Backlash Agent: A Trading Strategy Based On Directional Change

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Abstract — **Directional Change (DC) is a technique to summarize price movements in a financial market. According to the DC concept, data is sampled only when the magnitude of price change is significant according to the investor. Unlike with time series, DC samples data at irregular time intervals. In this paper, we propose a contrarian trading strategy that is based on the DC concept. We examine the profitability of our trading strategy using three currency pairs: EUR/CHF, GBP/CHF and EUR/USD. The results show that our proposed trading strategy is profitable with Alpha over than 10 in some cases. However, counting the bid and ask prices can decrease considerably the profits under particular settings.**

Keywords – Algorithmic trading; directional change; FX trading.

I. Introduction

The literature on trading strategies encompasses plenty of trading models. Many of the existing studies develop Neural Network models to forecast market's prices and provide trading strategies based on these models (e.g. [1, 2]). Other trading models are based on the stylized facts of a specific market (e.g. [3]). References [4, 5] provide trading strategies using technical trading rules. The literature also includes trading strategies those embrace momentum models (e.g. [6, 7]). Other research seeks to combine multiple trading strategies (e.g. [8]). The criterion common to all these studies is that the authors developed and tested their trading strategies using time series data. In other words, they sampled market prices at fixed time intervals, be it days, minutes, etc.

Directional change (DC) is another approach to summarize the movement of financial markets' prices [9]. Under the DC framework, in contrast to time series, the focus is on the magnitude of price change and time is the varying factor [10]. The DC concept has been proved many times to be helpful in the study of the FX market. For instance, in [11] the authors report 12 scaling laws by analyzing 14 different currency pairs using the DC concept. Reference [12] introduce the so-called Scale of Market Quakes (SMQ) based on the DC concept. SMQ aims to quantifying FX market activity at declarations of significant economic and political events. Furthermore, the author in [13] uses the DC concept to present a model that explains how minor differences in FX market activities can change price trends under definite conditions. Lately, [10] provide an approach to profile a specific asset based on innovative variables those derived from the DC analysis of high frequency price movements.

However, only a few studies sought to develop trading models based on the DC concept. For instance, [14] presents a DC-based contrarian trading strategy that attempt to exploit the scaling laws in the FX market. More recently, [15] introduces a trading strategy based on forecasting the daily closing price of a financial market. The proposed forecasting model embed a combination of the DC framework and Genetic Programming.

We believe that the benefit of using the DC framework to develop a trading model has not been fully exploited yet. In this paper we provide evidence that the DC concept can be helpful as the basis of a trading strategy. To this end, we propose a new contrarian trading strategy, named Backlash Agent, which is based on the DC concept. We provide a set of experiments to examine the profitability and in-depth analysis of our proposed strategy. These experiments are conducted using three currency pairs: EUR/CHF, GBP/CHF and EUR/USD.

This paper continues as follow: Section II provides an overview of the DC concept. Section III describes two types of our trading strategy, with the corresponding trading rules. Section IV provides a detailed description of our experiments and the evaluation metrics. We report and discuss the results in Section V. We conclude in Section VI.

II. Directional Changes: an Overview

The DC approach focuses on significant changes in price movements. Here, the significance is defined as price changes larger than, or equal to, a predetermined threshold decided by the investor. Let *theta* be this threshold. Usually, *theta* is expressed as a percentage. According to the DC concept, the market can be in downtrend or in uptrend. If we observe a price rise of magnitude *theta*, we say that the market is in uptrend [9]. Similarly, if we detect a price decline of magnitude *theta*, we say that the market is in downtrend. An uptrend is directly followed by a downtrend; and vice versa (see Fig.1). The price at which a downtrend, or an uptrend, begins is called P_{EXT}. In the case of an uptrend, the P_{EXT} is the lowest price of the uptrend. In the case of a downtrend, the P_{EXT} is the highest price of the downtrend. A trend comprises a directional change (DC) event and an overshoot (OS) event. Let P_c be the current price of the market. A DC event is detected when we observe a price P_c that satisfies (1).

$$\left|\frac{P_c - P_{EXT}}{P_{EXT}}\right| \geq theta \tag{1}$$

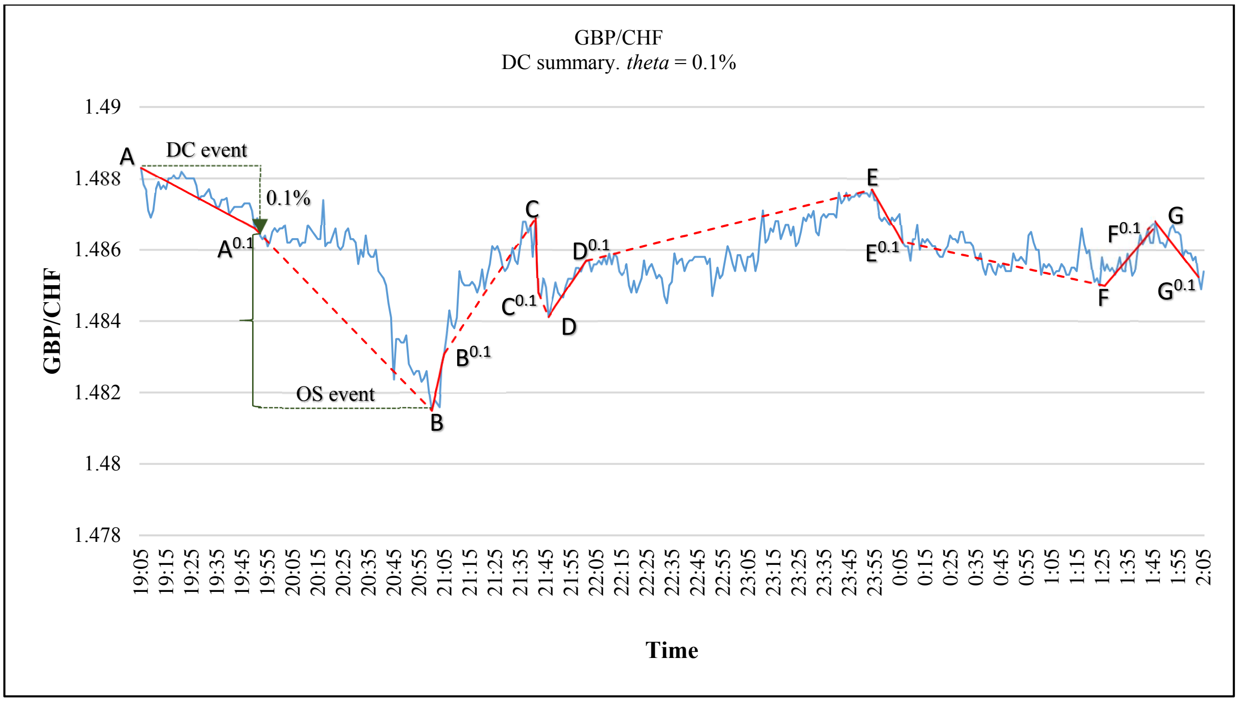

Fig. 1. An example of a DC-based summary. The blue line indicates GBP/CHF mid-prices sampled minute by minute from 1/1/2013 19:05 to 1/2/2013 02:05. *theta* = 0.1%. Solid red lines represent DC events. Dashed red lines represent OS events. Each of the points A, B, C..etc, represents a specific time-minute.

TABLE I: LIST OF NOTATIONS USED IN THIS PAPER ([10]).

Name / Description	**Notation**
Threshold	*theta*
Current price	P_c
Price at extreme point: a price at which one trend ends and a new trend starts	P_{EXT}
The highest price, during an uptrend's OS event, required to confirm that the market's direction has changed to downtrend (i.e. to confirm a downtrend's DC event).	$P_{DCC\downarrow *} = P_{EXT} \times (1 - theta)$
The least price, during a downtrend's OS event, required to confirm that the market's direction has changed to uptrend (i.e. to confirm an uptrend's DC event).	$P_{DCC\uparrow *} = P_{EXT} \times (1 + theta)$
Overshoot value (OSV) is defined at each price's observation during an OS event. Here, $P_{DCC*} = P_{DCC\downarrow *}$ if the current trend is downtrend; otherwise $P_{DCC*} = P_{DCC\uparrow *}$.	$OSV = ((P_c - P_{DCC*}) / P_{DCC*}) / theta$

If (1) holds, then the time at which the market traded at P_{EXT} is called an extreme point (e.g. points A and B in Fig.1), and the time at which the market trades at P_c is called a DC confirmation point (e.g. points $A^{0.1}$ and $B^{0.1}$ in Fig.1). The price movements between the two consecutive extreme points form the trend. A DC event starts with an extreme point and ends with a DC confirmation point. A DC event is recognized only in hindsight. It is recognized precisely at the DC confirmation point. We refer to a specific DC event by its starting point, i.e. extreme point, and its DCC point. For example, in Fig. 1 the DC event which starts at point B and ends at point $B^{0.1}$ is denoted as [$BB^{0.1}$]. The OS event start at the DCC point of one trend (e.g. $A^{0.1}$, $B^{0.1}$) and ends at the extreme point of the next trend (e.g. B, C).

The DC summary of a given market is the identification of the DC and OS events, governed by the threshold *theta*. Fig. 1 shows an example of a DC summary. Note that for a given time series and a predetermined threshold, the DC summary is unique. However, we can produce several DC summaries for the same considered prices series by selecting multiple thresholds. The chosen threshold controls what constitutes a directional change. Had a greater threshold been chosen, less directional changes would have been concluded between the points in Fig. 1. TABLE I lists some essential notations, adopted from [10], used in this paper.

III. BACKLASH AGENT (BA): A DC-BASED TRADING STRATEGY

In this section we introduce a new contrarian trading strategy named 'Backlash Agent', or BA for short. We describe two types of BA: BA-down and BA-up. For each of BA-down and BA-up, we provide two versions: static and dynamic. We provide the details of the static and dynamic versions of BA-down in Sections A and B respectively. BA-up is pretty similar to BA-down. We will describe the difference between BA-down and BA-up as we proceed in this section. In Section C we describe our money management approach.

A. Static BA-down (SBA-down)

We introduce a trading strategy named Static BA-down, or SBA-down for short. SBA-down is only applicable when the market is in downtrend (hence its name). SBA-down opens a long position when the value of *OSV* drops below a certain threshold, *down_ind,* during a downtrend's OS event. Note that the value of *down_ind* is the choice of the trader. SBA-down closes its position when the DC confirmation point of the next uptrend is confirmed. A common practice to represent a trading strategy is by identifying its trading rules (i.e. the condition(s) required to generates buy or sell signals) as in [3-5]. SBA-down consists of two rules:

Rule 1: (open long position)

If ($OSV \leq down\_ind$) and (current trend is downtrend) and (current event is OS event) then generate buy signal.

Rule 2: (close position)

If ($P_c \geq P_{DCC\uparrow^*}$) then generate sell signal.

Note that *Rule 2* is applicable only if a buy signal has been triggered. When SBA-down closes a position, it may generate profits or losses. Hence, *Rule 2* acts as a stop loss rule as well. Similarly, we introduce the Static version of BA-up named SBA-up. SBA-up is the mirror of SBA-down. SBA-up opens a short position while the market is in uptrend and only if the value of OSV exceeds a certain threshold, named *up_ind*. SBA-up generates buy signal when a new DC event of a downtrend is observed.

B. Dynamic BA-down (DBA-down)

When trading with SBA-down, we have no hint as to how SBA-down will perform if we choose a value of *down_ind* (in *Rule 1*) arbitrarily. Suppose that SBA-down performed well for a given value of *down_ind* during a trading period, x, there is no guarantee that SBA-down behave similarly during another trading period, y, using the same value of *down_ind*. These facts motivate the development of the dynamic version of SBA-down, namely 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, FIND_DOWN_IND, to a training dataset (i.e. training period) to determine the value of *down_ind*. In the second stage, DBA-down applies the same two rules of SBA-down to trade on an applied dataset (i.e. applied period) using the value of *down_ind* obtained using FIND_DOWN_IND.

The objective of the procedure FIND_DOWN_IND is to find an appropriate value for the parameter *down_ind* for the applied period based on its performance during the training period. The procedure FIND_DOWN_IND returns one numerical variable, *best_down_ind*. In order to determine *best_down_ind*, FIND_DOWN_IND applies SBA-down using 100 different values of *down_ind* (from – 0.01 to –1.00, with a step size of – 0.01) to the training period. For each value of *down_ind*, we compute the profits obtained by applying SBA-down to the training period. Consequently, for a given training period we get 100 profits. We define *best_down_ind* as the value of *down_ind* under which SBA-down generates the highest profits during the training period. In the second stage of DBA-down, *down_ind* is assigned the value of *best_down_ind.* 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 is to automatically compute the value of *up_ind* using the training period. The second stage consists of applying the same rules of SBA-up to the associated applied period.

C. Money Management Approach

In this section we describe our approach to money management. In this paper we apply the following approach to all versions of BA (i.e. SBA-down, SBA-up, DBA-down, and DBA-up). The entire amount of capital is used when SBA-down, or DBA-down, opens a long position. Similarly, SBA-down, or DBA-down, sells all available shares when closing all positions. Likewise in the case of SBA-up or DBA-up. When SBA-up or DBA-up opens a short position, it sells all available shares. When it generates a buy signal, it uses the entire capital to trade. Throughout this paper, 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 rollback to the previous transaction. In other words, we do not count this last trade when measuring any of the evaluation metrics (to be introduced later in Section IV (B)). It derives from this approach that if BA opens a position, either long or short, it will not be able to open any other position before the current position is closed (i.e. until *Rule 2*'s condition becomes *True*).

Normally, the adopted money management approach can affect the performance of given trading rules. However, the focus of this paper is to analyze the profitability of BA's trading rules. Therefore, we prefer to keep the adopted money management approach as simple as possible. Developing better money management approach and proving its efficiency could be the subject of future work(s).

To summarize, in Section III we introduced the trading rules of a new trading strategy named Backlash Agent, or BA for short. BA has two types: BA-down and BA-up. Each type has two versions: static and dynamic. We also described the money management approach adopted in our experiments throughout the rest of this paper.

IV. Experiments

We test our proposed trading strategy in the FX market. Trading in FX markets averaged $5.1 trillion per day in April 2016 [16]. Most of existing approaches for estimating transaction cost analysis for FX trading propose unpractical assumptions and, thus, are not very accurate [17]. Therefore, transaction costs are not considered in this paper. We use a rolling windows approach to evaluate the performance of BA. This section is organized as follows: In Section A, we describe how we compose a set of rolling windows using EUR/CHF mid-price series. In Section B, we list the evaluation metrics used to assess the performance of BA. Next, we provide four sets of experiments: 1) in Section C we evaluate the performance of the static versions SBA-down and SBA-up, 2) in Section D we evaluate the performance of the dynamic versions DBA-down and DBA-up, 3) in Section E we test the profitability of our trading strategy with other currency pairs, 4) in Section F we examine the impact of *theta* on the profitability of BA, and 5) in Section G we study the impact of using bid and ask price on the profitability of BA.

TABLE II: AN EXAMPLE OF A DC ANALYSIS USING EUR/CHF MID-PRICES SAMPLED FROM 31/7/2015 11:20:00 TO 31/7/2015 11:31:00 (UK TIME) (THETA = 0.1%). THE VALUES OF P_{DCC*} AND OSV ARE ROUNDED TO 5 DECIMAL PLACES.

Date	Time	Mid-Price	Event Type	P_{DCC*}	OSV
31/7/2015	11:20:00	1.06336	(start DC DOWNTREND)	0	0
31/7/2015	11:21:00	1.06290		0	0
31/7/2015	11:22:00	1.06333		0	0
31/7/2015	11:23:00	1.06320		0	0
31/7/2015	11:24:00	1.06258		0	0
31/7/2015	11:25:00	1.06230		0	0
31/7/2015	11:26:00	1.06241		0	0
31/7/2015	11:27:00	1.06242		0	0
31/7/2015	11:28:00	1.06155	(start OS DOWNTREND)	1.06299	– 0.70285
31/7/2015	11:29:00	1.06150		0	– 0.74992
31/7/2015	11:30:00	1.06190		0	– 0.37338

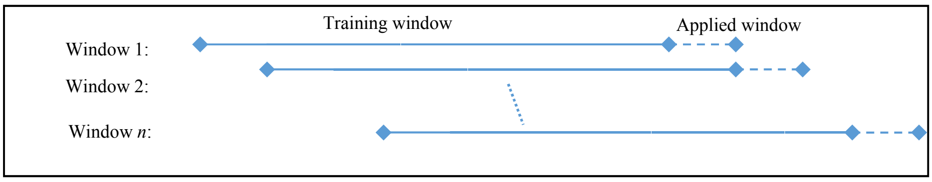

Fig. 2. Illustration of *n* rolling windows. The dashed lines represent the applied windows.

A. Preparing the Dataset and the Rolling Windows

In this paper we use a rolling window approach to test the profitability of our proposed trading strategies. In this section we describe how to prepare these rolling windows using the initial dataset. Our initial dataset is composed of 31 months of minute-by-minute EUR/CHF mid-prices sampled from 1/1/2013 00:01:00 to 31/07/2015 23:59:00 (UK time).

1) Producing DC Analysis for the Dataset

We apply the Directional change (DC) analysis to the initial dataset of EUR/CHF mid-prices. Given a threshold θ, the DC analysis encompasses the identification of all DC and OS events in the initial dataset and the computation of the variables *OSV* and P_{DCC*} (TABLE I). Arbitrarily, we set *theta* = 0.1% and apply the DC analysis to the initial dataset of EUR/CHF. Let *DC0.1* be the dataset exemplified in TABLE II. *DC0.1* comprises the date, time and the price of each observation of the initial dataset. In TABLE II, the column 'Event Type' marks the occurrence of any DC or OS event that starts at the corresponding observation. The columns 'OSV' and 'P_{DCC*}' refer to the variables already defined in TABLE I.

2) Composing the Rolling Windows

We use a rolling window approach (Fig. 2) to evaluate the performance of our proposed trading strategies. As the dataset *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). The seven applied windows are not overlapped (see dashed line in Fig. 2). The lengths of the training and applied windows are set arbitrarily. Let *RWDC0.1* represent the set of these seven rolling windows. 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). Note that although our initial dataset, EUR/CHF, was sampled as a time series (with interval of one minute), the BA's trading rules (presented in Section III (B)) are based on variables which originate from the DC analysis (e.g. *OSV* and P_{DCC*}).

B. Evaluation Metrics

We chose the following metrics to measure the performance of our proposed trading strategy. Most of these metrics have been reported as necessary to assess a given trading strategy [18].

- Total profit: The total profit symbolizes the bottom line for a trading system over a definite period of time. The total profit is computed by removing the gross loss of all losing trades from the gross profit of all winning trades.
- Profit factor: The profit factor is defined as the gross profit divided by the gross loss 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.
- Max drawdown (%): The drawdown is defined as the difference, in percentage, between the highest profit, previous to the current time point, and the current profit value. The Maximum Drawdown (MDD) is the largest drawdown observed during a specific trading period.
- Profitability percentage: This metric is calculated by dividing the number of winning trades by the total number of trades for a specified trading period.
- Alpha: Alpha is a measure of performance on a risk-adjusted basis. It quantifies the excess returns of a fund relative to the return of a benchmark index.
- Sortino ratio [19]: The downside risk (2) is defined as the standard deviation of negative asset return, called downside deviation. In (2) '*m*' denotes the number of trading periods. The '*return*' represents

the profits generated by a given trading strategy and the '*target return*' is the minimum acceptable return (MAR). The Sortino ratio, (3), uses the downside risk to measure the risk associated to a given investment.

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

Where $f(t) = \begin{cases} 1 & if\ return < target\ return \\ 0 & if\ return\ \geq target\ retun \end{cases}$

Sortino ratio = (3)

(return – target return) / downside risk

C. Experiment 1: Evaluation of the Static Versions of BA

The objective of this section is two-fold. Firstly, we want to evaluate the performance of the static versions of BA (i.e. SBA-up and SBA-down). Secondly, we want to examine whether there exists a particular value of the parameters, *down_ind* and *up_ind*, for which SBA-down and SBA-up will have the best performance consistently (i.e. for each rolling window of *RWDC0.1* in our case). In all of the following experiments, we apply the money management approach described in Section III (C).

3) Experiment 1.1: Measuring the Performance of SBA-down

The objective of this experiment is to evaluate the performance of SBA-down. For this purpose we apply SBA-down to each applied window in *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 profits (each profit corresponds to one distinct value of *down_ind*). For simplicity, we consider the profits as a key indicator of the performance of SBA-down. The highest generated profit provides evidence about the usefulness of BA. Whereas the lowest generated profit may give a clue about a possible drawback of BA. Thus, for each applied window we report the highest and the lowest generated profits together with the other defined evaluation metrics in Section IV.

4) Experiment 1.2: Measuring the Performance of SBA-up

The objective of this experiment is to evaluate the performance of SBA-up. Here, we follow the same approach as in Experiment 1.1. We apply SBA-up to each applied window in *RWDC0.1* using 100 different values of *up_ind* (from 0.01 to 1.00, with a step size of 0.01). For each applied window, we compute the generated 100 profits. Then, we report the highest and the lowest profits in addition to the introduced evaluation metrics for each applied window.

The results of the experiments 1.1 and 1.2 will allow us to estimate the best and worst possible performance (evaluated based on generated profits) of BA.

5) Is There One Optimal Value for the Parameters down_ind and up_ind?

The objective of this section is to investigate whether there is a specific value of the parameters, *down_ind* and *up_ind* under which SBA-down and SBA-up will produce the best performance for all applied periods. This can be done by observing and analyzing the values of parameters *down_ind* and *up_ind* corresponding to the highest profits generated by SBA-down and SBA-up in Experiments 1.1. and 1.2.

D. Experiment 2: Evaluation of the Dynamic Versions of BA

A trader cannot have a precise perception about how good, or bad, would be the performance of the static versions if he/she chose arbitrarily the value of parameters *down_ind* or *up_ind*. This fact motivates the development of the dynamic versions as explained in Section III. The objective of this experiment is to evaluate the performance of DBA-down and DBA-up. We therefore apply each of them to the seven rolling windows of *RWDC0.1*. For each of DBA-down and DBA-up, we measure the metrics reported in Section IV.

Furthermore, as part of the evaluation of dynamic BA, we compare the performance of the static versions to the performance of the dynamic versions of BA. Bear in mind that when trading with the static versions the trader must choose the values of the parameters *down_ind* and *up_ind*. Consider that a trader assigns a random value to the parameter *down_ind*, or *up_ind*, when trading with the static version SBA-down, or SBA-up. The question is: What is the probability that the dynamic version DBA-down, or DBA-up, will produce higher profits than the static version SBA-down, or SBA-up? Let α denote this probability. As there is no evidence that the performance of BA-down and BA-up are equal, we estimate α for each of BA-down and BA-up.

To compute α, we estimate the performance of the static versions using a set of randomly chosen values for input parameters *down_ind* and *up_ind*. For this purpose, we simulate trading with SBA-down on *RWDC0.1* 10,000 times. Each time, we trade with SBA-down on each applied window in *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 7 random values of *down_ind*, each random value is used for one applied window. With every trading simulation, we measure the profits generated by SBA-down. Hence, we obtain 10,000 profits. Each profit corresponds to one trade with SBA-down on the seven rolling windows of *RWDC0.1*. α can be calculated as the fraction of how many of these 10,000 profits are less than the profits generated by the dynamic version, DBA-down. Similarly, we apply SBA-up to the applied windows of *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 profits. Again, α is computed as the fraction of how many of these 10,000 profits are less than the profits generated by DBA-up.

E. Experiment 3: Applying DBA-up and DBA-down to Other Currency Pairs

The objective of this experiment is to evaluate the profitability of our strategy in other currencies. To this end, we apply DBA-down and DBA-up to GBP/CHF and EUR/USD mid-price series. Both, GBP/CHF and EUR/USD are sampled minute-by-minute for 31 months from 1/1/2013 00:01:00 to 31/7/2015 23:59:00. We follow the same procedure as in Experiment 2. We run DC analysis to GBP/CHF and EUR/USD with *theta* = 0.1%. Using these DC analysis, we compose two new sets of rolling windows (one for GBP/CHF and one for EUR/USD). Each rolling window comprises a training window of 24 months and an applied window of 1 month. We apply DBA-down and DBA-up to each window in these two sets.

F. Experiment 4: The Impact of Theta on the Profitability of DBA

The objective of this experiment is to study the impact of *theta* on the profitability of DBA. For this purpose we run seven DC analysis to GBP/CHF corresponding to 7 different values of *theta* (ranging from 0.1% to 0.7%; with step size of 0.1%). For each DC analysis (i.e. for each value of *theta*) we compose seven rolling windows; each of which comprises a training set (24 months in length) and an applied set (1 month in length) as we did in Section IV (B). In total, we get seven sets of rolling windows; each of which corresponding to a specific value of *theta*. We apply DBA-down and DBA-up to each of these seven sets; and we measure the profits cumulated over seven months (from Jan 2015 to Jul 2015); each month is the applied period of one rolling window.

G. Experiment 5: Impact of Bid and Ask Price on the Profitability of DBA

In all previous experiments we were evaluating BA using mid-price exchange rate when BA generates buy or sell signals. The objective of this experiment is to provide more realistic estimation of the profitability of BA. To this end, we examine the impact of the bid and ask price on the profits generated by DBA-down and DBA-up. Therefore, in this experiment, when trading with DBA-down and DBA-up we count the bid and ask price when DBA generates sell and buy signals respectively. We apply DBA-down and DBA-up to the same seven sets of rolling windows of GBP/CHF previously composed in Experiment 4 (each of which corresponding to a specific value of *theta*). We measure the cumulative profits generated by DBA-down and DBA-up same as in previous Experiment 4. Note that transaction cost are not counted in any of the previous experiments.

V. Results and Analysis

A. Experiment 1: Evaluation of the Static Versions of BA

Experiment 1 has two objectives. The first objective is to evaluate SBA-down and SBA-up. The second objective is to check if it is possible to have one single value of *down_ind* and *up_ind* for which SBA-down and SBA-up will regularly generate the best possible profits. In this paper we report the results corresponding to the applied windows only and we do not compute the transaction costs.

1) Experiments 1.1 and 1.2: Measuring the Performance of SBA-down and SBA-up

In this section we evaluate the performance of SBA-down and SBA-up. We apply both SBA-down and SBA-up to the seven applied windows of EUR/CHF. TABLE III show the best possible performance of SBA-down when applied to the applied window of *RWDC0.1* (see Section IV). This table include the following metrics: Profits, profit factor, maximum drawdown, and profitability percentage. In TABLE III, the first column defines the applied windows (i.e. the trading period). The column 'Total number of trades' is the number of trades executed by SBA-down during the specified applied window. In TABLE III the column '*down_ind*' defines the value of *down_ind* that corresponds to the highest profits that could be generated by SBA-down during the specified applied window.

At the beginning of the first applied window, i.e. January 2015, SBA-down starts with capital = 1,000,000; this represents the initial, hypothetically, invested amount of money. To compute the cumulative profits over the seven applied months, we sum up the profits of the seven applied windows in TABLE III. By doing so, we get 80.41% which represent the best cumulative profits that could be obtained by applying SBA-down to the applied windows of *RWDC0.1.* Note that each of these seven applied periods, each of 1 month length, is the trading period of one rolling window and they are not overlapped (see Fig. 2).

Likewise, TABLE IV report the best performance of SBA-up when applied to the seven applied windows of *RWDC0.1.* The value in the column '*up_ind*' in TABLE IV represents the value of *up_ind* that corresponds to the highest profits that could be generated by SBA-up during the specified applied window. In the case of SBA-up, we assume that we start trading with an amount of shares with a market value equal to 1,000,000. Again, we sum up the profits in TABLE IV to compute the cumulative profits. In the best case, SBA-up generates a total profit of 64.78%. The Sortino ratio and Alpha of the two versions of SBA are shown in TABLE V. Usually Alpha is computed using a stock market index as benchmark. As most currencies considered in this paper are from the Euro zone, we use the Euro STOXX 50 index as benchmark for the computation of Alpha.

TABLE III: The best possible performance of applying SBA-down to *RWDC0.1* (EUR/CHF).

Applied Window	*down_ind*	Profits (%)	Profit Factor (profit ÷ loss)	Total Number of Trades	Max Drawdown (%)	Profitability Percentage (%)
Jan 2015	– 0.84	10.72	1.32	382	– 10.85	69.4
Feb 2015	– 0.43	15.63	3.28	284	– 0.76	76.4
Mar 2015	– 0.01	12.65	2.11	328	– 0.67	70.1
Apr 2015	– 0.04	7.80	1.99	198	– 0.47	71.7
May 2015	– 0.07	8.12	2.04	192	– 0.68	72.9
Jun 2015	– 0.14	10.38	1.91	234	– 1.31	76.1
Jul 2015	– 0.39	15.11	3.46	180	– 0.59	84.4

TABLE IV: The best possible performance of applying SBA-up to *RWDC0.1* (EUR/CHF).

Applied Window	*up_ind*	Profits (%)	Profit Factor (profit ÷ loss)	Total Number of Trades	Max Drawdown (%)	Profitability Percentage (%)
Jan 2015	0.73	– 4.08	0.88	389	– 14.04	65.6
Feb 2015	0.04	10.60	1.98	371	– 0.76	67.7
Mar 2015	0.09	15.13	3.40	316	– 0.40	75.3
Apr 2015	0.11	7.80	1.99	200	– 1.93	76.0
May 2015	0.04	11.65	3.17	200	– 0.49	78.5
Jun 2015	0.01	11.00	1.92	268	– 0.95	72.8
Jul 2015	0.15	12.68	2.43	219	– 0.77	76.7

TABLE V: THE SORTINO RATIO AND ALPHA OF THE DIFFERENT VERSIONS OF BA COMPUTED BASED ON *RWDC0.1* (EUR/CHF).

	SBA-down (best case)	DBA-down	SBA-up (best case)	DBA-up
Alpha	10.62	8.67	10.11	9.44
Sortino ratio	Inf	Inf	5.99	4.62

The monthly returns of Euro STOXX 50 from January to July 2015 are successively: –3.10, 5.49, – 1.74, 0.85, 1.05, – 2.10, and 1.97 (source: http://www.investing.com/indices/eu-stoxx50-historical-data). The minimum acceptable return (MAR) is set to 1% per annum. We use the Package 'PerformanceAnalytics' from the statistical software R to compute the Sortino ratio and Alpha. In addition, we apply the buy and hold approach to the same seven applied windows of *RWDC0.1*. We buy on 1/1/2015 00:01:00 with a price of 1.20279; then we sell on 7/31/2015 23:59:00 with a price of 1.06120. The return of the buy-and-hold would be: – 14.16%.

2) Is there One Optimal Value for the Parameters down_ind and up_ind?

The objective of this section is to investigate whether there exists a specific value of the parameters *down_ind*, and *up_ind*, for which SBA-down, and SBA-up, will generate the highest profits consistently. Based on the results of Experiments 1.1 and 1.2, we highlight the following observations:

1. Concerning SBA-down: Concerning SBA-down: Based on TABLE III, we note that SBA-down may generate the best profits using a large value of *down_ind* (as in January 2015, when *down_ind* = – 0.84) or using small value of *down_ind* (as in Mars 2015, when *down_ind* = – 0.01).
2. Concerning SBA-up: In TABLE IV, we note that SBA-up may generate the best profits using a large value of *up_ind* (as in January 2015, when *up_ind* = 0.73) or using small value of *up_ind* (as in June 2015, when *up_ind* = 0.01).

Observations 1 and 2 suggest that there is no specific value for the parameters *down_ind* and *up_ind* for which SBA-down and SBA-up will have the best performance consistently. These observations show that the values of these parameters may affect the performance of BA. This note highlights the necessity of having dynamic versions.

B. Experiment 2: Evaluation of the Dynamic BA

The objective of these experiments is to evaluate the performance of DBA-down and DBA-up. We apply each of DBA-down and DBA-up to each of the seven rolling windows of *RWDC0.1*. In this experiment we didn't count the transaction cost. For each of DBA-down and DBA-up, we start with 1,000,000 as the initial invested capital. TABLE VI and TABLE VII report, respectively, the evaluation of the performance of DBA-down and DBA-up. TABLE VI and TABLE VII have the same interpretation as TABLE III and TABLE IV respectively. The cumulative profits generated by DBA-down and DBA-up, in TABLE VI and TABLE VII, are 63.61% and 59.60% respectively. The Sortino ratio and Alpha of DBA-down and DBA-up are reported in TABLE V.

As a second approach to evaluating DBA-down and DBA-up we compare them to SBA-down and SBA-up with randomly picked parameters. We apply each of SBA-down and SBA-up 10,000 times to the applied windows of *RWDC0.1* using randomly picked values for parameters *down_ind* and *up_ind*. We define α as the fraction of how many of these 10,000 profits are less than the profits obtained by DBA-down and DBA-up (reported in TABLE VI and TABLE VII). In the case of SBA-down we have α = 88% (i.e. the probability that DBA-down outperforms SBA-down with randomly picked parameter is 88%). In the case of SBA-up, the probability that DBA-up outperforms SBA-up with randomly picked parameter is α = 97%.

TABLE VI. RESULTS OF APPLYING DBA-DOWN TO *RWDC0.1* (EUR/CHF).

Applied Window	*down_ind*	Profits (%)	Profit Factor (profit ÷ loss)	Total Number of Trades	Max Drawdown (%)	Profitability Percentage (%)
Jan 2015	– 0.11	3.77	1.09	513	– 11.75	67.4
Feb 2015	– 0.10	13.56	2.45	345	– 0.90	73.9
Mar 2015	– 0.10	11.01	2.12	307	– 0.81	68.7
Apr 2015	– 0.09	5.99	1.86	186	– 0.47	71.0
May 2015	– 0.09	7.36	2.03	190	– 0.68	72.6
Jun 2015	– 0.09	8.94	1.83	237	– 1.39	75.5
Jul 2015	– 0.09	12.98	2.78	218	– 0.64	78.4

TABLE VII. RESULTS OF APPLYING DBA-UP TO *RWDC0.1* (EUR/CHF).

Applied Window	*up_ind*	Profits (%)	Profit factor (profit ÷ loss)	Total Number of Trades	Max Drawdown (%)	Profitability Percentage (%)
Jan 2015	0.17	– 4.87	0.88	504	– 14.74	63.1
Feb 2015	0.03	10.32	1.95	372	– 8.68	67.7
Mar 2015	0.03	14.71	3.21	324	– 0.44	74.4
Apr 2015	0.03	7.37	1.91	209	– 1.71	75.6
May 2015	0.03	11.42	3.14	201	– 0.37	78.1
Jun 2015	0.03	10.21	1.87	265	– 0.94	72.5
Jul 2015	0.03	10.44	2.08	229	– 0.81	73.4

C. Experiment 3: Applying DBA-up and DBA-down to Other Currency Pairs: GBP/CHF and EUR/USD

The objective of this section is to investigate the profitability of BA using mid-price of two other currency pairs: GBP/CHF and EUR/USD. We apply the same approach as in Section IV to compose two new sets of rolling windows based on DC analysis (with threshold 0.1%) of GBP/CHF and EUR/USD. We start with 1,000,000 as initial invested capital. The results of applying DBA-down and DBA-up to the rolling windows of GBP/CHF and EUR/USD are reported in TABLE VIII. In case of GBP/CHF, DBA-down and DBA-up generate cumulative profits of 73.39% and 77.44% respectively. The profit factor of DBA-down and DBA-up are 1.85 and 1.67 respectively. In case of EUR/USD, DBA-down and DBA-up generate cumulative profits of 12.66% and 25.62% respectively. The profit factor of DBA-down and DBA-up are 1.80 and 1.93 respectively. We consider these results as an endorsement of the profitability of our trading strategy.

D. Experiment 4: Impact of Threshold Theta on the Profitability of DBA

The objective of this experiment is to test whether the performances of DBA can be affected by the value of *theta*. To this end, we compose seven sets of rolling windows of GBP/CHF; each of which correspond to a specific value of *theta*. Each set comprises seven rolling windows; each of which encompasses a trading period of one month. We apply DBA-down and DBA-up to each set and measure the cumulative profits. The blue dashed lines in Fig. 2 and Fig.3 denote the variation of cumulative profits as function of *theta* when trading with DBA-down and DBA-up, respectively, over GBP/CHF. We can easily note that the cumulative profits increase as *theta* decreases. The shapes of these lines are clear evidence that the value of *theta* can affect the performance of DBA. However, starting a particular value of *theta* (e.g. 0.5% in Fig. 2) the variation of cumulative profits become slight.

E. Experiment 5: Impact of Bid/Ask Price on the Profitability of DBA

The objective of this experiment is to provide more realistic measurement of the profitability of DBA by considering bid and ask prices instead of mid-prices. To this end, we applied DBA to the seven sets of rolling windows of GBP/CHF previously produced in Experiment 4. However, in this experiment we count bid and ask prices when trading (instead of mid-prices as in Experiment 4). The solid red lines in Fig. 2 and Fig. 3 show the variation of the cumulative profits generated by DBA-down and DBA-up respectively.

In Fig. 2 and Fig. 3, we illustrate two sets of cumulative profits: set 1) those corresponding to mid-price (shown in dashed blue lines) and set 2) those corresponding to bid and ask prices (shown in solid red lines). Here, we focus on the difference between these two sets. As can be noted in both Fig. 2 and Fig. 3, the difference between these two sets of profits increases as *theta* decreases. Fig. 2 and Fig. 3 provide evidence that counting for bid and ask prices can severely affect the profitability of BA, especially for small values of *theta*. However, as the values of *theta* increases (e.g. larger than 0.4% in Fig. 2) the difference between the two sets of cumulative profits diminishes and becomes approximately invariant.

TABLE VIII. RESULTS OF APPLYING DBA-DOWN AND DBA-UP TO GBP/CHF AND EUR/USD.

Currency Pairs	Trading Strategy	Profits (%)	Profit Factor (profit ÷ loss)	Total Number of Trades	Max Drawdown (%)	Profitability Percentage (%)	Alpha	Sortino Ratio
GBP/CHF	***DBA-down***	73.39	1.85	2596	−10.74	72.1	9.11	Inf
	DBA-up	77.44	1.67	2606	− 23.20	70.3	10.84	Inf
EUR/USD	***DBA-down***	25.62	1.80	1919	− 3.89	65.4	2.95	1.24
	DBA-up	12.66	1.93	2142	− 4.68	66.0	3.59	Inf

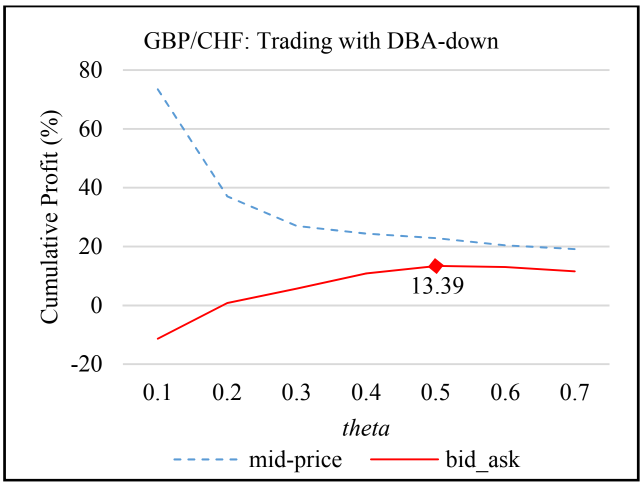

Fig. 2. Variation of cumulative profits generated by DBA-down using mid-prices (dashed blue line) and using bid/ask price (solid red line).

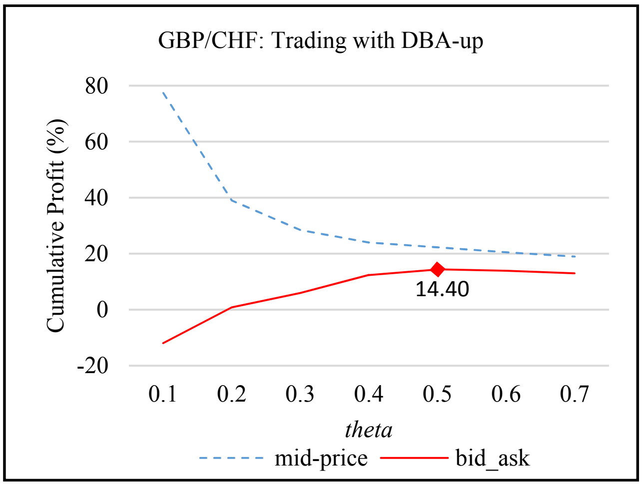

Fig. 3. Variation of cumulative profits generated by DBA-up using mid-prices (dashed blue line) and using bid/ask price (solid red line).

The highest cumulative profits generated by DBA-down is 13.39 and by DBA-up is 14.40 respectively (see Fig. 2 and Fig.3). The Sortino ratio of DBA-down and DBA-up are 2.49 and 2.58 respectively. The new Alpha's measures of DBA-down and DBA-up are 1.28 and 1.31 respectively. These observations show that BA is still profitable even if we take into account the bid and ask prices. Note that transaction costs are not counted in any experiment in this paper.

VI. Conclusion

Unlike time series, which sample prices at fixed intervals, Directional the Change (DC) approach samples prices based on the magnitude, named *theta*, of price changes. DC segments the market into alternating downtrends and uptrends. The majority of existing trading strategies provide trading rules based on time series. Very few trading models were developed under the DC framework. In this paper, we provide evidences that the DC concept is helpful in developing a consistently profitable trading strategy.

We introduce a new contrarian trading strategy, named Backlash Agent, or BA for short, which is based on the DC concept. We describe two types of BA: BA-down and BA-up. For each of BA-down and BA-up we provide two versions: static and dynamic. The static versions, named SBA-down and SBA-up, include parameters to be regulated by the trader. Such task may not be easy. The advantage of the dynamic versions of BA, named DBA-down and DBA-up, is that they automatically compute the values of the parameters used.

We prove that BA performs well according to some of the most commonly used criteria in finance (e.g. profit factor, max drawdown, profitability percentage, Sortino ratio, and Alpha). We use a rolling window approach to evaluate the performance of BA-down and BA-up. We provide a set of experiments using three currency pairs, namely EUR/CHF, GBP/CHF and EUR/USD.

The experimental results conducted using mid-prices show that the cumulative profits during seven months could be more than 100% for small threshold (in some cases, Alpha was over 10). We consider these results as proof of the profitability of our proposed trading strategy, which highlights the usefulness of the DC approach as the cornerstone of BA.

The results also suggest that counting the bid and ask prices may affect considerably the profitability of BA; especially for small values of *theta*. However, BA can still have a good Alpha in comparing to Euro STOXX 50.

To summarize, we prove that BA is profitable. However, the trader must check the impact of bid and ask price before implementing BA for a specific currency pairs. BA can still be enhanced in multiple ways. For example, we think that a deep analysis of the length of training and applied periods may improve the profitability of DBA. Besides, a good money management approach may have a positive impact on the performance of BA. Counting transaction costs may provide better estimation for the performance of BA.

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