a formal representation of any forecasting problem. The authors, in [78], did not identify any dependent or independent variables. Besides, they did not report any forecasting measurements (e.g. mean squared error, accuracy). Therefore, we could not conclude that the proposed strategy, in [78], does clearly employ a forecasting model.
2. With respect to the evaluation of the proposed DC-based strategy, the authors reported only the returns of the proposed trading strategy [78]. The reported returns are less than 10% over a trading period of 500 days for each considered market. Furthermore, they did not report any of: a) comparison to a benchmark (e.g. buy and hold), b) measurement of risk (e.g. MDD), nor

c) evaluation of risk-adjusted metrics (e.g. Sharpe ratio). Therefore we believe that the reported returns are not sufficiently convincing regarding the feasibility of the proposed strategy.

In contrast, we consider TSFDC to be founded on a well-formulated forecasting model. This forecasting model, established in Chapter 5, aims to forecast the change of a trend's direction under the DC framework. It has a clear objective and dependent and independent variables (see Section 5.4). By contrast, the study of Gypteau et al. [78] does not define any dependent or independent variables. Another difference is, that, in contrast to the study of Gypteau et al. [78], we provided a thorough evaluation of the risk and profitability of TSFDC (Section 6.6).

We should also note that TSFDC and the trading strategy proposed by Gypteau et al., have different trading approaches: TSFDC forecasts the change of a trend's direction to decide when to trigger a new trade, whilst Gypteau et al. employs a GP approach to develop an expression of a Boolean function, and several DC thresholds, which are then converted to trading rules.

Finally, we want to highlight that applying the strategy of Gypteau et al. to stock markets produced a maximum profit of less than 10% (over a trading period of more than 1 year). In Section 6.6.1, we examined the profitability of TSFDC in the FX market and concluded that it can produce rates of return of more than 41% in less than 7 months (after taking the bid-ask spread into concern). The authors in [78] evaluated the proposed trading strategy in a stock market where prices are sampled on a daily basis (i.e. with a time-interval of 24 hours). In contrast, TSFDC was evaluated in the FX market using minute-by-minute mid-prices (i.e. with a time-interval of 1 minute). Despite the fact that the *RR* results would indicate that TSFDC is much more profitable than the strategy of Gypteau et al., it would be better to evaluate both strategies using the same dataset in order to prove definitively that TSFDC is more profitable.

6.7.2 The DC-based trading strategy: 'DC+GA'

In this section, we compare TSFDC with the trading strategy named 'DC+GA' (Kampouridis and Otero [17]). The authors in [17] stated that their objective was "*to offer a more complete analysis on the directional changes paradigm from a financial forecasting perspective*." The details of this strategy were reviewed in Section 4.4.3. Here we briefly recap the mechanism of this strategy, then compare it with TSFDC.

DC+GA consists of running N_{theta} DC summaries concurrently using N_{theta} thresholds, these N_{theta} thresholds to be chosen by the trader. DC+GA uses some parameters: b_1, b_2, and Q (see Section 4.4.3 for more detail about these parameters). The first two parameters (b_1 and b_2) help DC+GA to decide when to initiate a trade during an OS event. The third parameter 'Q' denote the order size. For a given market's price, each DC threshold generates a buy or sell recommendation based upon the type of the detected DC event (either downward or upward). In addition, each DC threshold is assigned a 'weight'. For a given market's price, the N_{theta} DC-thresholds may produce N_{theta} recommendations. These thresholds are, then, clustered in two groups based on the proposed recommendations: the first group covers the thresholds that recommend a buy action, the second group covers those recommending a sell action. To make a buy or sell decision, DC+GA sums the weights of the thresholds belonging to each group: if the sum of the weights for all thresholds recommending a buy (sell) action is greater than the sum of the weights for all thresholds recommending a sell (buy) action, then the strategy's action will be to buy (sell).

The evolution of their GA module consists of finding the best set of weights of the N_{theta} DC thresholds along with the trading parameters (e.g. b_1, b_2, and Q) that maximize the total profits during the training process. The best set of the DC thresholds, and their associated weight and trading parameters, will be used for trading during the out-of-sample trading period (see Section 4.4.3). The employed fitness function is designed so that it maximizes *RR* and minimizes the *MDD* at the same time.

A common feature between TSFDC and DC+GA is that they both analyse uptrends and downtrends separately. Though, we can identify the following differences between TSFDC and DC+GA:

- DC+GA initiates a trade when the OS event lasts longer than a specific *time-threshold*. Whereas, TSFDC initiates a trade when the magnitude of a price's change reaches a certain value (see the trading rules in section 6.3).
- TSFDC relies on the forecasting approach presented in Chapter 5 to decide whether to initiate a trade when a new DC event is detected, whereas, DC+GA employs a GA module to anticipate the best *time-threshold* at which it should initiate a trade.
- TSFDC uses only two DC thresholds (*STheta* and *BTheta*), whereas DC+GA takes into consideration N_{theta} DC summaries at the same time.

Kampouridis and Otero [17] reported the mean *RR* results of applying DC+GA to five currency pairs (Table 6, page 158, [17]). We note that, overall, DC+GA incurred losses in two out of the five considered currency pairs. Moreover, when examining the detailed monthly returns (Table 5, page 158, [17]) we note that, in most months, DC+GA reported losses. By contrast, when inspecting the monthly returns of TSFDC reported in Tables 6.6 and 6.7, we note that in the majority of cases, TSFDC's monthly returns are positive. Furthermore, the overall *RR* of applying

TSFDC to the eight currency pairs (over the trading period of seven months) are mostly positive (Table 6.5). Thus, we can conclude that TSFDC is more profitable than DC+GA.

We then examine the risk-adjusted returns of DC+GA and TSFDC. The authors in [17] did not provide any risk-adjusted measurement for DC+GA. However, based on their reported monthly returns listed in Table 5 (page 158, [17]), we are able to compute the Sharpe ratio. If we consider a risk-free rate of 0.5% per annum, then we find that DC+GA will have a positive Sharpe ratio only in two out of the five considered currency pairs (see Section 4.4.3 for details). Whereas, our results shown in Table 6.10 (Section 6.6.1) indicate that TSFDC-up produces a positive Sharpe ratio in 7 out of 8 considered currency pairs. Based on this analysis, we conclude that TSFDC outperforms 'DC+GA' in terms of profitability and risk-adjusted returns. Obviously, the transaction costs is a function of the number of executed trades. However, the author that the authors in [17] did not report the number of trades executed by DC+GA. Therefore, it is hard to compare the impact of transaction cost on the RR produced by DC+GA and TSFDC. Finally, we should note that the authors in [17] did not consider the bid and ask prices in their experiments.

Finally, we compare the risk of TSFDC and DC+GA measured in terms of *MDD*. The *MDD* of DC+GA reported in [17] is no worse than – 0.15% (Table 8, [17]) in all considered currency pairs. This is better than the *MDD* of TSFDC reported in Table 6.5. To conclude, by comparing the results of DC+ GA (reported in [17]) and the results of TSFDC (Section 6.6.1) we deduce that TSFDC outperforms DC+GA in terms of *RR* and risk-adjusted returns. However, the results of *MDD* suggest that DC+GA is less risky than TSFDC.

6.8 Summary and conclusion

In this chapter, our objective was to develop a successful trading strategy based on forecasting DC. Following our findings in Chapter 5 concerning forecasting the change of the direction of a DC trend, this chapter used this forecasting model to develop a trading strategy named TSFDC. TSFDC is a contrarian trading strategy that relies on the forecasting model (summarized in Section 6.2) to decide when to generate a trade (Section 6.3). The trading rules of TSFDC were presented in Section 6.3.

The performance of TSFDC was examined using eight currency pairs. We utilized 1-minute trade records for these eight currency pairs covering the period between 1/1/2013 and 31/7/2015. We argued that these currency pairs exhibited various trend patterns during the considered trading period of seven months (Section 6.4.1). We evaluated TSFDC using a monthly-basis rolling window approach. Each rolling window comprised 1) a training period (24 months in length), which we used to train the forecasting model developed in Chapter 5, and 2) a trading period (1 month in length) to which we applied the trading rules of TSFDC (Section 6.4.4). We utilized a set of evaluation metrics to assess the performance of TSFDC. We considered the instantaneous bid and ask prices throughout the backtesting process. However, it should be noted that, like many other DC-based trading strategies (e.g. [15] [16] [17] [78]), the transaction costs were not considered in our experiments.

In our experiment, as a benchmark model, we implemented the buy and hold (B&H) strategy, buying at the opening price on a monthly basis, holding it over the course of the trading month and selling at the closing price. The inclusion of this zero-intelligence benchmark model was to assess the usefulness and potential outperformance of our trading strategies in general.

The experimental results (reported in Section 6.6.1) suggest that TSFDC is profitable in most cases. By examining the returns reported in Table 6.5 (Section 6.6.1), we concluded that TSFDC can be highly profitable (with an *RR* of more than 41%, as per EUR/NZD) but it suffers from a non-trivial level of risk (with *MDD* equal to – 7.2%). When examining the values of Jensen's Alpha (shown in Table 6.12, Section 6.6.1), we concluded that TSFDC generated promising rates of return compared to the level of risk it took in relation to the buy and hold method. From the Beta results detailed in Table 6.12 (Section 6.6.1), we see that in the majority of cases TSFDC was less volatile than the buy and hold method. This indicates that TSFDC is less risky than the buy and hold approach. In Section 6.7 we also argued that TSFDC outperforms other DC-based trading strategies. Finally, the conducted Wilcoxon tests suggest that the Buy and Hold approach cannot provides equal Sharpe ratio to that provided by TSFDC.

To conclude, in this chapter we developed a DC-based trading strategy, named TSFDC, which we believe to be the first DC-based trading strategy that is based on a well-formulated forecasting model. As our main contribution, we argued that TSFDC is more profitable than other DC-based trading strategies (Section 6.7). The experimental results indicate that TSFDC can be highly profitable (except in a few cases, Section 6.6.1). We examined the effectiveness of TSFDC over eight different currency rates that have different patterns. As a result, we believe that TSFDC could be successful in a broad range of currency pairs. Despite what would be considered as experimental weaknesses (e.g. ignoring the transaction costs), we consider these results as a proof of the usefulness of the DC framework as a basis of trading strategies.

7 Backlash Agent: A Trading Strategy Based on Directional Changes

In this chapter, we introduce a trading strategy named Backlash Agent, or BA for short. BA is designed so that it does not employ any forecasting model. We evaluate the performance of BA the same way we evaluated TSFDC in Chapter 6. The results indicate that: BA can generate profits of more than 30% within seven months after deducting the bid and ask spread; but not the transaction costs. We argue that BA outperforms another DC-based trading strategy.

7.1 Introduction

As stated in Section 1.2, the objective of this thesis is to explore, and consequently to provide a proof of, the usefulness of the DC framework as the basis of profitable trading strategies. Surveying the literature in Chapter 3, we observed that most trading strategies can be classified into two classes based on whether they rely on forecasting models or not. In keeping with the existing research, this thesis aims to establish two trading strategies based on the DC framework: the first relies on a forecasting model and the second does not employ any forecasting approach. This first strategy, named TSFDC, was introduced in Chapter 6 and relies on the forecasting model previously established in Chapter 5.

This chapter develops the second trading strategy, which is also based on the DC framework, but does not rely on any forecasting model. This strategy is called Backlash Agent, or BA for short. The chapter continues as follows: Section 7.2 is a brief recap of some essential DC notations. The trading rules of BA are provided in Section 7.3. The details of the experiments conducted to examine the performance of BA are described in Section 7.4. We report and discuss the experimental results in Section 7.5. Then, we compare the performance of BA with other DC-based strategies in Section 7.6. Finally, the major findings of this chapter are summarized in Section 7.7.

7.2 DC notations

This section is essentially a revision of the DC notations previously explained in Section 4.2. These notations are based on the study of Tsang et al., [77]. In the context of this chapter we recap that:

- P_c: denote the current price.
- Extreme point: is the point at which the current DC event starts.

- P_{EXT}: Is the price at the extreme point of the current DC event. In the case of a downward DC event, P_{EXT} will refer to the highest price in this trend. In the case of an upward DC event, P_{EXT} will refer to the lowest price in this trend.
- P_{EXT}^{next}: If the market is in a downtrend (uptrend), then P_{EXT}^{next} would refer to the lowest (highest) price in this downtrend (uptrend).
- $P_{DCC\downarrow}$ and $P_{DCC\uparrow}$: The interpretations of these two variables depend on whether the market is in uptrend or downtrend:
  - If the market is in uptrend, then $P_{DCC\uparrow}$ would denote the minimum price required to confirm the current uptrend. If the market is in downtrend then $P_{DCC\uparrow}$ would denote the minimum price required to confirm the next downtrend (see Section 4.2.3).
  - If the market is in downtrend, then $P_{DCC\downarrow}$ would denote the highest price required to confirm the current downtrend. If the market is in downtrend then $P_{DCC\downarrow}$ would denote the highest price required to confirm the next uptrend.
- $PDCC$: This is the price of the directional change confirmation point of the current trend. If the current trend is down then we have $= P_{DCC\downarrow}$; otherwise $PDCC = P_{DCC\uparrow}$. In the case of a downtrend, we compute $PDCC$ as:

$$PDCC = P_{EXT} \times (1 - theta) \tag{7.1.a}$$

Otherwise, $PDCC$ is computed as:

$$PDCC = P_{EXT} \times (1 + theta) \tag{7.1.b}$$

- OSV: The objective of Overshoot Value (OSV) is to measure the magnitude of an overshoot event. Instead of using the absolute value of the price change, we would like this measure to be relative to the threshold, $theta$. In relation to the variable named OSV_{BTheta}^{STheta}, which was introduced in Chapter 5 (Section 5.4.1), $OSV = OSV_{STheta}^{STheta}$. In other words, OSV is a special case of OSV_{BTheta}^{STheta} in which we have $STheta = BTheta$. OSV was initially formalized by Tsang et al. [77] as:

$$OSV = ((P_c - PDCC)/PDCC)/theta \tag{7.2}$$

  Where $PDCC$ denote the variable from equation (7.1.a), if the market is in downtrend, or (7.1.b) if the market is in uptrend.

7.3 Backlash Agent

In this section, we present the trading rules of BA. BA is a contrarian trading strategy. It generates buy and sell signals against the market's trend. We introduce two types of BA: Static

BA (SBA) and Dynamic BA (DBA). For each of SBA and DBA we provide two versions: down and up. In this way, we introduce four versions of BA in total: two static (SBA-down and SBA-up) and two dynamic (DBA-down and DBA-up). We provide the trading rules of SBA-down and SBA-up in Section 7.3.1 and Section 7.3.2 respectively. The two versions of dynamic BA (i.e. DBA-down and DBA-up) will be presented in Section 7.3.3. Each of these four versions consists of tracking a price's movements using only one threshold $theta,$ as we shall explain in this section.

7.3.1 Static BA-down (SBA-down)

In this section, we introduce a trading strategy named Static BA-down, or SBA-down for short. SBA-down is only applicable when the market is in a downtrend (hence its name). SBA-down consists of two rules:

Rule SBA-down.1: (generate buy signal)

If (the current OS event is on a downtrend) and ($OSV \leq$ *down_ind*) then generate buy signal.

Rule SBA-down.2: (generate sell signal)

If ($P_c \geq P_{DCC\uparrow}$) and (a buy order has been fulfilled) then generate sell signal.

In *Rule SBA-down.1*: OSV is the variable previously defined in Section 7.2 and *down_ind* is a trading parameter. In simple terms, SBA-down generates a buy signal when the Overshoot Value (OSV) drops below a certain threshold, *down_ind*, during a downtrend's OS event. The value of *down_ind* is the choice of the trader. SBA-down generates a sell signal when the DC confirmation point of the next upward DC event is confirmed.

In *Rule SBA-down.2*, $P_{DCC\uparrow}$ denote the minimum price required to confirm the observation of the subsequent uptrend DC event (see Section 7.2). The condition of *Rule SBA-down.2* denote the case under which we confirm the DCC point of the next uptrend DC event of threshold $theta$. Note that *Rule SBA-down.2* is applicable only if a buy signal has been triggered (i.e. no short position is allowed). In other words, no short selling is allowed. *SBA-down.2* plays two roles at the same time: *take-profit* and *stop-loss*. When *SBA-down.2* triggers a sell signal, it may incur losses (hence, functioning as *stop-loss*) or generate profits (thus, working as *take-profit*).

Table 7.1, shown below, illustrates an example of a DC summary. We use Table 7.1 to provide an example of how the trading rules of SBA-down function by examining the downward DC event [$CC^{0.1}$], of threshold 0.10%, which starts at time 21:41:00:

Table 7.1: An example of a DC summary of GBP/CHF mid-prices sampled minute-by-minute on 1/1/2013 from 21:00:00 to 22:01:00 (UK time). Excessive and unnecessary observation were omitted. $theta$ = 0.10%. We also compute the values of $PDCC$ and OSV.

Time	Mid-price	DC Event	$\boldsymbol{PDCC}$	Point	OSV
21:00:00	1.48150	start DC event (UPTREND)		B	
21:01:00	1.48180				
21:02:00	1.48170				
21:03:00	1.48159				
21:04:00	1.48280				
21:05:00	1.48310	start OS event (UPTREND)	1.48298150	$B^{0.1}$	0.07990659
21:06:00	1.48365				0.45078108
21:07:00	1.48430				0.88908729
21:08:00	1.48390				0.61936039
21:09:00	1.48380				0.55192867
………………………					
21:41:00	1.48690	start DC event (DOWNTREND)		C	2.64231213
21:42:00	1.48480	start OS event (DOWNTREND)	1.48541310	$C^{0.1}$	– 0.41274713
21:43:00	1.48470				– 0.48006847
21:44:00	1.48520				– 0.14346177
21:45:00	1.48495				– 0.31176512
21:46:00	1.48412	start DC event (UPTREND)		D	– 0.87053224
………………………					
22:01:00	1.48570	start OS event (UPTREND)	1.48560412	$D^{0.1}$	0.0645394

a) Suppose that the trader has chosen *down_ind* $= -$ 0.45.

b) At time 21:43:00 (shown in column 'Time'), we determine that the $OSV = -\ 0.48006847$ (shown in column 'OSV'), which is less than *down_ind* ($-$ 0.45). In this example, OSV is computed as follows:

- C is the extreme point of the downward DC event [$CC^{0.1}$]. As $theta = 0.001$, we get: $PDCC \quad = P_{EXT} \times (1 - 0.001) = 1.48690 \times 0.999 = 1.48541310$. At time 21:43:00, the mid-price is 1.48470. Thus:

$$OSV = ((P_c - PDCC \quad)/PDCC \quad)/theta$$
$$= ((1.48470 - 1.4854131)/1.4854131\ )/0.001 = -\ 0.48006847.$$

c) Based on a) and b), both conditions of *Rule SBA-down.1* are fulfilled. Therefore SBA-down generates a buy signal at time 21:43:00.

d) [$DD^{0.1}$] is the upward DC event, which immediately follows the downward DC event [$CC^{0.1}$]. At time 22:01:00, we confirm the DCC point of [$DD^{0.1}$] — which is $D^{0.1}$. Based on *Rule SBA-down.2*, SBA-down will generate a sell signal at time 22:01:00.

7.3.2 Static BA-up (SBA-up)

In this section, we introduce the second version of SBA named SBA-up. SBA-up is the mirror of SBA-down. SBA-up generates a sell signal while the market is in an uptrend and only if the value of *OSV* exceeds a certain threshold, named *up_ind*. SBA-up generates a buy signal when a new downward DC event is observed. SBA-up consists of two rules:

Rule SBA-up.1: (generate sell signal)

If (the current event is OS on an uptrend) and ($OSV \geq$ *up_ind*) then generate sell signal.

Rule SBA-up.2: (generate buy signal[o]*)*

If ($P_c \leq P_{DCC\downarrow}$) and (a sell order has been fulfilled) then generate buy signal.

Here, $P_{DCC\downarrow}$ denote the highest price required to confirm the observation of the next downward DC event. *up_ind* is a trading parameter. The condition of *Rule SBA-up.2* indicates the case under which we confirm the DCC point of the next downward DC event of threshold *theta*. Note that *Rule SBA-up.2* is applicable only if a sell signal has been triggered. *Rule SBA-up.2* plays two roles at the same time: *take-profit* and *stop-loss*. When *Rule SBA-up.2* triggers a buy signal, it may incur losses (hence, functioning as *stop-loss*) or generate profits (thus, working as *take-profit*).

We use Table 7.1 above to provide an example of how the trading rules of SBA-up function, by examining the upward DC event [$BB^{0.1}$], of threshold 0.10%, which starts at time 21:00:00.

a) Suppose that the trader sets *up_ind* $= 0.80$.

b) At time 21:07:00, we determine that $OSV = 0.88908729$. *OSV* is larger than *up_ind* (0.80).

   - B is the extreme point of the upward DC event [$BB^{0.1}$]. In this case, with *theta* $=$ 0.001, we get $PDCC \quad = P_{EXT} \times (1 + 0.001) = 1.48150 \times 1.001 = 1.48298150$. At time 21:07:00, the mid-price is 1.48430. Thus,

$$OSV = ((P_c - PDCC \quad)/PDCC \quad)/theta$$

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[o] We want to highlight that no short selling is allowed. In the case of trading SBA-up, we assume that the initial capital is provided in base currency. When SBA-up initiates a sell signal (based on *Rule SBA-up.1*), we use the base currency to buy counter currency.

$= ((1.48430 - 1.48298150\ )/1.48298150)/\ 0.001 = 0.88908729$

c) Based on a) and b) both conditions of *Rule SBA-up.1* are fulfilled and therefore SBA-up generates a sell signal at time 21:07:00.

d) [$CC^{0.1}$] is the downward DC event which follows the upward DC event [$BB^{0.1}$]. At time 21:42:00, we confirm the DCC point, $C^{0.1}$, of the next downtrend DC event, which is [$CC^{0.1}$]. Based on *Rule SBA-up.2*, SBA-up will generate a buy signal.

7.3.3 Dynamic Backlash Agent

When trading with static BA, we have no hint as to how SBA-down, or SBA-up, will perform if the value of *down_ind* or *up_ind* is chosen arbitrarily. Theoretically, the investor should use his/her expertise to choose the value of the parameters *down_ind* or *up_ind*. However, in some cases, the investor may not have sufficient experience to do so. Moreover, there is no guarantee, should SBA-down perform well for a given value of *down_ind* during a trading period, *x* that it will behave similarly during another trading period, y using the same value of *down_ind*. The same holds true for SBA-up. These facts are the motivation behind the development of the two versions of dynamic BA, namely DBA-down and DBA-up respectively.

7.3.3.1 Dynamic BA-down (DBA-down)

DBA-down comprises two stages. In the first stage, DBA-down automatically determines the value of the parameter *down_ind*. For this purpose, DBA-down applies a procedure, named FIND_DOWN_IND, to a training (i.e. in-sample) dataset to determine the value of *down_ind*. In the second stage, DBA-down uses the same two rules of SBA-down to trade over a trading, out-of-sample, dataset using the value of *down_ind* returned by FIND_DOWN_IND.

The objective of the procedure FIND_DOWN_IND is to find an appropriate value for the parameter *down_ind* to be utilized in trades with SBA-down during the applied period. The output of the procedure FIND_DOWN_IND is one numerical variable, named *best_down_ind*. In order to determine *best_down_ind*, FIND_DOWN_IND applies the trading rules of SBA-down to the training dataset using 100 different values of *down_ind* (from – 0.01 to –1.00, with a step size of – 0.01). For each value of *down_ind*, we compute the returns, either profits or losses, obtained by applying SBA-down to the training dataset. Thus, for a given training period we get 100 returns — one return for each distinct value of *down_ind*. We define *best_down_ind* as the value of *down_ind* under which SBA-down generated the highest returns using the training dataset. In the second stage of DBA-down, we follow the trading rules (*SBA-down.1* and *SBA-down.2*) with the input parameter '*down_ind*' being assigned the value of *best_down_ind* to trade over the trading dataset.

7.3.3.2 Dynamic BA-up (DBA-up)

DBA-up is the dynamic version of SBA-up, as DBA-down is to SBA-down. DBA-up also has two stages, like DBA-down. The first stage consists of automatically finding an appropriate value of *up_ind*, using the training period. This is done by a procedure called FIND_UP_IND. FIND_UP_IND has the same role as FIND_DOWN_IND. FIND_UP_IND uses the training dataset to compute one numerical variable named *best_up_ind*. To determine *best_up_ind*, FIND_UP_IND applies the trading rules of SBA-up to the training dataset using 100 different values of *up_ind* (from 0.01 to 1.00, with a step size of 0.01). For each value of *up_ind*, we compute the returns, either profits or losses, obtained by applying SBA-up to the training period. Consequently, for a given training dataset we get 100 returns — one return for each value of *up_ind*. We define *best_up_ind* as the value of *up_ind* under which SBA-up has generated the highest returns during the training period. The second stage of DBA-up follows the trading rules (*SBA-up.1* and *SBA-up.2*) with the input parameter '*up_ind*' being assigned the value of *best_up_ind* to trade over the trading period.

7.4 Evaluation of the Backlash Agent: Methodology and experiments

To evaluate the performance of all BA versions, we consider the minute-by-minute mid-prices of the eight currency pairs (EUR/CHF, GBP/CHF, EUR/USD, GBP/AUD, GBP/JPY, NZD/JPY, AUD/JPY, and EUR/NZD) for 31 months: from 1/1/2013 to 31/7/2015. For each currency pair, we run the DC analysis with $theta = 0.10\%$, and we compose a set of seven rolling windows. Each rolling window comprises a training window of 24 months in length and an applied (i.e. trading) period of 1 month in length. Basically, we use the same eight sets of rolling windows previously composed in Section 6.4.4; namely: *EURCHF_RWDC0.1*, *GBPCHF_RWDC0.1*, *EURUSD_RWDC0.1*, *GBPAUD_RWDC0.1*, *GBPJPY_RWDC0.1*, *NZDJPY_RWDC0.1*, *AUDJPY_RWDC0.1*, *and EURNZD_RWDC0.1*. . See Section 6.4.4 for details on how these eight sets are prepared.

In this chapter, we provide five sets of experiments: 1) the first experiment is designed to estimate the best and the worst performance of SBA-down and SBA-up; 2) the second examines whether there are specific values of the parameters *down_ind* and *up_ind* for which SBA-down and SBA-up perform best; 3) the third evaluates the performance of DBA-down and DBA-up; 4) the fourth compares the profitability of SBA and DBA; 5) the fifth experiment aims to compare the performances of DBA-down and DBA-up.

We use the same money management approach described in Section 6.5.1 for each of these experiments. In summary: when any version of BA generates a buy or sell signal, it uses the entire capital to trade. When we apply any version of the Backlash Agent, we make sure that no position is left open at the end of the trading period. Should we encounter an open position at the end of the trading period, then the last transaction will not be considered when computing the results — instead, we roll back to the previous transaction. In other words, we do not count this last trade when measuring any of the considered evaluation metrics. We consider the instantaneous bid and ask prices in all of our experiments, but not the transaction costs.

7.4.1 Experiment 7.1: Evaluation of Static BA

The objective of this section is to evaluate the best and the worst performance of static BA (both versions: SBA-down and SBA-up).

7.4.1.1 Experiment 7.1.1: Estimating the best and worst RR of SBA-down

For simplicity, we consider the rate of return (*RR*) as the primary performance indicator. *RR* is defined as the gain or loss on an investment, expressed as a percentage of the amount invested (see Section 3.4).We will use the currency pair EUR/CHF to describe our approach to estimating the maximum and minimum *RR* that could be produced by applying SBA-down to EUR/CHF, or more particularly to the set of rolling windows named *EURCHF_RWDC0.1*. The same method will apply to each of the remaining seven sets of rolling windows.

As stated in Section 7.2, static BA is not applicable unless the investor knows what values to assign to the parameters. Keep in mind that *EURCHF_RWDC0.1* includes seven applied windows. To provide a reasonable evaluation, we apply SBA-down to each applied window in *EURCHF_RWDC0.1*, using 100 different values of *down_ind* (from – 0.01 to –1.00, with a step size of –0.01). Consequently, for each applied window we will have 100 *RR* (each *RR* corresponding to one distinct value of *down_ind*). For each applied window, we consider the maximum and the minimum generated *RR*. So that, in total, we get seven maximum *RR* and seven minimum *RR*. To estimate the overall maximum *RR* of trading with SBA-down over *EURCHF_RWDC0.1*, we sum the seven maximum *RR* of these seven applied windows (starting from 1/12015 to 31/7/2015). This is complemented by other measures, mainly the profit factor, *MDD* and win ratio. Similarly, we apply SBA-down to the applied windows of each of the remaining seven sets of rolling windows (previously composed in Section 6.4.4) and we measure the maximum and the minimum produced *RR* of applying SBA-down to each set. In this experiment, as well as in the following experiments, we apply the money management approach described in Section 6.5.1. While there is no direct transaction fee, we consider the bid–ask spread as a kind of indirect charge as in ([6] [15] [16]).

7.4.1.2 Experiment 7.1.2: Estimating the best and worst RR of SBA-up

This experiment aims to evaluate the best and the worst performance of SBA-up. In line with the previous experiment, we apply SBA-up to each applied window in *EURCHF_RWDC0.1* using 100 different values of *up_ind* (from 0.01 to 1.00, with a step size of 0.01). Consequently, for each applied window we will have 100 *RR* (each *RR* corresponding to a distinct value of *up_ind*). *EURCHF_RWDC0.1* has seven applied periods. For each applied window we consider the maximum and the minimum generated *RR*. So that, in total we get seven maximum *RR* and seven minimum *RR*. To compute the maximum *RR* of trading with SBA-up over *EURCHF_RWDC0.1* we sum the seven maximum *RR*. We also measure additional metrics: the profit factor, *MDD* and win ratio. Similarly, we apply SBA-up to the applied windows of each of the remaining seven sets of rolling windows (previously composed in Section 6.4.4) and we measure the maximum and the minimum produced *RR* of applying SBA-up to each set.

7.4.2 Experiment 7.2: Is there one optimal value for the parameters down_ind and up_ind?

This experiment investigates whether there are specific values for the parameters *down_ind* and *up_ind*, under which SBA-down and SBA-up will consistently produce the maximum *RR*. For this purpose, we apply SBA-down and SBA-up to the eight currency pairs: EUR/CHF, GBP/CHF, EUR/USD, GBP/AUD, NZD/JPY, AUD/JPY, GBP/JPY, and EUR/NZD. In this experiment, we consider the period from 01/08/2014 to 31/07/2015 (12 months) as the trading period.

For each currency pair, for each month, we simulate 100 trades with SBA-down. For each trade, we use a different value of the *down_ind* parameter (from – 0.01 to –1.00, with a step size of – 0.01). Consequently, for each month we will have 100 returns (each return corresponds to a distinct value of *down_ind*). For each currency pair, and for each trading month, we compute the maximum *RR* generated by SBA-down. We select and report the values of the *down_ind* parameter that correspond to these maximum *RR*. In total, for each currency pair we obtain 12 values of *down_ind* that represent the best performance of SBA-down during the12 months (one value for each trading month).

A naïve assumption would be to consider *up_ind* = *down_ind*. This would not be an intelligent decision as some studies (e.g. [77]) have reported that the downtrends and uptrends for financial time series will, probably, have different characteristics. We perform the same 100 trade simulations, in the same trading period (12 months) and on the same eight currency pairs, using SBA-up — each time using a different value of the *up_ind* parameter. For each currency pair, we get another 12 values of *up_ind* corresponding to the highest possible *RR* generated by SBA-up during the12 months. We analyse these values of *down_ind*, or *up_ind*, to find out whether there exists a particular value for which SBA-down, or SBA-up, will deliver the best possible performance consistently.

7.4.3 Experiment 7.3: Evaluating the performance of DBA-down and DBA-up

If choosing the value of the parameters *down_ind* or *up_ind* arbitrarily, a trader cannot have any precise perception of how good, or otherwise, would be the performance of the static BA. With this point in mind, we developed the dynamic version, DBA, as explained in Section 7.2.3. In this experiment, we aim to evaluate the performance of both versions of DBA. To this end, we apply DBA-down and DBA-up to the eight sets of rolling windows detailed in Section 6.4.4; namely, *EURCHF_RWDC0.1, GBPCHF_RWDC0.1, EURUSD_RWDC0.1, GBPAUD_RWDC0.1, GBPJPY_RWDC0.1, NZDJPY_RWDC0.1, AUDJPY_RWDC0.1, and EURNZD_RWDC0.1*.

Each window comprises: 1) a training period (of 24 months in length), and 2) a trading window (of 1 month in length). For each rolling window, the training period is utilized to find the values of the *down_ind* or *up_ind* parameters, based on the procedures FIND_DOWN_IND or FIND_UP_IND described in Section 7.3.3. Then, we use these values in the trading period associated with the specified rolling window. The performance of DBA is evaluated by measuring the metrics reported in Section 3.3.

Furthermore, as we consider the buy and hold strategy (B&H) as a benchmark, we compare the Sharpe ratio of both versions of DBA with the Sharpe ratio obtained by the buy and hold approach. To validate this comparison statistically, we employ the Wilcoxon rank sum test [106] twice. Firstly, we apply the Wilcoxon test with the null hypothesis being that ‘the median difference between the Sharpe ratio produced by DBA-Down and B&H is zero’. Secondly, we apply the Wilcoxon test with the null hypothesis being that ‘the median difference between the Sharpe ratio produced by DAB-Up and B&H is zero’.

7.4.4 Experiment 7.4: Comparing the RR of DBA and SBA

The objective of this experiment is to figure out what is the probability that DBA produces higher *RR* than SBA provided that when trading with SBA, the parameters *down_ind* and *up_ind* are assigned random values. This probability will help us to evaluate the efficiency of the proposed procedures: FIND_DOWN_IND and FIND_UP_IND (Section 7.3.3) that are designed to find appropriate values for the parameters *down_ind* and *up_ind*. Note that when trading with the static versions, it is the trader who must choose the values of the parameters *down_ind* and *up_ind*. Choosing these randomly offers a way of assessing the relative performance of SBA-down, and SBA-up, against DBA-down, and DBA-up.

Consider that a trader assigns a random value to the parameter *down_ind*, or *up_ind*, when trading with SBA-down, or SBA-up. In such a case, the question is: What is the probability that the dynamic BA (DBA-down or DBA-up) will produce higher returns than the static BA (SBA-down or SBA-up)? Let γ denote this probability. To compute γ, we estimate the performance of the static version using a set of randomly chosen values for input parameters *down_ind* and *up_ind*. The following provides an example of how to estimate γ based on the EUR/CHF dataset.

We simulate trading with SBA-down on *EURCHF_RWDC0.1* 10,000 times[p]. Each time, we trade with SBA-down on each applied window in *EURCHF_RWDC0.1*. Every time, and for each applied window, we assign a new random value to the parameter *down_ind*. In other words, each time that we trade with SBA-down we use seven random values of *down_ind*, each random value being ranged between – 0.01 and – 1.00 and used for one applied window. With every trading simulation, we measure the *RR* generated by SBA-down. Hence, we obtain 10,000 *RR*. Each *RR* corresponds to one trade with SBA-down on the seven rolling windows of *EURCHF_RWDC0.1*. γ can be calculated as the fraction of how many of these 10,000 *RR* are less than the *RR* generated by the dynamic version, DBA-down, in Experiment 7.3 (Section 7.4.3). Similarly, we apply SBA-up to the applied windows of *EURCHF_RWDC0.1* 10,000 times with randomly picked values for parameter *up_ind*. Each time and for each applied window, we assign a new random value to the parameter *up_ind*. We obtain another 10,000 *RR*. Each return corresponds to one trade with SBA-up on the seven rolling windows of *EURCHF_RWDC0.1*. Again, γ is computed as the fraction of how many of these 10,000 *RR* are less than the *RR* generated by DBA-up in Experiment 7.3 (Section 7.4.3).

[p] In a preliminary experiment we considered various numbers of trading simulations to determine γ. We found that for more than 10,000 trading simulations (e.g. 13,000; 15,000) the value of γ changed (less than 0.5%).

The entire procedure is repeated for each of the remaining seven sets of rolling windows: *GBPCHF_RWDC0.1*, *EURUSD_RWDC0.1*, *GBPAUD_RWDC0.1*, *GBPJPY_RWDC0.1*, *NZDJPY_RWDC0.1*, *AUDJPY_RWDC0.1*, and *EURNZD_RWDC0.1*. For each of these sets, we apply SBA-down and SBA-up with randomly chosen parameters, *down_ind* and *up_ind*, to each of the seven applied periods 10,000 times. Hence, we obtain 10,000 *RR* resulting from trading with SBA-down and another 10,000 *RR* resulting from trading with SBA-up. For each set of rolling windows, we evaluate γ as the percentage of how many of these 10,000 *RR* are less than the *RR* generated by DBA-down and DBA-up in Experiment 7.3.

7.4.5 Experiment 7.5: Comparing the returns and risk of both versions of DBA

The objective of this experiment is to test whether there is difference between the performances of DBA-down and DBA-up. To this end, we compare the returns and risk of both versions of DBA. In this experiment, we consider the rate of returns (*RR*) and maximum drawdown (*MDD*) resulting from applying both versions of DBA to the eight currency pairs from Experiment 7.3. That is, we want to find out whether DBA-down and DBA-up provide similar RR and MDD. To validate this comparison statistically, we will apply the Wilcoxon Rank Sum test [106].

Initially, we compare the *RR* of DBA-down and DBA-up by composing two sets of *RR* based on the results of Experiment 7.3. The first set consists of the 8 *RR* resulting from trading with DBA-down over the eight currency pairs (1 *RR* for each currency pair). The second set consists of the 8 *RR* obtained by applying DBA-up to the eight considered currency pairs. Then, we apply the non-parametric Wilcoxon rank sum test with the null hypothesis being that the median difference of the two sets of monthly *RR* is zero.

Secondly, we compare the risks of DBA-down and DBA-up. To this end, we compare the *MDD* resulting from applying DBA-down and DBA-up to the eight currency rates. We compose two sets of *MDD* data. The first set contains the 8 *MDD* (1 *MDD* for each currency pair) corresponding to trading with DBA-down. Likewise, the second set contains the *MDD* resulting from applying DBA-up to the eight currency rates. We apply the Wilcoxon Rank Sum test to these sets with the null hypothesis being that the median difference of the two sets of *MDD* is zero.

7.5 Evaluation of Backlash Agent: Results and discussion

7.5.1 Experiment 7.1: Evaluation of Static BA

7.5.1.1 Experiments 7.1.1: Evaluating the performance of SBA-down

The objective of this experiment is to estimate the best and the worst possible performance of SBA-down. For simplicity, we consider the maximum and the minimum produced *RR* as the primary indicators of the best and the worst performance respectively. We consider eight currency pairs. We compose eight sets of rolling windows (one set for each currency pair). Each set is composed of seven rolling windows (see Section 6.4.4). We apply SBA-down to the applied windows of each set of rolling windows using 100 different values of *down_ind*. We adopt the money management approach described in Section 6.5.1. In this experiment, we are not concerned with a detailed monthly evaluation. Instead, we focus on the general performance of SBA-down during the overall seven months (i.e. the entire trading period) of each set of rolling windows. We also measure the overall profit factor, MDD, and win ratio. We consider the instantaneous actual bid and ask prices for each trade (either to buy or to sell) in all of our experiments.

Table 7.2 and Table 7.3 display, respectively, the best and the worst, estimated, performances of SBA-down when applied to the composed sets of rolling windows (see Section 7.3.1). These tables include the following metrics: rates of return (*RR*), profit factor, maximum drawdown, and win ratio (see Section 3.4 for more details about these metrics). For each currency pair, at the beginning of the first applied window, i.e. January 2015, SBA-down starts with capital = 1,000,000 monetary units[q], this represents the initial, hypothetically, invested amount of money. From Table 7.2, let us consider the case of EUR/CHF. The reported results have the following interpretation: the cumulative rates of return (*RR*) are 7.48% as shown in column 'RR'. This represents the maximum total *RR* that can be produced by applying SBA-down to the seven applied windows of *EURCHF_RWDC0.1*. In this case, SBA-down generates 1798 trades, as shown in column 'Total Number of Trades', with an overall win ratio of 0.73 as shown in column 'Win Ratio'. Whereas, in Table 7.3, in the case of EUR/CHF, we note that the minimum *RR*, during the trading period of seven months, is – 2.09%. In this case, SBA-down generates 1167 trades with an overall win ratio of 0.73. Based on Table 7.2, in the best case, SBA-down can generate *RR* of

[q] For each currency pair, trading with SBA-down, or DBA-down, we assume that we start with 1,000,000 units of counter currency. For example: in the case of EUR/CHF, we start with 1,000,000 CHF. Whereas in the case of NZD/JPY, we start with 1,000,000 JPY. However, in the case of SBA-up, or DBA-up, we assume that we start with 1,000,000 units of the base currency.

36.86% (see EUR/NZD, the last row in Table 7.2). Based on Table 7.3, in the worst case, SBA-down can generate *RR* of – 6.50% (see EUR/USD, as shown in Table 7.3).

Table 7.2: Summary of the best performance of the SBA-down model following the seven months out-of-sample period of the eight currency rates from 1/1/2015 to 31/7/2015.

Currency Pairs	RR	Profit Factor	Total Number of Trades	Max Drawdown (%)	Win Ratio
EUR/CHF	7.48	1.98	1798	– 4.3	0.73
GBP/CHF	8.53	1.92	2539	– 5.1	0.72
EUR/USD	1.90	1.15	1935	– 7.3	0.75
GBP/AUD	7.29	1.67	2707	– 5.6	0.74
GBP/JPY	2.64	1.22	1748	– 8.5	0.72
NZD/JPY	23.96	2.03	3409	– 2.7	0.73
AUD/JPY	10.33	1.97	2861	– 3.2	0.74
EUR/NZD	36.86	2.26	3919	– 1.3	0.71

Table 7.3: Summary of the worst performance of the SBA-down model following the seven months out-of-sample period of the eight currency rates.

Currency Pairs	RR	Profit Factor	Total Number of Trades	Max Drawdown (%)	Win Ratio
EUR/CHF	– 2.09	0.82	1167	– 8.0	0.59
GBP/CHF	– 2.41	0.83	1270	– 8.2	0.51
EUR/USD	– 6.50	0.65	1649	– 10.9	0.55
GBP/AUD	2.62	1.09	2571	– 11.5	0.61
GBP/JPY	– 5.89	0.60	1290	– 15.8	0.48
NZD/JPY	2.77	1.07	2515	– 7.4	0.62
AUD/JPY	3.41	1.28	2111	– 8.1	0.62
EUR/NZD	5.03	1.14	2873	– 6.3	0.63

When examining the difference between the maximum and minimum *RR* produced by SBA-down, by comparing the *RR* shown in Tables 7.2 and 7.3, it is evident that this difference can be significant. For example, in the case of AUD/JPY, the maximum *RR* estimated for SBA-down is 10.33% (Table 7.2). This is more than double the minimum *RR* obtained by applying SBA-down to AUD/JPY (which is 3.41%, as reported in Table 7.3). The same note holds true for the *RR* obtained by SBA-down for all other currency rates. Keep in mind that this difference between the maximum and minimum *RR* is as a result of the choice of the parameter *down_ind*. In other words, for a given currency pair, the max and min rates of return (*RR*) are obtained using two different values of *down_ind* (see Section 7.4.1). These results highlight the important impact of the *down_ind* value on the profitability of SBA-down. To conclude, SBA-down may have an attractive profitability in the best case. However, the value of *down_ind* may seriously affect the performance of SBA-down.

7.5.1.2 Experiments 7.1.2: Evaluating the performance of SBA-up

We apply SBA-up to each of the eight sets of rolling windows. Each set includes seven applied windows — the length of each is one month. For each set, and for each month of the applied windows, we use 100 different values of *up_ind*. We measure the maximum and the minimum *RR* as primary indicators of the best and worst performance of SBA-up respectively. We also measure the overall profit factor, *MDD*, and win ratio. We apply the same money management approach described in Section 6.5.1. Table 7.4 and Table 7.5 show, respectively, the estimated best and the worst performance of SBA-up when applied to the composed sets of rolling windows (see Section 7.3.2). Table 7.4 and Table 7.5 have the same interpretation as Tables 7.2 and 7.3. As in the previous experiment, we are mostly concerned with the general performance of SBA-up during the overall trading period (i.e. from 1/12015 to 31/7/2015) of each set of rolling windows.

Table 7.4: Summary of the evaluation of the best performance of applying SBA-up to the trading period of each set of rolling windows.

Currency Pairs	RR	Profit Factor	Total Number of Trades	Max Drawdown (%)	Win Ratio
EUR/CHF	7.64	1.98	1963	– 4.6	0.72
GBP/CHF	11.91	1.94	2435	– 5.3	0.71
EUR/USD	0.95	1.02	2000	– 7.1	0.76
GBP/AUD	8.32	1.70	2332	– 5.4	0.73
GBP/JPY	– 0.05	0.95	1545	– 8.1	0.73
NZD/JPY	26.52	2.13	3262	– 2.1	0.72
AUD/JPY	12.61	2.00	2486	– 3.5	0.75
EUR/NZD	35.68	2.26	3851	– 1.6	0.74

Table 7.5: Summary of the evaluation of the worst performance of applying SBA-up to the trading period of each set of rolling windows.

Currency Pairs	RR	Profit Factor	Total Number of Trades	Max Drawdown (%)	Win Ratio
EUR/CHF	– 1.92	0.88	1018	– 7.9	0.57
GBP/CHF	– 2.65	0.81	1313	– 8.5	0.55
EUR/USD	– 5.08	0.75	1709	– 10.1	0.50
GBP/AUD	2.79	1.25	1195	– 10.8	0.61
GBP/JPY	– 6.03	0.64	937	– 14.7	0.48
NZD/JPY	3.12	1.20	1968	– 8.1	0.63
AUD/JPY	3.52	1.36	1506	– 7.6	0.63
EUR/NZD	5.85	1.24	2334	– 6.2	0.62

For each currency pair, at the beginning of the first applied window, i.e. January 2015, SBA-up starts with capital equal to 1,000,000; this represents the initial, hypothetically, invested amount of money. From Table 7.4, using EUR/CHF, we note that the total *RR* are 7.64%. This represents the maximum possible *RR* that can be obtained by applying SBA-up to the seven applied windows of *EURCHF_RWDC0.1*. In this case, SBA-up generates 1963 trades with an overall win ratio of 0.72. Whereas, in Table 7.5, again using EUR/CHF, we note that the minimum possible *RR* generated by SBA-up during the same trading period of seven months is – 1.92%. In this case, SBA-up generates 1018 trades with an overall win ratio of 0.57.

The objective of this experiment is to estimate the best and worst performance of SBA-up. Based on Table 7.4, in the best case, SBA-up can generate *RR* of more than 35.68% (see the case of EUR/NZD, the last row in Table 7.4). Based on Table 7.5, in the worst case, SBA-down can generate returns of – 6.03% (see the case of GBP/JPY, as shown in Table 7.5).

When examining the difference between the maximum and minimum *RR* produced by SBA-up, by comparing the *RR* reported in Tables 7.4 and 7.5, it is clear that this difference can be considerable. For example, in the case of AUD/JPY, the maximum *RR* estimated for SBA-up is 12.61% (Table 7.4). This is more than double the minimum *RR* obtained by applying SBA-down to AUD/JPY (which is 3.52%, as reported in Table 7.5). The same note holds true for the *RR* obtained by SBA-up for all other currency rates. For a given currency pair, the best and worst rates of return (*RR*) are obtained using two different values of *up_ind* (see Section 7.4.2). These results highlight the important impact of the value of *up_ind* on the profitability of SBA-up. To conclude, SBA-up may have an attractive profitability level in the best case. However, the value of *up_ind* may seriously affect the performance of SBA-up.

7.5.2 Experiment 7.2: Is there one optimal value for the parameter down_ind or up_ind?

The objective of this experiment is to investigate whether there exists a specific value for the parameters *down_ind*, or *up_ind*, for which SBA-down, or SBA-up, will consistently generate the highest possible *RR*. We consider the same eight currency pairs as in Section 7.4 and apply SBA-down and SBA-up to each of these 100 times for a trading period of 12 months. Each time, for each month, we assign different values for the parameters *down_ind* and *up_ind* and measure the produced returns. In this experiment, our main interest is the values of the parameters *down_ind* and *up_ind* associated with the highest *RR*. Our goal is to analyse the values of these parameters. Table 7.6 shows the values of *down_ind* associated with the maximum monthly *RR* produced by SBA-down. For each currency pair (i.e. for each column in Table 7.6), the largest and the smallest values of *down_ind* are formatted in **bold** and *italic* respectively. For example, in column 'EUR/CHF' the numbers **– 0.01** and – *0.84* denote, respectively, the largest and the smallest values of *down_ind* under this column. These **bold** and *italic* figures, for the same column, indicate the range of the parameter *down_ind* in which the specified trading model performs best. Similarly, Table 7.7 shows the values of *up_ind* associated with the best monthly *RR* generated by SBA-up for each of the 12 trading months considered in this experiment.

Table 7.6: The values of *down_ind* corresponding to the highest RR generated by SBA-down for each month. For each currency pair, the figures in **bold** and *italic* indicate, respectively, the largest and the smallest values of *down_ind*.

Trading period		**EUR/ CHF**	**GBP/ CHF**	**EUR/ USD**	**GBP/ AUD**	**AUD/ JPY**	**NZD/ JPY**	**GBP/ JPY**	**EUR/ NZD**
2014	Aug	– 0.82	– 0.17	– 0.32	– 0.34	– 0.08	– 0.09	– 0.74	– 0.29
	Sep	– 0.08	– 0.04	– 0.92	**– 0.02**	– 0.15	– 0.43	– 0.62	– 0.16
	Oct	– 0.27	– 0.05	– 0.90	– 0.36	– 0.23	– 0.62	– 0.76	– 0.56
	Nov	– 0.40	– *0.93*	– 0.07	– 0.13	– 0.45	– 0.27	– 0.53	– *0.73*
	Dec	**– 0.01**	– 0.31	– 0.53	– 0.10	– *0.62*	– 0.33	– 0.40	– 0.50
2015	Jan	– *0.84*	– 0.30	– *0.96*	– 0.36	– 0.32	– *0.69*	– 0.25	**– 0.06**
	Feb	– 0.43	– 0.08	– 0.12	– 0.16	– 0.07	**– 0.03**	**– 0.05**	– 0.46
	Mar	– 0.01	**– 0.01**	– 0.57	– *0.49*	– 0.11	– 0.07	– 0.05	– 0.49
	Apr	– 0.04	– 0.10	– 0.23	– 0.34	– 0.15	– 0.32	– 0.12	– 0.54
	May	– 0.07	– 0.02	– 0.38	– 0.37	– 0.16	– 0.46	– 0.22	– 0.67
	Jun	– 0.14	– 0.12	– 0.07	– 0.18	– 0.10	– 0.08	– 0.15	– 0.38
	Jul	– 0.39	– 0.02	**– 0.05**	– 0.41	**– 0.07**	– 0.13	– *0.98*	– 0.28

Table 7.7: The values of *up_ind* corresponding to the highest *RR* generated by SBA-up for each month. Figures in **bold** and *italic* indicate, respectively, the largest and the smallest values of *up_ind* for each currency pair.

Trading period		EUR/ CHF	GBP/ CHF	EUR/ USD	GBP/ AUD	AUD /JPY	NZD /JPY	GBP/ JPY	EUR/ NZD
2014	Aug	0.06	0.03	0.41	0.01	0.13	**0.62**	0.07	0.31
	Sep	0.01	0.18	0.32	0.34	0.27	0.46	0.34	*0.15*
	Oct	0.15	0.03	0.05	0.12	0.46	0.24	0.12	0.35
	Nov	0.42	0.06	0.18	0.32	0.35	0.36	0.32	0.48
	Dec	0.36	**0.59**	0.06	0.10	0.51	0.13	0.10	0.46
2015	Jan	**0.73**	0.38	0.24	0.03	*0.03*	0.04	0.13	0.54
	Feb	0.04	0.28	0.13	**0.39**	0.23	0.02	0.29	0.43
	Mar	0.09	0.16	0.51	0.07	0.02	0.04	0.18	0.61
	Apr	0.11	0.06	0.42	0.10	**0.86**	0.16	*0.05*	0.62
	May	0.04	0.04	**0.61**	*0.01*	0.13	*0.01*	0.13	**0.71**
	Jun	*0.01*	*0.03*	0.51	0.20	0.07	0.07	0.72	0.51
	Jul	0.15	0.28	*0.04*	0.24	0.03	0.02	**0.96**	0.64

Experiment 7.2: Results' discussion

The objective of this experiment is to discover whether there exists a unique value of *down_ind* or *up_ind* for which SBA-down or SBA-up can consistently provide the best performance. By examining the **bold** and *italic* figures reported in Tables 7.6 and 7.7, we highlight the following observations:

1. Concerning SBA-down (Table 7.6): we note that SBA-down can generate maximum *RR* using either a small value or a large value of *down_ind*. For example, in the case of EUR/CHF: the maximum returns generated by SBA-down in January 2015 obtained by *down_ind* = *– 0.84*. However, the maximum returns generated by SBA-down in December 2014 obtained by *down_ind* = **– 0.01**. The majority of the results corresponding to the other currency pairs support this note: the maximum *RR* can be attained using either a small value or a large value of *down_ind*. For example, in the case of EUR/USD, SBA-down may generate the highest returns using a small value (as in January with *down_ind* = *– 0.96*) or with a large value (as in July 2015 with *down_ind* = **– 0.05**).

   In general, we note that the difference between the smallest and the largest values of *down_ind* (see numbers formatted in **bold** and *italic* for each column in Table 7.6) is more than 0.60 in most cases (the only exception is in the case of GBP/AUD).
2. Concerning SBA-up (Table 7.7): we note that SBA-up is able to generate higher returns using either a small value or a large value of *up_ind*. For example, in the case of EUR/CHF,

the maximum return generated by SBA-up in June 2015 is obtained with a low value of *up_ind* = *0.01*. However, the maximum profits produced by SBA-up in January 2015 are obtained with a large *up_ind* = **0.73**. The majority of the results corresponding to the other currency pairs validate this note. For example, in the case of AUD/JPY, SBA-up may generate the highest returns with a small value of *up_ind* (as in January 2015 with *up_ind* = *0.03*) or using a large value of *up_ind* (as in April 2015, with *up_ind* = **0.86**).

In general, we note that the difference between the smallest and the largest values of *up_ind* shown in bold in Table 7.7 is more than 0.50 in most cases (the only exception is the case of GBP/AUD).

3. The results of Tables 7.6 and 7.7 suggest that it would be wrong to assume that *up_ind* = *down_ind.* This indicates that downtrends and uptrends may have different behaviours; which conforms to the findings of Tsang et al. [77].

To conclude, these two observations above (1. and 2.) suggest that, in most cases, there is no specific value, or a tight range, for the parameters *down_ind* and *up_ind* for which SBA-down and SBA-up will exhibit the best performance consistently. This conclusion raises the need for a dynamic version of BA.

7.5.3 Experiment 7.3: Evaluation of the performance of DBA-down and DBA-up

In this experiment we apply DBA-down and DBA-up to the eight sets of rolling windows (previously composed in Section 6.4.4). For each of DBA-down and DBA-up, we start with 1,000,000 monetary units as the initially invested capital. We use the same money management approach described in Section 6.5.1. Table 7.8 reports the general performance, during the overall trading period of seven months, of both versions of DBA in this experiment. We consider the bid and ask prices in our experiments. When DBA-down or DBA-up triggers a buy (or sell) signal we use the ask (or bid) price as quoted by the market maker. The annualized RR are reported in Appendix E.

The column 'Currency Pair' denote the considered currency pair. The column 'Trading Strategy' indicates which version of DBA is applied. The column 'RR' is the total *RR*. The column 'Profit Factor' is calculated by dividing the sum of all generated returns by the sum of incurred losses during the overall trading period of seven months. The column 'Max Drawdown (%)' refers to the worst scenario measured as the worst peak-to-trough decline in capital during the trading period of seven months. The column 'Win Ratio' is the overall probability of having a wining trade. The last row in Table 7.8 is interpreted as follows: applying DBA-up to EUR/NZD generates a rate of return (*RR*) of 32.81% during the trading period of seven months. In this case, DBA-up executes 2960 trades with an overall win ratio of 0.71. The maximum drawdown in capital is –3.2 %. The details of the monthly Rates of Return (*RR*) corresponding to applying DBA-down and DBA-up to these currency pairs are shown below in Tables 7.9 and 7.10 respectively.

Table 7.8: Summary of trading performance of the DBA-down and DBA-up models following the seven months out-of-sample period (from 1/1/2015 to 31/7/2015) for the eight currency pairs.

Currency Pairs	Trading Strategy	RR	Profit Factor	Total Number of Trades	Max Drawdown (%)	Win Ratio
EUR/CHF	DBA-down	5.93	1.88	2008	– 13.9	0.69
	DBA -up	5.79	1.86	2105	– 15.4	0.68
GBP/CHF	DBA-down	6.66	1.90	2486	– 12.8	0.67
	DBA -up	10.41	1.91	2606	– 15.2	0.67
EUR/USD	DBA-down	– 1.61	0.81	1919	– 5.5	0.62
	DBA-up	0.21	1.01	2142	– 6.0	0.63
GBP/AUD	DBA-down	7.07	1.67	2542	– 5.0	0.62
	DBA-up	6.14	1.68	2469	– 5.1	0.63
GBP/JPY	DBA-down	– 1.00	0.84	1792	– 6.6	0.62
	DBA-up	– 0.52	0.92	1752	– 4.8	0.61
NZD/JPY	DBA-down	18.29	2.04	3194	– 4.9	0.66
	DBA-up	23.18	2.04	3196	– 5.6	0.65
AUD/JPY	DBA-down	12.91	1.93	2717	– 4.7	0.67
	DBA-up	11.95	1.97	2567	– 4.0	0.68
EUR/NZD	DBA-down	28.41	2.28	2892	– 3.1	0.72
	DBA-up	32.81	2.21	2960	– 3.2	0.71

Table 7.9: Summary of monthly *RR* of trading with the DBA-down model following the seven months out-of-sample period of each of the eight currency pairs shown in Table 7.8.

Trading period	**EUR/ CHF**	**GBP/ CHF**	**EUR/ USD**	**GBP/ AUD**	**GBP/ JPY**	**NZD/ JPY**	**AUD/ JPY**	**EUR/ NZD**
Jan 2015	0.14	0.93	– 0.50	1.44	0.41	2.87	1.53	2.56
Feb 2015	1.27	0.85	– 1.20	1.69	0.64	2.09	2.30	2.54
Mar 2015	1.02	0.99	– 1.39	0.24	– 0.22	3.04	1.81	3.29
Apr 2015	0.28	0.40	0.03	0.27	0.41	3.60	1.12	4.24
May 2015	0.97	0.58	0.60	2.10	0.42	3.11	2.15	5.74
Jun 2015	0.93	1.47	0.49	0.44	0.30	1.63	2.30	4.99
Jul 2015	1.32	1.44	0.36	0.89	– 2.96	1.95	1.70	5.05
Sum	**5.93**	**6.66**	**– 1.61**	**7.07**	**– 1.00**	**18.29**	**12.91**	**28.41**

Table 7.10: Summary of monthly *RR* of trading with the DBA-up model following the seven months out-of-sample period of each of the eight currency pairs shown in Table 7.8.

Trading period	**EUR/ CHF**	**GBP/ CHF**	**EUR/ USD**	**GBP/ AUD**	**GBP/ JPY**	**NZD/ JPY**	**AUD/ JPY**	**EUR/ NZD**
Jan 2015	– 1.56	0.82	0.23	1.62	1.68	3.06	2.62	1.73
Feb 2015	1.46	2.04	0.25	0.50	– 0.04	2.61	1.67	4.24
Mar 2015	2.00	2.66	– 0.18	1.08	0.56	3.61	1.29	3.9
Apr 2015	0.87	1.36	– 0.32	1.16	0.52	1.63	1.37	5.57
May 2015	0.10	0.36	0.31	0.82	0.14	3.4	2.58	4.65
Jun 2015	1.44	1.41	0.17	0.62	0.05	3.37	1.08	5.29
Jul 2015	1.48	1.76	– 0.25	0.34	– 3.43	5.5	1.34	7.43
Sum	**5.79**	**10.41**	**0.21**	**6.14**	**– 0.52**	**23.18**	**11.95**	**32.81**

The monthly *RR*, reported in Tables 7.9 and 7.10, will be utilized to compute the Sharpe and Sortino ratios and Jensen's Alpha and Beta. The computation of these evaluation metrics take into consideration the minimum acceptable return (MAR) and risk-free rate (see Section 3.4 for more details). In this thesis we consider the interest rate for each currency to be both the MAR and the risk-free rate as well. Table 7.11, shown below, reports the interest rate of each currency as determined by the corresponding central banks during the considered trading period. To determine the MAR and the risk free rate for each currency pair, we consider the highest interest rate between the base and counter currencies. For example, in the case of GBP/JPY: the yearly interest rate of JPY was 0.00% whereas the interest rate of GBP was 0.50% (Table 7.11). Therefore, we consider 0.50% as the MAR and risk-free rate of GBP/JPY (Table 7.12). Table 7.12, shown below, displays the employed values of MAR and risk-free rates for each currency pair. These values, shown in

Table 7.12, will be used to compute the Sharpe and Sortino ratios and Jensen's Alpha and Beta. The Sharpe and Sortino ratios are shown in Table 7.13. We use the monthly *RR* of the buy and hold method to calculate Jensen's Alpha and Beta of DBA. The values of Jensen's Alpha and Beta are reported in Table 7.15.

Table 7.11: The interest rates of the 7 currencies (in %) considered as risk-free rates for each currency pair (source: World Bank's data bank http://databank.worldbank.org/data/home.aspx)

EUR	USD	AUD	JPY	NZD	GBP	CHF
0.05	0.25	2.50	0.00	3.50	0.50	– 0.75

Table 7.12: The employed values of MAR and risk-free rates for each currency pair.

EUR/ CHF	GBP/ CHF	EUR/ USD	GBP/ AUD	GBP/ JPY	NZD/ JPY	AUD/ JPY	EUR/ NZD
0.05	0.50	0.30	2.50	0.50	3.50	2.50	3.50

Table 7.13: The Sortino ratio and Sharpe ratios of the two versions of DBA.

Currency pair	DBA-down		DBA-up	
	Sortino ratio	Sharpe ratio	Sortino ratio	Sharpe ratio
EUR/CHF	∞	1.97	9.7	0.73
GBP/CHF	∞	2.45	∞	2.05
EUR/USD	– 3.35	-0.34	0.19	0.02
GBP/AUD	∞	1.16	∞	1.63
GBP/JPY	– 1.13	-0.16	– 0.62	– 0.08
NZD/JPY	∞	3.46	∞	2.78
AUD/JPY	∞	4.03	∞	2.55
EUR/NZD	∞	3.18	∞	2.72

Table 7.14: Summary of the monthly RR (%) obtained by applying the buy and hold strategy to each of the eight considered currency pairs. The trading period is from 1/1/2015 to 31/7/2015.

Trading period	EUR/ CHF	GBP/ CHF	EUR/ USD	GBP/ AUD	GBP/ JPY	NZD/ JPY	AUD/ JPY	EUR/ NZD
Jan 2015	– 12.88	– 9.68	– 6.48	2.07	5.43	– 9.04	– 7.28	0.54
Feb 2015	1.75	5.17	– 1.07	1.45	4.59	6.6	3.02	– 5.08
Mar 2015	– 1.95	– 2.01	– 3.66	– 1.42	– 3.73	– 1.14	– 2.26	– 2.54
Apr 2015	0.10	– 0.60	3.96	– 0.45	3.34	1.60	3.49	2.38
May 2015	– 1.41	0.57	– 2.31	2.32	3.32	– 2.93	0.49	4.43
Jun 2015	0.99	1.92	1.72	1.59	1.34	– 5.41	0.27	6.12
Jul 2015	1.77	2.69	– 1.38	3.18	0.81	– 1.84	4.48	1.79
Sum	**– 11.63**	**– 1.94**	**– 9.22**	**8.74**	**15.10**	**–12.16**	**2.21**	**7.64**

Table 7.15: The values of Jensen's Alpha and Beta of both versions of DBA with reference to the buy and hold approach as benchmark. The values are rounded to one decimal digit.

Currency pair	DBA-down		DBA-up	
	Jensen's Alpha	Beta	Jensen's Alpha	Beta
EUR/CHF	0.74	0.06	0.49	0.20
GBP/CHF	0.90	0.02	1.43	0.05
EUR/USD	– 0.38	0.09	0.05	– 0.03
GBP/AUD	1.10	0.28	0.56	– 0.11
GBP/JPY	0.15	0.16	0.16	0.13
NZD/JPY	2.32	0.00	3.16	– 0.07
AUD/JPY	1.64	0.00	1.49	– 0.08
EUR/NZD	3.98	0.27	4.51	0.15

Furthermore, as we consider the B&H as a benchmark, we compare the Sharpe ratio produced by the B&H to that of DBA. Table 7.16, shown below, summarizes the Sharpe ratios produced by B&H (named SR_BH), DBA-down (named SR_DBA_Down) and DBA-up (named SR_DBA_Up). The values of SR_DBA_Down and SR_DBA_Up are extracted from Table 7.13, shown above. The Sharpe ratios of the buy and hold approach (denoted as SR_BH in Table 7.16) are computed based on the monthly RR of the B&H previously reported in Table 7.14. To validate the comparison between the Sharpe ratios of DBA and B&H statistically, we applied the Wilcoxon test with the null hypothesis being that the median difference between the Sharpe ratios of DBA and the buy and hold approach is null. The test statistics 'W' resulting from the two Wilcoxon tests are reported in Table 7.17.

Table 7.16: The Sharpe ratio values corresponding to the buy and hold (SR_BH), DBA-down (SR_DBA_Down), and DBA-up (SR_DBA_Up).

	EUR/ CHF	GBP/ CHF	EUR/ USD	GBP/ AUD	GBP/ JPY	NZD/ JPY	AUD/ JPY	EUR/ NZD
SR_BH	– 0.35	– 0.07	– 0.42	0.69	0.74	– 0.44	0.03	0.22
SR_DBA_Down	1.97	2.45	– 0.34	1.16	– 0.16	3.46	1.4	3.18
SR_DBA_Up	0.73	2.05	0.02	1.63	– 0.08	2.78	1.65	2.72

Table 7.17: The test statistics '**W**' of the conducted Wilcoxon tests of comparing the Sharpe ratios of B&H with DBA-down and DBA-up based on the values reported in Table 7.16. The level of significance are denoted as: ****=1% and **=5%.*

	SR_DBA_Down	SR_DBA_Up
W	10^{**}	10^{**}

Experiment 7.3: Results' Discussion and Analysis

To begin, we examine the profitability of both versions of DBA. The monthly *RR* reported in Tables 7.9 and 7.10 indicate that both versions of DBA are, in most cases, profitable (except in a few cases; e.g. trading with DBA-down on EUR/CHF in January 2015, seen in Table 7.10). The total rates of return (*RR*), reported in Table 7.8, suggest that DBA can be attractively profitable (with *RR* of up to 32.81%; as in the case of applying DBA-up to EUR/NZD). The overall win ratio of DBA (i.e. the probability of having a winning trade) ranges between 0.72 (as in the case of applying DBA-down to EUR/NZD, see Table 7.8) and 0.62 (as in the case of applying DBA-down to EUR/USD, see Table 7.8). We consider this range to be reasonably acceptable.

We also note that the profitability of DBA can vary largely from one currency pair to another. For instance, from Table 7.8 we can observe that in the case of EUR/NZD, DBA-up generates *RR* of 32.81%; whereas it incurs losses of –1.61% in the case of EUR/USD (in the same table). This indicates that the performance of DBA may vary substantially from one currency pair to another. This in turn suggests that a trader may want to consider other currencies, given that DBA may, possibly, perform better with these than those reported in this chapter. We want to iterate that we consider the instantaneous actual bid and ask prices for every trade in all experiments.

We then inspect the risk of DBA. Based on the results reported in Table 7.8, we identify that, in most cases, the maximum drawdown (*MDD*) is no worse than – 6.0% (except in a few cases). We consider these values of *MDD* to be reasonably low. Furthermore, the downside risk (Section 3.3) of DBA is null in most of these experiments, which is why most values of the Sortino ratio reported in Table 7.13 are at positive infinity (denoted as ∞). Also, all the values of the figures in the 'Beta' column (indicated in Table 7.15) range between –1.0 and 1.0. This range indicates that DBA is less volatile than the buy and hold approach. Keep in mind that the volatility of *RR* is usually used as an indicator of risk.

Furthermore, we examine the risk-adjusted performance of DBA. For this purpose, we consider the values of the Sharpe ratio and Jensen's Alpha shown in Tables 7.13 and 7.15 respectively. The Sharpe ratio is mostly positive. A positive Sharpe ratio indicates that the DBA has surpassed the chosen risk-free rate of interest shown in Table 7.13. This result indicates that, in most cases, DBA generates worthy excess returns for each additional unit of risk it takes. The Jensen's Alpha results (in Table 7.15) are, generally, consistent with the Sharpe ratio scores. We conclude that, generally, DBA earns more than enough returns to be compensated for the risks it took over the trading period.

Lastly, as part of evaluating the risk-adjusted performance of DBA, we compare the Sharpe ratio of buy and hold to that of DBA. To validate this comparison statistically, we employ the Wilcoxon test to find out whether there is any difference between the Sharpe ratio produced by DBA and the buy and hold approach. The test statistics ‘W’ of these tests, reported in Table 7.17, are both marked as (**). Therefore, we reject the null hypothesis at the 5% level of significance. In other words, the Wilcoxon test suggests that the B&H approach cannot provide equal Sharpe ratios to that provided by DBA-down and DBA-up.

We conclude from the above analysis that DBA-down and DBA-up generate more returns and are less risky than the buy and hold method. Additionally, both versions of DBA can be highly profitable, with total *RR* of more than 30% (Table 7.8). We also argue that DBA can, in most cases, deliver a positive Sharpe ratio. Finally, the established variety of the selected currency pairs in the initial dataset (Section 6.4.1) suggests that DBA can be profitably applied to a wide range of currency pairs.

7.5.4 Experiment 7.4: Comparing the RR of DBA and SBA

In this section we compare the *RR* of DBA to SBA (with SBA being assigned randomly picked parameters). We should mention that in Section 7.4.1 we evaluated the maximum possible *RR* of both versions of SBA. Rationally, DBA is not capable of producing higher *RR* than the estimated maximum *RR* of SBA (reported in Tables 7.2 and 7.4). Our objective in this experiment is rather to answer the question: What is the probability that the dynamic BA will produce higher *RR* than the static BA provided that the parameters of SBA (i.e. *down_ind* and *up_ind*) have been assigned random values?

To answer this question, in the case of EUR/CHF, we apply each of SBA-down and SBA-up 10,000 times to the seven applied windows of *EURCHF_RWDC0.1* using randomly picked values for the *down_ind* and *up_ind* parameters. Thus we obtain 10,000 *RR* for simulated trading with SBA-down and another 10,000 *RR* for simulating trading with SBA-up. We define γ as the fraction of how many of these 10,000 *RR* are lower than the returns obtained by DBA-down and DBA-up (reported in Table 7.9). The *EURCHF_RWDC0.*1 is one out of eight sets of rolling windows composed in Section 6.4.4. We repeat the same procedure to compute γ based on each of the remaining seven sets of rolling windows.

The results of γ are shown below in Table 7.18. The number shown in the last row of column ‘EUR/USD’ is 89. This indicates that the probability that DBA-up generates higher *RR* than SBA-up (with randomly selected values of *up_ind*) is 89%. Similarly, the number shown in the last row of column ‘EUR/NZD’ is 91. This indicates that the probability that DBA-up generates higher *RR* than SBA-up (with randomly assigned values of *up_ind*) is 91%. The rest of the numbers in this table are interpreted similarly.

Table 7.18: The values of the probability γ (%) for the considered currency pairs.

	EUR/ CHF	GBP/ CHF	EUR/ USD	GBP/ AUD	AUD/ JPY	NZD/ JPY	GBP/ JPY	EUR/ NZD
DBA-down vs. SBA-down	88	85	81	70	91	86	92	93
DBA-up vs. SBA-up	97	87	89	99	84	87	89	91

When examining the results in Table 7.18, we note that the probability that DBA will produce higher *RR* than SBA (with randomly chosen parameters) is, mostly, over 80%. We consider this probability as very good. The minimum value of γ is 70% (as in the case of GBP/AUD), which we consider as acceptable. We take these results as evidence of the efficiency of our procedures (FIND_DOWN_IND and FIND_UP_IND, Section 7.3.3) to find appropriate values for the parameters *down_ind* and *up_ind*.

7.5.5 Experiment 7.5: Compare the RR and risk of both versions of DBA

The objective of this experiment is to test whether both versions of DBA provide similar returns and risk (based on Experiment 7.3, Section 7.4.3). We consider the rates of return (*RR*) and the *MDD* as the main indicators of the profitability and the risk respectively. We consider the values of *RR* and *MDD* obtained by trading with both versions of DBA. The values of these *RR* and *MDD* are summarized in Table 7.19 below (based on the performance of DBA-down and DBA-up reported in Table 7.8.). Firstly, we apply the Wilcoxon test with the null hypothesis being that the median difference between the two sets of *RR* of DBA-down and DBA-up (shown in the column *RR* in Table 7.19) is zero. Secondly, we apply the Wilcoxon test to the two sets of *MDD* of DBA-down and DBA-up (shown in the column *MDD* in Table 7.19), the null hypothesis being that the median difference between them is zero.

The test statistics ‘W’ returned by the Wilcoxon test, reported in Table 7.20 below, are not statistically significant, at the level of 5%. In other words, the Wilcoxon test could not reject the hypothesis that the medians of *RR* of DBA-down and DBA-up are equal. Similarly, the Wilcoxon test could not reject the hypothesis that the medians of *MDD* of DBA-down and DBA-up are equal. We consider this result as rational; because both versions of DBA, DBA-down and DBA-up, have, essentially, mirrored trading rules.

Table 7.19: The summaries of *RR* and *MDD* resulted from trading with DBA-down and DBA-up

Currency Pair	***RR***		***MDD***	
	DBA-down	**DBA-up**	**DBA-down**	**DBA-up**
EUR/CHF	5.93	5.79	– 13.9	– 15.4
GBP/CHF	6.66	10.41	– 12.8	– 15.2
EUR/USD	– 1.61	0.21	– 5.5	– 6.0
GBP/AUD	7.07	6.14	– 5.0	– 5.1
GBP/JPY	– 1.00	– 0.52	– 6.6	– 4.8
NZD/JPY	18.29	23.18	– 4.9	– 5.6
AUD/JPY	12.91	11.95	– 4.7	– 4.0
EUR/NZD	28.41	32.81	– 3.1	– 3.2

Table 7.20: The test statistics ‘**W**’ of the conducted Wilcoxon tests of comparing the *RR* and *MDD* of DBA-down and DBA-up based on the numbers reported in Table 7.19. The levels of significance are denoted as: ****=1% and **=5%*. The table of critical value of ‘**W**’ can be found at http://sphweb.bumc.bu.edu/otlt/mph-modules/bs/bs704_nonparametric/BS704_Nonparametric4.html

	RR	***MDD***
W	30	34

7.6 DBA vs. other DC-based trading strategies

In this section, we compare DBA to two DC-based trading strategies, namely: ‘DCT1’ (Aloud [15]) and ‘Alpha Engine’ (Golub et al., [16]). The authors of these trading strategies did not claim to employ any forecasting models. The details of these two strategies can be found in Sections 4.4.1 and 4.4.4 respectively. We will compare these strategies with DBA in terms of both concept and performance.

7.6.1 The DC-based trading strategy: DCT1

In this section, we compare DBA with the trading strategy named ‘DCT1’ (Aloud [15]). The details of this strategy was reviewed in Section 4.4.1. Here we briefly recap the mechanism of this strategy, then we compare it with DBA.

DCT1 runs a DC summary with a specific threshold named Δ_{xDC}. DCT1 consists of two trading rules:

- DCT1 initiates a new position (either buy or sell) at the DC confirmation point of one DC event.
- DCT1 closes this trade at the DC confirmation point of the following DC event.

Initially, the trader defines a range of thresholds. DCT1 examines this range to automatically compute: (1) the DC threshold Δ_{xDC}, and (2) the type of trade (whether contrarian or trend follower). For this purpose, DCT1 examines the profitability of each threshold in the specified range using historical price data (as a training set). For each threshold value, DCT1 will apply the above trading rules from two points of view: counter trend (CT) and trend follow (TF). Based on its produced *RR* during the training period, DCT1 returns the type of trade (CT or TF) and the threshold Δ_{xDC} corresponding to the highest produced returns. These parameters (type of trade and threshold) are then utilized to trade over the applied (out-of-sample) period.

We highlight the following differences between DBA and DCT1:

- Both versions of DBA, DBA-up and DBA-down, are contrarian. Whereas, DCT1 could be either contrarian or trend follower.
- DBA triggers a new trade only if the price change during the OS event exceeds a certain threshold. DCT1 triggers a new trade exactly at the DCC point of a DC event.

Nevertheless, DCT1 and DBA have a common feature which is: they both close trade at the DC confirmation point of the next DC event.

In terms of the evaluation of DCT1 and DBA, we have the following observations:

- DCT1 was backtested using high frequency data of one currency pair: EUR/USD. Evaluating a trading strategy using one asset is not convincing according to Pardo [52], who emphasizes the importance of backtesting using a set of assets with different trends. In this chapter, DBA was backtested using eight currency pairs that exhibit different trends (see Section 6.4.1).
- The author reported that DCT1 was able to produce a rate of return of 6.2% during a testing period of one year using data sampled with time-intervals of 1 millisecond. The *RR* produced by DBA-up is 0.21% within seven months using minute-by-minute data (the case of EUR/USD, Table 7.8, Section 7.5.3). Therefore, it would be oppressive to confirm that DCT1 outperforms DBA.

- The author in [15] did not report any measurement of risk (e.g. MDD) or risk-adjusted metrics (e.g. Sharpe ratio) of DCT1. Therefore we cannot compare DCT1 with DBA from these perspectives.
- The author that the authors in [15] did not report the number of trades executed by DCT1. Therefore, it is hard to compare the impact of transaction costs on the RR produced by DCT1 and DBA.

7.6.2 The DC-based trading strategy: The ‘Alpha Engine’

In this section, we compare DBA with the trading strategy named ‘Alpha Engine’ (introduced by Golub et al., [16]). The details of this strategy were reviewed in Section 4.4.4. Here we briefly recap the mechanism of this strategy, then compare it with DBA.

The Alpha Engine consists of opening a counter-trend position when the overshoot value (*OSV*) exceeds a specific threshold named ‘ω’:

$$\omega = \alpha \times theta \tag{7.3}$$

Where, $theta$ is the employed DC threshold and α is a parameter. The value of α depends on the inventory size denoted as ‘I’.

The Alpha Engine does not have an explicit stop-loss rule. Instead, it employs a sophisticated money management approach: When the Alpha Engine opens a position, it keeps increasing and decreasing the size of this position until a profit is reached. The increasing and decreasing of the position is designed to mitigate the accumulation of large inventory sizes during trending markets. The generation of a new trade (either buy or sell) depends on two factors:

- The inventory size denoted as ‘I’; which is used to manage the value of α in (7.1). Thus, I serves to control the time at which Alpha Engine triggers a new trade.
- The size of a trade is a factor of a probability indicator (denoted as ‘$\mathcal{L}$’). The value of $\mathcal{L}$ is used as an estimation of the probability that the trend will move up or down provided the current state. The value of $\mathcal{L}$ is determined using a transition network model which has two states: the DC threshold $theta$ and the threshold ‘ω’. If the markets show normal behavior then $\mathcal{L} \approx 1$. On the other hand, in the case of abnormal market behavior $\mathcal{L} \approx 0$. The objective of $\mathcal{L}$ is to prevent the Alpha Engine from building up large positions which it cannot unload.

To summarize, the management of the position is a function of two variables: the size of inventory ‘I’ and the probability indicator ‘$\mathcal{L}$’. This approach of computing, and managing, the size of a position is an integrated part of the Alpha Engine. The Alpha Engine considers the uptrends and downtrends separately so that it adopts two instances of the parameter ω; namely ω_{down} and ω_{up}. For more details about the mechanism of Alpha Engine see Golub et al., [16].

The Alpha Engine has three common features with Dynamic Backlash Agent (DBA):

- The positions of both trading strategies are countertrend, meaning that a price move down triggers a buy; a price move up, a sell.
- They both try to analyse the uptrends and downtrends separately.
- They both open positions when the *OSV* exceeds certain *thresholds*. In the case of DBA, we have two thresholds (denoted as *down_ind* and *up_ind*). Similarly, in the case of the Alpha Engine, the authors identified two thresholds (denoted as ω_{down} and ω_{up}).

As for the differences between DBA and Alpha Engine, we have the following observations:

- The most important difference between DBA and Alpha Engine is that the former has an explicit stop-loss rule (Section 7.3.3) whereas the latter does not. The money management approach employed by Alpha Engine makes it pretty complicated in comparison to DBA.
- The Alpha Engine may manage multiple positions simultaneously. Whereas, at any time, DBA can have only one position opened (based on the adopted money management approach described in Section 6.5.1).
- Both DBA and Alpha Engine employ some parameters to decide when to initiate a new trade (i.e. *down_ind* and *up_ind* in the case of DBA; ω_{down} and ω_{up} in case of Alpha Engine). However, they have different approaches to compute these parameters. DBA adopts a computational approach, as explained in Section 7.3.3, whereas, Alpha Engine uses the size of the inventory '*I*' to manage ω_{down} and ω_{up}.
- An important advantage of Alpha Engine is that the authors did not fine-tune any parameters to maximize performance. In the case of DBA, the value of DC threshold $theta$ is to be set by the user. Further experiments should be done in this regard. For instance, we do not know how the value of the DC threshold $theta$ may affect the performance of DBA.

The performance of Alpha Engine was examined using a portfolio comprising 23 currency rates, sampled tick-by-tick, over a period of 8 years and yielded a return of 21.34% (including bid and ask price). As can be seen in Table 7.8 (Section 7.5.3), DBA may have generated *RR* of more than 30% within 7 months (see the last row in Table 7.8). These results indicate that DBA is able to produce higher *RR* than Alpha Engine. However, the author that the authors in [16] did not report the number of trades executed by the Alpha Engine. Therefore, it is hard to compare the impact of transaction costs on the RR produced by the Alpha Engine and DBA.

The authors in [16] reported that Alpha Engine has an annual Sharp ratio of 3.06. The Sharpe ratio is intended to measure the return earned in excess of the risk-free rate per unit of volatility (7.2). However, the authors did not specify the risk-free rate in [16]! On the other hand, the results, shown in Table 7.13 (Section 7.5.3) suggest that DBA-down delivered a higher Sharpe ratio than Alpha Engine (e.g. in the case of NZD/JPY the Sharpe ratio was 3.46 and in the case of EUR/NZD it was 3.18).

$$\text{Sharpe ratio} = \frac{R_p - R_f}{\sigma_p} \tag{7.4}$$

where: R_p denote the expected portfolio return and R_f is the risk-free rate. σ_p refers to the standard deviation of the portfolio's returns and is utilized to measure the volatility of the returns.

To conclude, we argue that DBA has simpler trading rules than Alpha Engine. We also argue that DBA could be more profitable than Alpha Engine. However, it could be argued that Alpha Engine is more robust than DBA, in the sense that a trader does not have to fine-tune any parameter to maximize the performance.

7.7 Summary and conclusion

In this chapter, we introduced a contrarian trading strategy, named BA, which is based on the DC framework. BA opens a position when the overshoot value (OSV) exceeds the values of specific parameters (Section 7.2). BA has two types: Static and Dynamic. The static type of BA, SBA, relies on the expertise of the investor to set these parameters. By contrast, the dynamic type of BA, DBA, applies a DC-based computational approach to examine historical prices to automatically find appropriate values for the parameters. Then, DBA uses these values to trade over the out-of-sample (trading) period (Section 7.3). We consider DBA, the autonomous type of BA, as our original trading strategy, whereas, SBA serves to compute the best and worst possible performances of BA (Section 7.5.1).

To evaluate the performance of DBA we adopted the same methodology employed in Chapter 6 to assess the performance of TSFDC: We applied DBA to the eight sets of rolling windows previously composed in Section 6.4.4, each set corresponding to one currency pair. Each set comprises a training period to which we applied the predetermined DC-based computational approach to compute the values of the parameters. We used a set of evaluation metrics to measure the profitability and risk of DBA, taking into account the instantaneous actual bid and ask prices throughout the backtesting process. However, like all other DC-based trading strategies (e.g. [15] [16] [17] [78]), the transaction costs were not considered in our experiments. As a benchmark model, we implemented the standard buy and hold strategy. We also compared the performance of DBA to other DC-based trading strategies (Section 7.6).

The experimental results (reported in Section 7.4.2) suggest that DBA is mostly profitable. By examining the returns reported in Table 7.8 (Section 7.4.2), we can conclude that DBA can be attractively profitable (with total *RR* of more than 30%) and yet retain an attractive level of risk (with an *MDD* equal to –3.2%). When examining the values of Jensen's Alpha (shown in Table 7.15, Section 7.4.2), we can see that DBA generates promising returns compared to the level of risk it takes in relating to the buy and hold method. The values of Beta (Table 7.15, Section 7.4.2) would indicate that in all cases DBA is less volatile than the buy and hold method. We compared the DBA to two other DC-based trading strategies (Section 7.6) and argued that DBA outperforms one of them. Finally, the conducted Wilcoxon tests suggest that the Buy and Hold approach cannot provides equal Sharpe ratio to that provided by DBA.

To conclude, in this chapter we developed a DC-based trading strategy, named DBA; which does not rely on any forecasting model. As our main contribution, we argue that DBA can be highly profitable. We also argue that DBA can provide better Sharpe ratios and RR than another DC-based trading strategy (Section 7.6.2). We examined the effectiveness of DBA over eight different currency pairs that have different patterns, leading us to conclude that DBA could be successful in a broad range of currency pairs. Despite what would be considered as experimental weaknesses (e.g. ignoring the transaction costs), we argue that these results provide an evidence as to the usefulness of the DC framework as a basis for trading strategies.

8 Comparing TSFDC with DBA

In this thesis, we have presented two trading strategies TSFDC (Chapter 6) and DBA (Chapter 7). In this chapter, we aim to compare the performances of TSFDC and DBA. The objective is to find out whether one of them outperforms the other. More particularly, we focus on three aspects: profitability, drawdown and risk-adjusted returns. We rely on the results of the experiments organized in Chapters 6 and 7 to compare TSFDC and DBA.

We start this chapter with a brief summary of the two trading strategies, TSFDC and DBA. We then list the adopted metrics that will be utilized to compare TSFDC and DBA. Next, we summarize the results of our experiments (carried out in Chapters 6 and 7). Finally, we compare TSFDC and DBA based on these results.

8.1 Introduction

In Chapter 5, we presented a forecasting model that aims to predict the change in direction of a market's trend under the DC framework. In Chapter 6, we introduced a trading strategy named TSFDC, which is based on the forecasting model proposed in Chapter 5. TSFDC uses the historical prices of a given currency pair as an in-sample dataset to train this forecasting model. It then relies on the formed prediction model to decide when to trigger a buy or a sell signal during the out-of-sample (i.e. trading) period.

In Chapter 7, we introduced a trading strategy named DBA. In contrast to TSFDC, DBA does not employ any forecasting model. DBA initiates a trade when the magnitude of price change exceeds specific thresholds. DBA runs a predefined procedure, which examines historical (in-sample) prices using a DC-based approach, to determine the value of these thresholds. Then, DBA uses the values of these thresholds to decide when to start a trade during the out-of-sample (i.e. trading) period.

Both TSFDC and DBA are contrarian strategies. We have evaluated both strategies using the same methodology and datasets. We utilized eight currency pairs from the FX market, sampled minute-by-minute. For each currency pair, we composed seven rolling windows (see Section 6.4.4) and applied both strategies to these rolling windows. Our results indicated that both strategies could be attractively profitable. We concluded that both strategies, TSFDC and DBA, outperform the buy and hold approach as well as other DC-based trading strategies.

In this chapter, we compare the performances of TSFDC and DBA with the objective of studying whether one of them outperforms the other. Mainly, we focus on three fundamental aspects: profitability, maximum drawdown and risk-adjusted returns. For this purpose, we use the results of the experiments undertaken and discussed in Chapters 6 and 7.

8.2 Comparing the performances of TSFDC and DBA: Criteria of comparison

In this section, we list the metrics that will be considered to compare the performance of TSFDC and DBA. The detailed description of these metrics has been provided in Section 3.4, but we provide a recap of each metric here. These metrics are selected to represent three aspects:

- *Profitability*: We consider the 'Rate of Return (*RR*)' as the main metric to evaluate the profitability of a trading model. Let Total Profit (*TP*) represent the overall losses or gains during the entire trading period. We define *RR* as the gain or loss expressed as a percentage of the amount invested. In (8.1) *INV* denote the initial capital employed for investment.

$$RR = \frac{TP}{INV} * 100 \tag{8.1}$$

- *Maximum Drawdown*: We use the Maximum Drawdown (*MDD*) to measure the risk of a trading strategy (as in [4] [16] [17]). The *MDD* measures the risk as the worst-case-scenario of a given trading strategy. In (8.2), $capital\ (t_i)$ denote the value of capital at time (t_i). The *maximum capital*(t_i) refers to the maximum capital's value that has been reached since the beginning of trading up to time (t_i). Thus, $drawdown\ (t_i)$, (8.2), is interpreted as the peak-to-trough decline in capital from the start of the trading period up to time (t_i). The *MDD* (8.3) is the maximum value of all computed $drawdown\ (t_i)$.

$$drawdown\ (t_i) = \left|\frac{capital\ (t_i) - maximum\ capital(t_i)}{maximum\ capital(t_i)}\right| \tag{8.2}$$

$$MDD = Max\left(drawdown\ (t_i)\right), \qquad \forall\ time\ t_i \in trading\ period \tag{8.3}$$

- *Risk-adjusted return*: To assess this aspect, we use the 'Sharpe ratio' [68]. The Sharpe ratio is the average return earned in excess of the risk-free rate per unit of volatility. The formula to calculate the Sharpe ratio is:

$$\text{Sharpe ratio} = \frac{R_p - R_f}{\sigma_p} \tag{8.4}$$

  Where: R_p denote the expected portfolio returns; R_f is the risk-free rate; σ_p designs the standard deviation of the portfolio's returns.

8.3 Comparing the performances of TSFDC and DBA: The results

In this section, we summarize the results of the evaluations of TSFDC and DBA (from Chapters 6 and 7). More particularly, we consider the results corresponding to the metrics of the three aspects listed above. The results of each aspect are summarized in one table. For example, Table 8.1 summarizes the results of the *RR* of both strategies TSFDC and DBA. Similarly, Table 8.2 shows the results of *MDD*, and Table 8.3 shows the results of the Sharpe ratio. The last row, of each of these tables, denote the average of the results of each trading model for the selected metrics. Although not statistically significant, comparing these averages for both strategies can provide a general indication of the superiority of one of them, if any.

In these tables, for each currency pair (i.e. each row), one number is formatted in **bold**. This formatting is to highlight the best performance among the four trading models: TSFDC-down, TSFDC-up, DBA-down and DBA-up. For example, in Table 8.1, let us take the results of the currency pair EUR/CHF. The number '**9.13**' is formatted in **bold**, which implies that the best obtained *RR* by the four models is 9.13% and this was produced by TSFDC-down (as shown in the corresponding column's header). The same interpretation applies for the remaining rows (i.e. currency pairs) of Table 8.1.

Table 8.1: Comparing the profitability, measured as 'Rate of return (*RR*)', of TSFDC and DBA. For each currency pair, the **bold** figure represents the best performance across the four strategies: TSFDC-down, TSFDC-up, DBA-down, and DBA-up.

Currency pair	TSFDC-down	TSFDC-up	DBA-down	DBA-up
EUR/CHF	**9.13**	4.83	5.93	5.79
GBP/CHF	10.82	**12.07**	6.66	10.41
EUR/USD	– 1.46	– 1.46	– 1.61	**0.21**
GBP/AUD	**9.02**	0.67	7.07	6.14
GBP/JPY	– 2.72	– 4.93	– 1.00	**– 0.52**
NZD/JPY	**26.98**	26.37	18.29	23.18
AUD/JPY	12.09	**15.40**	12.91	11.95
EUR/NZD	**41.87**	41.22	28.41	32.81
Average *RR*	**13.22**	11.77	9.58	11.25

Likewise, for each currency pair (i.e. each row) shown in Tables 8.2 and 8.3, the number formatted in **bold** denote the supremacy of a trading strategy under the specified metric. In the next section we focus on the figures formatted in **bold** to compare the performances of TSFDC and DBA.

Table 8.2: Comparing the Maximum Drawdown (*MDD*) of TSFDC and DBA. For each currency pair, the **bold** figure represents the best performance across the four strategies.

Currency pair	TSFDC-down	TSFDC-up	DBA-down	DBA-up
EUR/CHF	– 19.4	– 21.1	**– 13.9**	– 15.4
GBP/CHF	– 14.0	– 13.8	**– 12.8**	– 15.2
EUR/USD	– 10.5	– 9.1	**– 5.5**	– 6.0
GBP/AUD	– 6.4	– 6.5	**– 5.0**	– 5.1
GBP/JPY	– 7.8	– 7.7	– 6.6	**– 4.8**
NZD/JPY	– 5.9	– 6.5	**– 4.9**	– 5.6
AUD/JPY	– 6.9	– 7.2	– 4.7	**– 4.0**
EUR/NZD	– 7.0	– 7.2	**– 3.1**	– 3.2
Average *MDD*	– 9.7	9.9	**– 7.1**	– 7.4

Table 8.3: Comparing the risk-adjusted return, in terms of the Sharpe Ratio, of TSFDC and DBA. For each currency pair, the **bold** figure represents the best performance across the four strategies.

Currency pair	TSFDC-down	TSFDC-up	DBA-down	DBA-up
EUR/CHF	1.79	1.58	**1.97**	0.73
GBP/CHF	1.94	1.15	**2.45**	2.05
EUR/USD	– 0.18	**0.19**	– 0.34	0.02
GBP/AUD	**1.81**	1.00	1.16	1.63
GBP/JPY	– 0.22	– 0.32	– 0.16	**– 0.08**
NZD/JPY	1.60	**4.59**	3.46	2.78
AUD/JPY	1.37	**5.08**	4.03	2.55
EUR/NZD	1.50	2.20	**3.18**	2.72
Average *Sharpe ratio*	1.20	1.93	**1.97**	1.55

8.4 Comparing TSFDC and DBA

8.4.1 In terms of profitability

In this section, we analyze the rate of return *RR* results shown in Table 8.1. The analysis of the **bold** figures in Table 8.1 suggests that TSFDC generates more *RR* than DBA in 6 out of 8 currency pairs. The averages of the *RR* (shown in the last row of Table 8.1) indicate that TSFDC generates higher returns than DBA. For instance, the average *RR* of TSFDC-down over the eight currencies is 13.22%, whereas neither DBA-down nor DBA-up has an average *RR* of more than 11.50% (the last row in Table 8.1). These observations suggest that TSFDC is more profitable than DBA.

8.4.2 In terms of maximum drawdown

In this section, we compare the estimated *MDD* of TSFDC and DBA. The analysis of the **bold** figures in Table 8.2 indicate that TSFDC has a worse *MDD* than DBA in all cases. Although purely indicative, the averages of the MDD results (the last row in Table 8.2) indicate that both versions of DBA have better *MDDs* than both versions of TSFDC. Some studies (e.g. [4] [16] [17]) consider the maximum drawdown *MDD* as a metric to measure the risk of a trading strategy. Thus, we conclude from the results of *MDD* that DBA is more advantageous than TSFDC in terms of risk.

8.4.3 In term of risk-adjusted performance

In this section, we compare the risk-adjusted returns of TSFDC and DBA. When we examine the values of Sharpe's ratio (in Table 8.3), we note that the average Sharpe ratio of DBA-down is larger than the average Sharpe ratios of both versions of TSFDC (as shown in the last row of Table 8.3). However we also note that the average Sharpe ratio of DBA-down (which is 1.55) is less than the average Sharpe ratio of TSFDC-up (which is 1.93). We also note that DBA provides a greater Sharpe ratio only in 4 out of 8 currency pairs (see **bold** figures in Table 8.3). Therefore, we do not consider the supremacy of DBA over TSFDC, in terms of risk-adjusted returns, as considerable.

8.5 Conclusion

In this thesis, we have introduced two trading strategies based on the DC framework, namely TSFDC (Chapter 6) and DBA (Chapter 7). The former employs a forecasting approach to decide when to trade while the latter does not. In this chapter, we compared the performances of TSFDC and DBA with the objective of finding out whether either of these strategies outperforms the other. Principally, we considered three aspects: profitability (measured as rate of returns *RR*), maximum drawdown *MDD* (used as a measure of risk) and risk-adjusted return (as measured by the Sharpe ratio). The comparisons carried out in this chapter indicate that TSFDC is more profitable than DBA. However, DBA is less risky than TSFDC. We also observed that DBA marginally outperforms TSFDC in terms of risk-adjusted returns. We conclude that neither TSFDC nor DBA outperforms the other in all aspects. These results conform to the Modern Portfolio Theory (MPT) of Markowitz [107], which states that to generate more profit an investor must undertake higher risk. With TSFDC being more profitable but riskier than DBA, choosing which model to implement relies on the level of risk the investor is willing to withstand.

Part III

Concluding Remarks

9 Conclusions

The Directional Change (DC) Framework is an approach to studying price movements in financial markets. Many studies have reported that the DC framework is helpful in analysing the price movements and traders' behaviors in the FX market. Some studies have tried to develop trading strategies based on the DC framework. This study set out to explore, and consequently to provide a proof of, the potential of the Directional Changes framework as the basis of a profitable trading strategy. This chapter provides a summary of the thesis, points out its contributions, and discusses possible future research work.

9.1 Summary

The DC framework is an event-based technique to summarize price movements in the financial market. Under the DC framework the market is cast into alternating upward and downward trends. A trend is identified as a change in market price larger than, or equal to, a given threshold. This threshold, named $theta$, is set by the observer and usually expressed as a percentage. In Section 4.3 we reviewed some studies (e.g. [11] [12] [13] [77]) that have demonstrated the usefulness of the DC framework in analyzing price movements in the FX market. The consensus amongst these studies is that, whilst an ideal DC-based trading strategy could be amazingly profitable, nonetheless, the full promise of the DC framework for developing trading strategies has not been completely exploited [16] [19]. In Chapter 3, we arranged existing trading strategies into two groups: 1) strategies that embed forecasting approaches (e.g. [6] [41] [42] [43] [44] [45] [46]); and 2) strategies that do not rely on any forecasting model (e.g. [7] [8] [54] [57] [58] [59] [61]).

Our intended aim of this research was to explore, and consequently to provide a proof of, the convenience of the Directional Changes (DC) framework as a basis of a profitable trading strategy. To attain our stated objective, and in line with existing research, we developed two DC-based trading strategies: one strategy, named TSFDC, which is based on forecasting DC (Chapter 6); and a second strategy, named DBA, which is based on the DC framework but does not employ any forecasting method (Chapter 7). We examined the performance of TSFDC and DBA in the foreign exchange (FX) market using the same methodology and datasets.

In this chapter, we summarize the functionalities of TSFDC and DBA. We also highlight the differences between our proposed trading strategies, TSFDC and DBA, and some existing DC-based trading strategies. Finally, we list our contributions and suggest future research.

9.2 In a nutshell: TSFDC and DBA

9.2.1 TSFDC: A trading strategy based on forecasting Directional Changes

In Chapter 6 we introduced our first DC-based trading strategy, named TSFDC. TSFDC was designed as a forecasting-based trading strategy. Forecasting the change of a trend's direction in a financial time series is a common problem (e.g. [41] [80] [81] [87]), however, this problem has never been formalized under the DC context. Therefore, as a first step, we provided a formalization of the problem of forecasting the change of a trend's direction under the DC framework (Section 5.2.2). To this end, we tracked price movements using two DC thresholds: *STheta* and *BTheta*. We formalized the problem as the following: 'to forecast whether the magnitude of total price change of a DC trend, as observed under *STheta*, will be at least equal to *BTheta* before the trend changes'.

We also discovered an original DC-based indicator, named OSV_{BTheta}^{STheta}, and selected an appropriate machine learning procedure to propose a solution for the established forecasting problem (Section 5.4.1). We applied our forecasting model to eight currency pairs from the foreign exchange market. The experimental results suggested that the accuracy of our prediction model ranged between 62% and 82%, outperforming the traditional ARIMA technique (Section 5.6.1). These results indicate that our proposed indicator, OSV_{BTheta}^{STheta}, is useful for forecasting purposes under the DC framework.

The second step consisted of employing the established forecasting model to develop a trading strategy named 'TSFDC' (Chapter 6). TSFDC relies on this forecasting model to decide when to initiate a new trade. To evaluate the performance of TSFDC, we applied it to eight currency pairs, using a monthly-based rolling windows approach, for an overall out-of-sample trading period of seven months. The experimental results suggested that TSFDC can be highly profitable (Section 6.6). We also argued that TSFDC outperforms another DC-based trading strategy (Section 6.7).

9.2.2 DBA: The second DC-based trading strategy

The second trading strategy, named DBA, was introduced in Chapter 7. The objective was to develop a successful DC-based trading strategy that does not rely on any forecasting model. DBA opens a position when the overshoot value exceeds a particular *threshold*. DBA examines historical prices using a DC-based computational approach to determine the *threshold*. To evaluate the performance of DBA, we followed the same experimental methodology and utilized the same datasets previously adopted to evaluate the performance of TSFDC in Chapter 6. Our experimental results suggested that DBA can be highly profitable (Section 7.5.3). We also argued that DBA outperforms another DC-based trading strategy (Section 7.6).

It is worth highlighting an important difference between TSFDC and DBA: in contrast to DBA, TSFDC relies on a forecasting model which: 1) has clearly-defined dependent and independent variables and 2) employs a machine learning procedure to predict the dependent variable (Section 5.4). Thus, in contrast to DBA, we consider TSFDC to be a forecasting-based trading strategy.

A comparison between the performances of TSFDC and DBA was carried out in Chapter 8. The objective was to find out whether either TSFDC or DBA could outperform the other. This comparison focused on three principle aspects: profitability, drawdown and risk-adjusted returns. The results suggested that, in general, TSFDC generates higher returns than DBA (Section 8.3). However, they also suggested that DBA has a better maximum drawdown than TSFDC (Section 8.3). In addition, the results indicated that DBA has a slightly better risk-adjusted performance than TSFDC (Section 8.3). We concluded that neither DBA nor TSFDC could outperform the other in every aspect. These results suggest that either DBA or TSFDC could be an attractive choice for different types of traders. Choosing which strategy to adopt, TSFDC or DBA, would depend on the level of risk the trader is willing to undertake.

Despite what would be considered as defects in our experiments (e.g. ignoring the transaction costs), we argue that the results of the evaluation of the performances of TSFDC (Section 6.6.1) and DBA (Section 6.5.3) support our objective of providing proof of the usefulness of the DC framework as a basis for profitable trading strategies.

9.3 Comparing TSFDC and DBA with other DC-based trading strategies

In Section 4.4 we reviewed some existing DC-based trading strategies. In Chapters 6 and 7 we compared TSFDC and DBA to some of these trading strategies. In this section we review the differences between our proposed strategies, TSFDC and DBA, and other existing DC-based trading strategies.

9.3.1 Comparing TSFDC with other DC-based trading strategies

In Section 6.7, we compared TSFDC to two DC-based trading strategies proposed by Gypteau et al., [78] and Kampouridis and Otero [17]. The reason for choosing these particular trading strategies was that the authors of both studies, [17] and [78], stated that they were proposing trading strategies that employed forecasting models. In this section we summarize these comparisons.

1. It was in Section 6.7.1 that we compared TSFDC to the trading strategy presented by Gypteau et al., [78] and we recap the following differences here:

- TSFDC is founded on the well-articulated forecasting approach established in Chapter 5 which has clearly identified dependent and independent variables. Despite the fact that the authors in [78] declared that they aimed "*…to find an optimal trading strategy to forecast the future price moves of a financial market"*; they did not identify any dependent or independent variables.
- TSFDC relies on forecasting the change in direction of a market's trend to decide when to start a new trade, whereas the trading strategy by Gypteau et al., [78] was presented as a GP-tree. This GP-tree comprises multiple DC thresholds. The detection of DC events at these thresholds is interpreted as 'True' or 'False' values. Based on the detected event(s), the expression represented by a GP tree is a Boolean value that indicates the action (either buy or sell) to be taken.
- In Section 6.7.1 we argued that TSFDC was able to generate higher *RR* than the trading strategy introduced by Gypteau et al., [78].

2. We compared the trading strategy named DC+GA presented by Kampouridis and Otero [17] with TSFDC in Section 6.7.2. Here, we recap the following remarks:
   - TSFDC has different trading rules as to when to start or end a trade than DC+GA: For instance, TSFDC focuses on the magnitude of price change (e.g. *STheta* and *BTheta*) to decide when to start a trade. Whilst, DC+GA initiates a trade when the *time* length of an OS event lasts longer than a specific *time-threshold* (see Section 6.7.1 for details).
   - TSFDC relies on the forecasting approach presented in Chapter 5 to decide when to trigger a new trade. Whereas, DC+ GA employs a GA module to anticipate the best *time-threshold* at which it should initiate a trade.
   - TSFDC uses two DC thresholds, whilst DC+GA may consider up to N_{theta} thresholds to decide when to initiate a trade.
   - The authors in [17] claimed that their objective was "*to offer a more complete analysis on the directional changes paradigm from a financial forecasting perspective*." However, in contrast to our forecasting approach established in Chapter 5, they did not identify any dependent or independent variables!
   - We compared the results of TSFDC and DC+GA in Section 6.7.2. We argued that TSFDC outperforms DC+GA in terms of produced *RR* and risk-adjusted returns.
   - However, the results of *MDD* suggest that DC+GA is less risky than TSFDC.

- A common feature between TSFDC and DC+GA is that they both try to analyse the uptrends and downtrends separately.

9.3.2 Comparing DBA with other DC-based trading strategies

In Section 7.6 we compared DBA to two other DC-based trading strategies, namely 'DCT1' [15] and 'the Alpha Engine' [16]. The authors of DCT1 and Alpha Engine did not state that their proposed trading strategies employed any forecasting model. In this section we briefly recap the differences and similarities between these trading strategies and DBA.

1. As for the differences between DBA and DCT1 [15], we have the following comments:
   - DBA is a contrarian strategy. Whereas DCT1 can be either contrarian or a trend follower.
   - DBA triggers a new trade only if the price change during the OS event exceeds certain thresholds. DCT1 does not use 'thresholds'. DCT1 triggers a new trade when a DC event is confirmed (i.e. at the DCC point).
   - In contrast to DBA, the performance of DCT1 was evaluated using only one currency pair (the EUR/USD). Furthermore, the authors did not report any measurement of risk or risk-adjusted performance for DCT1 in [15]. Therefore, we concluded that the employed methodology to evaluate the performance of DCT1 is not convincing.
   - Nevertheless, DCT1 and DBA have a common feature which is: they both close trade at the next DC confirmation point.

2. As for the differences between DBA and Alpha Engine [16], we have the following observations:
   - The most important difference between DBA and Alpha Engine is that the former has an explicit stop-loss rule (Section 7.3.3), whereas the latter does not. Alpha Engine employs a sophisticated money management approach. The Alpha Engine uses a transition network model to control the size of each new trade (Section 4.4.4).
   - As a result of the above point, Alpha Engine is able to manage multiple positions simultaneously, whereas at any time DBA can have only one open position.
   - DBA employs a computational approach to decide the *OSV* at which it should make a new trade. Whereas, Alpha Engine takes into consideration the total amount of inventory to decide the value of *OSV* at which it should make a new trade.
   - An important advantage of Alpha Engine is its robustness, in the sense that it automatically fine-tunes its own parameters. In the case of DBA, the user must specify the DC threshold

$theta$. Further experiments should be done to examine how the value of $theta$ may affect the performance of DBA.

- According to our experiments, DBA can produce higher *RR* than Alpha Engine. For instance, in the case of EUR/NZD, DBA was able to produce an RR of more than 28% in just seven months (see Table 7.8, Section 7.5.3), whereas the *RR* produced by Alpha Engine over a trading period of eight years was 21.34%!

Nevertheless, we can note some similarities between DBA and Alpha Engine:

- They both trigger contrarian trades.
- They both open positions during the overshoot when the price change reaches a specific threshold.
- They both try to analyse the uptrends and downtrends separately.

9.4 Contributions

This thesis contributes toward providing evidence as to the potential of the DC framework as a foundation for trading strategies. The major contributions of this work can be summarized as follows:

- We formulated the problem of forecasting the change of a trend's direction under the DC framework (Chapter 5). The objective was to forecast whether the current DC trend, of threshold *STheta*, will continue so that its total price change will reach another threshold named *BTheta* (Section 5.3). This objective was shortened in order to predict one Boolean variable named *BBTheta*.
- The second contribution was discovering a useful DC-based indicator named OSV_{BTheta}^{STheta}. We proved that this indicator is helpful in forecasting the change in direction of a market's trend within the DC context. We used this indicator to establish a forecasting model that demonstrated relatively good accuracy ranging between 62% and 82% (Section 5.6.2). We also proved that our forecasting model has better accuracy than the ARIMA model (Table 5.4, Section 5.6.1).
- We employed the proposed forecasting model to develop a successful trading strategy, named TSFDC (Chapter 6). We argued that TSFDC outperforms another DC-based trading strategy (Section 6.7). The results of the preliminary tests suggested that TSFDC could produce a positive Sharpe ratio in most cases (Section 6.6.1).
- We presented a second trading strategy, named DBA, which although based on the DC concept, does not rely on any forecasting model (Chapter 7). DBA follows a

computational approach to examine the historical prices in order to discover profitable trading rules as to when to initiate a trade. We argued that DBA can be highly profitable (Sections 7.6.1). We also argued that DBA outperforms another DC-based trading strategy. The results of the preliminary tests suggested that DBA could produce a positive Sharpe ratio in most cases (Section 7.5.3).

The comparison of TSFDC and DBA, carried out in Chapter 8, suggested that TSFDC produces more profit than DBA; but, DBA is less risky than TSFDC. Therefore, either strategy could be more advantageous for different types of traders, based on the level of risk the trader is willing to withstand (Section 8.4).

To conclude, the objective of this thesis was to explore, and consequently to provide a proof of, the usefulness of the DC framework as the basis of profitable trading strategies. Despite some experimental flaws (e.g. ignoring the transaction costs), the results of the evaluation of the performances of our proposed trading strategies, TSFDC (Section 6.6.1) and DBA (Section 7.5.3), support our stated objective. Although the rates of return (*RR*) generated by TSFDC and DBA are much less than the estimated maximum annual *RR* that could be possibly generated by a DC-based trading strategy (which is 1600% [19]), in our opinion, our strategies nevertheless represent a vital step in the right direction.

9.5 Future works

We believe that both the strategies introduced in this thesis, TSFDC and DBA, can be further improved in many ways.

9.5.1 Money management: Controlling order size

In this thesis we focused on discovering profitable trading rules under the DC framework. However, a trading system must consider two other essential parts: risk control and money management [33]. Money management refers to the actual size of the trade to be initiated [86]. Some studies (e.g. [52] [100]) reported that models that do not take into consideration effective money management decisions can lead to sub-optimal solutions. In this thesis we adopted a naïve approach to money management (previously described in Section 6.5.1). Thus, the overall performances of TSFDC and DBA could be improved by developing a good money management module. For this purpose, a worthy objective would be to relate the sizing of a new trade to periodic patterns of market activity. In other words, to discover the time at which TSFDC or DBA would mostly be profitable and, then, to use this discovery to decide the size of a new trade. Aloud el al., [19] reported that periodic patterns do exist under the DC framework. For example, Fig. 9.1, shown below, reports the number of events of two DC thresholds (0.03% and 0.10%) in different time periods of the 5th, 7th and 9th January 2009 in a EUR/CHF mid-price time series. This figure pinpoints two important observations: (a) the same periods of time with the same threshold size on different days may contain a different number of events, and (b) with the same threshold size, some periods on the same day have more events than others [19].

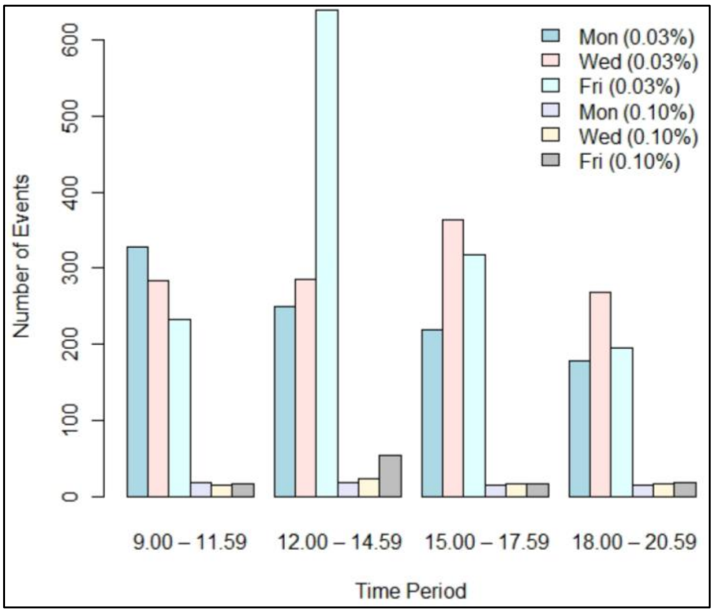

Fig. 9.1 Number of DC events of threshold 0.03% and 0.10% in different periods of the 5th (Monday), 7th (Wednesday) and 9th (Friday) January 2009 in a EUR/CHF mid-price time series. Source Aloud et al. [19]

Based on these observations, a DC-based trading strategy will probably perform differently during different time periods. As a future work, we propose to analyze the returns of TSFDC and DBA as a function of a time period (similar to Fig. 9.1). In other words, we would suggest discovering a relationship between time periods (i.e. hours of the day, days of the week) and the generated returns of each trade triggered by TSFDC and DBA. For this purpose, we can examine the existence of 'association rules' between the returns of all trades and time periods. Association rules can be utilized to discover and analyze the existence of strong rules among several variables, in databases, using some measures of interest [108]. Some machine learning algorithms (e.g. A priori algorithm [109], OPUS search algorithm [110]) could be of use for such a task. Then, the discovered association rules could be utilized to establish a function which determines the size of a trade.

9.5.2 *Identifying favorable markets conditions*

The experimental results reported in Chapters 6 and 7 showed that the performance of TSFDC and DBA can vary substantially from one currency pair to another. Knowing the market characteristics under which TSFDC and DBA perform best is an interesting topic. This knowledge could be achieved by applying the DC-based market profiling approach introduced by Tsang et al., [77]. They proposed a set of DC-based indicators that aim to characterize price dynamics (e.g. volatility, fluctuation, and maximum possible returns) over a specified period of a given market. They suggested that the proposed indicators can help a trader to decide which market to trade in (e.g. normal market condition, stress market condition).

The performance of TSFDC and DBA was tested using a rolling window approach (Section 6.5.1). In this context, we can consider the training period of a rolling window as the profiling period (i.e. we compute the profiling indictors based on the dataset of training periods of each rolling window). We could then measure selected evaluation metrics (e.g. rate of return, RR, maximum drawdown, MDD) when trading with TSFDC and DBA during the associated trading period of the same window. Table 9.1, shown below, illustrates our idea. The columns ‘TMV’, ‘R’, and ‘T’ are profiling indicators identified in Tsang et al., [77]. They would be utilized to characterize a given market during the training period of a rolling window. The columns ‘RR’ and ‘MDD’ represent the performance of TSFDC, or DBA, during the corresponding trading period.

The objective would be to find a relation between these profiling indicators and the selected evaluation metrics. The establishment of such a relationship will be useful in order to better anticipate the performance of TSFDC and DBA during the trading period. The examination of such a relationship could be effected using many machine learning algorithms. For example, if we consider *RR* as a set of qualitative elements (e.g. ‘profitable’, ‘unprofitable’) then the problem of finding such a relation becomes a classification problem which can be solved using algorithms such as C5.0 and J48graft. On the other hand, if we measure *RR* as a number (e.g. 2.1%, –1.5%), then we would have other algorithms at our disposal, such as M5P, to examine that relationship. Either route would enable us to decide whether a specific market is ‘favorable’ or ‘unfavorable’ for trading with TSFDC or DBA. Such market classification would allow us to allocate our capital more efficiently.

Table 9.1. An illustration of potential profiling indicators (which would be computed based on a training period) and evaluation metrics (which would be computed based on the associated trading period) of the same rolling window. The column named ‘….’ symbolises other profiling indicators presented in the study of Tsang et al. [77].

Market profiling during training period				**Evaluation of TSFDC and DBA during trading period**	
TMV	**R**	**T**	**….**	**RR**	**MDD**

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Appendix A: R-Code to Detect Directional Changes

In this appendix, we provide the R code, named '*DCSummary'*, which produces the DC summary of a particular price series, given a threshold $theta$, as explained previously in Section 4.2.

DCSummary.r

 # In the code below, the variable 'prices' denote the vector of price series. The codes of loading prices from a given file is irrelevant and, therefore, omitted.

```
l = length(prices) # 'prices' denote the vector of prices. l denote the number of prices' #observations in the prices series.
x_ext_index=1
while (i< l)
{
    if (mode <  1)# mode is downtrend
    {
        if (prices [i]< x_ext)
            {
            x_ext = prices [i]
            x_ext_index = i
            is_double_ext = 0
            }
            else if (((prices [i]– x_ext)/x_ext)>= theta)
            {
            nb_up=nb_up + 1
                if (is_double_ext < 1)
                {Event[x_ext_index] = "(start EXT UP)"
                }
                else
                {Event[x_ext_index] = "(OS DOWN & start EXT UP)"
                }
            Event[i] = "(start OS UP)"
            OS_up_OS_down_indicator[i] = 1
            x_os_index = i
            DCC = prices [x_ext_index]*(1+ theta)
            DCCs[i] = DCC
            OSV_OS[i]= (( prices [i]– DCC)/DCC)/theta
            x_ext_index = i
            x_ext= prices [i]
            mode =1
```

```
            is_double_ext =1
            }
      }
      else if( mode > 0) # mode is uptrend
      {
            if (prices [i] >x_ext)
            {
            x_ext = prices [i]
            x_ext_index = i
            is_double_ext = 0
            }
            else if (((prices [i]– x_ext)/x_ext) <= – theta)
            {
            nb_down=nb_down+ 1
                  if (is_double_ext < 1)
                  {Event[x_ext_index]= "(start EXT DOWN )"
                  }
                  else
                  {Event[x_ext_index] = "(OS UP & start EXT DOWN)"
                  OS_up_OS_down_indicator[x_ext_index] = 1
                  }
            Event[i] = "(start OS DOWN)"
            downTrendID = downTrendID + 1
            DCC = prices [x_ext_index] * (1– theta)
            trace_DCC = DCC
            DCCs[i] = DCC
            OSV_OS[i] = (( prices [i]– DCC)/DCC)/theta
            x_os_index = i
            x_ext_index = i
            x_ext = prices [i]
            is_double_ext =1
            mode = 0
            }
      }
i = i+ 1 # proceed with the next price's observation
}
DCSummary = data.frame(prices, EventType=Event, DCC_Prices=DCCs, OSV=OSV_OS)
```

At the end of the above R code, the *dataframe* named *DCSummary* will comprise four vectors:

- '*prices*': the initial price series,
- '*EventType*': comprising all DC and OS events detected
- '*DCC_Prices*': denote the price required to confirm the detection of a new DC event of the specified threshold *theta*.
- '*OSV*': the overshoot values computed at the DCC point of each DC event.

The *DCC* prices and the *OSV* are computed at the *DCC* point of each DC event (See Section 4.2.3).

Appendix B: The Big-Theta theorem

In this appendix, we introduce the Big-Theta theorem. This theorem states that: *"Each DC event of threshold BTheta will embrace another DC event of threshold STheta such that they both have the same extreme point*". In this appendix we firstly present the Big-Theta theorem. We will then prove it and provide an example.

Before going into the details, it is important to note that this appendix is not related to our contributions in this thesis. The conducted experiments, the reported results and conclusions in this thesis are completely independent of the material provided in this appendix. The objective of this appendix is rather to gain more insight into the DC framework and the Big-Theta theorem which could be helpful for future researches.

The Big-Theta theorem

In this appendix, we present the Big-Theta theorem which states that: *Each DC event of threshold BTheta will embrace another DC event of threshold STheta such that they both have the same extreme point*. In this section, we clarify this new theorem; then we will prove it in the next section. To exemplify this theorem, we consider Fig. B.1 shown below. Fig. B.1 illustrates two DC summaries, for a GBP/CHF price series, using two thresholds: *STheta* (0.1%) and *BTheta* (0.2%). In Fig. B.1, we can see that each DC event of threshold 0.2% embraces a DC event of threshold 0.1% *which starts at the same extreme point*. More explicitly, in Fig. B.1, we recognize three DC events of threshold *BTheta* (0.2%); namely [$AA^{0.2}$], [$BB^{0.2}$], and [$EE^{0.2}$] (shown in solid green lines). The extreme points of these DC events are A, B, and E. We can easily note that each of these extreme points is also the extreme point of another DC event of another threshold *STheta* (0.1%) namely [$AA^{0.1}$], [$BB^{0.1}$], and [$EE^{0.1}$]. Fig. B.1 exemplifies the fact that each extreme point observed under threshold 0.2% is also recognized as extreme point under threshold 0.1%.

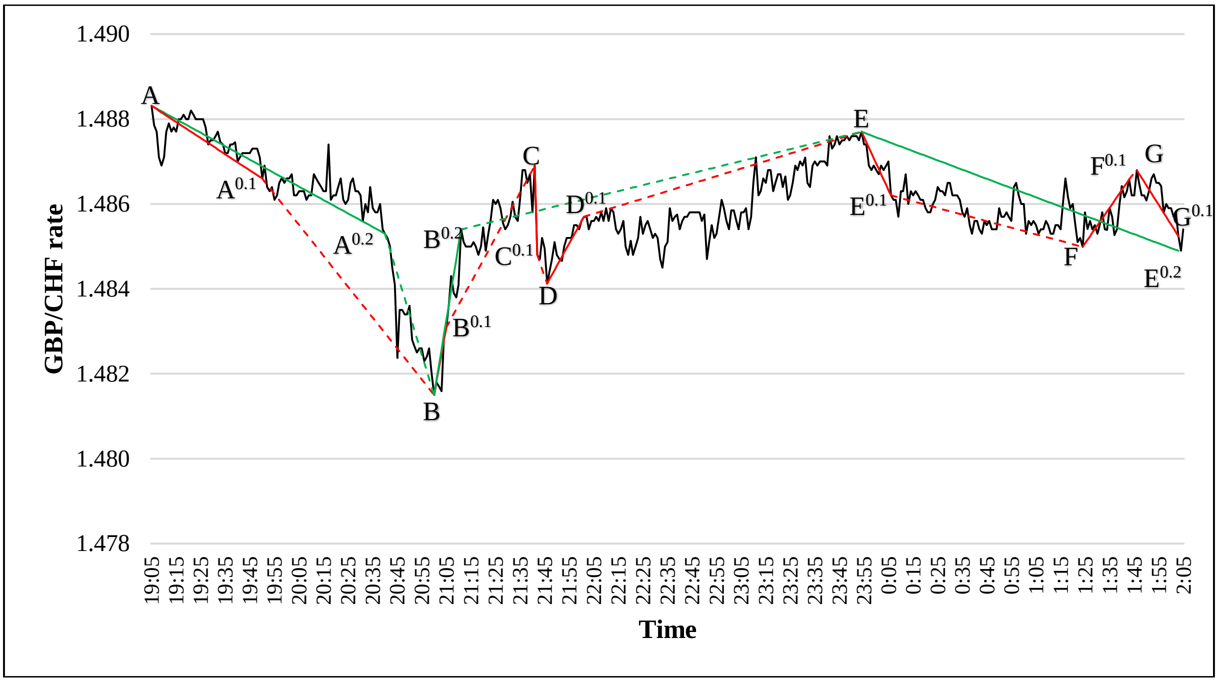

Fig. B.1. The synchronization of the two DC summaries using two thresholds: *STheta* (0.1%) and *BTheta* (0.2%). The black line indicates GBP/CHF mid-prices sampled minute by minute from 1/1/2013 19:05 to 1/2/2013 02:05. Solid red lines represent DC events. Dashed red lines represent OS events for threshold *STheta*. Solid red lines represent DC events. Dashed red lines represent OS events for threshold *BTheta*.

The proof

The objective of this section is to prove that "*An extreme point of a DC event of threshold BTheta is also an extreme point of another DC event of threshold STheta"*. In this section, we provide the proof for the case for which the market exhibit an upward trend under the DC summary of threshold *BTheta*. In other words, we will prove that "*the extreme point of an upward DC event of threshold BTheta is also an extreme point of another DC event of thresholds STheta"* (with *BTheta* > *STheta*). The argument in the case where the market exhibits a downtrend under threshold *BTheta* would be similar.

First, we reiterate the definition of *extreme point*. As previously stated in Section 4.2.1, the detection of a new DC event of thresholds *BTheta* is a formalized inequality:

$$\left|\frac{P_c - P_{EXT}^{next}}{P_{EXT}^{next}}\right| \geq BTheta \tag{B.1}$$

where:

- P_c: is the current price.
- P_{EXT}^{next}: If the market exhibits a downtrend, then P_{EXT}^{next} would refer to the lowest price observed so far in this particular downtrend. Similarly, if the market exhibits an uptrend, then P_{EXT}^{next} would refer to the highest price observed in this uptrend.

- If the inequality (B.1) holds, the time at which the market traded at P_{EXT}^{next} is called an 'extreme point'. Let $P_{EXT\_BTheta}^{next}$ denote the variable P_{EXT}^{next} as observed under the DC summary of threshold *BTheta.*

According to the DC framework, given a particular threshold, *BTheta,* an uptrend must be preceded by a downtrend with the same threshold (Section 4.2.1). Thus, the detection of a new uptrend under threshold *BTheta* can be done by analysing the preceding downtrend. If the market exhibits a downtrend under threshold *BTheta*, then, by definition, $P_{EXT\_BTheta}^{next}$ will refer to the lowest price for this particular downtrend. Let Ext_{BTheta}^{down} denote the extreme points of this particular downtrend observed under threshold *BTheta*. Similarly, let Ext_{BTheta}^{up} denote the extreme points of the following uptrend observed under threshold *BTheta*. Ext_{BTheta}^{up} is detected once we have

$$\frac{P_c - P_{EXT\_BTheta}^{next}}{P_{EXT\_BTheta}^{next}} \geq BTheta \qquad \text{(B.2)}$$

Suppose that we are tracking price movement of one price series with two DC thresholds *STheta* and *BTheta* simultaneously (with *BTheta* $>$ *STheta*). Let $P_{EXT\_STheta}^{next}$ denote the variable P_{EXT}^{next} as observed under the DC summary of threshold *STheta.*

<u>*Lemma B.1:*</u>

If the market exhibits a downtrend, as observed under threshold *BTheta*, then Ext_{BTheta}^{up} can occur only during a downward DC trend as observed under threshold *STheta* (for *STheta* $<$ *BTheta*).

<u>*Proof B.1:*</u>

Reasoning by contradiction, suppose that Ext_{BTheta}^{up} has occurred during an uptrend under threshold *STheta*. Let Ext_{STheta}^{up} denote the extreme point of this particular DC uptrend under threshold *STheta*. Note that Ext_{STheta}^{up} must be observed after Ext_{BTheta}^{down} (for *STheta* $<$ *BTheta*). This is because, based on the DC concept, we can identify a price drop, of threshold *BTheta,* which starts at the extreme point Ext_{BTheta}^{down}. Thus, we can implicitly, deduce the existence of a price drop of threshold *STheta* which starts at, or after, the observation of Ext_{BTheta}^{down} (as *STheta* $<$ *BTheta*). In other words, the market must have shown a downtrend, under threshold *STheta.* Let *down_STheta* denote this downtrend (with *down_STheta* being observed after the observation of Ext_{BTheta}^{down}). Consequently, if Ext_{BTheta}^{up} was observed during an uptrend under a threshold *STheta*, then the extreme point Ext_{STheta}^{up} must be observed after *down_STheta* and, consequently, after Ext^{down}_{BTheta} as well. In this scenario, we have an uptrend under threshold *STheta* that was preceded by *down_STheta*.

Provided that the market exhibits downtrend under threshold *BTheta*, then, by definition, $P^{next}_{EXT\_BTheta}$ will refer to the lowest price for this particular downtrend (Section 4.2). Following our reasoning by contradiction, if Ext^{up}_{BTheta}, with price $P^{next}_{EXT\_BTheta}$, has occurred during an uptrend observed under a threshold *STheta;* then we have two possible cases:

Case A: Ext^{up}_{BTheta} is actually overlapped with Ext^{up}_{STheta} (i.e. Ext^{up}_{STheta} and Ext^{up}_{BTheta} are actually the same point). In this case, the two uptrend DC events of thresholds *STheta* and *BTheta* have actually the same extreme point. In this case, the proof is done.

Case B: $Ext^{up}_{STheta}$is a distinct point other than Ext^{up}_{BTheta} and $Ext^{up}_{STheta}$is observed before Ext^{up}_{BTheta}. In this case, there must exist a point *X*, that fits in the uptrend of threshold *STheta*, such that $P_X < P^{next}_{EXT\_BTheta}$ (P_X denote the price at point *X*). This, however, contradicts with the fact that $P^{next}_{EXT\_BTheta}$ must be the lowest price for the preceding downtrend under threshold *BTheta*. Thus, Case B can never hold true, and the anticipated assumption that Ext^{up}_{BTheta} has occurred during an uptrend under threshold *STheta* was wrong.

Based on the above analysis, we can conclude that Ext^{up}_{BTheta} can occur only during a downward DC trend as observed under threshold *STheta* (for *STheta* < *BTheta*). Note that this analysis is independent from any other uptrends or downtrends those could possibly have occurred before the observation of Ext^{down}_{BTheta}. This is because, by definition, the value of $P^{next}_{EXT\_BTheta}$ is calculated with reference to the current trend only (Section 4.2.3).

Lemma B.2:

Let P_c denote the current price. Given that the market exhibits a downtrend under threshold *BTheta*, if $P_c < P^{next}_{EXT\_BTheta}$ (i.e. if the current price turns out to be the lowest price observed so far in this particular downtrend under threshold *BTheta*), then we will have $P_c < P^{next}_{EXT\_STheta}$ (i.e. the current price is also the lowest price observed so far for another downtrend as observed under threshold *STheta*).

Proof B.2:

If the market exhibits a downward trend under DC summary of thresholds *BTheta* then, by definition, $P^{next}_{EXT\_BTheta}$ denote the lowest price in this particular downtrend. From the description of the DC framework, we know that the value of $P^{next}_{EXT\_BTheta}$ may vary as the price movement continues (Section 4.2.1). By definition, in the case of a DC downtrend of threshold *BTheta*, the value of $P^{next}_{EXT\_BTheta}$ changes only if we encounter a new 'lowest price' (i.e. if $P_c < P^{next}_{EXT\_BTheta}$). In such a case, the value of $P^{next}_{EXT\_BTheta}$ will be assigned the value of the current price (P_c); that is $P^{next}_{EXT\_BTheta} = P_c$ (see Section 4.2.1).

We consider the following notes:

a. At the time of when $P^{next}_{EXT\_BTheta}$ is observed, the market exhibits downward trend under both thresholds *BTheta* and *STheta* (based on *Lemma B.1*).
b. By definition, $P^{next}_{EXT\_STheta}$ refers to the lowest price in a downtrend under threshold *STheta*.
c. By definition, $P^{next}_{EXT\_BTheta}$ refers to the lowest price in a downtrend under threshold *BTheta*.
d. Based on the points b. and c. above, both variables $P^{next}_{EXT\_STheta}$ and $P^{next}_{EXT\_BTheta}$ must refer to the lowest price observed so far in this particular downtrend.

Based on the four points above, if P_c turns out to be the lowest price observed so far for a particular downtrend under threshold *BTheta* (i.e. if $P_c < P^{next}_{EXT\_BTheta}$), then we must have $P_c < P^{next}_{EXT\_STheta}$. In such a case, the values of both variables $P^{next}_{EXT\_BTheta}$ and $P^{next}_{EXT\_STheta}$ must be updated so that they both become equal to P_c. In other words, if P_c is the lowest price of the current downtrend, under threshold *BTheta*, then we will have $P^{next}_{EXT\_BTheta} = P_c$ and $P^{next}_{EXT\_STheta} = P_c$.

<u>*Summary*</u>

Based on *Lemma B.1* and *Lemma B.2*, the above analysis can be summarized as follow:

If (the market exhibits a downtrend under threshold BTheta) then
If ($P_c < P^{next}_{EXT\_BTheta}$) *then*
$P^{next}_{EXT_{STheta}} = P_c$
$P^{next}_{EXT_{BTheta}} = P_c$

The objective of this section is *to prove that the extreme point of an upward DC event of threshold BTheta is also an extreme point of another DC event of thresholds STheta*. This can be proved as follows:

a. Based on the DC framework, if the market currently exhibits a downtrend under threshold *BTheta*, then the next DC event will be an upward DC event of the same threshold (Section 4.2.1).
b. By definition, if the market exhibits a downtrend under threshold *BTheta*, then $P^{next}_{EXT\_BTheta}$ would refer to the lowest price observed so far in this particular downtrend. As

the price movement continues, whenever we encounter a new price P_c such that $P_c < P^{next}_{EXT\_BTheta}$ then we adjust $P^{next}_{EXT\_BTheta}$ to become equal to P_c (i.e. $P^{next}_{EXT\_BTheta} = P_c$).

c. Based on the *Summary* above, if ((the market exhibits a downtrend under threshold *BTheta*) and ($P_c < P^{next}_{EXT\_BTheta}$)) then $P^{next}_{EXT\_STheta} = P^{next}_{EXT\_BTheta}$.

d. As the price movement continues, the value of P_c changes. The detection of the *extreme point* of the next upward DC event threshold *BTheta* is possible when (B.2) hold true. Let *Up_BTheta* denote this uptrend.

$$\frac{P_c - P^{next}_{EXT\_BTheta}}{P^{next}_{EXT\_BTheta}} \geq BTheta \tag{B.2}$$

e. Provided inequalities (B.2) and (B.3), we can conclude (B.4) and (B.5).

$$STheta < BTheta \tag{B.3}$$

$$\frac{P_c - P^{next}_{EXT\_BTheta}}{P^{next}_{EXT\_BTheta}} \geq BTheta > STheta \tag{B.4}$$

$$\frac{P_c - P^{next}_{EXT\_BTheta}}{P^{next}_{EXT\_BTheta}} > STheta \tag{B.5}$$

f. Based on point c. above, we have $P^{next}_{EXT\_STheta} = P^{next}_{EXT\_BTheta}$. Thus, if we replace $P^{next}_{EXT\_BTheta}$ by $P^{next}_{EXT\_STheta}$ in (B.5), we get

$$\frac{P_c - P^{next}_{EXT\_STheta}}{P^{next}_{EXT\_STheta}} > STheta \tag{B.6}$$

The inequality (B.6) denote the condition under which we can confirm the recognition of a new upward DC event of threshold *STheta*. Let *Up_STheta* denote this uptrend. The extreme point of *Up_STheta* is Ext^{up}_{STheta} which is specified by the time at which the market traded at $P^{next}_{EXT\_STheta}$ (see Section 4.2.1). Similarly, the inequality (B.2) denote the condition under which we can confirm the recognition of a new upward DC event of threshold *BTheta*. The extreme point of this new upward DC event is specified by the time at which the market traded at $P^{next}_{EXT\_BTheta}$. Based on point c. above, we will have $P^{next}_{EXT\_STheta} = P^{next}_{EXT\_BTheta}$. In other words, the extreme points of the new detected upward trends under thresholds *STheta* and *BTheta, Up_BTheta* and *Up_STheta*, are actually the same point.

Based on the analysis of the inequalities (B.2), (B.6), and point c. above, we can conclude that, the extreme point of the upward DC event of threshold *BTheta Up_BTheta* (corresponding to $P^{next}_{EXT\_BTheta}$ in point d. above) is also an extreme point of another upward DC event of threshold *STheta Up_STheta* (corresponding to $P^{next}_{EXT\_STheta}$ in point f. above).

An example

Next, we consider Table B.1 shown below as an example of the proof provided above. Table B.1 exemplifies the detection of new extreme points for DC analysis of two thresholds *STheta* and *BTheta* (0.2%) and sketching the progress of the value of P_{EXT}^{next} for both thresholds. The column P_c denote the current price at the given time. The columns 'DC analysis STheta (0.1%)' and 'DC analysis BTheta (0.2%)' are employed to highlight the observation of DC and OS events of thresholds *STheta* (0.1%) and *BTheta* (0.2%) respectively. The columns 'P_{EXT}^{next} *STheta*' and 'P_{EXT}^{next} *BTheta*' denote respectively the variables $P_{EXT\_STheta}^{next}$ and $P_{EXT\_BTheta}^{next}$ for the two DC summaries with the two thresholds *STheta* (0.1%) and *BTheta* (0.2%). The values in the columns 'Price change *STheta'* and 'Price change *BTheta'* are computed as the prices change between the values of P_c and P_{EXT}^{next}:

$$Price\ Change\ STheta = \left|\frac{P_c - P_{EXT\_STheta}^{next}}{P_{EXT\_STheta}^{next}}\right| \tag{B.7}$$

$$Price\ Change\ BTheta = \left|\frac{P_c - P_{EXT\_BTheta}^{next}}{P_{EXT\_BTheta}^{next}}\right| \tag{B.8}$$

when the value of (B.7) becomes larger than *STheta* we can confirm the detection of a new DC event of threshold *STheta*. Similarly, when the value of (B.8) becomes larger than *BTheta* we can confirm the detection of a new DC event of threshold *BTheta*.

In Table B.1, at time 20:45, we assume that the market exhibits a downtrend under threshold *BTheta*. Thus, based on *Lemma B.1*, the market also exhibits a downtrend under threshold *STheta* (based on Fig. B.1 above). Based on the DC framework, the next DC event would be an upward for both DC summaries (*STheta* and *BTheta*). At time 20:56, $P_{EXT\_BTheta}^{next}$ records a new value which is 1.48230 (see column P_{EXT}^{next} *BTheta*). In other words, the condition ($P_c < P_{EXT\_BTheta}^{next}$) holds true at time 20:56. Therefore, at time 20:56, we update $P_{EXT\_BTheta}^{next} = P_c = 1.48230$. Similarly, at time 20:56, we have $P_c < P_{EXT\_BTheta}^{next}$. Thus, we also update $P_{EXT\_STheta}^{next} = P_c = 1.48230$. Thus, we get $P_{EXT\_STheta}^{next} = P_{EXT\_BTheta}^{next}$ (the value of $P_{EXT\_STheta}^{next}$ can be seen under the column P_{EXT}^{next} *STheta*). At time 21:00, the value of $P_{EXT\_BTheta}^{next}$ hits a new record P_c =1.48150. Thus, the same rules apply again and we have $P_{EXT\_STheta}^{next} = P_{EXT\_BTheta}^{next} = 1.48150$.

Table B.1 An example of sketching the progress of the value of P_{EXT}^{next} and the detection of DC and OS events of thresholds *STheta* and *BTheta*. P_{EXT}^{next} *STheta* denote $P_{EXT\_STheta}^{next}$ and P_{EXT}^{next} *BTheta* denote $P_{EXT\_BTheta}^{next}$. All numbers are rounded to 5 decimal digits.

Time	P_c	DC analysis STheta (0.1%)	P_{EXT}^{next} *STheta*	Price change STheta	DC analysis BTheta (0.2%)	P_{EXT}^{next} *BTheta*	Price change BTheta	Point
20:45	1.48237		1.48237	0		1.48237	0	
20:46	1.48350		1.48237	0.00076		1.48237	0.00076	
20:47	1.48350		1.48237	0.00076		1.48237	0.00076	
20:48	1.48340		1.48237	0.00069		1.48237	0.00069	
20:49	1.48340		1.48237	0.00069		1.48237	0.00069	
20:50	1.48360		1.48237	0.00083		1.48237	0.00083	
20:51	1.48280		1.48237	0.00029		1.48237	0.00029	
20:52	1.48265		1.48237	0.00019		1.48237	0.00019	
20:53	1.48250		1.48237	0.00009		1.48237	0.00009	
20:54	1.48260		1.48237	0.00016		1.48237	0.00016	
20:55	1.48260		1.48237	0.00016		1.48237	0.00016	
20:56	1.48230		1.48230	0		1.48230	0	
20:57	1.48240		1.48230	0.00007		1.48230	0.00007	
20:58	1.48260		1.48230	0.00020		1.48230	0.00020	
20:59	1.48200		1.48200	0		1.48200	0	
21:00	1.48150	Start upward DC event	1.48150	0	Start upward DC event	1.48150	0	B
21:01	1.48180		1.48150	0.00020		1.48150	0.00020	
21:02	1.48170		1.48150	0.00014		1.48150	0.00014	
21:03	1.48159		1.48150	0.00006		1.48150	0.00006	
21:04	1.48280		1.48150	0.00088		1.48150	0.00088	
21:05	1.48310	Start upward OS event	1.48150	0.00108		1.48150	0.00108	$B^{0.1}$
21:06	1.48365		1.48365	0		1.48150	0.00145	
21:07	1.48430		1.48430	0		1.48150	0.00189	
21:08	1.48390		1.48430	0.00027		1.48150	0.00162	
21:09	1.48380		1.48430	0.00034		1.48150	0.00155	
21:10	1.48410		1.48430	0.00014		1.48150	0.00176	
21:11	1.48540		1.48540	0	Start upward OS event	1.48150	0.00263	$B^{0.2}$
21:12	1.48510		1.48540	0		1.48540	0	

At time 21:11, the value in the column 'Price change *BTheta*' becomes 0.00263; which is larger than *BTheta* (0.2%). Therefore, we confirm the detection of a new DC event of threshold *BTheta* (0.2%). The extreme point of this DC event, i.e. Ext_{BTheta}^{up}, corresponding to the least recorded price $P_{EXT\_BTheta}^{next}$, is point B which was observed at time 21:00. In this example, our objective can be rephrased as "*to prove that point B is also an extreme point for another DC event of threshold STheta (0.1%)*"

In this example, we can detect a DC event for threshold *STheta* when the value of the column 'Price change *STheta*' exceeds *STheta* (0.1%). At time 21:05, the value of 'Price change *STheta*' is 0.00108 which is larger than 0.1%. Thus, at time 21:05 we can confirm the observation of a DC event of threshold *STheta*. The extreme point of this DC event, i.e. Ext^{up}_{STheta}, is also point B as shown in Table B.1 at time 21:00 (as $P^{next}_{EXT\_STheta} = P^{next}_{EXT\_BTheta}$).

To conclude, in this appendix we proved that when the market exhibits an uptrend under threshold *BTheta*, the extreme point of a DC event of threshold *BTheta* is also an extreme point of another DC event of threshold *STheta*. However, the same logic (*Lemma B.1* and *Lemma B.2*) holds true in the case for which the market exhibits a downtrend under the threshold *BTheta*.

Appendix C: The Impact of *BTheta* on the Accuracy of our Forecasting Model

This appendix lists the results of Experiment 5.2 '*The Impact of BTheta on the Accuracy of our Forecasting Model*' (presented in Section 5.6.2) for the remaining four currency pairs: GBP/JPY, NZD/JPY, AUD/JPY, and EUR/NZD. *STheta* is fixed to 0.10%. The reported accuracy corresponds to the testing (out-of-sample) period. For each of these currency pairs, the testing period is 7 months.

For each of these tables, we apply the linear regression model to examine the impact of *BTheta* on the accuracy of our approach. The resulting *p*-values for all cases are consistently above the common level of 0.05. This indicates that *BTheta* has a significant impact on the accuracy of our approach. We also note that the accuracy of our approach is fairly high for most levels of True-False imbalance (α). In each table, the accuracies range between 0.62 and 0.82; which conforms to the conclusion reported in Section 5.6.2.

Table B.1: Analyzing the impact of *BTheta* on the accuracy of our forecasting approach. The case of GBP/JPY. The testing period is 7 months in length. The reported accuracy corresponds to the testing (out-of-sample) period. The number of DC events of threshold *STheta* (0.1%) is 2056 (i.e. number of instances of *BBTheta* is 2056).

Uptrends of DC summary with *STheta* = 0.10%				Downtrends of DC summary with *STheta* = 0.10%		
BTheta (%)	**Accuracy**	**α**		**BTheta (%)**	**Accuracy**	**α**
0.13	0.81	0.64		0.13	0.82	0.64
0.14	0.77	0.55		0.14	0.76	0.55
0.15	0.73	0.49		0.15	0.73	0.49
0.16	0.71	0.43		0.16	0.71	0.43
0.17	0.68	0.38		0.17	0.69	0.38
0.18	0.66	0.34		0.18	0.67	0.34
0.19	0.64	0.31		0.19	0.64	0.31
0.20	0.63	0.28		0.20	0.62	0.28
0.21	0.62	0.26		0.21	0.61	0.26
0.22	0.61	0.23		0.22	0.60	0.23

Table B.2: Analyzing the impact of *BTheta* on the accuracy of our forecasting approach. The case of NZD/JPY. The testing period is 7 months in length. The reported accuracy corresponds to the testing (out-of-sample) period. The number of DC events of threshold *STheta* (0.1%) is 3609 (i.e. number of instances of *BBTheta* is 3609).

Uptrends of DC summary with *STheta* = 0.10%				Downtrends of DC summary with *STheta* = 0.10%		
BTheta (%)	**Accuracy**	**α**		**BTheta (%)**	**Accuracy**	**α**
0.13	0.82	0.63		0.13	0.82	0.63
0.14	0.78	0.54		0.14	0.78	0.54
0.15	0.74	0.48		0.15	0.74	0.48
0.16	0.72	0.42		0.16	0.72	0.42
0.17	0.70	0.37		0.17	0.70	0.37
0.18	0.67	0.33		0.18	0.67	0.33
0.19	0.65	0.30		0.19	0.65	0.30
0.20	0.64	0.27		0.20	0.64	0.27
0.21	0.63	0.25		0.21	0.63	0.25
0.22	0.62	0.22		0.22	0.62	0.22

Table B.3: Analyzing the impact of value of *BTheta* to the accuracy of our forecasting approach. The case of AUD/JPY. The testing period is 7 months in length. The reported accuracy corresponds to the testing (out-of-sample) period. The number of DC events of threshold *STheta* (0.1%) is 3184 (i.e. number of instances of *BBTheta* is 3184).

Uptrends of DC summary with STheta = 0.10%				Downtrends of DC summary with STheta = 0.10%		
BTheta (%)	**Accuracy**	**α**		**BTheta (%)**	**Accuracy**	**α**
0.13	0.79	0.56		0.13	0.79	0.56
0.14	0.78	0.53		0.14	0.77	0.53
0.15	0.75	0.51		0.15	0.76	0.51
0.16	0.70	0.49		0.16	0.70	0.49
0.17	0.68	0.48		0.17	0.69	0.48
0.18	0.66	0.45		0.18	0.66	0.45
0.19	0.65	0.42		0.19	0.66	0.42
0.20	0.64	0.35		0.20	0.64	0.35
0.21	0.64	0.31		0.21	0.65	0.31
0.22	0.63	0.28		0.22	0.63	0.28

Table B.4: Analyzing the impact of *BTheta* on the accuracy of our forecasting approach. The case of EUR/NZD. The testing period is 7 months in length. The reported accuracy corresponds to the testing (out-of-sample) period. The number of DC events of threshold *STheta* (0.1%) is 4735 (i.e. number of instances of *BBTheta* is 4735).

Uptrends of DC summary with STheta = 0.10%				Downtrends of DC summary with STheta = 0.10%		
BTheta (%)	**Accuracy**	**α**		**BTheta (%)**	**Accuracy**	**α**
0.13	0.82	0.63		0.13	0.82	0.63
0.14	0.78	0.55		0.14	0.78	0.55
0.15	0.74	0.50		0.15	0.74	0.50
0.16	0.72	0.47		0.16	0.72	0.47
0.17	0.70	0.40		0.17	0.70	0.40
0.18	0.67	0.39		0.18	0.67	0.39
0.19	0.65	0.33		0.19	0.65	0.33
0.20	0.64	0.29		0.20	0.64	0.29
0.21	0.63	0.27		0.21	0.63	0.27
0.22	0.62	0.25		0.22	0.62	0.25

Appendix D: Pseudo code of TSFDC-down

In this appendix we provide the pseudo code of TSFDC-down. This code should clarify how the trading strategy uses the forecasting model established in Chapter 5 to trade. In a nutshell, there are two stages:

- Stage 1: In which we learn the forecasting model using an in-sample dataset. This forecasting model returns a decision tree model.
- Stage 2: In which we use the decision tree, shaped in Stage 1, and apply the trading rules of TSFDC-down to trade over the applied period.

TSFDC-down

```
STheta = smaller threshold
BTheta = bigger threshold
 Stage 1: learning the forecasting model (see Chapter 5 for details)
Set the training period. Initialize:
                    Start_training_date
                    End_training_date
For each price in Start_training_date up-to End_training_date
         Apply DC summary  using threshold STheta
End for
DC_STheta_TRENDS = all detected trends based on the threshold theta
For each price in Start_training_date up-to End_training_date
         Apply DC summary  using threshold BTheta
End for
DC_BTheta_TRENDS = all detected trends based on the threshold BTheta
For each trend in DC_STheta_TRENDS
       Compute $OSV_{BTheta}^{STheta}$ and BBTheta. //use DC_BTheta_TRENDS for this purpose
End for
DecisionTree = Learn_Forecasting_model (J48,$OSV_{BTheta}^{STheta}$, BBTheta)
     Stage 2: use the forecasting model to trade on the applied period
Set the applied period. Initialize:
              Start_applied_date
              End_applied_date
Open_position = False // initially we do not have any opened position
For each price in Start_applied_date  up-to End_applied_date
     Run DC analysis
    If [a DC downtrend (STheta) is observed] and [Open_position = False] then
         Compute $OSV_{BTheta}^{STheta}$
         FBBTheta = DecisionTree ($OSV_{BTheta}^{STheta}$)// DecisionTree () returns True or False
               If FBBTheta = False then
```

```
30.                 Trigger buy signal
31.                 Open_position = True
32.             Else
33.                 If a DC downtrend (BTheta) is observed then
34.                     Trigger buy signal
35.                     Open_position = True
36.                 End if
37.             End if
38.         End if   //line 25
39.         If [Open_position = True] and [a DC uptrend (STheta) is confirmed] then
40.             Trigger sell signal
41.             Open_position = False
42          End if
43.     End for   //line 23
44.     End TFDC-down
```

Appendix E: Annualized rate of return produced by TSFDC and DBA

In this appendix we estimate the annualized rate of return of the developed trading strategies TSFDC and DBA. We follow a simple mathematical rule to compute the estimated annualized rate of return based on the results of the experiments described in Section 6.6.1 and 7.5.3:

$$Annulatized\ RR\ = \frac{12}{7} \times\ RR$$

where RR denote the rates of return produced by a trading strategy throughout the trading period of 7 months for a given currency pair (see Sections 6.6.1 and 7.5.3)

Table E.1: Annualized RR for TSFDC and DBA

	TSFDC-down	**TSFDC-up**	**DBA-down**	**DBA-up**
EUR/CHF	15.65	8.28	10.16	9.93
GBP/CHF	18.54	20.69	11.42	17.85
EUR/USD	– 2.50	1.15	– 2.76	0.36
GBP/AUD	15.46	7.87	12.12	10.53
GBP/JPY	– 4.66	– 8.45	– 1.71	– 0.89
NZD/JPY	46.25	45.21	31.35	39.74
AUD/JPY	20.73	26.40	22.13	20.48
EUR/NZD	71.78	70.67	48.70	56.25