Time Series Analysis Indicators under Directional Changes: The Case of Saudi Stock Market

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ABSTRACT

We introduce a set of time series analysis indicators under an event based framework of directional changes (DC) and overshoots. Our aim is to map continuous financial market price data into the so-called DC Framework - A state based discretization of basically dissected price time series. The DC framework analysis relied on understanding the price time series as an event-based process, as an alternative of focusing on their stochastic character. Defining a scheme for state reduction of DC Framework, we show that it has a dependable hierarchical structure that permits for analysis of financial data. We show empirical examples within the Saudi Stock Market. The new DC indicators represent the foundation of a completely new generation of financial tools for studying volatility, risk measurement, and building advanced forecasting and automated trading models.

Keywords: Directional Changes, Financial Forecasting, Automated Trading, Financial Markets, Saudi Stock Market
JEL Classifications: G11, G14, G1

1. INTRODUCTION

Classical theories of economics are established on strong assumptions such as perfect rationality, homogeneity and efficient market hypothesis (EMH) which are flawed Cowles (1933), Bachlier (1964), Cootner (1964), Fama (1965). In previous decades, several empirical financial, economic studies have engaged in an intense debate about the concept of market efficiency Leroy (1973), Beja (1977), Lucas (1978), Grossman and Stiglitz (1980), Tirole (1982), Lo (1988), Tsang and Martinez-Jaramillo (2004). The EMH states that financial markets (FMs) are "informationally efficient" if the price reflects all the available information Fama (1970). In terms of the EMH, the information set is considered to be anything that may possibly affect the movement of an asset's price. Based on the information set available, there are three common forms of the EMH Dixon and Holmes (1996): The weak form efficiency hypothesis asserts that all relevant available information is fully reflected in current and historical asset prices. The semi-strong form efficiency hypothesis asserts that all publicly available information is fully reflected in current and historical asset prices. The strong form efficiency hypothesis asserts that

all information, including public and private information, is fully reflected in current and historical asset prices.

The concept of market efficiency has indicated that price changes follow a random walk Malkiel (1973). The random walk hypothesis states that asset returns are serially independent, which means that they do not follow any trend or pattern. Thus, the next period return is not a result of the previous ones Tsang and Martinez-Jaramillo (2004). Therefore, historical data cannot be used to predict the future movements of the asset price time series in such a way as to outperform the market. Whereas the facts derived from the statistical analysis of the FM data evidently now show the opposite Lo (1988), Cont (1999). The observed statistical properties of the FM data are referred to as stylized facts Dacorogna et al. (2001). Researchers attempt to discover and report the stylized facts of FM data to understand better and analyze financial and other markets. Many empirical studies have been conducted to examine the concept of the EMH by explaining the stylized facts of assets' prices, such as Leroy (1973), Lucas (1978). The variance between classical economics theories and the stylized empirical facts observed in FMs data are the main driving

force for the development and the usage of different approaches to studying the behavior of such markets. For instance, the concept of bounded rationality has exclusively replaced the concept of full rational homogeneous representative agents Simon (1982; 1990), Arthur (1991), Simon (1995), Arthur et al. (1997). Such a change in conception motivates the need to study and revise some of the existing economic theories which are based on many idealized assumptions. Beyond the debates with regard to EMH and the concept of a random walk, our work sheds some light into explaining stylized facts in price time series and, most importantly, provides time series analysis indicators for studying and analyzing the price time series in FMs.

High-frequency data (HFD) in finance refers to an enormous quantity of data, which is the comprehensive record of transactions and their associated characteristics at frequencies higher than on a daily basis Engle (2000). According to Dacorogna et al. "The number of observations in one single day of a liquid market is equivalent to the number of daily data within 30 years" (Dacorogna et al., 2001. p. 6). The HFD by nature are inherently irregularly spaced in time where time flows unevenly in term of price changes Dacorogna et al. (2001). The structure of an HFD is based on the policy of the organization that generates and gathers the data Brownlees and Gallo (2006). The analysis of HFD is valuable to numerous issues in FMs, including price trends and patterns detection, establishing stylized facts, defining scaling properties Dacorogna et al. (2001), Bingcheng and Zivot (2003). The study of HFD exposes various properties of market behavior that consequently requires the revision of some of the classical economics theories Dacorogna et al. (2001). An excellent review of the effectiveness of studying HFDs is provided in Dacorogna et al. (2001), Bingcheng and Zivot (2003), Andersen (2000), Engle (2000), Ghysels (2000).

Many analytical approaches have been used to study and analyze the price time series in FMs using physical fixed time intervals – homogeneous time series - Dacorogna et al. (2001). This is because most of these studies deal with low-frequency datasets of FM data, such as daily closing price data Dacorogna et al. (2001). There are two main causes: (i) To a certain extent it is still expensive and time consuming to gather, store and process HFD, (ii) most of the analytical approaches established to date have been intended for homogeneous time series, while there have been few works completed for data that arrive at random time intervals Dacorogna et al. (2001), Bingcheng and Zivot (2003), Andersen (2000). However, with the advance in computer technology, the hitches linked with HFD availability is a minor issue. New challenges have emerged with concern to the processing and analysis of these HFDs giving the vast amounts of data that are characterized by irregular time spacing and which exhibit enormous patterns in price and trade activities Dacorogna et al. (2001), Bingcheng and Zivot (2003), Andersen (2000). Time flows unevenly in FMs: On the announcement of the political or economic news, there tends to be a sharp rise in the number and volume of transactions in response to the news. Thus, an imperative decision has to be made with reference to the time intervals over which to analyze the dataset. If fixed time intervals are used, in that case, the analyst has to aggregate the time series data to fixed time intervals, known that the data are inherently irregularly spaced over time Russell

(1999). Nevertheless, such a process directs to losing information as a result of the data aggregation in the time series.

In light of this, this paper aims to use a data-driven approach called "directional-change (DC)" for studying the price time series in FMs. Guillaume et al. (1997) introduced the concept of DC as an alternative way to sample FMs data in which the price time series is dissected based on price events where the direction of the price trend changes from uptrend to downtrend or *viz*. DC approach is based on intrinsic time where a DC event is characterized by a fixed threshold, and any occurrence of a DC event represents a new intrinsic unit, independent of the notion of physical time changes. Therefore, using DC approach we identify alternating DC events as a price move of magnitude λ from the last price extreme, a high or a low price when a downward or upward DC event is to be detected, respectively. The DC approach is well suitable to process HFD analytically because it is not constrained by any fixed time grid and naturally adapts to the changes in price activity. With this approach, we can model the price curve as different price curves based on the used magnitude of DC event.

In time series analysis, an analyst should use practical time series analysis indicators to summarize price changes. In this paper, we offer potentially practical time series analysis indicators for profiling price time series under DC framework at a given price scale λ. Two groups of stock indices from the Saudi Stock Market (SSM) are used in this study: Banks and Financial Services Indices and Telecommunication and Information Technology indices, all of which cover the period from December 1, 2014, to May 25, 2015. The results of this study can be used further to develop decision support systems for FMs. We believe that profiling price time series in FMs under DC will provide the market analyst with potentially useful information regarding market dynamics, compared with traditional time series analysis based on fixed time intervals.

The remainder of the paper is structured in the following way: Section 2 presents brief literature on related works. Section 3 describes the dataset provided by SSM. Section 4 describes the concept of DC and its components. Section 5 introduces a set of time series analysis indicators for profiling price time series under DC framework. Section 6 presents the results of profiling the two groups of stock indices from the SSM under different threshold magnitudes. In Section 7, we discuss empirical analysis of the results while Section 8 gives concluding remarks and discussed potential future work.

2. RELATED WORKS

The price time series in FMs is usually analyzed as a homogeneous sequence of price data over a defined period Dacorogna et al. (2001). Preferably, the time has to be a dynamic object that adapts itself to the evolution of prices. Guillaume et al. (1997) explain the evolution of prices in the time series by the frequency of price DCs of a given amplitude λ, which provides an indicator for alternative quantify of the risk. Using DC approach, time flows to the beat of DC events and is as a result enhanced fitting to form the dynamics of the underlying price evolution.

In 2011, using statistical analysis method based on the DC event approach, Glattfelder et al. (2011) presented 12 new empirical scaling laws related to foreign exchange (FX) market data series across 13 currency exchange rates. These 12 scaling laws enhance our understanding of the price behavior in FMs, giving us new insights. Scaling laws establish quantitative relationships between the magnitude of price movements and the market transactions as a function of the time interval at which they are measured. The discovered scaling laws provide a measurement of the length of the price curve coastline as a function of the threshold of observation that shows to be lengthy. The initial scaling law presented in Glattfelder et al. (2011) relates the average number of price ticks observed throughout a price move of size λ to the magnitude of that threshold λ. In Glattfelder et al. (2011), a tick is defined as a price change larger than 0.02%. The second scaling law counts the yearly average number of price changes of magnitude λ. The third scaling law relates the average difference between two extreme price levels during a time interval Δt to the size of that time interval Δt. Law four relates the average time interval for a price change of magnitude λ to occur to the scale of the threshold and correspondingly law five considers DC instead of a price move of magnitude λ. A set of six scaling laws emerges from the so-called total move of the price, which decompose into DC and overshoot (OS) events. The latest scaling law considers cumulative price moves for a price move of magnitude λ to this threshold λ. These scaling laws have the potential to deliver effective insights into the dynamics of FMs.

Aloud et al. (2013) has extended the work for Glattfelder et al. (2011) by presenting four new scaling laws on the FX market transaction data, next to establishing six quantitative relationships amongst them, holding across EUR/USD and EUR/CHF transactions. Bisig et al. (2012) describe the so-called Scale of Market Quakes (SMQ), designed based on the DC event approach. The intention of SMQ is to measure the FX market activity on a continuous basis at major economic and political developments announcements in FX markets to use it as a decision support system for policy makers. Kablan and Ng (2011) developed a new method of capturing volatility using the DC event approach. Aloud et al. (2011) results highlighted that the length of the price curve coastline (PCC) as a function of the threshold of observation defined by DC events shows a long coastline of price changes. The length of the coastline is the result of the continuing imbalance between buy, sell orders, and mirrors a need of market liquidity, when there are not a sufficient number of participants equipped to take the other side of the immediate buy or sell flow Golub et al. (2014).

3. DATASET

We used HFD of SSM indices historical prices. Two groups of stock indices from the SSM are employed in this study. These two groups are the Banks and Financial Services Indices and the Telecommunication and Information Technology indices, all of which cover the period from December 1, 2014, to May 25, 2015. The Banks and Financial Services Indices are the Saudi American Bank (SAMBA), the Saudi British Bank (SABB), Al Rajhi bank

(RAJHI). The Telecommunication and Information Technology indices are Saudi Telecom Company (STC) and ZAIN Mobile Telecommunications Company (ZAIN). Figure 1 shows the time evolution of the five stock indices over the whole test period. For each stock index, we use Bloomberg DataStream to acquire HFD information. The raw trading information was tick data, including bid and ask price, and each record is time stamped. The time-span of the price dataset is vital in the study, known that different amounts of data assessment possibly will endow with ratios of precision interesting to study.

4. DC

Price time series in FMs are unevenly spaced in time in a complex set which makes the flow of physical time discontinuous. Serving the literature, three major approaches handle the issue of studying inhomogeneous time series Dacorogna et al. (2001), Engle and Russell (2006). The first approach applies aggregating price data through injecting prices between permanent and resolute times which effects in a loss of price data throughout major time periods. The second approach studies a price time series of price change occurrences which referred to as point process Bauwens and Hautsch (2009). The advantage of such approach is the combination of several durations which permits analytical results to be resolute. In contrast, the disadvantage of the point processes approach is that time is measured in terms of physical time units. Motivated by the need to better characterize and understand the FMs, the third approach offered studying the price time series by DC event approach which produces an event-based time scale called "intrinsic time" that ticks with reference to an evolution of a price move Guillaume et al. (1997), Glattfelder et al. (2011), Aloud et al. (2011), Tsang (2010).

The advantages of DC event approach for studying HFD in FMs can be viewed in three-fold Golub et al. (2014); initially,

Figure 1: Price time evolution of (X-axis) five stock indices closing prices and (the Y-axis) the corresponding closing prices over the period from December 1, 2014, to May 25, 2015. The Banks and Financial Services indices are the Saudi American Bank (SAMBA), the Saudi British Bank (SABB), Al Rajhi bank (RAJHI). The Telecommunication and Information Technology indices are Saudi Telecom Company (STC) and ZAIN Mobile Telecommunications Company (ZAIN)
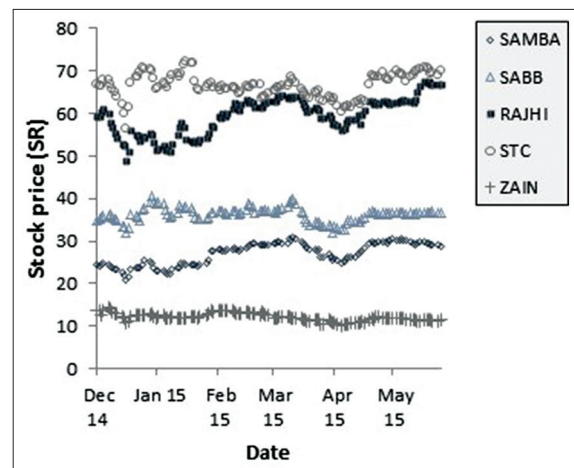
it can be used to non-homogeneous time series without the need for supplementary data transformations. Secondly, several DC thresholds can be used at the same time for the same HFD. Thirdly, it captures the level of market activity in time series of a certain size (threshold) with that respective threshold at any one time. This section offers a novel framework to define the evolution of a price time series by dissecting the price moves over several scales and forming it as evolutions on a structure called intrinsic network.

4.1. Physical Time

The majority of the analytical approaches studying the price time series in FMs are based on physical fixed time intervals, ranging from seconds through hourly to daily changes, wherein the time flow of periodic patterns of fixed magnitude is discontinuous. The availability of HFD, in which data, by its nature, is non-homogeneous in time, it has become gradually more complex and challenging to study and analyze the price time series in FMs through the use of physical fixed time intervals. Figure 2 show price activities for the SAMBA stock index on December 1st, 2014. From Figure 2, it is evident that considerable patterns of the price changes are ignored when studying the price time series based on daily and hourly changes (physical fixed time intervals). By way of illustration, in Figure 2, the price movement in hour 11:00:01 represents an investment opportunity, with the price droping by 8.91%. This was overlooked in both the end of that day's return and the hourly return.

Studying the price time series through physical fixed time intervals fail to visibly capture the significant movement of price changes in a significant way, in view of the fact that the variety of a price change evidently depends on the time of day. Using physical fixed time intervals to detect periodic patterns of fixed magnitude in a price time series, maps a variety of patterns with different magnitudes, which makes the flow of physical time discontinuous. Computational effort is compulsory to analyze and study the price time series in FMs, which results in apparent costs associated with the study process. To deal with this critical

Figure 2: Saudi American Bank price time series on December 1st, 2014. The (X-axis) represents price tick number and (the Y-axis) the corresponding prices. The straight line indicates the gradient of the price changes for that day. The dashed lines show hourly prices for that day. Even with hourly prices, some activity is still overlooked. The graph illustrates a major part of the price movement is overlooked when chopping off the price time series based on the daily closing price and hourly prices since it eliminates many significant price movements
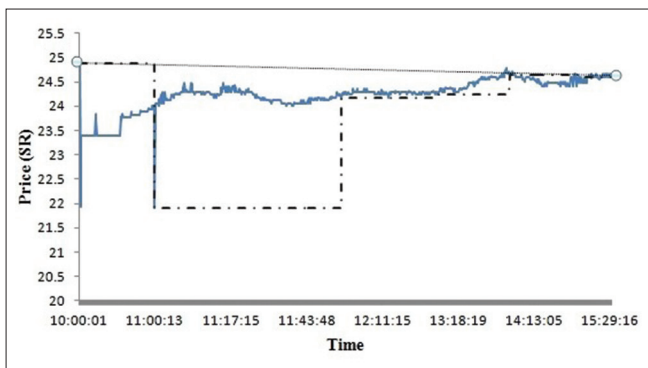
issue, different solutions have been proposed among them is the study of price time series using intrinsic time, which provides a consistent solution.

4.2. Intrinsic Time

In intrinsic time, time is defined by events where the direction of the price trend changes from upward to downward or vice versa. An event is the basic unit of intrinsic time and characterized by a threshold (λ) of fixed magnitude. An event is defined as the absolute price change between two local extremal values exceeding the given threshold λ Aloud et al. (2011). Intrinsic time adopts an event-based system while physical time takes a point-based system. The physical time scale is homogenous in which time scales equally spaced on any chosen time scale (e.g. seconds scale, minutes scale, etc.). In contrast, intrinsic time is inhomogeneous in time and independent of the notion of physical time scales where any occurrence of an event represents a new intrinsic time.

4.3. DC Trends

A DC trend can take one of the two forms - A downturn trend or an upturn trend Tsang (2010). A downward trend run is a period between a downturn DC event and the next upturn DC event while an upward trend run is a period between an upturn DC event and the next downturn DC event. A DC downturn event terminates an trend upward run, and starts a downward trend run, whereas an upturn DC event terminates a downward DC run and starts an upward DC run. Therefore, the DC event approach defines a price time series in FMs as a sequence of

$\cdots \rightarrow$ downturn DC event $\rightarrow$
downturn OS event $\rightarrow$
upturn DC event $\rightarrow$
upturn OS event $\rightarrow$
downturn DC event $\rightarrow \cdots$

4.4. DC Event

A DC event is a particular form of events and can take one of the two forms - A downturn DC event or an upturn DC event. A DC event is defined as the total price change of magnitude λ from the last price extreme, a high or low when a downward or upward DC is to be detected, respectively.

At the establishment of the studying the sequence of the price time series, we define a price extreme p_{ext} which set to the initial market price p_0 at the beginning of the sequence. During a downward trend run, the last price extreme p_{ext} is continuously updated to the minimum of: (a) The current market price p_t at time t and (b) the price extreme p_{ext}. Correspondingly, during an upward trend run, the last price extreme p_{ext} is continuously updated to the maximum of: (a) The current market price p_t at time t and (b) the price extreme p_{ext} Glattfelder et al. (2011).

In an upward trend run, a downturn DC event is an event when the absolute price change between the current market price p_t and the price extreme p_{ext} is lower than the given threshold (λ).

$$p_t \leq p_{ext} \times (1-\lambda) \qquad (1)$$

The starting point of a downturn DC event is a downturn point which is the point at which the price last peaked (p_{ext}). The end of a downturn DC event is a downturn DC point which is the point at which the price has dropped from the last downturn point by the threshold.

In a downward trend run, an upturn DC event is an event when the absolute price change between the current market price p_t and the price extreme p_{ext} is higher than a given threshold (λ).

$$p_t \geq p_{ext} \times (1 - \lambda) \qquad (2)$$

The starting point of an upturn DC event is an upturn point which is the point at which the price last troughed (p_{ext}). The end of an upturn DC event is an upturn DC point which is the point at which the price has risen from the last upturn point by the threshold (λ).

4.5. OS Event

A DC event is frequently followed by the so-called a price OS event rather than a reverse DC event direction Glattfelder et al. (2011). The OS event signifies the price move beyond the DC event and is defined as the divergence between the price level at which the last DC event occurred and the price extreme before the next DC is triggered. Therefore, an OS event can take one of two forms: A downturn OS event or an upturn OS event. A total price movement Δx_{TM} between two local extremal prices (minimum and maximum price) is decomposed into a DC event and an OS event Glattfelder et al. (2011), and is defined by:

$$\Delta x_{TM} = \lambda + \Delta x_{OS} \qquad (3)$$

Where, λ is the size of a DC event while Δx_{OS} is the size of an OS event. Figure 3 demonstrates how the price curve is dissected into DC and OS events.

4.6. Pseudo Code

Let $\lambda = \{\lambda_0, \lambda_1, ., \lambda_{n-1}\}$ be the set of n_λ DC thresholds on which price time series is mapped. Using a threshold of magnitude λ, we map the price time series into a sequence of price DCs and OSs. The initial states of the sequence is as follow: The initial price p_0 and last price extreme p_{ext} is assign as initial value the asset's price at the start of the price time series sequence p_0 at time t_0; the initial physical time is t_0; the initial price trend mode m_0 which alterations between upward and downward run indicating the expected mode of the DC event. An initial state affects at most the first two pairs (DC, OS), and allow the following pairs in the sequence to synchronize in the company of any other sequence acquired with different initialization. Algorithm 1 demonstrates how to define DC and OS events during a time period T.

A given λ_i discretises the price time series into a set of prices x_i $(t) = \{x_0(t_0^i), x_1(t_1^i), ., x_n(t_n^i)\}$ take place at times $T_i(t) = \{t_0^i, t_1^i, ., t_n^i\}$ where $x(t) = \dfrac{bid(t) + ask(t)}{2}$ is the mid-price at time t.

4.7. Spectral Analysis

Studying the price time series under physically fixed time intervals require the divination of time into periods of equal length which

have the drawback of missing major price movements (Section 4.1). Therefore, diverse time periods in a price time series possibly will enclose a different number of DC (NDC) events of a different magnitude. Such fact demonstrates that the price evolution is independent of physically fixed time changes.

Figure 4 reports the NDC events of 3%, 6%, and 9% magnitudes during diverse time periods of the 1st and 2nd December 2014 in

Figure 3: The evolution of the price time series within 24 h are shaped by directional changes (DC) event points (diamond) with a threshold $\lambda = 0.4\%$. A total price movement between two local price values (minimum and maximum price) is decomposed into DC (solid lines) and overshoot (dashed lines) events
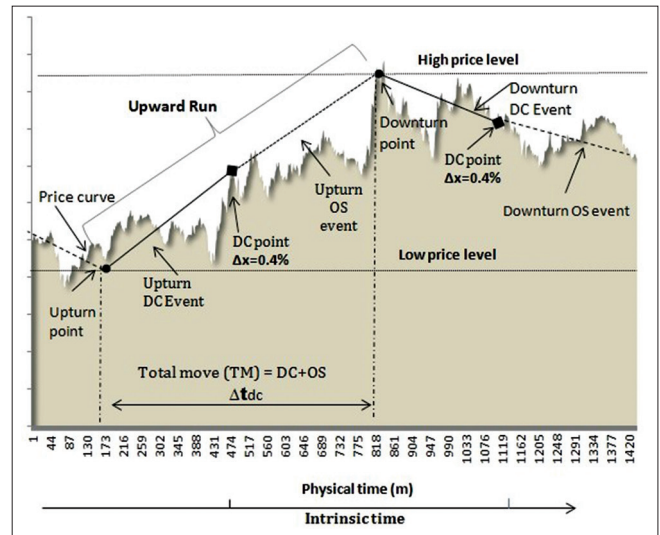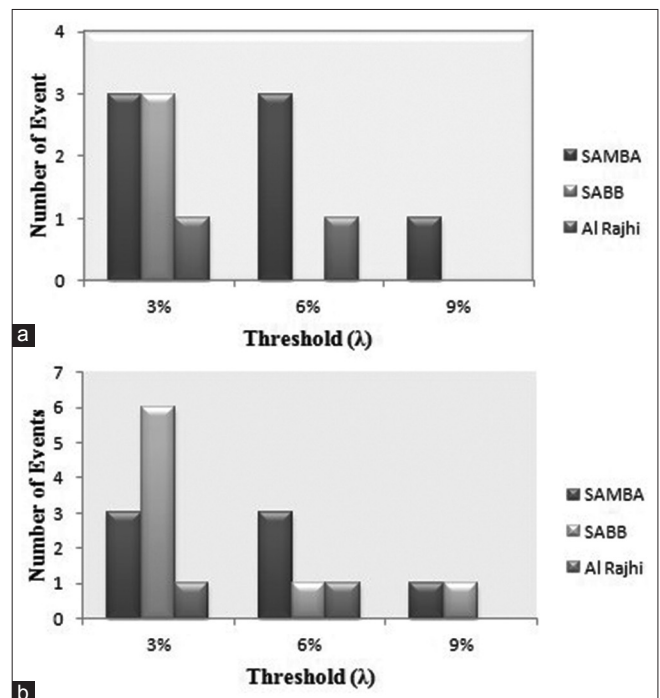

Figure 4: Number of directional changes events of 3%, 6% and 9% magnitudes during diverse time periods of the, (a) 1st and (b) 2nd December 2014 in Saudi American Bank (SAMBA), Saudi British Bank (SABB) and Al Rajhi bank (Al RAJHI) price stock indices

SAMBA, SABB and Al RAJHI price stock indices. For SAMBA and Al RAJHI, we can detect from the results in Figure 4, that the NDC events using the three thresholds are the same on both days. In contrast, for SABB the NDC events on the 2nd December is twice as for the 1st December. For illustration, on the 2nd December there is one DC event with a 9% threshold while this was not the case on the 1st of December.

The reported results in Figure 4 draw attention to two vital observations: (a) For different stock indices the same time periods with the same threshold magnitude on different days may possibly enclose a different NDC events, and (b) with the same threshold magnitude, some time periods on the same day have more DC events than others. These two observations point out those DC events of different magnitude are independent of physical time changes.

5. DC INDICATORS

Using the DC event framework, we propose a set of time series analysis indicators for summarizing price changes in an FM time series. With these indicators, we aim to link together concepts like the price moves, duration, and frequency. We believe DC indicators will offer a value in mapping the dynamic of price change in a time series and hence avoiding time risks at the same time. The DC indicators can be used in different ways; financial decision makers can use the DC indicators as a tool to filter the significance of the price dynamics in a time series. The analytical results of the DC indicators can be used as an input to forecasting or automated trading models to identify investment opportunities and adjust the input factors. These DC indicators can be computed from Algorithm 1.

5.1. NDC Events

NDC indicator records the NDC events over a defined period T for the given threshold λ. Therefore, such indicator relates the average absolute price change Δp and the time interval Δt to its occurrence. As results, the NDC indicator records the number of upturn and downturn DC price events of a certain magnitude (threshold) with that respective threshold.

5.2. Number of OS Events (NOS)

NOS indicator records the NOS events over a defined period T for the given threshold λ. In particular, the NOS indicator records the number of upturn and downturn OS price events of a certain magnitude (threshold) with that respective threshold.

5.3. OS Magnitude (OSM)

OSM indicator measures the average magnitude of OS events over a defined period T for the given threshold λ. The magnitude of OS event is the difference between the price level at which the last DC event of magnitude λ occurred and the price extreme before the next DC event is triggered. Therefore, OSM is an indicator for measuring the average price distance between fixed points, the DC event confirmation point, and the next price extreme point. Therefore, we define OSM as follows:

$$PCC_\lambda = \frac{1}{NDC_\lambda} \sum_{i=1}^{NDC_\lambda} |p_{i+1} - p_i| \qquad (4)$$

Where, λ is a fixed threshold, NDC_λ is the total number of DC events on which the length of the PCC is measured. Hence, the NDC events is determined by the threshold magnitude λ that we use. pi is the price of the ith DC event point and p_{ext} last price extreme, whether upturn or downturn DC event point.

5.4. Trend Time (TT)

A price trend (complete price movement) is comprised of a DC event, and an OS event follows. Measuring the time taken for a price trend to complete is a significant time series analysis indicator. TT indicator measures the average time taken from the beginning price extreme point to the end price extreme point of a price trend. Using the TT indicator, we can relate the time taken during which DC and OS events happened to the magnitude of these events. TT indicator as measured by time could be defined as follows:

$$TT_\lambda = \frac{1}{NDC_\lambda} \sum_{i=1}^{NDC_\lambda} |t_{i+1} - t_i| \qquad (5)$$

Where, λ is a fixed threshold, NDCλ is the total NDC events on which the length of the PCC is measured. t_i is the time of the ith price extreme point, whether upturn or downturn price extreme point.

5.5. PCC

Glattfelder et al. (2011) presented 12 independent new scaling laws in FX price data under intrinsic time. These scaling laws provide an estimation of the length of the PCC which turns to be long Aloud et al. (2011), Glattfelder et al. (2011). Assuming ideal foresight, the length of the PCC over a defined time period T, signify the profit potential. Under intrinsic time, the PCC is defined in dynamic time intervals, which is established by price changes.

PCC indicator estimates the length of the PCC based on the price distance between fixed points as defined by intrinsic time. In particular, PCC indicator is the average magnitude of the upwards and downwards price trend of DC event threshold (λ) over a time period T. The downward price trend is the total price move from a downturn DC event point to the next upturn DC event point. In other words, the downward price trend is defined as the absolute difference between p_i and p_{i+1}, where p_i is the price of the ith downturn DC event point and p_{i+1} is the price of the next upturn DC event point. Correspondingly, the upward price trend is the total price move from an upturn DC event point to the next downturn DC event point. Under intrinsic time, the length of the PCCλ is measured by,

$$PCC_\lambda = \frac{1}{NDC_\lambda} \sum_{i=1}^{NDC_\lambda} |p_{i+1} - p_i| \qquad (6)$$

Where, λ is a fixed threshold, NDC_λ is the total number of DC events on which the length of the PCC is measured. p_i is the price of the ith DC event point, whether upturn or downturn DC event point.

6. RESULTS

In this section, we present the results of summarizing the price time series under DC framework. The input data file is a CSV

file with one data record per time-stamped price point for each stock index. A set of selected threshold magnitudes has been specified for computing the DC indicators. Table 1 is an example of DC market summary under a fixed threshold magnitude of 9% for the banks and financial services stock indices while Table 2 provides the DC market summary for the Telecommunication and Information Technology stock indices. Tables 3 and 4 are examples of DC market summary under a fixed threshold magnitude of 3%.

Table 1 shows on average that a DC event is followed by an OS event. Despite the fact that RAJHI has the highest NDC events, the average physical time that each price trend (TT) takes to complete is about twice as estimated for TT of SAMBA and half TT for SABB. RAJHI DC price uptrend takes less time to complete than downtrends, while this is the opposite fact for SAMBA and SABB in which on average price rise slowly in uptrend and drops rapidly in downtrend. Such observation reflects the risk of trading for stock indices. Although SAMBA has the lowest NDC events, the magnitude of OS event (OSM) is the highest with the minimal time price trend (TT) takes to complete. For all the three stock indices, the average OSM for DC price downtrend is higher than for the up trends. This indicates that the downtrends have more potential profit and hence less risk for arbitrage investment opportunities. The average lengths of the PCC are 6.80%, 22.63% and 23.61% for SAMBA, SABB and RAJHI respectively.

PCC represents the highest possible profit that one could earn in the profiling period according to trading under DC framework. The PCC results show that the profit one can earn is astonishingly long.

Table 2 is a paradigm of DC market summary for the Telecommunication and Information Technology stock indices under a threshold of 9%. The NDC and NOS events are correlated with PCC which is in line with the results reported for the banks and financial services stock indices. For STC on average the up trends take significantly more time to complete while for ZAIN is the opposite. The average OSM for DC price downtrends is higher than for the up trends for both STC and ZAIN. Accordingly the STC downtrends enclose additional potential profit and a reduced amount of risk for the traders. The average lengths of the PCC are 18.62% and 7.62% for STC and ZAIN respectively. The results in Tables 1 and 2 draw attention to the fact that the length of the PCC depends on the frequency of changes in the price.

7. DISCUSSION

The DC indicators address the problem of detecting and characterizing pattern variability in price time series and as well other forms of sequential financial data. These DC indicators can facilitate the construction of DC profiles for the FM data. The price

Table 1: Profile summary file of Banks and Financial Services Indices (SAMBA, SABB, and RAJHI) spanning December 1, 2014, to May 25, 2015, determined by a fixed threshold 9%

DC Indicator	SAMBA	SABB	RAJHI
NDC	12	39	58
NOS	7	12	32
OSM	6.01%	5.10%	5.21%
OSM ↑	5.55%	3.38%	2.95%
OSM ↓	6.62%	10.26%	13.28%
TT	484,552 s	2,066,178 s	1,077,083 s
TT ↑	827,567 s	2,420,293 s	933,114 s
TT ↓	27,198 s	1,003,834 s	1,591,258 s
PCC	6.80%	22.63%	23.61%

NDC: Number of directional changes, NOS: Number of overshoot, OSM: Overshoot magnitude, TT: Trend time, PCC: Price curve coastline, SAMBA: Saudi American Bank, SABB: Saudi British Bank, Al RAJHI: Al Rajhi bank

Table 3: Profile summary file of Banks and Financial Services Indices (SAMBA, SABB, and RAJHI) spanning December 1, 2014, to May 25, 2015, determined by a fixed threshold 3%

DC Indicator	SAMBA	SABB	RAJHI
NDC	36	157	206
NOS	35	156	204
OSM	4.47%	2.61%	3.26%
OSM ↑	3.32%	2.01%	1.76%
OSM ↓	6.00%	3.26%	8.39%
TT	915,979 s	857,729 s	369,066 s
TT ↑	1,027,733 s	831,632 s	258,386 s
TT ↓	766,974 s	886,001 s	747,934 s
PCC	2.62%	7.60%	9.38%

NDC: Number of directional changes, NOS: Number of overshoot, OSM: Overshoot magnitude, TT: Trend time, PCC: Price curve coastline, SAMBA: Saudi American Bank, SABB: Saudi British Bank, Al RAJHI: Al Rajhi bank

Table 2: Profile summary file of Telecommunication and Information Technology Indices (STC and ZAIN) spanning December 1, 2014, to May 25, 2015, determined by a fixed threshold 9%

DC Indicator	STC	ZAIN
NDC	44	26
NOS	20	15
OSM	2.93%	7%
OSM ↑	2.86%	4.84%
OSM ↓	4.35%	9.97%
TT	431,446 s	1,335,109 s
TT ↑	453,840 s	433,473 s
TT ↓	5967 s	2,365,552 s
PCC	18.62%	7.62%

NDC: Number of directional changes, NOS: Number of overshoot, OSM: Overshoot magnitude, TT: Trend time, PCC: Price curve coastline, STC: Saudi Telecom Company, ZAIN: ZAIN Mobile Telecommunications Company

Table 4: Profile summary file of Telecommunication and Information Technology Indices (STC and ZAIN) spanning December 1, 2014, to May 25, 2015, determined by a fixed threshold 3%

DC Indicator	STC	ZAIN
NDC	76	154
NOS	74	152
OSM	3.69%	3.23%
OSM ↑	2.59%	2.49%
OSM ↓	5.64%	4.86%
TT	364,107 s	1,991,226 s
TT ↑	288,056 s	896,213 s
TT ↓	498,316 s	4,407,808 s
PCC	10.25%	3.59%

NDC: Number of directional changes, NOS: Number of overshoot, OSM: Overshoot magnitude, TT: Trend time, PCC: Price curve coastline, STC: Saudi Telecom Company, ZAIN: ZAIN Mobile Telecommunications Company

process displays diverse periodic patterns, revealed by the power of the data process in the high-frequency domain.

According to the reported results in Tables 1-4, the period linked with the identified patterns (DC events) tends to increase as the magnitude of the threshold increases, confirming similar results in other FX market studies Aloud et al. (2011), Glattfelder et al. (2011). Therefore, the values of DC indicators are related to the threshold's magnitude. Obviously, with a threshold of smaller magnitude, the NDC and OS events increases. We examined the DC profiles under a different threshold of 3% and 9%, results are shown in Tables 1-4. With a threshold of 9%, we observed 86 DC events for SABB (refer to row NDC under SABB column in Table 1), whereas with a smaller threshold of 3%, we observe 172 DC events (refer to row NDC under SABB column in Table 3). Cautiousness in deciding on a suitable threshold is vital to reflect the dynamic of the price evolution, known that, when a threshold which is either excessively large or excessively small is used, the values of DC indicator will possibly fail to mark numerous significant patterns on the price time series.

The reported results have demonstrated how DC indicators can be used to summarize price changes in the high-frequency stock market. Through these DC indicators, we can discover and capture valuable information as regards the profiled price data period. For instance, in the profiled SABB stock index, price rises slowly in uptrends and drops rapidly in downtrends. The opposite information was observed in RAJHI and ZAIN indices. The results show that OSs took place in FMs price time series, and accordingly investment arbitrage opportunities emerge. A DC event depicts a pattern set up for the price move which possibly will influence decision makers, assuming that the current trend will continue in the same direction. The DC framework can be generalized to a multivariate scheme which allows the analysis of dependencies between different variables of DC indicators (e.g. NDC, NOS, OSM, etc.). Such statistical results cannot be easily captured by existing econometric models in the literature.

It is vital to be aware with how fit intrinsic time (DC framework) and physical fixed time intervals capture the evolution of prices in a time series. This allows the evaluation of their performance by means of which is a premium at describing the price changes in a time series. The reported results in this paper emphasize the significance of considering DC and OS events in studying the price curve, rather than physical fixed time intervals knowing the long coastline of price changes under DC framework. For every threshold that we have experienced, the length of the PCC defined by DC framework is long. The length of PCC increases with the increased threshold. The potential profit in SABB trading is under a 9% (22.63%), which is greater than the potential profit for 3% threshold (7.60%).

DC framework allows the analyst to capture the short term of price evolution by presenting significant information and a clear picture of price behavior since it can be easily applied to multivariate data. In addition, studying the price time series in FMs under DC framework reduces the computational load and the complexity of price time series known the small number of price points for evaluation. The computational costs (which consist of the cost of evaluating data rows) necessity not to be ignored. Therefore, computational costs have to be part of the criteria when it comes to choosing a method for studying price time series.

8. CONCLUSION

To construct efficient and superior investment solutions in FMs, we need to process the financial data as a natural science: Groundwork for the analysis of raw price data, natural investment, and arbitrage opportunities emerge. In this paper, we use a DC event based framework intended to map continuous FM data into the so-called intrinsic network. We define a set of time series analysis indicators under DC event based framework and show that the DC indicators have a consistent hierarchical structure, permitting multi-scale analysis of FM price time series. DC indicators are different from the traditional time series analysis indicators and they valuable tools for risk management, volatility modeling and for creating automated trading models. These indicators present a different angle for capturing price changes in an FM time series.

This paper offers a plain and adequate definition of the DC framework, in conjunction with the motivation behind introducing this framework, its advantages, and significance, and the working mechanisms. The DC framework has the potential to become a robust foundation framework for studying price time series in FMs, which possibly will present new findings as regards to the FMs behavior in different situations. The measurement of the length of the PCC under DC framework which represents the profit potential shows a long coastline of price changes, confirming similar results in Aloud et al. (2011), Glattfelder et al. (2011) for FX market. The PCC indicator shows that studying the price under DC framework gives an advanced description of price changes than does using physical time with fixed intervals. We believe that the DC indicators can improve our study of the dynamic behavior of price time series and advance the quality of the predictions and inference we formulate regarding the behavior of prices in FMs.

With the DC indicators presented in this paper, one essential direction of future research is to extend the catalogue of DC indicators by discovering and defining new indicators for DC profiles. The more practical DC indicators one defines, the more valuable information we can capture from the financial data. One promising research direction is to use the DC framework in studying volatility and measuring trading risk in the FMs. Going further, the DC indicators can be of significant use in building automated trading algorithms and forecasting models. With reference to the well know FM crisis, we argue and demonstrate that the new DC indicators have the ability to stand for an early warning system by means of detecting and predicting a crisis in FMs. A mechanism for forecasting financial crises and price collapse in a time series have to be developed, along with resources by which we can identify and analyze patterns with regard to early signs of market crisis.

9. ACKNOWLEDGMENTS

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Algorithm 1: Dissect the price time series from time t_0 and measure DC and OS with a λ price threshold.

Require: Initialise variables (mode is upturn event, price threshold λ (Fixed) ≥ 0, $p^{ext} = p(t)$ at time t_0) update latest t_i with t if mode is upturn event then

if $p(t)_t \leq p^{ext} \times (1-\lambda)$ then

        DC event ← downturn event

        $p^{ext} ← p(t)$

        $t_{DC,1}$ ← t//End time for a downturn DC event

        $t_{OS,0}$ ← t+1//Start time for a downward OS event

    else

        $p^{ext} ← max (p^{ext}, p(t))$

        $t_{DC,0}$ ← t//Start time for a downturn DC event

        $t_{OS,1}$ ← t−1//End time for an upward OS event

    endif

    else//mode is downturn event

    if $p(t) \geq p^{ext} \times (1 + \lambda)$then

        DC event ← upturn event

        $p^{ext} ← p(t)$

        $t_{DC,1}$ ← t//End time for an upturn DC event

        $t_{OS,0}$ ←t+1//Start time for an upward OS event

    else

        $p^{ext} ← min (p^{ext}, p(t))$

        $t_{DC,0}$ ←t//Start time for an upturn DC event

        $t_{OS,1}$ ← t−1//End time for a downward OS event

    endif

endif