# Using Directional Change for Information Extraction in Financial Market Data

A thesis submitted for the degree of PhD in Computational Finance

Department of Centre for Computational Finance and Economic Agents (CCFEA), University of Essex

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Ran Tao

Supervisor: Edward PK Tsang, Carmine Ventre

Ran Tao

# *Abstract*

*Directional change (DC) is a new concept for summarizing market dynamics. Instead of sampling the financial market at fixed intervals as in the traditional time series analysis, by contrast, DC is data-driven: the price change itself dictates when a price is recorded. DC provides us with a complementary way to extract information from data. The data sampled at irregular time intervals in DC allows us to observe features that may not be recognized under time series. In this thesis we propose our new method for the summarizing of financial markets through the use of the DC framework. Firstly, we define what is the vocabulary needed for a DC market summary. The vocabulary includes DC indicators and metrics. DC indicators are used to build a DC market summary for a single market. DC metrics help us quantitatively measure the differences between two markets under the directional change method. We demonstrate how such metrics could quantitatively measure the differences between different DC market summaries. Then, with real financial market data studied using DC, we aim to demonstrate the practicability of DC market analysis, as a complementary method to that of time series, in the analysis of the financial market.*

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# Table of Contents

## List of Figures

## List of Tables

## List of Algorithms

# Chapter 1 Introduction

This chapter is an introduction to the themes of the thesis. It provides a general overview of the research work that has been carried out and discusses its aims and main objectives. The structure of the thesis is described in detail.

## 1.1 Overview

The complex and difficult subject of how to understand the operational dynamics of financial markets has long been attempted by researchers. Firstly, the question arises what are markets? They can be broadly and straightforwardly defined as where buyers and sellers operate to both create and trade in financial assets, which can be stocks, bonds or commodities. Market movement thus is a reflection of supply and demand, and therefore plays a crucial role in the outcome of local, national and international economies, which in turn impact on pretty much every feature of life. According to Johnson (2010), financial markets are an example of "complexity in action": a real world complex system whose evolution is dictated by the decisions of traders who are continually trying to win in a vast global 'game.' The long and complex operation and history of the financial markets also changes rapidly over time, linked as they are to continuous and rapid technological innovations and changes. This huge field of study is aptly summed up by Paul Krugman (2018), the Nobel prizewinning economist, in his view, studying such topics: "involved making assumptions about how unmeasurable things affected other unmeasurable things." However, in the 21st century, with the development of high frequency trading, of computerisation, and the intricacies of electronic trading platforms in the modern financial market, this offers the latest development of being able to study financial data from global, 24 hour financial markets, to be able to empirically and rationally analyse the market, and to gain new insights into its working, through computer based research, and consequently being able to handle large amounts of data-based information. In our view, these rapidly evolving new technologies and techniques offer a chance to gain new insights from the data into the evolving market dynamics. Modern market analysis is mainly based on time series analysis. It provides us with the basic tools to analyse the market using time series and to gain experience of financial market price movements (Harvey 1990, Tsay 2005). Using the data sampled from time series analysis, researchers have been able to study the impact of traders' psychology, heterogeneous expectations and technical trading on the market (Barberis 2003, Menkhoff and Taylor 2007, Shleifer 2000, Subrahmanyam 2007), explore the market microstructure (Calamia 1999, Evans 2008, Hasbrouck 2007, Madhavan 2000, Osler 2008, Vitale 2007), and apply agent based modelling and artificial intelligence techniques (Hommes 2006, LeBaron 2001, LeBaron 2006, Samanidou 2007). All these are attempts to gain insights into the market and its dynamics.

However, time series analysis is based on the samples in which the observer samples prices at fixed time intervals (Hamilton 1994). On the other hand, the concept of 'directional changes' (DC) was introduced as an alternative way to summarise price changes in the financial market (Guillaume 1997). In DC, by contrast to time series, the sample points are data-driven, thus the observer lets the data determine when to sample the market. In DC, two decisions then have to be made by the researcher to achieve an effective DC result. The first decision relates to what price-change threshold the observer considers to be of significance, e.g. 5%, 1% or 0.5%, etc. The next decision involves perception of the market as alternating between uptrends and downtrends. A change from a downtrend (uptrend) to an uptrend (downtrend) is accepted when the price data points are sampled, when the market changes direction by that of the chosen predefined threshold. Therefore, DC provides us a new way to sample prices from the financial market. By the data sampled through this method, researchers can develop trading strategies (Gypteau 2015), forecasting market price movements (Masry 2013). And also, it is eligible to help build a new methodology for analysing market dynamics, which is what this thesis is looking at.

With most market research based on the use of time series, the question needs to be asked as to why DC should be introduced as a new way to analyse data? Researchers have developed useful indicators in time series analysis - e.g. return and volatility. We argue in our research that the DC-approach provides an insight into data, which is not revealed in using time series analysis. During our research, we have demonstrated that information extracted through DC-based analysis is complementary to information extracted from time series in another published paper (Tsang et al 2015). In time series analysis, the researcher determines how often data is sampled, in other words the researcher determines the time-scale of the x-axis and observes price changes in the y-axis. By contrast, in DC-based analysis, the researcher determines how large a change is considered significant, in other words the researcher is able to determine the price-scale of the y-axis and therefore lets the movement of the data dictate when to record price movements. With data sampled at irregular time intervals, most statistical analysis is not applicable to DC-based sampling. Our research therefore firstly defines and introduces the indicators for DC-based sampling and builds a DC market profile. Then the second step is to define metrics to contrast DC profiles from different markets or different time periods. The DC indicators and metrics make up our DC vocabulary, which facilitates our DC market analysis. Through the application of DC market analysis in the currency and commodity markets, we aim to demonstrate how DC market information can be extracted through DC metrics based on empirical analysis. Time series and DC-based analysis both look at the data from two different angles and provide different perspectives of the same data. They both highlight different features of market analysis and complement each other in their ability to make effective use of market data information extraction.

## 1.2 Research motivations and objectives

The aim of this research is to introduce DC market analysis as a new approach in financial market information extraction and show its application and results in the financial market. In order to present a clear illustration for the whole process, this thesis comprises the following objectives:

1. Introducing the definition of DC and showing its concept on how to sample data from the market.

2. Defining our new indicators to build a DC market profile. We write our program to generate our DC profile from the market data. This profile contains all our DC indicators values for a single market in a certain time period, which can be used for analysing single market price movement. The DC profile, as a complement to time series analysis, can provide us a new angle to observe the market dynamics and extract useful market information.

3. Defining DC metrics as an advanced way for market comparison through DC. We also write another program to generate metrics results through comparison. By comparing DC profiles from different markets or different time periods, DC metrics are able to provide us with a quantitative way to measure the differences between different financial markets in the same time period, or the same market in different

time periods. Thus, it can present us more useful information about the financial market.

4. After defining DC indicators and metrics and proving its usefulness, we apply our DC approach to actual financial market data. We use minute-by-minute data from five main currency pairs in the currency market and four main commodities in the futures market. All of the data has been provided by Thomson Reuters and Kibot. Through profile comparisons between different assets in the same time period or the same assets in different time periods, we try to extract some useful information about these assets and the financial market, which can only be captured by DC.

## 1.3 Thesis structure

The thesis structure is based on the aims and objectives discussed in the previous section. It begins with a background and literature review in Chapter 2, describing the previous studies researchers have done in financial market data analysis. It also explains the concept of DC and its component events.

Chapter 3 introduces the DC indicators we defined for extracting information from data under the DC framework. Compared with time series analysis indicators, DC indicators provide us a new perspective to observe the market dynamics. We wrote a program called TR1 to help us calculate these indicators values and to generate a DC market profile from the market data. Then we have given an example to show the process of TR1 from the currency markets. At the end of the chapter, we have shown the performance of our DC indicators and demonstrate its usefulness through the equity market data, which was provided by Thomson Reuters.

Chapter 4 introduces our DC metrics for quantitative measurement of the differences between two DC market profiles. Similar to the time series analysis, which can measure the difference between two markets using correlation regression, DC market analysis also needs metrics to quantitatively measure the differences between two market states. We also have a program called TR2 to calculate metrics values in this chapter, and an example to show the process of TR2 using currency market data. The example demonstrates the practicality of DC metrics in market comparison.

Chapter 5 and 6 are empirical results of DC market analyses applications in information extraction from the financial market. We used minute-by-minute open prices between 2011 and 2015 from the currency and the commodity market, which are provided by Kibot. The database includes five main currency pairs and four main commodities in the market. Chapter 5 shows the application results of DC indicators, which are from single market data, for example, the gold market in a certain time period. Chapter 6 offers the results of market comparisons between different markets in the same time period or the same market in different time period.

The thesis is concluded in Chapter 7. It summarizes the work we have done in the thesis, lists its main contributions, and discusses further work on DC as a new way to provide market information extraction.

# Chapter 2 Background and Literature review

In this chapter we present the introduction of financial market analysis and the work about DC that researchers have done before. After that we will explain the concept of DC and its component events.

## 2.1 Introduction of market analysis

The financial markets are marketplaces where traders buy or sell financial assets like stocks, futures and currencies. With the development of financial industries around the world, the financial market has grown rapidly and impacts on people's daily lives. For example, the currency (foreign exchange) market, is open 24 hours a day, 5 days a week, and is the largest financial market worldwide, with a daily average turnover of 4 trillion USD and an average daily transaction volume for spot currencies of 1.4 trillion USD or equivalent of 10 per cent of the GDP of the US, according to the Bank for International Settlements (BIS) Triennial Survey in 2010 (BIS 2010). Analysing and understanding the financial market is therefore significant for market traders, observers and analysts because of its national and global reach.

Financial market analysis is therefore concerned with accurately understanding what has happened, and what will happen in the future in that marketplace, and therefore to better estimate what positions that the traders should take in the market. Considering the large amount of trading data in the market, the first step for market analysis is to sample data that the researchers need. The traditional way to conduct financial market analysis is time series analysis (Blake 1990), which is analysing the market data sampled by fixed time intervals from the market data. Based on the time series analysis, researchers have made plenty of contributions in many aspects of financial markets. Roberts (1959) has defined some classical patterns about the stock market. Campbell et al (1997) and Alexander (2011) introduced several basic models for financial data analysis. Gabaix et al (2003) discovers power law distribution in financial market fluctuations. Pincus and Kalman (2004) and Los (2009) defined the financial market risks based on time series analysis. Bollerslev et al (1992), Francq (2011) and Brooks (2014) use time series to build models for market volatility forecasting in econometrics, for example, ARCH, GARCH and ARMA model. Time series analysis, which uses samples collected by fixed time intervals, has become a basic tool for analysing and understanding market dynamics (Kirkpatrick 2010, Taylor 1992, Murphy 1999). Some methods in time series analysis, like the ARMA and Fourier analysis, are widely used for forecasting future values based on the existing time series (Shumway 2010). Besides that, another significant application of time series analysis is for the comparison between different time series. The underlying aim of this kind of analysis is to uncover similarities and patterns that might exist in the data. For most of these activities it is necessary to compare time series using an appropriate similarity measure (Ye 2003). Similarity measures can be divided into metric or non-metric measures, which compare two time series objects and return a value that measures how similar the two objects are (Tapinos 2013). Distance metrics are commonly used similarity measures to define if two time series are similar (Keogh 2003). In those cases, it is more desirable to carry out the data mining analysis on shorter representations of the time series. Many methods exist for creating such representations and estimating the distance between pairs of time series approximations, such as discrete Fourier transform (Agrawal 1993), discrete wavelet transform (Chan 1999), piecewise aggregate approximation (Keogh 2001), or symbolic aggregate approximation (Lin 2007). These methods are widely used in the work of econometrics.

## 2.2 Background of DC research

This section will examine what is the available literature on the recent field of directional change (DC) and will then go on to examine what is directional change's ability to offer a new perspective on summarizing the changing dynamics of the financial market.

Given the rapid growth of advanced information technology and an increasingly global 24-hour financial system, there is a huge amount of high frequency financial data available for analysis. Thus, the ability to correctly understand and interpret market data for both national and international markets has a growing importance for investors, traders and regulators. And what DC analysis can offer in the way of the ability to accurately extract information from the data is one of the central questions of this thesis, and then to go on to create our DC market indicators and metrics, in order to achieve effective and reliable market summaries.

The traditional method used to do market summary has usually been that of the use of time series analysis, which has been able to both model the data and analyse it. However, we try to demonstrate that DC is able to do this as effectively, as well as being able to bring a different perspective to such market analysis. The traditional time series analysis is based on the physical time interval. However, as Ye et al (2017) pointed out: ‘‘time is considered as an absolute entity, where the time ticks are independent of the events in the market.’’ The models in time series analysis are unable to characterize the nature of the price changes consistently across all time intervals. A time series model that explains the changes in the financial variable at low frequency time intervals is not successful at high frequency time intervals. Unlike low frequency market, in high frequency market like currency market, the transaction price is irregularly spaced. This is why Engle and Russell (1998) and Engle (2000) developed the ACD model to describe the transaction data movements in currency market. Besides that, for the time series analysis, the financial data is collected at regular time intervals. ‘‘But it is a well-known fact that the trading events (or price changes) are a sequence of irregularly time-distributed events and they need not be occurring at uniform time intervals. ” (Ye et al 2017). In other words, market data is sampled by fixed time interval in time series analysis. For example, as Figure 1 shows, researchers can use fixed time interval every 10000 minutes to sample prices (green points in Figure 1) from the USD/CNY market in five years. Then some extreme points (red points in Figure 1) will not be captured by time series analysis. Thus, as Ye et al indicates, there is a difficulty with regular interval time series in that there is no guarantee that the events or price changes in the market fall in the regularly spaced time ticks of physical time, and thus the ignored details in between the time ticks are not necessarily significant enough. (Ye et al 2017).

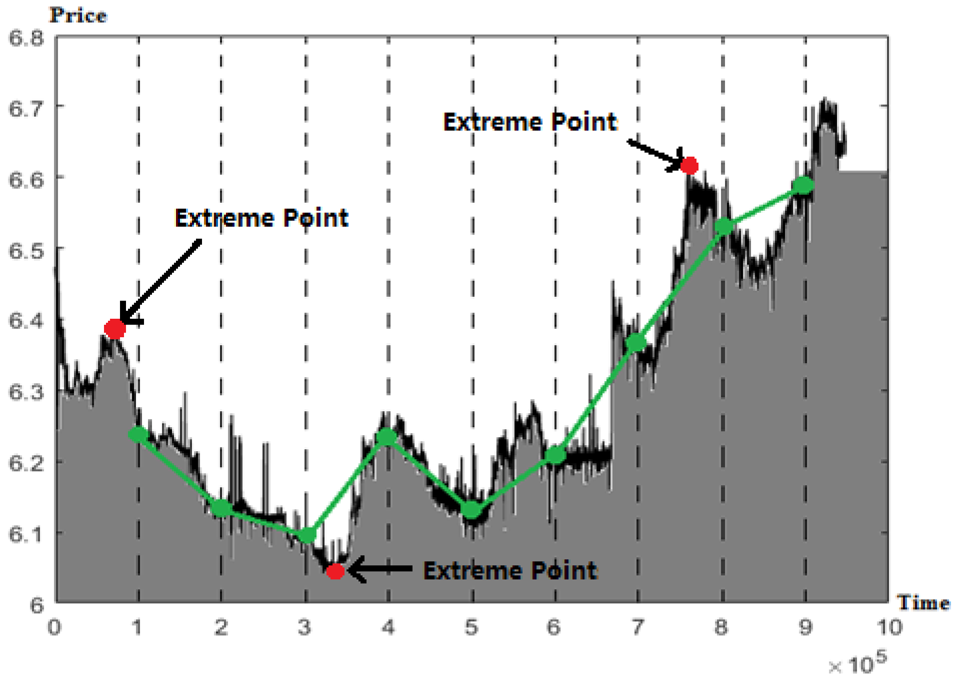


Figure 1: Example: Price movements of minute-by-minute market data for USD/CNY, spanning from 2011to 2016. Some market extreme points (red point) is missed if the researcher uses fixed time interval every 100000 minutes (green point) to sample a price from the market data.

By contrast, directional change (DC) can therefore be described as being an empirical, data-led system with the ability to sample price movements, fluctuations and volatility in the financial markets in an uneven time space, or in intrinsic time. In that case a time scale is irregularly spaced as it is an event-based timing.  The distinguishing feature of DC is that it has the ability to register movement of data only by the threshold chosen by the observer (Aloud et al. 2011). Therefore, it ignores insignificant price fluctuations, and has the ability to observe financial events over a significant period of time.  This is in comparison to time series, which, as indicated by Tsang (2016), if only the end of day financial prices had been recorded, the flash crash which took place on the 6$^{th}$ May 2010 would have gone unnoticed. Thus, time series is unable to characterise all significant market changes across all time periods, as financial movements are unevenly spaced across physical time.

The concept of using DC to study the financial market was first introduced by Gillaume et al in 1997, and was used to study the currency data, and estimated the average number of directional price changes of a chosen threshold over the data sample to interpret an alternative measure of the risk.  However, the idea of following directional change in the market had also been used earlier by financial traders under the name of zigzag (Sklarew 1980). In fact, both Zigzag and DC can summarise the market price movements when a threshold is given. Zigzag focuses more on market technical patterns, while DC can summarise deeper market information for the price changes. Tsang (2011), went on to provide a formal definition of the workings of directional change. According to Tsang (2011), a DC event is confirmed by a fixed price changes and followed by an overshoot event. As the Figure 2 below shows, in the same market data, DC has its advantage to help researchers to catch the market extreme points. The details of the definition of DC will be illustrated in the next section.

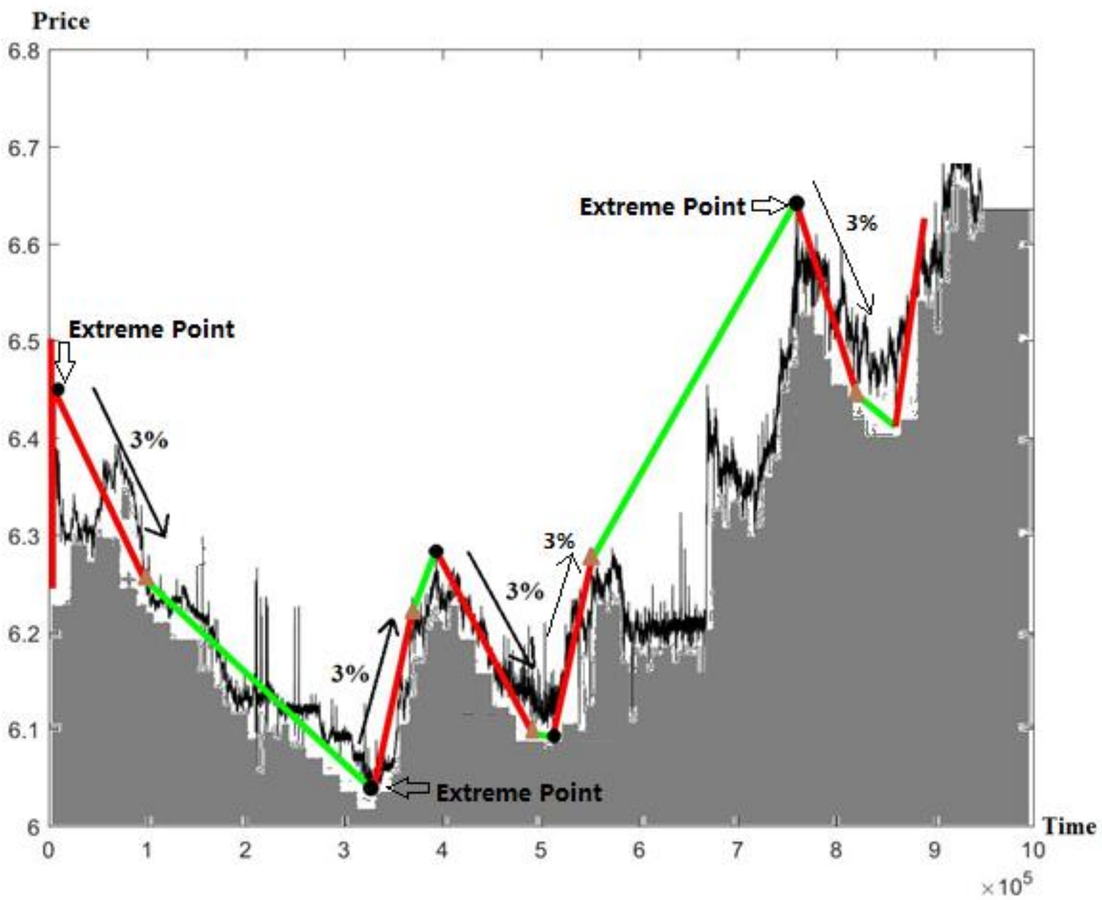


Figure 2: Example: Price movements of minute-by-minute market data for USD/CNY, spanning from 2011to 2016. Directional Changes(DC) has its advantage to help researchers to catch the market extreme points (black point).

The possible uses of DC were further developed by Glattfelder et al, (2011), who used a DC-based summary to examine the 12 scaling laws, which are found in the foreign exchange markets. The scaling laws measure the relationship between different types of events across 13 currency exchange rates. It was found that the length of the price curve coastline was surprisingly long under these scaling laws. Kablan and Ng (2011) examined volatility in the financial market, using the event-driven approach of directional change within pre-specified thresholds. Aloud et al (2012), worked on the length of the price-curve coastline as revealed by directional change, and showed a long coastline of potential price changes. Other studies are looking into how to use the ideas of DC to further understand the operation of the financial markets. Masry looked into currency markets based on using the ideas of DC and explored the idea that small differences in market activities can change price trends (Masry 2013). Gypteau (2015) and Kampouridis (2017) used genetic programming to help generate DC-based trading strategies.

Depuis and Olsen went on to examine how to use DC in High Frequency Trading models (HFT) (2011). Bisig et al (2012), proposed the concept of the Scale of Market Quakes (SMQ), based on DC research. Their proposal, with SMQ, was that the currency market is affected and quantified by the declarations of political and economic significance (2012). Their work analysed the average overshoot event, to calculate the magnitude of the quake, similar to assessing an earthquake. The authors claim that because the SMQ responds to compelling market events, the analyst can observe a larger size of SMQ when the market is in an unstable period, and a smaller magnitude of SMQ which corresponds to a stable period. The SNQ shows that the measurement of an overshoot event can be used to quantify the price behaviour that occurs in the financial market at periods of major economic and political periods (Bisig et al 2012). This work led on us to developing the work further by creating a set of DC-based indicators for profiling the financial market (Tsang et al 2016).

Therefore, using DC to sample data focuses on getting around the problem outlined by Tsang (2017), that using time series alone to summarize prices in the financial market means that the prices are sampled only at fixed time intervals, usually with the final transaction price recorded as the daily closing price. However, Tsang (2017) also argues that time series and directional change are not competing ways to study the price dynamics, as in his view they complement each other, and offer different perspectives on the financial market. This, according to Tsang (2017), can ensure that volatility observed under time series can be used alongside the observed frequency and volatility values observed under directional change. ‘By sampling different data points, DC sees price movement from an angle different from time series.  Under time series, one fixes time (in the x-axis) and measures changes in price (in the y-axis).  Under DC, one fixes the threshold in price change (in the y-axis), and let data determine when to sample the next extreme point, ie. Let data determine the next value on the x-axis.  This also determines the time at which the next data point is sampled.’  (Tsang, 2017).

## 2.3 Definition of DC

### 2.3.1 Directional Change (DC) event

According to Tsang (2010), a DC event can take one of two forms - a downturn DC event or an upturn DC event. Besides that, there is a period called downward run which lies in the gap between a downturn DC event and the next upturn DC event, while an upward run lies between an upturn DC event and the next downturn DC event. A downturn DC event terminates an upward run, and starts a downward run, whereas an upturn DC event terminates a downward run and starts an upward run, as it is shown in Figure 3.

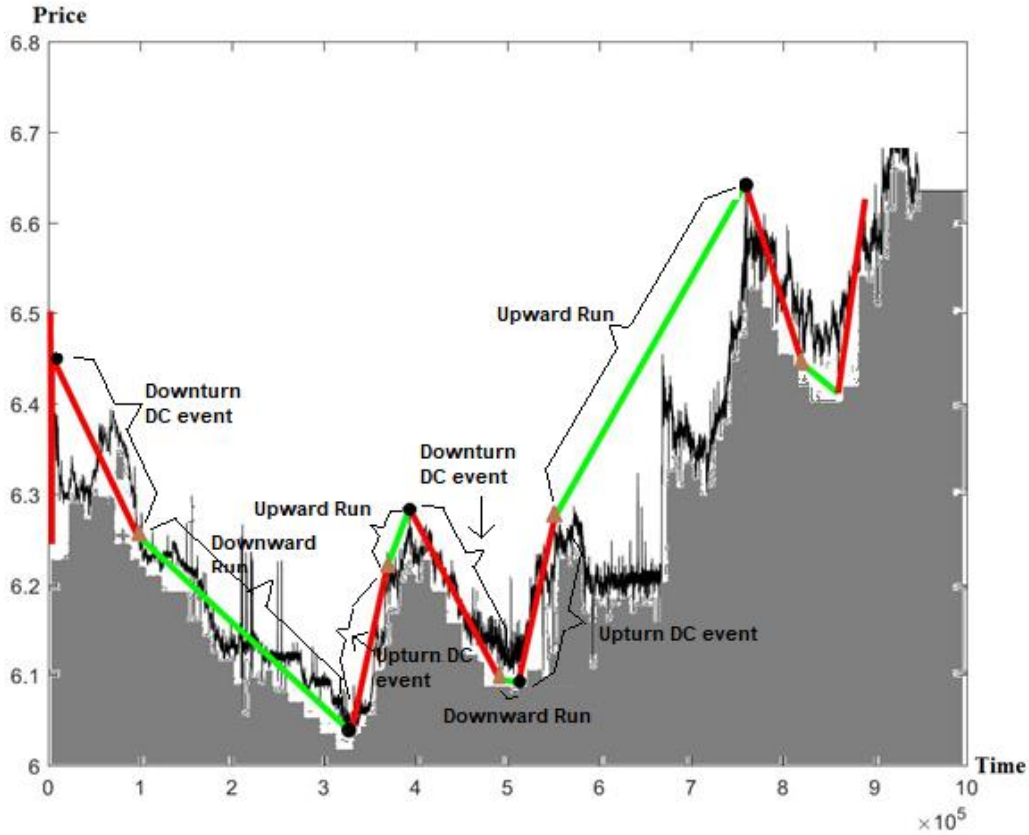


Figure 3: Uptrend DC event, upward run, downtrend DC event and downward run in Directional Changes (minute-by-minute data in USD/CNY market from 2011 to 2016, determined by a threshold 3%)

During a downward run, a last low price $P_l$ is continuously updated to the minimum of $P_t$ (the current market price) and $P_l$ (the last low price). Similarly, during an upward run, a last high price $P_h$ is continuously updated to the maximum of $P_t$ (the current market price) and $P_h$ (the Last High price) (Tsang 2010). At the beginning of the sequence, the last high price $P_h$ and last low price $P_l$ are set to the initial market price $P_{t0}$ at the beginning of the sequence (Tsang 2010).

A downturn DC event is an event when the absolute price change between the current market price $P_t$ and the last high price $P_h$ is lower than a fixed threshold (a percentage) θ:

$$P_t \leq P_h \times (1- \theta) \quad (1)$$

The starting point of a downturn DC event is a downturn point which is the point at which the price last peaked - $P_h$. 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 θ (Tsang 2010).

In a downward run, an upturn DC event is an event when the absolute price change between the current market price Pt and the last low price $P_l$ is higher than a fixed threshold θ:

$$P_t \geq P_l \times (1+\theta) \qquad (2)$$

The starting point of an upturn DC event is an upturn point, which is the point at which the price last troughed - $P_l$. 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 θ.

### 2.3.2 Overshoot (OS) Event

A downturn DC event is followed by a downward overshoot event, which is ended by the next upturn DC event, which is itself followed by an upward overshoot event, which is ended by the next DC downturn event (Tsang 2010), as it is shown in Figure 4. The overshoot event (OS) therefore represents the time interval of price movement beyond the DC event.

Under the DC framework, price movement is summarized in a four-events cycle:

… → *Downturn DC Event* →

*Downward Overshoot Event* →

*Upturn DC Event* →

*Upward Overshoot Event* →

*Downturn DC Event* → …

**Pseudo-code: Defining directional change (DC) and overshoot (OS) events**

Require: Initial variables (event is Upturn Event, $P_h = P_l = P(t_0)$, $\theta > 0$, $t_{dc\_0} = t_{dc\_1} = t_{os\_0} = t_{os\_1} = t_0$)

```
if event is Upturn Event then
  if P(t) ≤ P_h * (1 - θ) then
    Event ← Downturn Event
    P_l ← P(t)
    t_dc_1 ← t   % End time for a Downturn DC Event
    t_os_0 ← t   % Start time for a Downward Overshoot Event
  else
    if P_h < P(t) then
      P_h ← P(t)
      t_dc_0 ← t   % Start time for a Downturn DC Event
      t_os_1 ← t   % End time for an Upward Overshoot Evet
    end if
  end if
else
  if P(t) ≥ P_l * (1 + θ) then
    event ← Upturn Event
    P_h ← P(t)
    t_dc_1 ← t   % End time for an Upturn DC Event
    t_os_0 ← t   % Start time for an Upward Overshoot Event
  else
    if P_l > P(t) then
      P_l ← P(t)
      t_dc_0 ← t   % Start time for an Upturn DC Event
      t_os_1 ← t   % End time for a Downward Overshoot Event
    end if
  end if
end if
```

### 2.3.3 Total Move (TM)

A total price movement (TM) price movement is constituted by a downturn event and a downward overshoot event follows, or an upturn event and an upward overshoot event follows (Glattfelder et al, 2011). Or in other words, TM is the price movements between two consecutive market extreme points in DC, as shown in Figure 4.

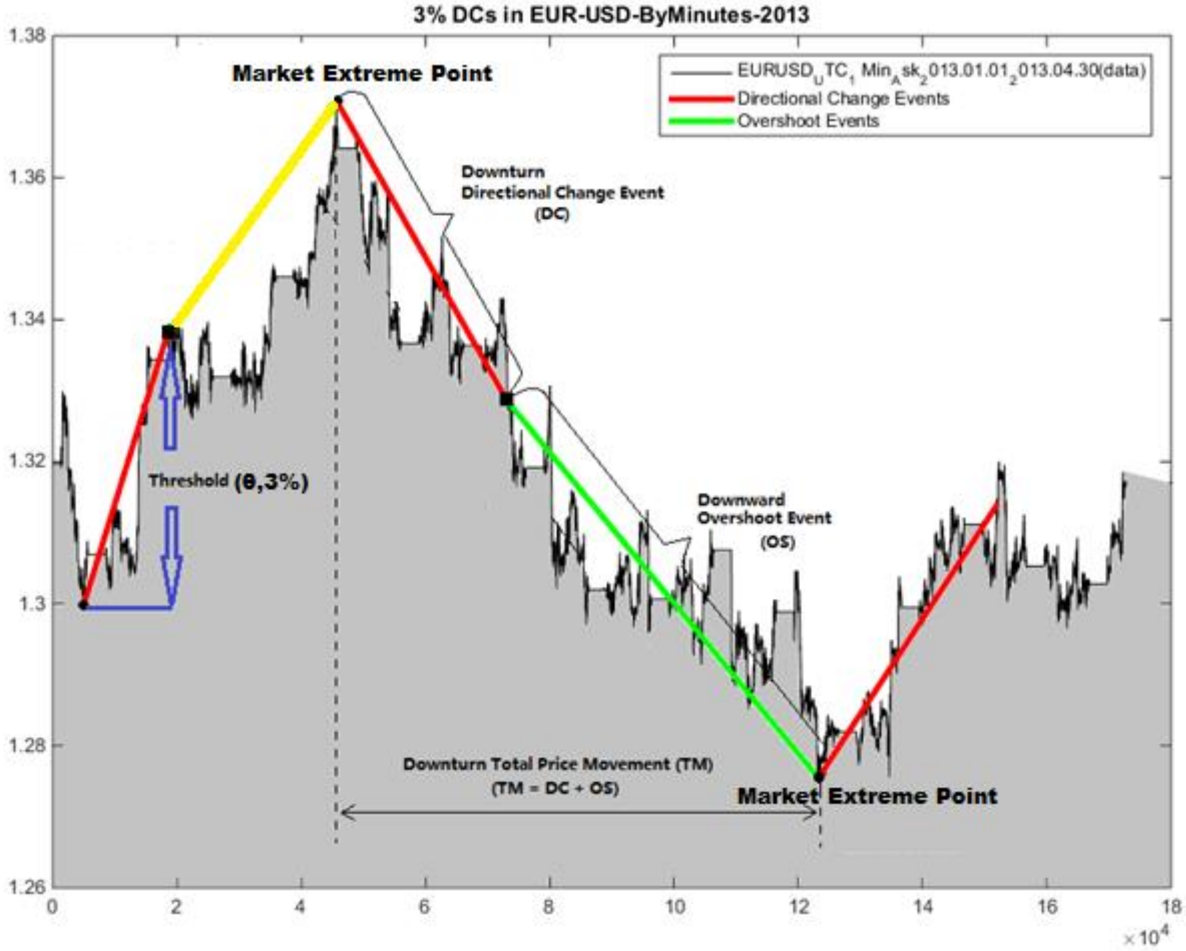


Figure 4: Directional Changes in EUR/USD (threshold = 3%)

# Chapter 3 DC market profiling

In this chapter we will introduce the DC indicators we defined for extracting information from data under the DC framework. We write a program called TR1 to help us calculate these indicators values and generate a DC market profile from the market data. Then we have an example to show the process of TR1 from currency markets. At the end of the chapter, we show the performance of our DC indicators and demonstrate its usefulness through the equity market data which is provided by Thomson Reuters.

## 3.1 Overview

DC market profiling is the first step of DC market information extraction. It focuses on single market dynamics profiling. In this chapter, we defined our own DC indicators to help us build DC market profiles. Compared with time series analysis indicators, the indicators in DC market profiles can provide us some significant information in another angle. We applied them into real equity market and provide a comparison between the results from time series analysis and DC market profiles of the market. to demonstrate the usefulness of DC market profiling.

It begins with an introduction of DC market summarizing in Section 3.2, including the definition of some key points in DC summarizing theory. In Section 3.3 we will continue to introduce the indicators we defined for DC market profiling. We write a program called TR1 to help us calculate these indicators values and generate a DC market profile from the market data. The specification of TR1 is showed in Section 3.4. Then we have an example to show the process of TR1 from currency markets in Section 3.5. The comparison between DC indicators and time series analysis indicators is shown in Section 3.6. After the comparison, in Section 3.7 we show the performance of our DC indicators and demonstrate its usefulness through the equity market data which is provided by Thomson Reuters. The chapter is summarized in Section 3.8.

## 3.2 Summarizing time series with DCs

In this section, we shall propose a procedure for summarizing market price movements with DC. The first step for summarizing time series with DC theory is to locate the significant points of each DC event: Directional Change Extreme Point (EXT), Directional Change Confirmation Point (DCC) and Theoretical Directional Change Confirmation Point (DCC*). As they are shown in Figure 5.

Directional Change Extreme Point (EXT) is the starting point that is an Upturn Point or Downturn Point. It can be also seen as the end of one TM event (Figure 4). Directional Change Confirmation Point (DCC) is the point at which to confirm one DC event. For an Upturn Event, it is the first point that rises above at $P_{EXT} \times (1+ \theta)$. θ is the threshold we set before using DC. And for a Downturn Event, it is the first point that drops at $P_{EXT} \times (1- \theta)$ (Figure 4).

The Theoretical Directional Change Confirmation Point (DCC*) is the minimal or maximum directional change confirmation price for an upturn or downturn directional change event. It does not really exist in the real market in most time. The reason we need DCC* apart from DCC is because in reality, the market price movement may rise or drop sharply in a short time period. Under this kind of circumstance, EXT point and DCC point can be the same point under a fixed threshold, just like the downturn event in Figure 5. We believe the use of DCC* may avoid some troubles for our indicator calculation in the next section. The price of DCC* is defined in the following way:

In an uptrend: $P_{DCC\uparrow*} = P_{EXT} \times (1+ \theta) \leq P_{DCC\uparrow}$;

In a downtrend: $P_{DCC\downarrow*} = P_{EXT} \times (1+ \theta) \geq P_{DCC\downarrow}$,

Here $P_{EXT}$ is the price of directional change extreme point (EXT). $P_{DCC}$ is the price of directional change confirmation point (DCC), θ is the fixed threshold. ↑and ↓ here represents Upturn and Downturn event. Therefore $P_{DCC\uparrow*}$ is the DCC* price of an upturn directional change event and $P_{DCC\downarrow*}$ is the DCC* price of a downturn directional change event.

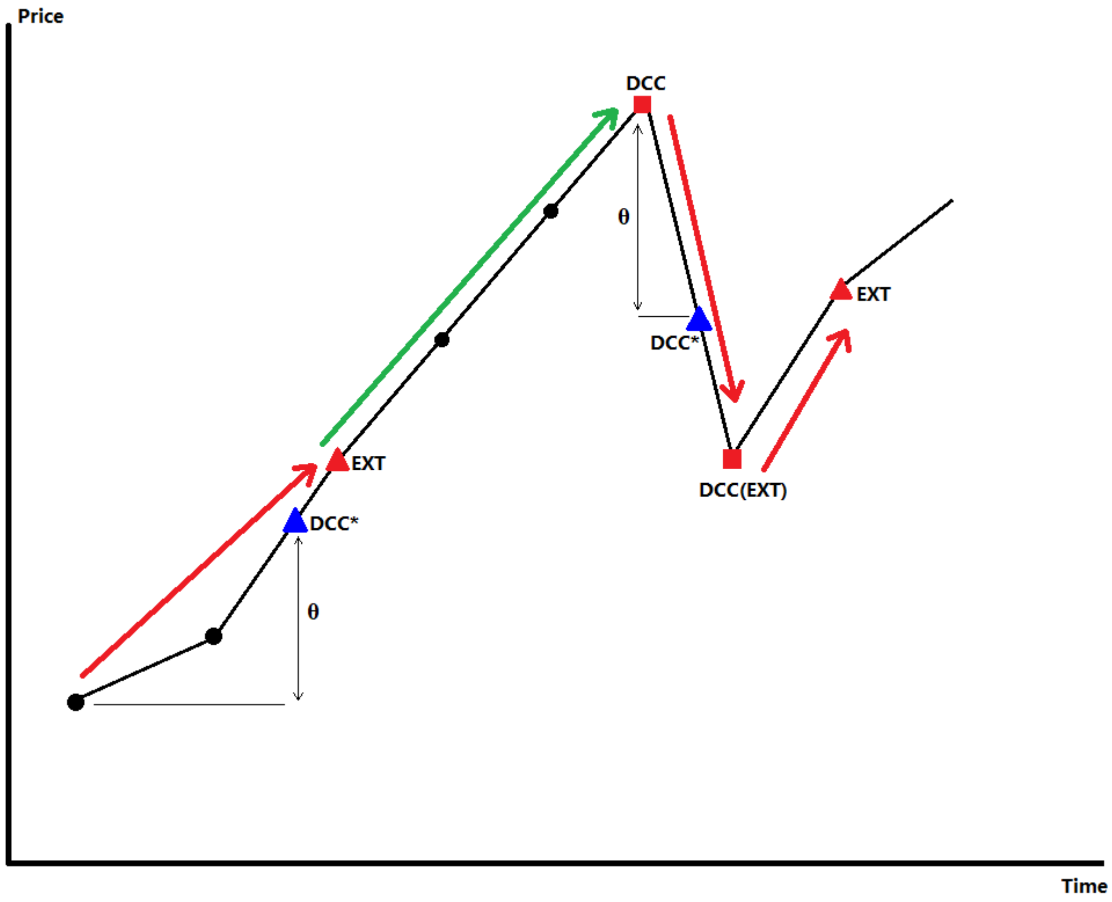


Figure 5: Stylised diagram of EXT, DCC and DCC* in DC. Black round dot represents the market price. Red triangle and square points represent EXT and DCC respectively. Blue triangle point represents DCC*. θ is the threshold. $P_{DCC\uparrow *} = P_{EXT} \times (1+\theta)$. There is no such DCC* existing in a real market, so a DC event is only confirmed in an upturn DC run once it has passed the first DCC, which exists as a market price in real market. And, $P_{DCC\uparrow}$ will not be smaller than $P_{DCC\uparrow *}$. The example of definition of $P_{DCC\downarrow *}$ in a downturn DC run is also shown in this figure.

After the DCC, DCC* and EXT points have been located, the second step is to define useful indicators for directional change market summarizing. These indicators are all calculated from the value of the points and the time intervals. For instance, some indicators are to define the market trend, another indicator is used to measure the directional change trading volatility, or the risk. The introduction of these indicators will be described in the next section. All these indicators will be generated from our programme TR1, after the sample data was introduced into it. The specification of TR1 will be presented in section 3.4 and appendix 8.1.

The programme TR1 will generate two files: the DC-Data file and the Profile Summary File. The DC-Data file includes all details of every point and indicators of it, which is machine readable for testing the correctness of the Profile Summary File. The Profile Summary File is converted from the DC-Data file, while it only has a few indicators in it. These few indicators show the whole of the market price movements. Users will be able to obtain the characteristics of market in directional change terms through these indicators values. This is the whole process of summarizing time series with directional changes through TR1.

## 3.3 DC market profile vocabulary (DC indicators)

In order to analyse price dynamics, we need to extract useful information from DC summaries. In this section, we propose indicators which could be useful for extracting information. With these indicators, we aim to construct profiles for price changes summarized under the DC framework.

### 3.3.1 Number of directional change events ($N_{DC}$)

$N_{DC}$ is the total number of DC events that happened over the profiled period, which measures the frequency, or volatility of DC events. For example, there may have 17 DC events in one market data under a fixed threshold. So $N_{DC}$ = 17. Based on the same threshold, the time period which has higher $N_{DC}$ value is more volatile than other time periods. By recording the $N_{DC}$ within the profiled period, DC provides us with another way to measure the volatility of market price movements.

### 3.3.2 Overshoot Values at Extreme Points ($OSV_{EXT}$)

The magnitude of an overshoot is the price change from the last directional change confirmation price (DCC) to the current price. We define Overshoot Value (OSV) for measuring the magnitude of an overshoot. Instead of using the absolute value of the price change, we would like this measure to be relative to the threshold, θ. Therefore, we define OSV as follows:

$$OSV = ((P_c - P_{DCC}) \div P_{DCC}) \div \theta \quad (3)$$

Here $P_c$ is the current price, $P_{DCC}$ is the last directional change confirmation price, θ is the threshold. At DC confirmation, $P_c = P_{DCC}$, so OSV = 0.

Overshoot values at extreme points ($OSV_{EXT}$) is an indicator for measuring the magnitude of an overshoot based on the price distance between fixed points. It measures how far the overshoot goes from the theoretical directional change confirmation point (DCC*) to the next extreme point (EXT). We define $OSV_{EXT}$ as follows:

$$OSV_{EXT} = ((P_{EXT} - P_{DCC^*}) \div P_{DCC^*}) \div \theta \quad (4)$$

Here $P_{EXT}$ is the price at the extreme point that ends the current trend, $P_{DCC^*}$ is the price of the theoretical directional change confirmation point of the current trend, θ is the threshold. For example, in a downturn DC trend, $P_{EXT\_1} = 1.4629$, $P_{EXT\_2} = 1.4521$. then $P_{DCC^*} = P_{EXT\_1} \times (1-\theta) = 1.4629 \times (1-0.4\%) = 1.457048$. So $OSV_{EXT\_1} = ((1.4521-1.457048) \div 1.457048) \div 0.004 = -0.84905$. This means the magnitude of overshoot event in this trend is 0.84905 times of θ.

In the calculations of OSV and $OSV_{EXT}$, we normalised the indicator values by θ so we can avoid the effect of θ in our DC market summary. In other words, our calculations of OSV and $OSV_{EXT}$ are threshold-independent.

As we emphasised in section 3.2, the reason we use DCC*, rather than DCC, to calculate $OSV_{EXT}$ is because in reality, EXT point and DCC point can be the same point under a fixed threshold. In other words, $P_{EXT}$ may be equal to $P_{DCC}$. So $OSV_{EXT}$ will be equal to 0. Especially if the sample is in a low volatile period, $OSV_{EXT}$ can be a bunch of zero, which will make $OSV_{EXT}$'s calculation meaningless, and therefore no useful information can be extracted through DC market profiling.

### 3.3.3 Time for completion of a trend (T)

DC is defined as being based on events, so it uses intrinsic, as opposed to physical, time (Glattfelder et al 2011). However, that does not mean that it ignores physical time. The amount of physical time that a trend takes to complete, or the frequency of price direction changes, is a significant piece of information for market volatility. We define an indicator

$T_{DC}$ as the time that it takes between the extreme points that begin and end a trend (Figure 6). For example, if the one trend takes six seconds to complete, and time unit for T is second, then T= 6.


Figure 6: Example: T, $P_{EXT}$ and θ in EUR/USD, θ = 3%, $P_{EXT}$ is the price at directional change extreme point (solid black squares), $P_{DCC}$ is the last directional change confirmation price, $T_{DC}$ is the time that it takes between two consecutive directional change extreme points.

### 3.3.4 Total Price Movements Value at Extreme Points (TMV)

Total price movements value at extreme points (TMV) measures the price distance between the extreme points that begin and end a trend, normalized by θ, which is the threshold used for generating the directional change summary. It measures the maximum possible profit for each trend and the magnitude, or scale of price change in each trend. In other words, TMV measures the one aspect of market volatility in DC market summary. Everything being equal, the bigger the scale of changes, the more volatile one may consider the market to be. TMV is defined by:

$$TMV_i = \frac{P_{EXT\_i+1} - P_{EXT\_i}}{P_{EXT_i} * \theta} \tag{5}$$

Here $P_{EXT\_i}$ represents the price at the i-th directional change extreme point, $P_{EXT\_i+1}$ represents the price at the (i+1)-th directional change extreme point, θ is the threshold used (Figure 6). For example, in a downturn DC trend, $P_{EXT\_1}$ = 1.4629, $P_{EXT\_2}$ = 1.4521. Then TMV = ((1.4521-1.4629) ÷ 1.4629) ÷ 0.004 = - 1.84565. This means the scale of price changes in this trend is 1.84565 times θ.

The calculation process of TMV also makes it a threshold-independent indicator, just like OSV and $OSV_{EXT}$.

### 3.3.5 Number of directional change events in Sub-threshold (Sub-$N_{DC}$)

$N_{DC}$ measures the volatility of market price movements over the profiled period. However, the price movement is not smooth from the last EXT point to next EXT point. There still exist some price fluctuations in every DC trend. These price fluctuations are also important information about the market which is not able to be observed by $N_{DC}$. So here we introduced another indicator - Sub-$N_{DC}$. By choosing another smaller threshold, Sub-$N_{DC}$ measures the total number of DC events that happened in each DC trend based on the smaller threshold. For example, as Figure 7 shows, compared with the threshold 3%, we set another smaller threshold, called sub-threshold, which is 1%. Based on the same sub-threshold, the DC trend which has higher Sub-$N_{DC}$ value is more volatile than other DC trends.

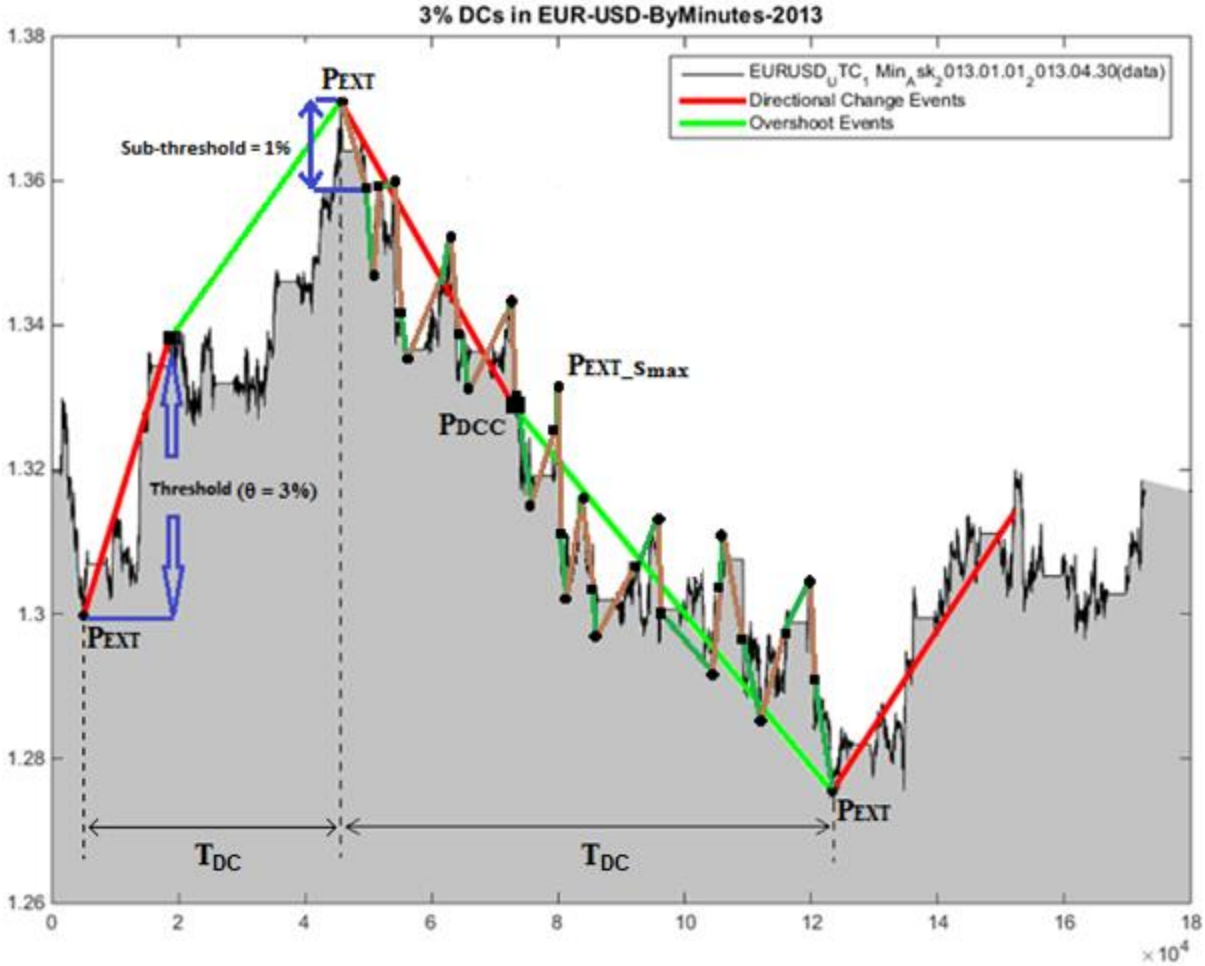


Figure 7: Using sub-threshold 1%, we found 17 DC events between two EXT points. So Sub-$N_{DC}$ is 17 in this DC trend.

### 3.3.6 Undershoot Value at Extreme Points ($USV_{EXT\_s}$)

Undershoot Value at Extreme Points ($USV_{EXT\_s}$) is also based on the sub-threshold. It measures the highest price change in each DC trend according to the sub-threshold. In a downward DC trend, $USV_{EXT\_s}$ is defined by:

$$USV_{EXT\_s} = \begin{cases} \frac{P_{EXT\_smax} - P_{DCC*}}{P_{DCC*} \times \theta}, & P_{EXT_{s\_max}} - P_{DCC*} > 0 \\ 0, & \text{Otherwise} \end{cases} \quad (6)$$

Here $P_{EXT\_Smax}$ is the highest price after the DC confirmation point, which is based on sub-threshold. As Figure 7 shows. $P_{DCC*}$ is the price of the theoretical directional change confirmation point of the current trend which is based on the threshold, θ is the threshold.

In an upward DC trend, $USV_{EXT\_s}$ is defined by:

$$USV_{EXT\_s} = \begin{cases} \frac{P_{DCC*} - P_{EXT\_smin}}{P_{DCC*} \times \theta}, & P_{DCC*} - P_{EXT_{s\_min}} > 0 \\ 0, & \text{Otherwise} \end{cases} \quad (7)$$

Here $P_{EXT\_S_{min}}$ is the lowest price after the DC confirmation point, which is based on sub-threshold. As Figure 7 shows. $P_{DCC*}$ is the price of the theoretical directional change confirmation point of the current trend which is based on the threshold, θ is the threshold.

Compared with Sub-$N_{DC}$ which measures the frequency of price changes in each DC trend, $USV_{EXT\_s}$ measures the magnitude of price changes in the trend. Trader may see Sub-$N_{DC}$ and $USV_{EXT}$ as measurements of risk in trading through DC. Based on the same sub-threshold, the DC trend which has higher $USV_{EXT\_s}$ value is more volatile than other DC trends.

The calculation process of $USV_{EXT\_s}$ also makes it a threshold-independent indicator, just like OSV and $OSV_{EXT}$.

### 3.3.7 Time independent Coastline ($C_{DC}$)

Since TMV represents the maximum possible profit of each TM event, we define the length of the price-curve coastline under DC (θ) as the sum of all absolute value of TMV over the profiling period:

$$C_{DC} = \sum_{i=1}^{N(\theta)} |TMV_i| \quad (8)$$

Here θ is the threshold (in %), N (θ) is the total number of DC events over the profiling period under θ and $TMV_i$ is the Total Price Movements Value at each directional change extreme point.

The calculation of $C_{DC}$ only pays attention to price changes; time is ignored. It shows us the maximum possible profit available from the profiled period. According to the definition of TMV, it measures the price distance between the extreme points that begin and end a trend, normalized by θ. So we can measure the maximum potential profit in %. For example, if $C_{DC}$ = 100, θ = 0.4%, then the maximum potential profit for the profiled time period is 100×0.4% = 40%.

### 3.3.8 Time-adjusted return of DC ($R_{DC}$)

We define time-adjusted return of DC ($R_{DC}$) to measure the return in each upturn or downturn event, i.e. the ratio between each TM event and time interval (T). A high $R_{DC}$ means the profit can be earned in a short time period. Since TMV measures the number of thresholds in up/downtrend. We define $R_{DC}$ as:

$$R_{DC} = \frac{|TMV| * \theta}{T} \tag{9}$$

Here TMV is total price movement value at extreme points and T is the time interval between each EXT, θ is the threshold used. Here $R_{DC}$ measures the percentage of price rising/dropping per time unit. For example, TMV = -1.84565, T = 25740 seconds. Then $R_{DC}$ = |TMV| × threshold / T = 1.84565 × 0.004 ÷ 25740 = $2.87\times 10^{-7}$. In other words, the second return is 0.0000287%

One could define a coastline based on time-adjusted returns $R_{DC}$. For example, one could take the accumulative returns to represent coastline. However, its equivalence in time series is unfamiliar to researchers. Therefore, while it is potentially useful, we leave this option open at this stage.

### 3.3.9 Up and down trends asymmetry in time intervals ($A_T$)

In a DC profile, because of DC's definition, the uptrend and down trend are always consecutive to each other (See Figure 2) and the amount of uptrend and downtrend are almost equal to each other. This is different from time series analysis. We argue that the difference between the u trend and the down trend are also significant information about the market. So in DC we have two indicators to measure the difference between the uptrend and the down trend. One is for measuring the differences in $T_{DC}$ between the uptrend and the down trend. We call it $A_T$. We defined $A_T$ as:

$$A_T = \frac{T_{m\uparrow} - T_{m\downarrow}}{T_{m\uparrow} + T_{m\downarrow}} \tag{10}$$

Here Where $T_m$ represents the median values of $T_{DC}$ in up trends in each DC profile. $T_m$ represents the median values of $T_{DC}$ in down trends in each DC profile. Here the reason we are using median value instead of average value is also to avoid the effects from extreme value in $T_{DC}$ series. For example, $T_{m\uparrow}$ = 44389 seconds, $T_{m\downarrow}$ = 25740 seconds. Then $A_T$ = (44389 - 25740) ÷ (44389 + 25740) = 0.2659. The range of $A_T$ is always between –1 and 1. The closer $A_T$ is to 0, the less differences between up and down trends in time intervals will be. On the other hand, the closer $A_T$ is to -1 or 1, the more differences between up and down trends in time intervals will be.

### 3.3.10 Up and down trend asymmetry in returns ($A_R$)

Another indicator is $A_R$. It is to measure the asymmetry in the returns ($R_{DC}$) between the uptrend and the downtrend. We call it $A_R$. We defined $A_R$ as:

$$A_R = \frac{R_{DC\_m\uparrow} - R_{DCa\_m\downarrow}}{R_{DC\_m\uparrow} + R_{DCa\_m\downarrow}} \qquad (11)$$

Where $R_{DC\_m}$ represents the median values of $R_{DC}$ in up trends in a DC profile. $R_{DC\_m}$ represents the median values of $R_{DC}$ in down trends in a DC profile. Here we use the median value instead of the average value also in order to avoid the effects from extreme values in the $R_{DC}$ series. For example, $R_{DC\_m\uparrow} = 1.48\times10^{-7}$, $R_{DC\_m\downarrow} = 2.46\times10^{-7}$. Then $A_R = (1.48\times10^{-7} - 2.46\times10^{-7}) \div (1.48\times10^{-7} + 2.46\times10^{-7}) = -0.2589$. The range of $A_R$ is always between –1 and 1. The closer $A_R$ is to 0, the less differences between up and down trends in returns will be. On the other hand, the closer $A_R$ is to -1 or 1, the more differences up and down trends in returns will be.

## 3.4 Specification of TR1

TR1 is a program that reads in time-stamped prices (which we call the Input Data File) and outputs a profile of the input data. The profile includes two parts. First, TR1 outputs a file that contains all the data points at extreme points and directional change confirmation points. We call this the DC-Data File. Secondly, TR1 outputs a summary of the profile. We call it the Profile Summary File. The full specification of TR1 is in Appendix 8.1.

The Profile Summary File is summarized from the DC-Data file, which only has a few indicators in it. These indicators show the information of the whole market price movements, such as the market trend, and the price curve volatility. Combined with time series analysis, users are able to have a different understanding of the market price movements in directional change term as a complementary metric.

### 3.4.1 Input to TR1

The Input file is a csv file with one record per data point, timed.

### 3.4.2 Output of TR1

The program will produce two files: (1) "DC-Data File" and (2) "Profile Summary File".

**DC-Data file contains:**

**Header**: It contains information for reproducing the results, including the program version, input and output files and the threshold used for computing the DCs. The full specification of the Header and the Body (below) can be found in Appendix 8.1.

**Body**: It contains a chronological report of all the trends in the whole period which has been summarized. This includes the extreme point, and directional change confirmation point of each trend, together with indicators $OSV_{EXT}$, TMV, T, $R_{DC}$, Sub-$N_{DC}$ and $USV_{EXT\_s}$ as defined in Section 3.2.

**Profile Summary File contains:**

**Header**: It is the same one as the DC-Data file.

**Body:** It contains market information that concludes from the indicators in the DC-Data file. This includes the number of directional changes ($N_{DC}$) and the median value of $OSV_{EXT}$, TMV, T, $R_{DC}$, Sub-$N_{DC}$ and $USV_{EXT\_s}$ for DC uptrends, downtrends, and the whole trends.

**Snapshot profile –** it only contains market information at the ending point in DC-Data file. This includes the final time and price displayed in the Input Data File, together with the spot indicators OSV, TMV, T and $R_{DC}$ as defined in Section 3.2.

## 3.5 Example of DC profiling

The DC-Data file will be fully displayed in Appendix 8.2, which is used to check the correctness of Profile Summary File in Table 1.

Figure 8 shows the price movements of second-by-second Forex market data for EUR/USD, which spans from October 1, 2009 to October 30, 2009. The data is randomly chosen as an example for showing the process of DC profiling. Figure 8 also shows the highest and lowest price points. Figure 9 shows the one-month data is summarized that in the DC method, under a fixed threshold 0.4%. Table 1 is the DC Profile file, and Table 2 is the Snapshot file.

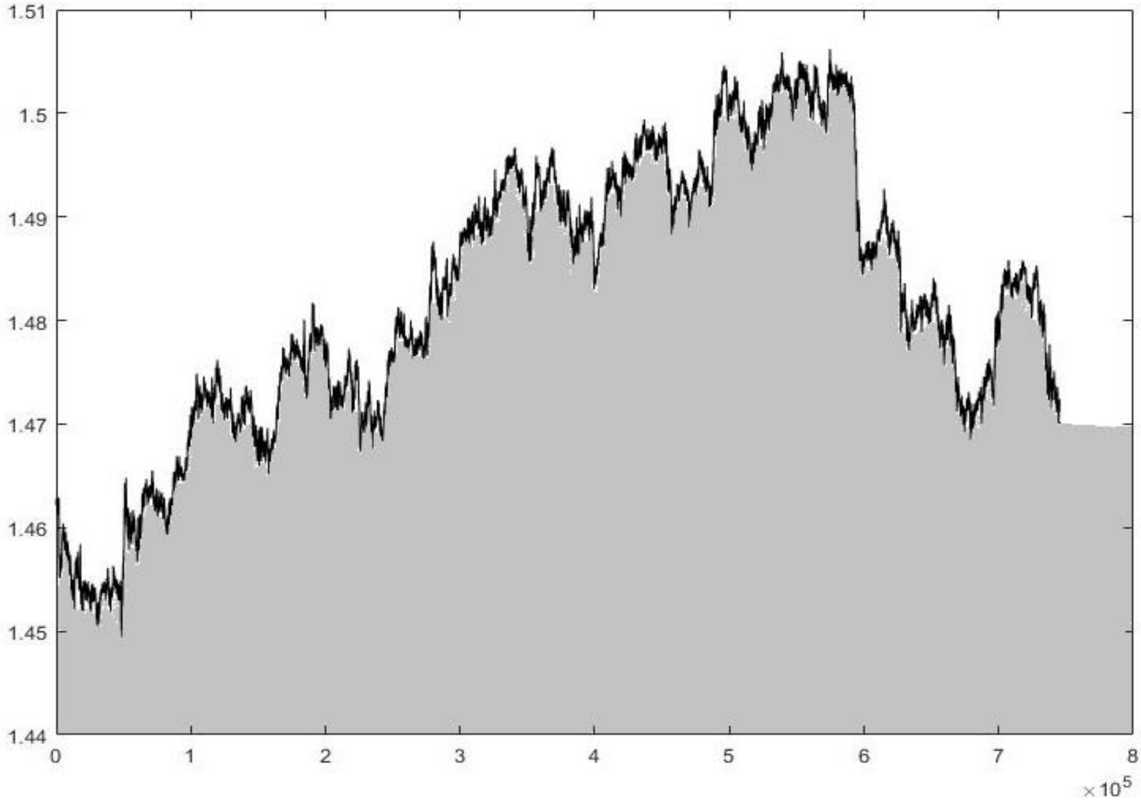


Figure 8: Price movements of second-by-second market data for EUR/USD, spanning October 1, 2009 to October 30, 2009, which includes around 745,466 data points.

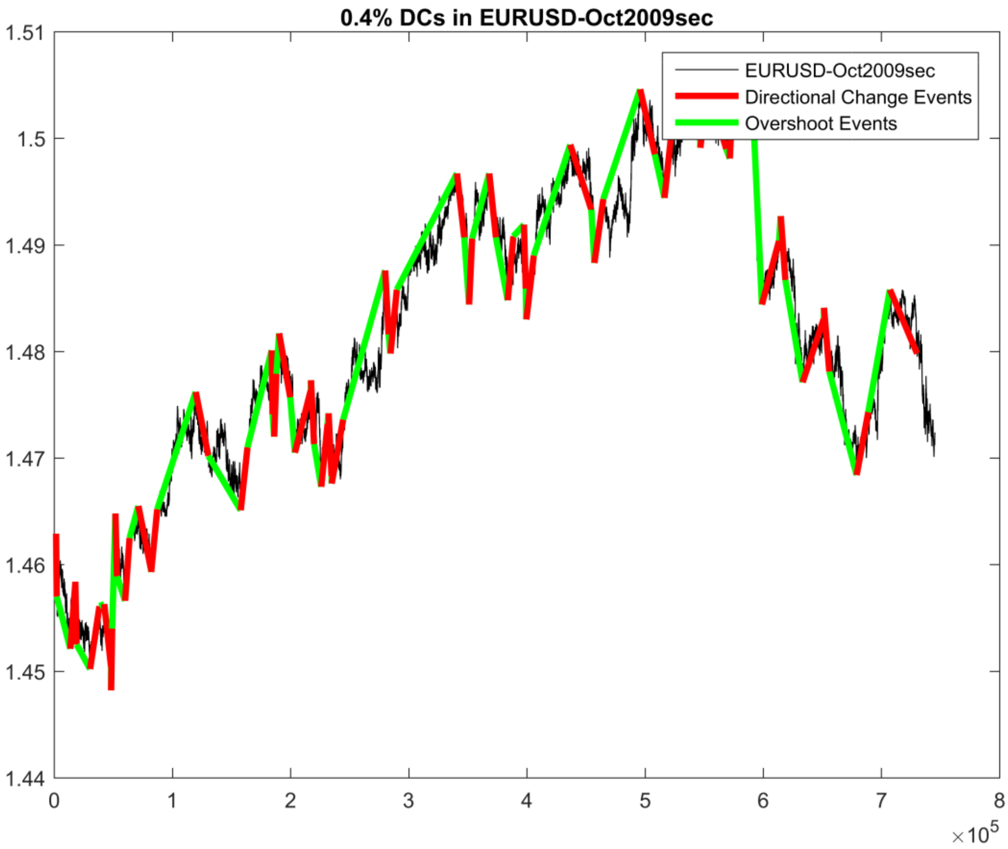


Figure 9: Price movements of second-by-second market data for EUR/USD, spanning October 1, 2009 to October 30, 2009, determined by a fixed threshold 0.4%. The total price movements between two consecutive extreme points are decomposed into directional change events (red lines) and an overshoot events (green lines).

Profile Summary File:

| | |
|---|---|
| Program_ID:TR1.3 | |
| Author: Ran Tao | |
| Date | 2016.03.03 22:20:37 |
| File_input | EURUSD-Oct2009sec |
| Threshold(Theta) | 0.004 |
| Sub-Threshold | 0.001 |
| Tstart | 01/10/2009,00:00:00 |
| Tfinal | 30/10/2009,16:58:58 |
| TL | 745266 |
| NDC | 43 |
| PC | 1.015654 |
| MedianOSV_overall | 0.669948 |
| MedianOSV_up | 0.644839 |
| MedianOSV_down | 0.695057 |
| MedianT_overall | 37378 |
| MedianT_up | 44389 |
| MedianT_down | 25740 |
| MedianR_DC_overall | 1.79E-07 |
| MedianR_DC_up | 1.48E-07 |
| MedianR_DC_down | 2.46E-07 |
| LenC | 77.42177 |
| MeanLenC | 1.843376 |
| MedianSub_NDC | 13 |
| MedianUSV | 0.166625 |

Table 1: Profile Summary File of second-by-second market data for EUR/USD, spanning October 1, 2009 to October 30, 2009, determined by a fixed threshold 0.4% and sub-threshold 0.1%.

| Snapshot | |
|---|---|
| Tfinal | 30/10/2009,16:58:58 |
| Pfinal | 1.4722 |
| SPC | 1.006701 |
| SOSV | -1.28396 |
| STMV | -2.28833 |
| ST | 38042 |
| SR_DC | 6.02E-05 |

Table 2: Snapshot at the final point of second-by-second market data for EUR/USD, spanning October 1, 2009 to October 30, 2009, determined by a fixed threshold 0.4%.

Table 1 is an example of DC market summary. It summarizes the 745,266 seconds (TL) in the one-month period in the EUR/USD market under a threshold of 0.4%. The market price movement is going up as the price changes (PC) from first extreme point (EXT) to the last extreme point which is slightly greater than 1 (1.015654). It shows that there are 43 DC events ($N_{DC}$). The median time that each trend takes is 37,378 seconds (MedianT_overall). The uptrends take more time, which is 44,389 seconds per trend (MedianT_up). While the downtrends only take 25,740 seconds (MedianT_down). Downtrends shows more frequency in price changes.

The median range of price change ($OSV_{EXT}$) is 0.669949 (MedianOSV_overall). The price change in up trends (MedianOSV_up = 0.644839) is smaller than down trends (MedianOSV_down = 0.695057). So the downtrends have more potential profit and less risk for the DC traders.

The profile can also tell us about the time-adjusted return ($R_{DC}$) in up and downtrends. MedianR_DC_up is $1.79 \times 10^{-7}$, or 0.0646% per second. MedianR_DC_up ($1.48 \times 10^{-7}$) is smaller than MedianR_DC _down ($2.46 \times 10^{-7}$). In other words, the price rises 0.053% ($0.053\% = 1.48 \times 10^{-7} \times 3600$) per hour while drops 0.089% ($0.089\% = 2.46 \times 10^{-7} \times 3600$) per hour in each trend. This profile shows that downtrends have higher potential return than uptrends in EUR/USD market.

The price-curve coastline (LenC) is 77.42177. According to the definition of coastline in DC, coastline is the sum of all absolute value of TMV over the profiling period. This means the profit that one can potentially make in the profiling period is 77.42177 × threshold (0.4%) = 30.9687%. It represents the highest possible profit that one could make according to the DC profile. Furthermore, the profile shows that the MeanLenC is 1.843376. This means on average threshold (0.4%) × 1.843376 =0.7373504% of potential profit can be earned in each trend.

The sub-threshold we choose for this DC profile is 0.1% for as a default quarter of the threshold. So the median DC events based on the sub-threshold that happened in each trend is 13 (MedianSub_$N_{DC}$). The median undershoot value at extreme points is 0.166625 (MedianUSV).

### 3.6 Comparison between time series analysis and DC market summary

DC is still in its infancy. It is still limited in how we can use DC indicators to profile market dynamics. But useful information can be gained from the research so far. This has been explained in the above subsections. Here is a summary.

The returns that time series look at are returns over fixed periods of time, chosen by the researcher, while by contrast, the returns that DC looks at ($R_{DC}$) are returns over directional change events, recorded at a threshold decided by the researcher, so it is data-led. Given the same number of data points, DC coastlines are often longer than time series coastlines for the same period, because by definition, DC is able to capture the extreme points when they occur (Aloud et at 2012).

Many researchers (Baillie 1991, Pictet 1997, Chang 1999, Osler 2008, Tsay 2010) have tried to model and forecasting the volatility of financial returns in time series analysis. The most frequently used indicator to measure market historical volatility in time series analysis is the standard deviation of the returns (Hull, 1998). The five indicators ($N_{DC}$, TMV, T, Sub-$N_{DC}$ and $USV_{EXT}$) introduced in DC provide five additional measures of volatility. The introduction of overshoot enabled Glattfelder et al (2011) to observe power laws in the foreign exchange market. Table 3 summarizes the indicators discussed so far.

| | **Time Series Indicators** | **Directional Change Indicators** |
|---|---|---|
| **Return:**<br>Different angles on returns | Returns measured in each (fixed) period | Percentage of price changes measured in each trend. Since they are sampled in irregular times, this percentage must be time adjusted for comparison |
| **Coastlines:**<br>DC coastlines are often longer than time series coastlines (Aloud et at 2012) | Accumulation of Returns | $C_{DC}$: maximum possible returns over the profiled period |
| **Volatility:**<br>Time series and DC provide different perspectives on volatility | Standard deviation on Returns | $N_{DC}$: measures the frequency of DCs<br>TMV: measures the scale of price changes<br>T: measures the time that it takes to complete a trend<br>Sub-$N_{DC}$: measures the frequency of DCs in each DC trend<br>$USV_{EXT\_s}$: measures the scale of price changes in each DC trend |
| **Up and down trend asymmetry** | N/a | $A_T$: measure the difference in $T_{DC}$ between up and down trend |
| | | $A_R$: measure the difference in $R_{DC}$ between up and down trend |
| **Statistical observations:**<br>Different observations made possible by different indicators | Many observations, such as fat tails and volatility clustering | Power law found on overshoot event, which is made possible by the introduction of overshoot value at extreme points (Glattfelder et al 2011) |

Table 3: Contrast between time series indicators and DC-based indicators (Source: modified from [Tsang et al 2016])

## 3.7 Useful information extracted through DC indicators - Profiling high frequency price movements in equity markets

In this section we explain how DC profiling could help us to observe price movements in four companies. These four companies were chosen to represent four sectors in the FTSE 100 Index, which are shown in Table 4.

### 3.7.1 Profiling four blue chip companies

| **Key** | **Company name** | **Sector** |
|---|---|---|
| **AZN** | AstraZeneca PLC | Healthcare |
| **BT** | BT Group PLC | Technology |
| **HSBA** | HSBC Holdings PLC | Financial |
| **MKS** | Marks & Spencer Group PLC | Services |

Table 4: Four companies and the four sectors which they represent (Source: modified from [Tsang et al 2016])

We used tick transaction prices in two time periods, September 2014 and February 2015, to profile each of the four equities. Since the value of threshold will affect the results of profiles, we applied the same threshold (1%) for these four equities. In DC profiles, we calculated the DC indicators which we presented in Section 3.5. The profiles also included some simple statistical analysis of the indicators, such as the median, mean and standard value of the indicators. We developed a program TR1 based on Matlab platform for producing DC profiles.

### 3.7.2 Profiles of the companies

| Time | September 2014 | | | | February 2015 | | | |
|---|---|---|---|---|---|---|---|---|
| Company | AZN | BT | HSBA | MKS | AZN | BT | HSBA | MKS |
| $N_{DC}$ | 82 | 37 | 43 | 57 | 138 | 126 | 81 | 46 |
| MedianTMV | 1.74 | 1.53 | 1.66 | 2.14 | 1.76 | 1.67 | 1.74 | 1.5 |
| Standard deviation of TMV | 1.26 | 0.88 | 0.7 | 1.23 | 1.19 | 1.2 | 1.33 | 0.7 |
| Median T (minutes) | 79.41 | 115.56 | 145.2 | 78.79 | 19.7 | 32.46 | 88.44 | 112.75 |
| Standard deviation of T | 178.77 | 391.37 | 381.85 | 290.07 | 129.61 | 148.9 | 162.61 | 307.93 |
| $C_{DC}$ (%) | 171.84 | 65.28 | 80.84 | 132.28 | 304.69 | 261.72 | 176.78 | 75.27 |

Table 5: Summarized DC Profiles with a threshold of 1% on AZN, BT, HSBA and MKS with second-by-second transaction prices, September 2014 and February 2015 (Source: modified from [Tsang et al 2016])

In Table 5, we included six significant indicators values, as shown in the first column. The last row of Table 5 and Figure 10 show the maximum potential profit for each company during the time periods.

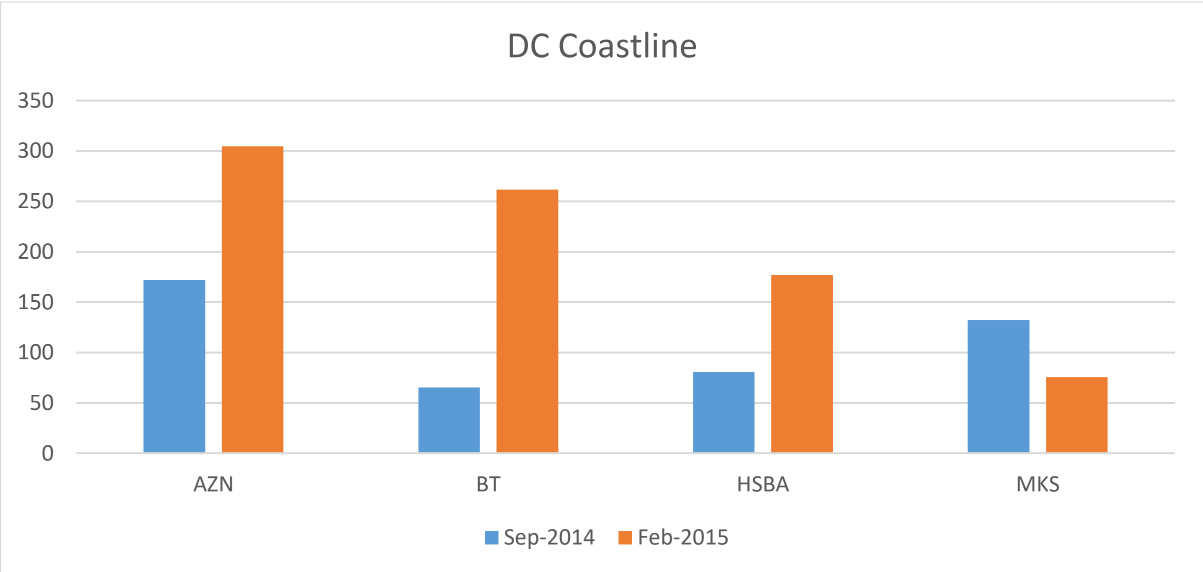


Figure 10: The coastline ($C_{DC}$) from DC profiles for AZN, BT, HSBA and MKS in two different time periods. Blue column is for September 2014 and orange column is for February 2015. (Source: modified from [Tsang et al 2016])

The coastline ($C_{DC}$) of AZN is 171.84% in September 2014 and 304.69% in February 2015. Compared with other three companies in the same time period, AZN always has longest coastline in DC profiles. That means there is the potential to generate more profit in AZN than in the other three companies. Besides, among these four companies, only the coastline of MKS drops from September 2014 to February 2015. It drops from 132.38% to 75.27%. Other three companies' coastlines all rise substantially. For AZN, BT and HSBA, February 2015 presented traders with more profit potentials.

The volatility can be reflected by two indicators in the DC profiles: the frequency of DCs and the magnitude of price changes in each trend. The frequency of DCs is reflected by the time that it takes to complete a trend, T. The magnitude of price change is reflected by the total price movements in each trend, TMV.

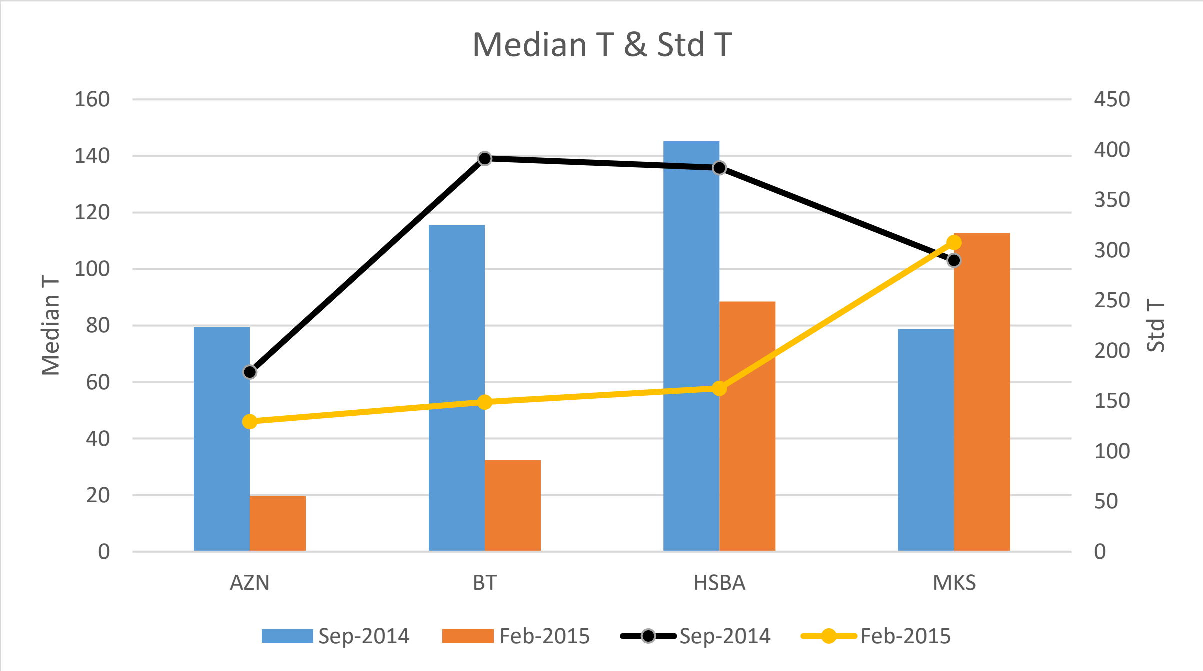


Figure 11: The median and standard deviation of T from DC profiles for AZN, BT, HSBA and MKS in two different time periods. Blue and orange column represent median T. Black and yellow line stand for standard deviation of $T_{DC}$. (Source: modified from [Tsang et al 2016])

T is the physical time that an up or a down trend takes to complete. Everything being equal, the longer time one trend takes to complete, the less volatile one may consider a market to be. In Figure 11, we have reported the median $T_{DC}$ and its standard deviation.

Figure 11 shows that the median value of T for HSBA in February 2015 is 88.44 minutes, which is over four times of the median value of T for AZN in the same time period. HSBA has the second highest value of median $T_{DC}$ among the four companies during February 2015. Considering market volatility in T, we conclude that HSBA in February 2015 has small risks in trading comparatively. As far as T is concerned, HSBA has the lowest volatility in September 2014, and MKS has the lowest volatility in February 2015 among the four companies studied.

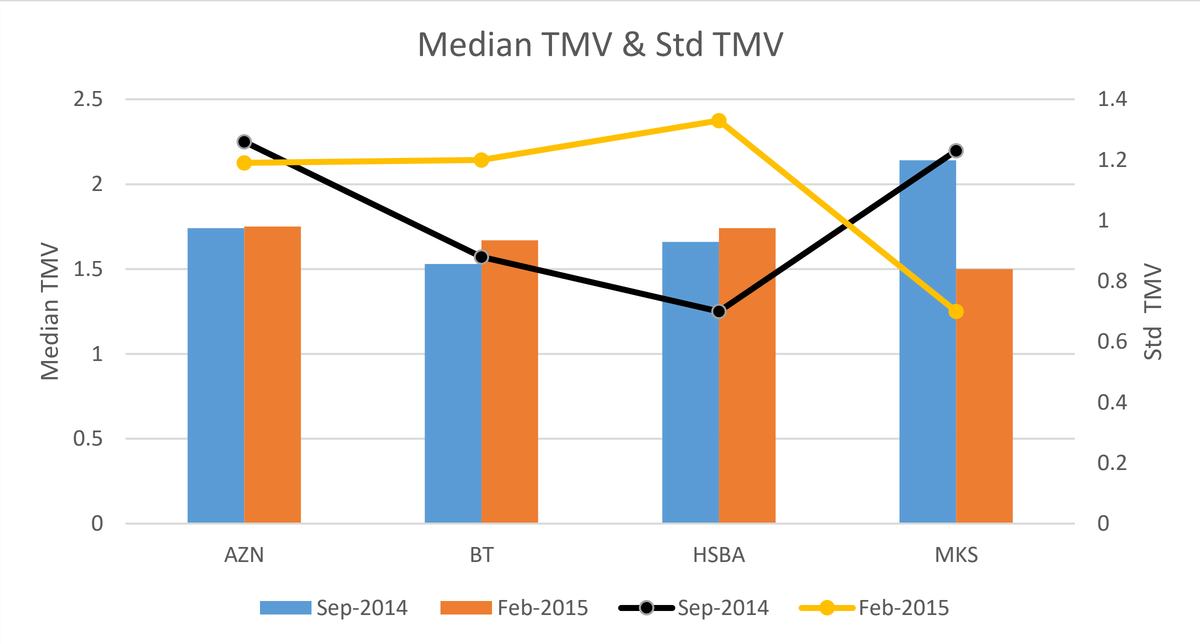


Figure 12: The median TMV and standard deviation of TMV from DC profiles for AZN, BT, HSBA and MKS in two different time periods. Blue and orange column represent median TMV. Black and yellow line stand for standard deviation of TMV. (Source: modified from [Tsang et al 2016])

T only tells half of the story about volatility. TMV tells the other. TMV measures the scale of price changes. Everything being equal, the bigger the scale of changes, the more volatile one may consider the market to be. In Figure 12, we reported the median value of TMV as well as their standard deviations.

Figure 12 shows that all the median TMV values are comparable to each other in the range between 1.5 and 1.76, apart from MKS in September 2014, which has a value of 2.14. This suggests that, as far as TMV is concerned, the profiled periods (apart from MKS in September 2014) have similar risks. That means we can rely on the other indicator, $T_{DC}$, to measure volatility of the profiled periods.

What we have shown in this section is that the coastline, frequency of directional changes and magnitude of directional changes enrich our analysis in studying return and risk in markets. As mentioned above, the new indicators introduced allow researchers to statistically observe the market, such as the power law (Glattfelder et al 2011), which discovered some significant characteristics of market movements. Glattfelder et al (2011) discovered 12 independent new empirical scaling laws in foreign exchange data, with three orders of magnitude and across 13 currency exchange rates, resulting in the discovery of scaling laws giving an accurate estimation of the length of the price-curve coastline, which turned out to be surprisingly long.

### 3.7.3 Contrast between time series and DC-based analyses

Starting with the same data, one can study price changes with both time series and DC. They extract different information from the same data – in this case, tick data. Therefore, what they observe should be consistent with each other. However, they provide us with different perspectives. In this section, we use AZN February 2015 data to illustrate our point.

We used a threshold of 1% to generate a DC profile from the tick-to-tick data for this period. This gives us 138 trends. We sample 138 points at fixed intervals within this period to form the time series. Then we extract the information from both time series and DC-based analyses. In Table 6 we summarize some of the indicators which can be extracted by both approaches.

| | **Time Series Indicators** | **Directional Change Indicators** |
|---|---|---|
| **Return:** Time series and DC provide different angles on returns | The mean and median absolute returns were 0.36% and 0.27%, respectively | The mean and median absolute percentage price differences from beginning to end of trend were 2.22% and 1.76%, respectively |
| **Coastlines:** It measures of maximum possible profit available | Coastline as measured by Sum of absolute returns is 49% | Coastline as measured by $C_{DC}$ is 305% |

Table 6: Contrast between time series indicators and DC-based indicators (with threshold=1%) in AZN, February 2015; DC was summarized with a threshold of 1%, which resulted in 138 trends observed; to enable fair comparison, 138 data points were sampled from the high frequency data in the same period to form the time series. (Source: modified from [Tsang et al 2016])

As explained in Section 3.6, "returns" from time series and "time-adjusted returns" from DC-based analysis generated are not directly comparable with each other because the data is sampled in irregular intervals in DC profiling. Table 6 shows that mean return for time series was 0.36%, while mean time-adjusted return for DC-profiling is 2.22 %. The substantial difference is in fact partly explained by the way that DC sampled the data. The DC-based analysis used a threshold of 1% to generate results in Table 6. Therefore, every trend would see at least a 1% change in each trend (the rest is overshoot). The time-adjusted return in DC profiles tells us the magnitude of overshoot.

Coastline is a useful indicator in DC profiles. By stipulation, DC captures extreme points in market trends. Therefore, DC coastlines should be at least as long as time series coastlines (Aloud et at 2012. As Table 4 shows, coastline in DC is 305% in AZN, February 2015, which is over six times bigger than the coastline in time series analysis in the same time period (49%). So, everything being equal, there is more potential to gain from forecasting and trading using DC than in time series. This motivates us to develop DC indicators to forecast directional changes points.

In Section 3.7.2, we explained that there are two ways to measure volatility in DC profiling. Table 6 shows that the standard deviation of returns for time series was 0.51%. Volatility in DC profiling is measured by two dimensions: (a) the frequency of directional changes is measured by median time to complete a trend ($T_{DC}$), which was 19.7 minutes. The smaller this number, the more frequent that direction changes; (b) the magnitude of price changes in the trends is measured by median return (TMV), for which 1.76% was recorded. All three numbers, 0.51% (for time series), 19.7 minutes and 1.76% (for DC profiling), are useful for assessing the volatility of the profiled period. None of them can be replaced by the other.

## 3.8 Summary

In this chapter, we introduced the theory of DC market profiling as the first step for the market information extraction process through DC. To build DC market profiles, we introduced the indicators that we defined and provided an example to show the way that these indicators work. After the example, we applied DC market profiling into the equity market and provided a comparison between DC indicators and time series analysis indicators. For instance, DC profile provides different ways to measure market volatility and captures more potential profit. All these results have demonstrated the usefulness of DC market profiling in real market data analysis.

# Chapter 4 DC Market Profiles Comparison and DC metrics

Chapter 4 introduces our DC metrics for quantitative measurement of the differences between two DC market profiles. We also have a program called TR2 to calculate metrics values in this chapter and an example to show the process of TR2 using currency market data. The example demonstrates the practicality of DC metrics in market comparison.

## 4.1 Overview

After defining and introducing DC market profiling in Chapter 3, Chapter 4 is the second step of DC market summarizing. In this chapter, we will continue develop our DC market information extraction method by introducing DC metrics, which are used for DC market comparison. DC indicators in DC profiles and DC metrics together constitute our DC vocabulary, which facilitates our DC market analysis. As the same way for DC indicators in last chapter, we applied these DC metrics into real currency market and extracted some useful market information and demonstrated the usefulness of these DC metrics.

After this section, this chapter begins with an introduction of the reasons why we need these DC metrics in Section 4.2. We will include some examples in this section to demonstrate the necessary of DC metrics. In Section 4.3 we will continue to introduce the metrics we defined for DC market analysis. We write a program called TR2 to help us calculate these metrics values and generate a DC metrics file from the two DC market profiles. The specification of TR2 is showed in Section 4.4. Then we have an example to show the process of TR2 from currency markets in Section 4.5. After the comparison, in Section 4.6we discuss and show the performance of our DC metrics and demonstrate its usefulness through the currency market data which is provided by Kibot. The chapter is summarized in Section 4.7.

## 4.2 Reasons for Comparing DC profiles

The creation of DC metrics is aimed to help us define the distance between two DC market profiles. Our work has demonstrated that with the DC based indicators, DC market profiles can summarize price changes and market volatility under the DC framework (Tsang et al 2016). However, compared with time series analysis, it is still difficult for researchers to quantitatively define the differences, or in other words, the distance between two DC market profiles.

For example, Table 7 and 8 are snapshots of two DC data files from same market in different time periods, determined by the same threshold. In time series analysis, the researcher can use methods like discrete wavelet transform (Chan 1999) as a quantitative way to measure the relationship between pairs of time series. However, in DC there is no quantitative way to measure the differences, or distance between these two DC market profiles, as the Figure 13 shows. It is not easily visible for researchers to confirm the differences between these two DC market profiles and how different these two profiles are with each other. Even with the same threshold, the frequency of DC event and the magnitude of time intervals of DC trend (T) may vary in different markets. In that case, DC market analysis is lack of a quantitative way to measure differences between markets.  This is the reason we continue to define DC metrics, based on our previous work on DC indicators, to measure the distance between two DC profiles.

| $T_{EXT}$ | $P_{EXT}$ | $T_{DCC}$ | $P_{DCC}$ | TMV | T | $R_{DC}$ |
|---|---|---|---|---|---|---|
| 11/08/2014,03:22 | 102.02 | 08/09/2014,19:56 | 106.11 | 1.97 | 53394 | 0.77 |
| 30/09/2014,22:18 | 110.07 | 15/10/2014,09:37 | 105.66 | -1.10 | 15083 | 1.51 |
| 15/10/2014,09:41 | 105.24 | 31/10/2014,00:45 | 109.88 | 3.94 | 53774 | 1.52 |
| 07/12/2014,17:57 | 121.83 | 16/12/2014,03:31 | 116.96 | -1.28 | 9424 | 2.82 |
| 16/12/2014,07:01 | 115.59 | 23/12/2014,08:19 | 120.22 | 1.13 | 7723 | 3.02 |
| 23/12/2014,15:44 | 120.80 | 15/01/2015,17:12 | 115.93 | -1.02 | 20904 | 1.01 |
| 15/01/2015,21:47 | 115.86 | 06/03/2015,08:32 | 120.61 | 2.15 | 144693 | 0.31 |

Table 7: A snapshot of DC data file for minute by minute data USD/JPY spanning from August, 2014 to August, 2015, determined by a fixed threshold 4 %. It includes the indicators values of each trend

| $T_{EXT}$ | $P_{EXT}$ | $T_{DCC}$ | $P_{DCC}$ | TMV | T | $R_{DC}$ |
|---|---|---|---|---|---|---|
| 12/08/2015,00:15 | 125.26 | 24/08/2015,06:24 | 120.20 | -1.82 | 12052 | 3.14 |
| 24/08/2015,09:12 | 116.12 | 27/08/2015,11:51 | 120.77 | 1.62 | 103873 | 0.32 |
| 02/12/2015,12:28 | 123.66 | 04/01/2016,03:21 | 118.72 | -1.55 | 46538 | 0.69 |
| 20/01/2016,04:02 | 116.01 | 28/01/2016,22:39 | 120.75 | 1.22 | 10443 | 2.42 |
| 29/01/2016,10:05 | 121.66 | 04/02/2016,10:02 | 116.75 | -3.31 | 96102 | 0.71 |
| 03/05/2016,04:03 | 105.56 | 18/05/2016,10:07 | 109.79 | 1.39 | 27332 | 1.05 |
| 30/05/2016,03:38 | 111.42 | 03/06/2016,10:01 | 106.92 | -2.80 | 27059 | 2.14 |
| 23/06/2016,22:44 | 98.96 | 24/06/2016,03:48 | 103.04 | 2.15 | 27265 | 1.63 |

Table 8: A snapshot of DC data file for minute by minute data USD/JPY spanning from August 2015 to August 2016, determined by a fixed threshold 4 %.

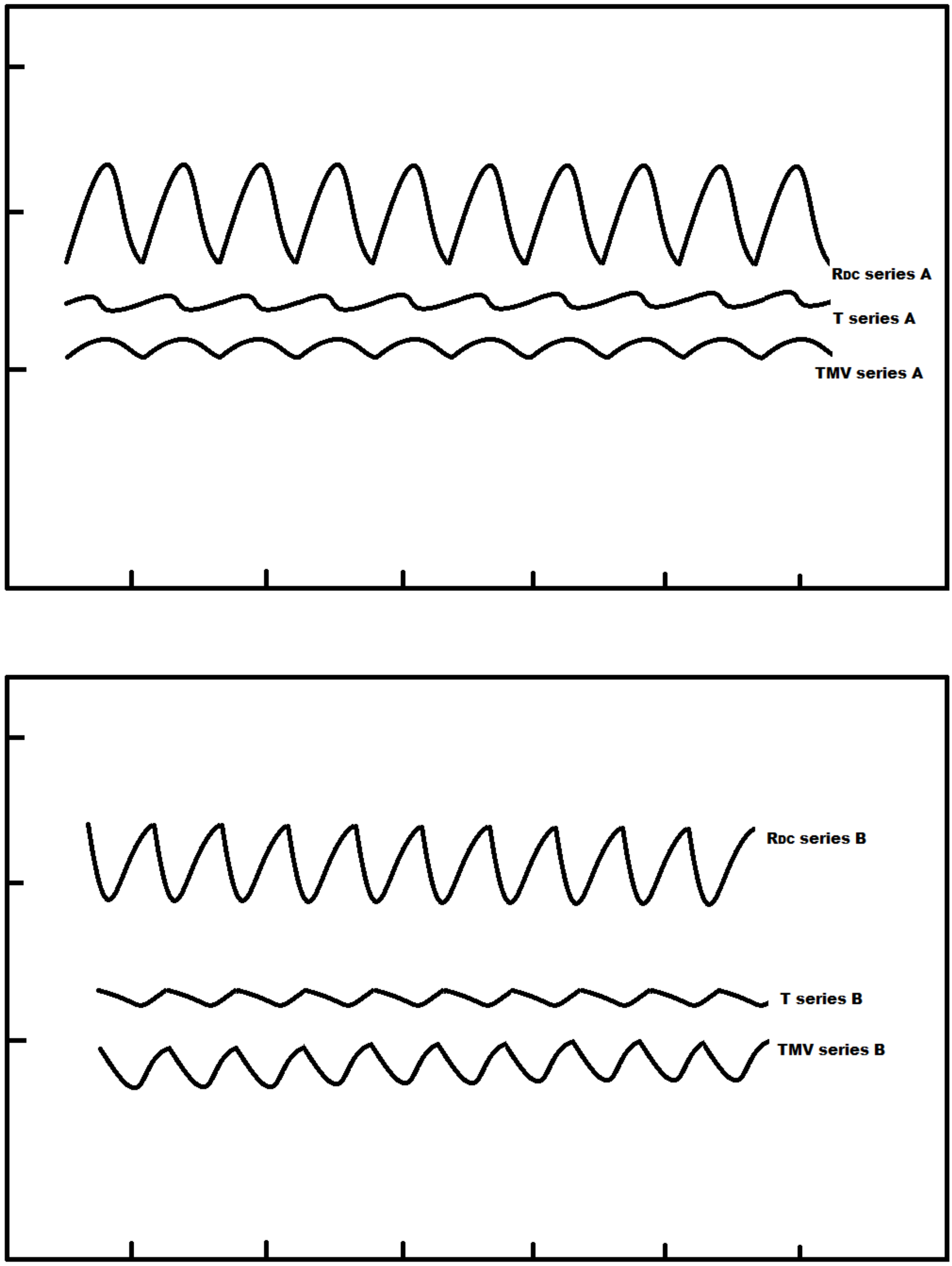


Figure 13 : The models of series of three indicator values from two DC profiles.

Apart from the differences between two DC profiles, DC metrics are also able to measure the differences between two DC profiles in different aspects, for instance, the two T series in

Figure 13. In other words, the differences in time intervals of DC trends. As the same value of correlation coefficient in time series analysis, the range of our metrics is also limited between -1 and 1. The closer the metric value is to 0, the shorter the distance is between two DC profiles. By contrast, the closer the metric value is to 1 or -1, the longer distance the two DC profiles will have between each other. With DC metrics, DC market profiles are comparable with each other with a quantitative distance measurement. Apart from single DC market profiles, DC metrics are a significant complement to DC market analysis and to be able to help researchers to extract market information under the DC framework easily. In this section we will present our DC metrics and demonstrate how they measure the distance between two DC profiles.

All our metrics values will be calculated from our program TR2. The specification of TR2 will be presented in Section 4.4 and Appendix 8.3. The program TR2 will read two DC-Data files which are generated from TR1 in one time, based on the same threshold and then generate the DC Metrics file. The DC Metrics file includes all DC metrics values, which is machine readable. These metrics values show the differences, or distance between two DC profiles. By DC market comparison, users will be able to obtain the characteristics of different financial markets in directional change terms more easily. This is the whole process of summarizing time series with directional changes through TR2.

## 4.3 DC metrics in profiles comparison

The aim to define DC metrics is to quantitatively measure the differences between two DC profiles and the differences between two DC profiles in different aspects. We will introduce the six DC metrics we defined so far in this section.

### 4.3.1 Majority of price changes ($D_{P1}$)

We defined a metric call $D_{P1}$. It measures the differences between the median values in the two TMV series. Here we defined $D_{P1}$ as:

$$D_{P1} = (\left|(a)TMV_{EXT\_m}\right| - \left|(b)TMV_{EXT\_m}\right|) / (\left|(a)TMV_{EXT\_m}\right| + \left|(b)TMV_{EXT\_m}\right|) \qquad (12)$$

Where (a) TMV_m and (b) TMV_m represent the median values of TMV series in each DC profile.

$D_{P1}$ focus on the differences in majority of price changes between two DC profiles (Figure 14). We used median values to avoid the affect from extreme values in TMV series. The range of $D_{P1}$ is always between –1 and 1. The closer $D_{P1}$ is to 0, the less differences between two DC profiles in majority price changes will be. On the other hand, the closer $D_{P1}$ is to -1 or 1, the more differences between two DC profiles in majority price changes will be.

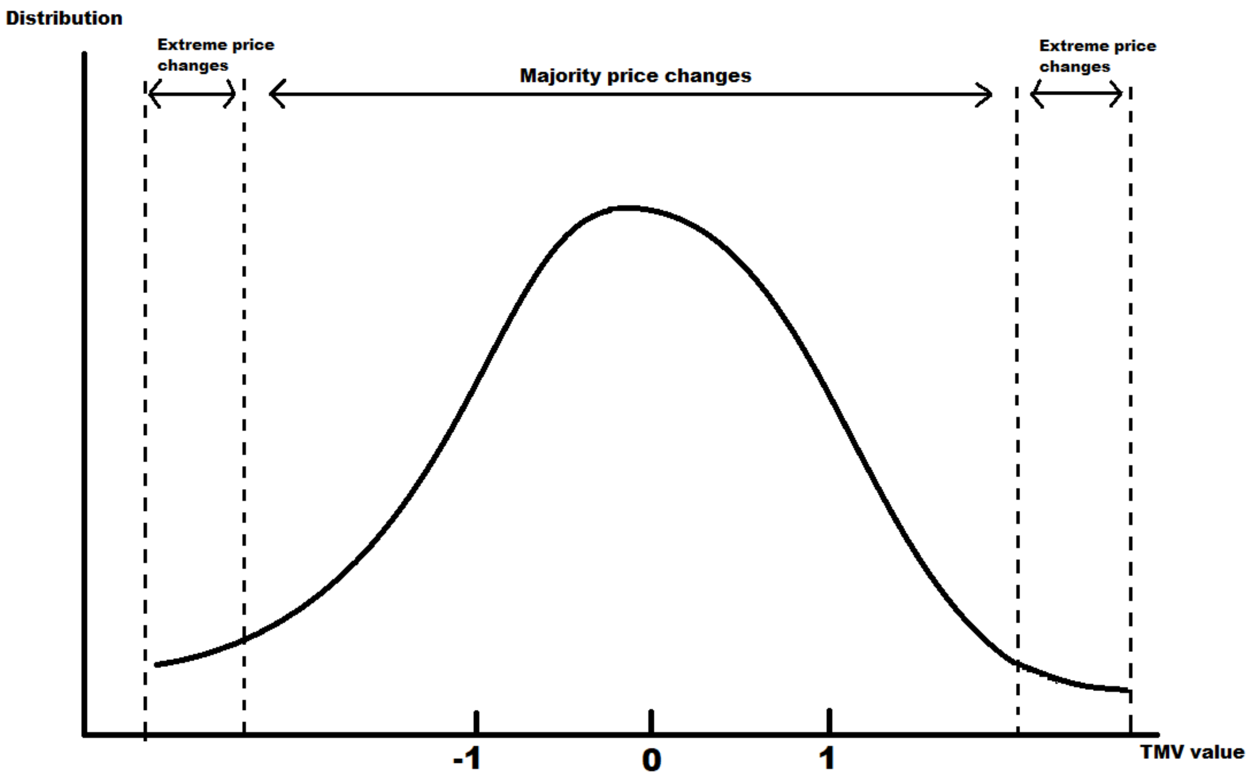


Figure 14: Distribution of TMV values. $D_{P1}$ focus on the difference in majority price changes. $D_{P2}$ focus on the difference in extreme price changes.

### 4.3.2 Extreme price changes ($D_{P2}$)

Metric $D_{P2}$ is defined to measure the difference in extreme price changes between two DC profiles. Here we defined $D_{P2}$ as:

$$D_{P1} = (\left|(a)TMV_{EXT\_e}\right| - \left|(b)TMV_{EXT\_e}\right|) / (\left|(a)TMV_{EXT\_e}\right| + \left|(b)TMV_{EXT\_e}\right|) \quad (13)$$

Where (a) $TMV_{\_e}$ and (b) $TMV_{\_e}$ represent the average of top n% values of TMV in each DC profile. n is a number that the user set to collect TMV values.

$D_{P2}$ focus on the differences in the extreme price changes between two DC profiles (Figure 14). We used median values to avoid the affect from extreme values in TMV series. The range of $D_{P2}$ is always between –1 and 1. The closer $D_{P2}$ is to 0, the less differences between two DC profiles in extreme price changes will be. On the other hand, the closer $D_{P2}$ is to -1 or 1, the more differences between two DC profiles in extreme price changes will be.

### 4.3.3 Time interval difference ($D_T$)

To compare two T series in two profiles, we define metric $D_T$ to measure the difference between two DC profiles in time intervals:

$$D_T = (\left|(a)T_{\_m}\right| - \left|(b)T_{\_m}\right|) / (\left|(a)T_{\_m}\right| + \left|(b)T_{\_m}\right|) \tag{14}$$

Where (a) $T_{\_m}$ and (b) $T_{\_m}$ represent the median values of time intervals in each DC profile.

$D_T$ focus on the differences in the time intervals between two DC profiles. We used median values to avoid the affect from extreme values in T series. The range of $D_T$ is always between –1 and 1. The closer $D_T$ is to 0, the less differences between two DC profiles in time intervals will be. On the other hand, the closer $D_T$ is to -1 or 1, the more differences between two DC profiles in time intervals will be.

### 4.3.4 Difference in time interval asymmetry ($D_{TA}$)

To compare two $A_T$ in two profiles, metric $D_{TA}$ here is to measure the asymmetry between the two DC profiles. We defined $D_{TA}$ as:

$$D_{TA} = (|(a)A_T| - |(b)A_T|) / (|(a)A_T| + |(b)A_T|) \tag{15}$$

Where (a) $A_T$ and (b)$A_T$ represents the up down trends time interval ($T_{DC}$) asymmetry in each DC profile. They are introduced in Section 3.3.

$D_{TA}$ focus on the differences in the time intervals asymmetry between two DC profiles. The range of $D_{TA}$ is always between –1 and 1. The closer $D_{TA}$ is to 0, the less differences between two DC profiles in time intervals asymmetry will be. On the other hand, the closer $D_{TA}$ is to -1 or 1, the more differences between two DC profiles in time intervals asymmetry will be.

### 4.3.5 Return difference ($D_R$)

We define $D_R$ as the metric to compare and to measure the differences between the median values in the two $R_{DC}$ series. $D_R$ is defined as:

$$D_R = (|(a)R_{DC\_m}| - |(b)R_{DC\_m}|)/ (|(a)R_{DC\_m}| + |b)R_{DC\_m}|) \tag{16}$$

Where (a) $R_{DC\_m}$ and (b) $R_{DC\_m}$ represent the median values of returns in each DC profile.

$D_R$ focus on the differences in the returns between two DC profiles. We used median values to avoid the affect from extreme values in $R_{DC}$ series. The range of $D_R$ is always between –1 and 1. The closer $D_R$ is to 0, the less differences between two DC profiles in returns will be. On the other hand, the closer $D_R$ is to -1 or 1, the more differences between two DC profiles in returns will be.

### 4.3.6 Difference in return Asymmetry ($D_{RA}$)

As the similar reason to measure time intervals asymmetry in the $T_{DC}$ series is, we define $D_{RA}$ as the metric to compare and to measure the differences between up and down trend asymmetry for $R_{DC}$ in two DC profiles. $D_{RA}$ is defined as:

$$D_{RA} = (|(a)A_R| - |(b)A_R|)/ (|(a)A_R| + |(b)A_R|) \tag{17}$$

Where (a)$A_R$ and (b)$A_{Rb}$ represents the up down trends returns ($R_{DC}$) asymmetry in each DC profile. They are introduced in Section 3.3.

$D_{RA}$ focus on the differences in the returns asymmetry between two DC profiles. The range of $D_{RA}$ is always between –1 and 1. The closer $D_{RA}$ is to 0, the less differences between two DC profiles in returns asymmetry will be. On the other hand, the closer $D_{RA}$ is to -1 or 1, the more differences between two DC profiles in returns asymmetry will be.

| Time series analysis measurement | DC metrics |
| --- | --- |
| Covariance | $D_{P1}$: the differences in majority price changes between two DC profiles |
| Discrete Fourier transform | $D_{P2}$: the differences in extreme price changes between two DC profiles |
| Discrete wavelet transform | $D_T$: the differences in time intervals of DC trends between two DC profiles |
| Piecewise aggregate approximation | $D_{TA}$: the differences in time intervals asymmetry of DC trends between two DC profiles |
| Symbolic aggregate approximation | $D_R$: the differences in time adjusted returns of DC trends between two DC profiles |
| …… | $D_{RA}$: the differences in time adjusted returns asymmetry of DC trends between two DC profiles |

Table 9: Comparison in time series data distance measurement between time series analysis and DC metrics. The methods in time series analysis to measure the differences is based on time series data. While DC metrics is based on DC market profiles. Time series analysis and DC metrics are measure the market differences in two different angles.

In order to generate enough DC events to make a precise DC market analysis in this thesis, the threshold we used was very small. This caused the problem in calculation of the indicators Sub-$N_{DC}$ and $USV_{EXT\_S}$, which we defined in Chapter 3. These two indicators will be generated by sub-threshold, which we set as a default as half of the threshold. In most of the experiments we conducted later in this thesis, the sub-threshold is too small to make the application of these two indicators in metrics meaningless. This is the reason we have not applied these two indicators values into the metrics calculation.

## 4.4 Specification of TR2

TR2 is the program that we used to calculate DC metrics value between two DC market profiles and quantitatively measure the market difference. The completed specification of TR2 is shown in the Appendix 8.3.

### 4.4.1 Input to TR2

The Input files are two csv files called DC Profile File which are generated from program TR1.

### 4.4.2 Output of TR2

The program will produce a csv file called 'Metrics File'.

**Metrics File contains:**

**Header**: It contains information for reproducing the results, which include the program version, input and output files and the threshold used for computing the DCs.

**Body:** It contains market information that concludes with the indicators in the DC- Data file. This includes the majority of price changes ($D_{P1}$), extreme price changes ($D_{P2}$) and other metrics that we introduced in Section 4.3.

## 4.5 Example of DC data comparison: comparing USD/AUD and USD/JPY markets

This section will introduce an example of a DC metrics file.

Figure 15 shows the price movements of minute-by-minute market data for USD/AUD and USD/JPY, spanning from September, 2009 to August, 2016, determined by a fixed threshold 0.8%. Table 10 is the metrics file.

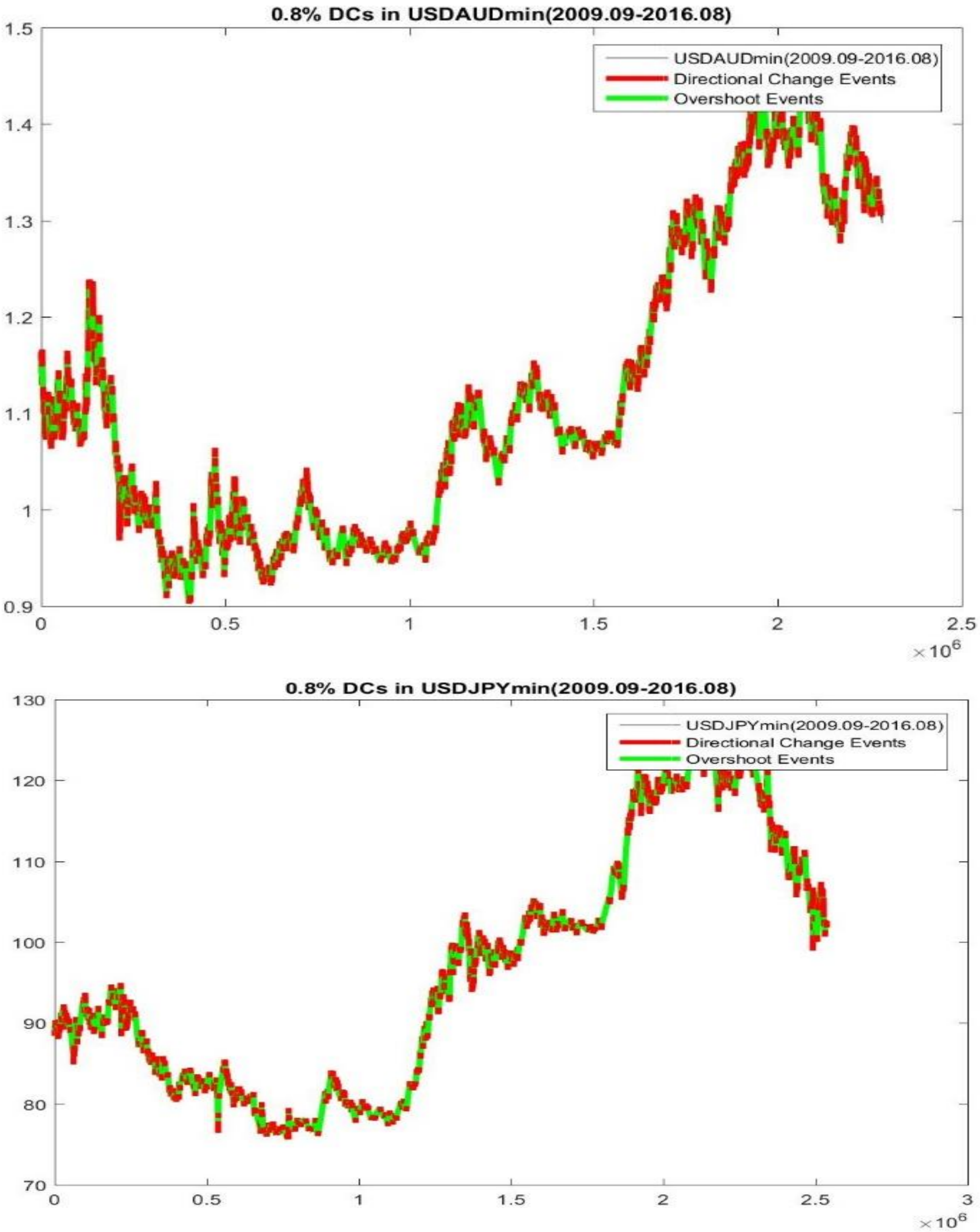


Figure 15: Price movements of minute-by-minute market data for USD/AUD and USD/JPY, spanning from September, 2009, to August, 2016, determined by a fixed threshold 0.8%. The total price movements between two consecutive extreme points are decomposed into directional change events (red lines) and overshoot events (green lines).

Table 10: This is a metrics file of minute-by-minute market data for USD/AUD and USD/JPY, spanning from September, 2009, to August, 2016, determined by a fixed threshold 0.8% and sub-threshold 0.2%.

| | |
|---|---|
| Program_ID:TR2.0 | |
| Author: Ran Tao | |
| Date | 2016.10.18 17:51:24 |
| File_input | USDAUDmin(2009.09-2016.08) |
| | USDJPYmin(2009.09-2016.08) |
| Threshold(Theta) | 0.008 |
| Sub-Threshold | 0.002 |
| Tstart | 27/09/2009,17:00:0 |
| Tfinal | 10/08/2016,03:59:0 |
| $D_{P1}$ | 0.002761591 |
| $D_{P2}$ | 0.071172589 |
| $D_T$ | 0.196400813 |
| $D_{TA}$ | 0.914524269 |
| $D_R$ | 0.223340914 |
| $D_{RA}$ | 0.074108509 |

Table 10: Metrics file of USD/AUD and USD/JPY markets.

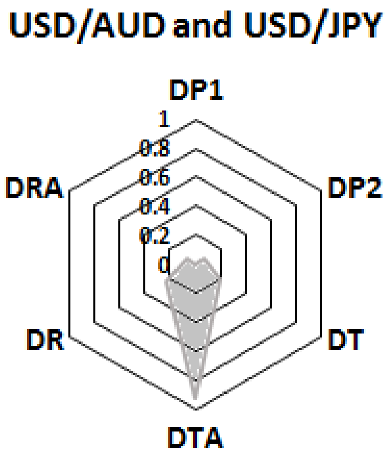


Figure 16: Radar chart of six metrics of USD/AUD and USD/JPY markets.

Table 10 is an example of DC market metrics which measure the difference between two DC profiles. Our definition of these metrics limits them between -1 and 1. While to make them easily followed by the users in a radar chart, we opted for the absolute values of these metrics. This means these metrics output from TR2 are all between 0 and 1. The closer the metric to 0 means the more similarities in the aspect which the metric measures. However, the closer the metric to 1 means the more differences in the aspect which the metric measures.

From Table 10, the majority of price changes ($D_{P1}$) showed the smallest differences, which is 0.002761591. Besides that, extreme price changes ($D_{P2}$) also have shown small differences. In other words, there is not much difference in the magnitude of price between USD/AUD and USD/JPY markets. On the other hand, metrics measuring time intervals ($D_T$) and time interval asymmetry difference ($D_{TA}$) presented more differences. It is especially the case for time interval asymmetry difference ($D_{TA}$), as it shows in Figure 16. This showed the biggest difference, 0.914524269, which means there is a large difference in asymmetry of the time intervals for up and down trends between USD/AUD and USD/JPY market.

## 4.6 Discussion of DC metrics

This section is a discussion for the application of DC metrics to capture market information, and an examination and explanation of the metrics we created in our Radar Figures. Based on the DC metrics, we tested eight years of minute by minute Forex currency data - AUD, CHF, JPY and CNY which were all against USD. The range of DC metrics values is between -1 and 1. The distance between two profiles is measured by the absolute values of the metrics in section 4.3. Therefore, the larger and the significantly visible grey area in Figure 17, the longer the distance will be between two DC profiles. In our view, this demonstrates that the application of DC metrics makes the use of DC market analysis more effective.

### 4.6.1 DC metrics in demonstration of the significant differences between two DC profiles

For example, in Figure 17, USD/AUD and USD/CNY DC market profiles showed a long distance between each other through DC metrics. This is indicated by the large grey area in Figure 17. Although, $D_{P1}$ and $D_{P2}$ are both close to 0. In other words, these two DC market profiles showed shorter distances over the aspects of prices changes. However, these two markets profiles are very different from each other in the other three aspects in which the three DC metrics are measured. In Figure 17, the values of $D_T$, $D_{TA}$ and $D_R$ are all very close to 1. From section 4.3, $D_T$ measures the distance between two $T_{DC}$ series. $D_{TA}$ measures the distance between two DC profiles in the asymmetry between up and down trend time intervals. $D_R$ measures the distance between two DC profiles in the time adjusted returns in each trend.

The significance of our DC metrics as illustrated in Figure 17 is that the DC metrics demonstrate three significant differences ($D_T$, $D_{TA}$ and $D_R$). In our view, this provides useful new market information. First of all, it shows the differences between two DC profiles in time intervals of each trend ($D_T$). As we mentioned in Section 4.3, the amount of physical time that a DC trend takes to complete (T) represents the frequency of directional changes in the market, or in other words, the volatility of markets in DC. $T_{DC}$ is a significant piece of information for researchers. Volatility is a measure of risk. Traders with different risk appetite may choose to trade in different markets. By looking at a $T_{DC}$ value of a single market, a trader may not be able to appreciate how volatile the market is. If a trader is given two T values, he will be able to see the difference. However, $D_T$ tells the traders how big the difference in volatility between the two markets are, in terms of their $T_{DC}$ values in a metric form. In addition, in Figure 17, the values of $D_{TA}$ and $D_R$ are also both closer to 1. From section 4.3, $D_{TA}$ shows the differences between two DC profiles in $T_{DC}$ between up trends and down trends. $D_R$ shows the differences between two DC profiles in returns of every DC trends. These two DC metrics values are also significant information for the traders and market analysts. Using our information, traders may adopt different trading strategies in trading frequency. For instance, the hedging of risk and of arbitrage, because of the differences between USD/AUD and USD/CNY DC market profiles, as $D_T$, $D_{TA}$ and $D_R$ shows. DC metrics therefore can help the traders and market analysts to quantitatively measure the differences and limit the difference of range between two DC market profiles, which can advance DC in market information extraction.

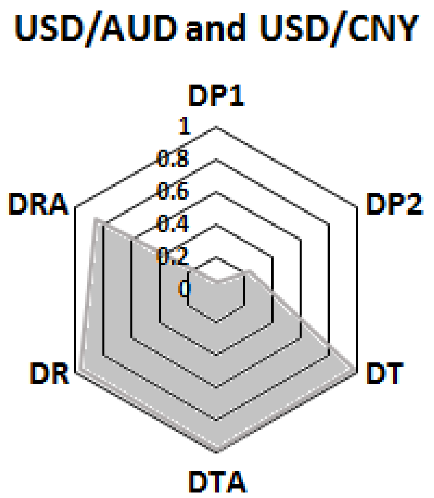


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Figure 17: The radar chart of six metrics ($D_{P1}$, $D_{P2}$, $D_T$, $D_{TA}$, $D_R$ and $D_{RA}$) for measuring distances between USD/AUD and USD/CNY DC market profiles, spanning from September, 2009 to August, 2016, determined by a threshold 0.8%.

### 4.6.2 DC in extraction of different information from time series data

Another significant and interesting feature is that, USD/CHF and USD/JPY DC market profiles showed the shortest distance between each other in general. This is shown by the grey area in Figure 18. If we look at the plot of the price movements of these two markets in Figure 19, the price movements of these two markets are very different from each other between 2009 and 2016. In time series, the standard deviation of the minute by minute returns in the USD/CHF market was 0.0610. While the standard deviation of the minute by minute returns in the USD/JPY market was 15.0376. The difference in the volatility of return between these two markets is very big. However, they showed the short distance between each other through all the six DC metrics. Even in the aspects of time intervals and returns, the values of $D_T$, $D_{TA}$, $D_R$ and $D_{RA}$ are all close to 0. The two time series are very different from each other in terms of volatility of their minute by minute returns. Therefore, traders may call for different trading strategies when trading in these two markets through time series analysis. However, by contrast, if the DC metrics show a short distance between two DC profiles (as in Figure 18), this indicates market similarities. Therefore traders may adopt similar trading strategies across these markets through DC market analysis. In other words, by looking at the markets from a different angle (using DC instead of using time series), researchers can extract different information from the market. Such information can then help the traders to develop tailored trading strategies to take advantage of the information that has been extracted.

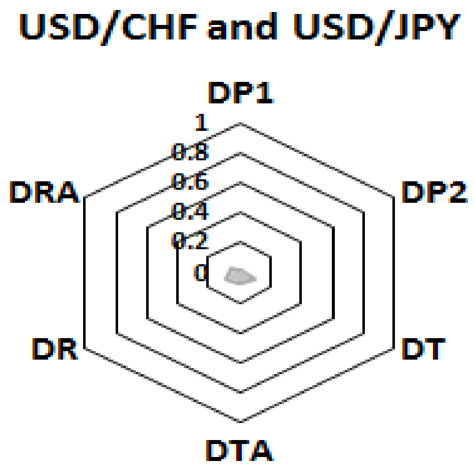
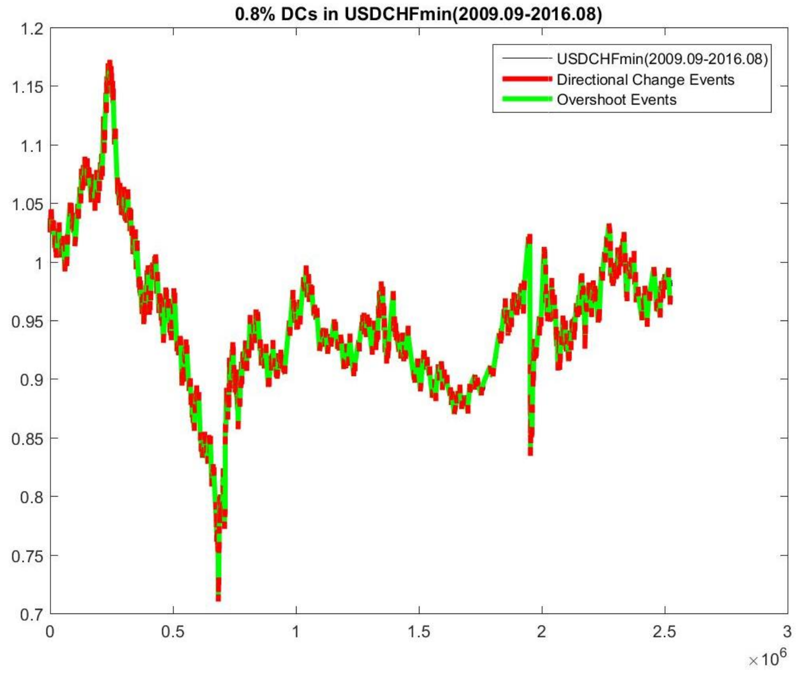



Figure 18: The radar chart of six metrics ($D_{P1}$, $D_{P2}$, $D_T$, $D_{TA}$, $D_R$ and $D_{RA}$) for measuring distances between USD/CHF and USD/JPY DC market profiles, spanning from September, 2009 to August, 2016, determined by a threshold 0.8%.



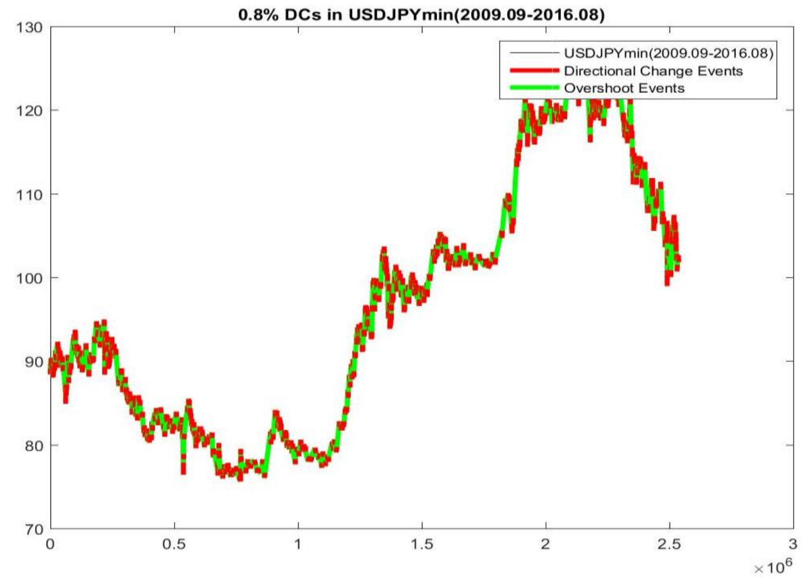




Figure 19: Price movements of minute-by-minute market data for USD/CHF and USD/JPY, spanning from September, 2009, to August, 2016, determined by a fixed threshold 0.8%. The total price movements between two consecutive extreme points are decomposed into directional change events (red lines) and overshoot events (green lines).

In our view, the establishment of DC metrics provides us with a more effective understanding of different financial markets than just the DC indicators in Chapter 3. It leads to a more focused and targeted trading strategy for traders if they trade in two markets using our DC market analysis.

## 4.7 Summary

In this chapter, we introduced the definition of DC metrics and build DC metrics file as the second step for the market information extraction process through DC. We provided an example to show the way that these metrics work. After the example, we applied DC metrics into the currency market and extracted useful market information through DC market profiles comparison, which provided us a more effective understanding of different financial markets dynamics. For instance, through DC metrics values, we found more similarities between USD/CHF and USD/JPY DC market profiles, compared with time series analysis results. All these results have demonstrated the usefulness of DC metrics in advancing DC vocabulary in DC market data analysis.

# Chapter 5 Application and Discussion of DC profile in market information extraction

This chapter is the application of DC market profiles in a large financial market data set.

## 5.1 Overview

After the introduction and demonstration of DC vocabulary for DC market information extraction in Chapter 3 and 4. In Chapter 5 we apply DC market profiling into a larger market data set. In this chapter we track and analyse the currency and commodity market activities from a microscopic perspective, using the minute-by-minute prices provided by Kibot. By applying DC market profiles to real market data, our study shows some useful information about the market price movements. All the information is extracted from an angle that is different from that of traditional time series analysis.

## 5.2 DC market profiles analysis

In this section we apply DC indicators and profiles in observing the single currency and commodity market. The financial assets we used are shown in table 11.

### 5.2.1 Single market analysis

| Key | Asset name | Sector |
|---|---|---|
| **AUD/USD** | Australian Dollar against US Dollar | Currency |
| **GBP/USD** | British Pound against US Dollar | Currency |
| **EUR/USD** | Euros against US Dollar | Currency |
| **CHF/USD** | Swiss Francs against US Dollar | Currency |
| **JPY/USD** | Japanese Yen against US Dollar | Currency |
| **Gold** | Gold against US Dollar | Commodity |
| **Oil** | Crude oil against US Dollar | Commodity |
| **Copper** | Copper against US Dollar | Commodity |
| **Gas** | Natural gas against US Dollar | Commodity |

Table 11: Nine DC market analyses of assets and the sectors they represent

We chose minute-by-minute open prices of five main currencies (BIS, 2016) in the currency market, and four representative commodity assets from the commodity market. The prices for nine assets are all between August, 2011, to August, 2015. Since the value of the threshold will affect the results of profiles, we applied the same threshold (0.4%) for these assets. They are shown in Table 11. To extract more specific market information that happened in each time period through DC analyzing work, we used a quarter of a year as a fixed time period to sample market data and applied DC analyzing on it. In other words, each part of the data includes three months' market data. We also advanced our way in analyzing DC market profiles, which is shown in Chapter 3. As the example shows in Figure 20 and Figure 21, we refined our DC indicators and added the analyzing work of the uptrends and downtrends of DC events.

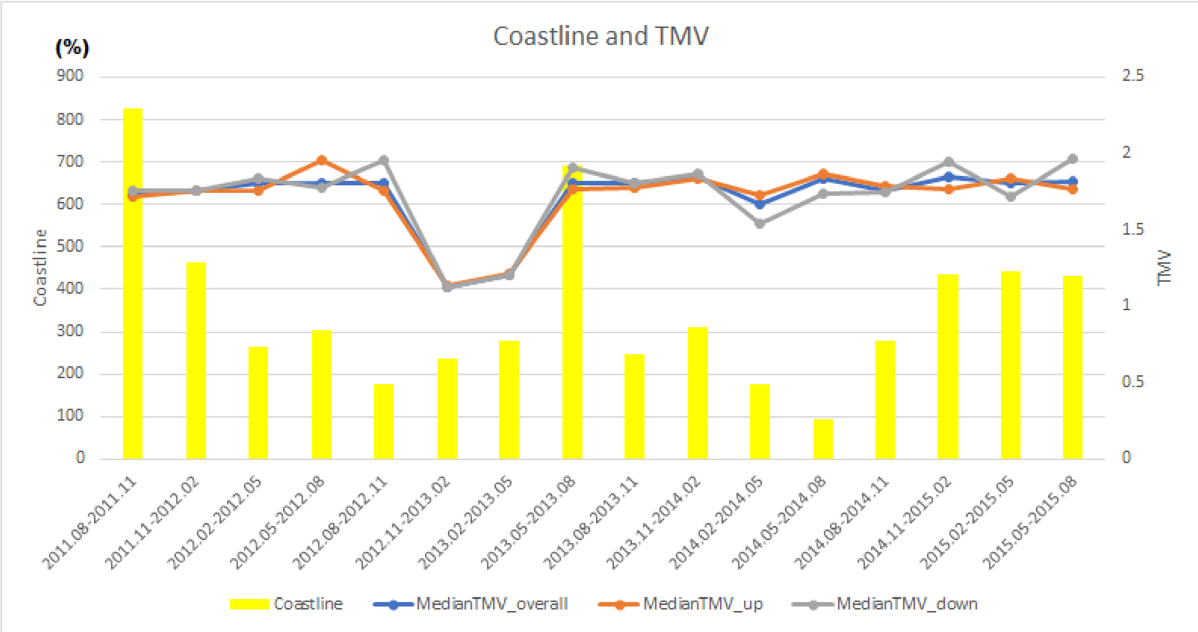



Figure 20: An example of the coastline and TMV values from AUD/USD DC profiles in 16 continuous time periods. The yellow column represents the coastline and blue, orange and grey line stand for the median TMV value in all, uptrends and downtrends DC events. The left axis is for coastline and right axis is for TMV values.

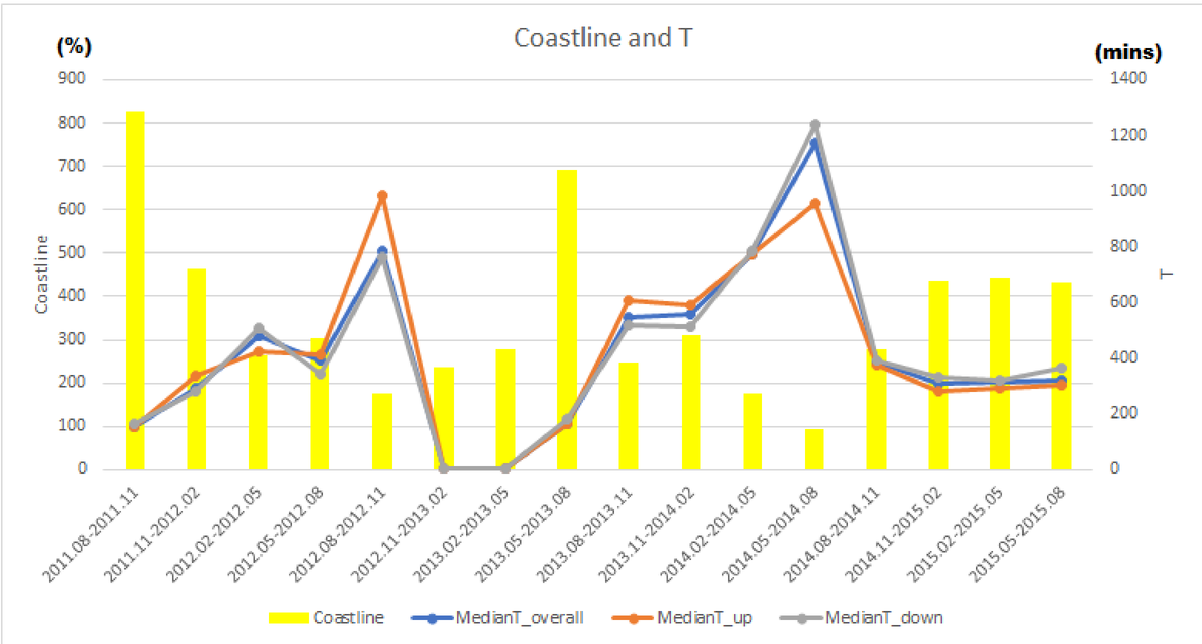



Figure 21: An example of the coastline and T values from AUD/USD DC profiles in 16 continuous time periods. Yellow column represents the coastline and blue, orange and grey line stand for the median T value in all, uptrends and downtrends DC events. Left axis is for coastline and right axis is for T values.

The example market, AUD/USD, in Figure 20 showed stable value of TMV from May 2013 to August 2013 and higher value of the coastline. TMV measures market volatility in the magnitude of price changes in DC market analysis. So we may conclude May 2013 to August 2013 is a profitable time period for market traders with comparable lower market risk. Figure 21 showed a comparable low value of T and coastline from November 2012 to May 2013. T measures the frequency of trends changes in DC market analysis. Low T value means higher frequency of trends changes and risks for trader. So November 2012 to May 2013 is not a recommended time period for market traders.

### 5.2.2 Profiles of currency and commodity markets' assets

| Average(Median) | AUD/USD | GBP/USD | EUR/USD | CHF/USD | JPY/USD | Gold | Oil | Copper | Gas |
|---|---|---|---|---|---|---|---|---|---|
| TMV | 1.72 | 1.75 | 1.75 | 1.70 | 1.78 | 1.77 | 1.83 | 1.81 | 1.88 |
| TMV↑ | 1.72 | 1.82 | 1.74 | 1.69 | 1.78 | 1.74 | 1.85 | 1.78 | 1.88 |
| TMV↓ | 1.73 | 1.75 | 1.79 | 1.72 | 1.80 | 1.81 | 1.80 | 1.82 | 1.89 |
| T (minutes) | 416.72 | 987.81 | 845.56 | 642.13 | 752.22 | 212.47 | 92.22 | 163.91 | 34.94 |
| T↑(minutes) | 417.22 | 914.94 | 873.78 | 597.63 | 647.19 | 199.00 | 95.81 | 159.19 | 35.91 |
| T↓(minutes) | 419.09 | 1043.56 | 819.03 | 646.25 | 803.22 | 225.75 | 90.22 | 165.63 | 34.19 |
| $R_{DC}$ (%) | 77.06 | 51.46 | 6.65 | 13.89 | 6.68 | 26.12 | 69.97 | 37.13 | 142.68 |
| $R_{DC}$↑(%) | 77.63 | 115.34 | 6.44 | 14.00 | 7.22 | 27.65 | 69.88 | 37.68 | 139.72 |
| $R_{DC}$↓(%) | 76.70 | 41.30 | 6.95 | 13.93 | 6.28 | 24.81 | 70.17 | 37.18 | 146.44 |
| $C_{DC}$ (%) | 353.49 | 150.07 | 213.03 | 321.17 | 205.98 | 680.46 | 1625.14 | 1081.80 | 2862.18 |

Table 12: Summarized average median values of DC profiles with a threshold of 0.4% on nine assets from currency and commodity markets with minute-by-minute open prices, 2011 to 2015.

In Table 12, we included average median values of ten significant indicators, as shown in the first column. The last row of Table 12 and Figure 22 show the average maximum potential profit for each asset during the time periods. We also have a table to record the average standard deviation of the DC indicator values, which is shown in the Appendix 8.4.

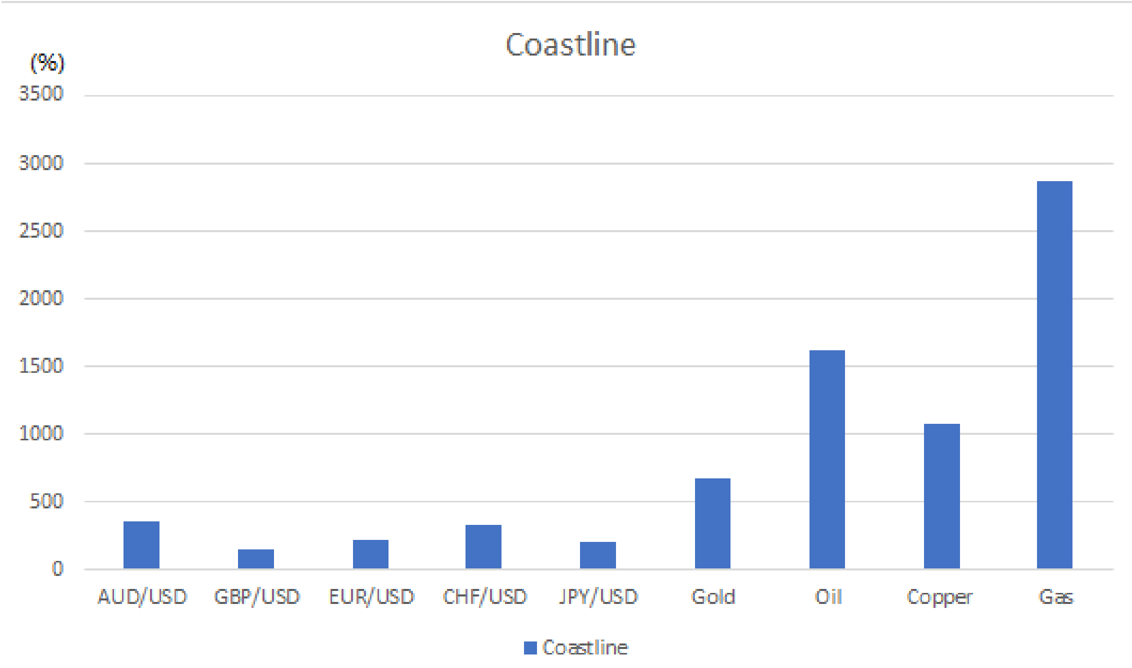



Figure 22: The average coastline from DC profiles for nine assets from currency and commodity markets between 2011 and 2015.

From Table 12 and Figure 20, DC profiles conclude that commodity markets tend to generate more potential profit than the currency market. Especially for the energy assets of, oil and gas, they have the longest coastline. The coastline of gas is 2862.18%. This is over 19 times the length of the coastline of GBP/USD in the same time period, which has the shortest coastline 150.07% among all the assets. In currency market, AUD/USD and CHF/USD showed the longer coastline against other three currencies.

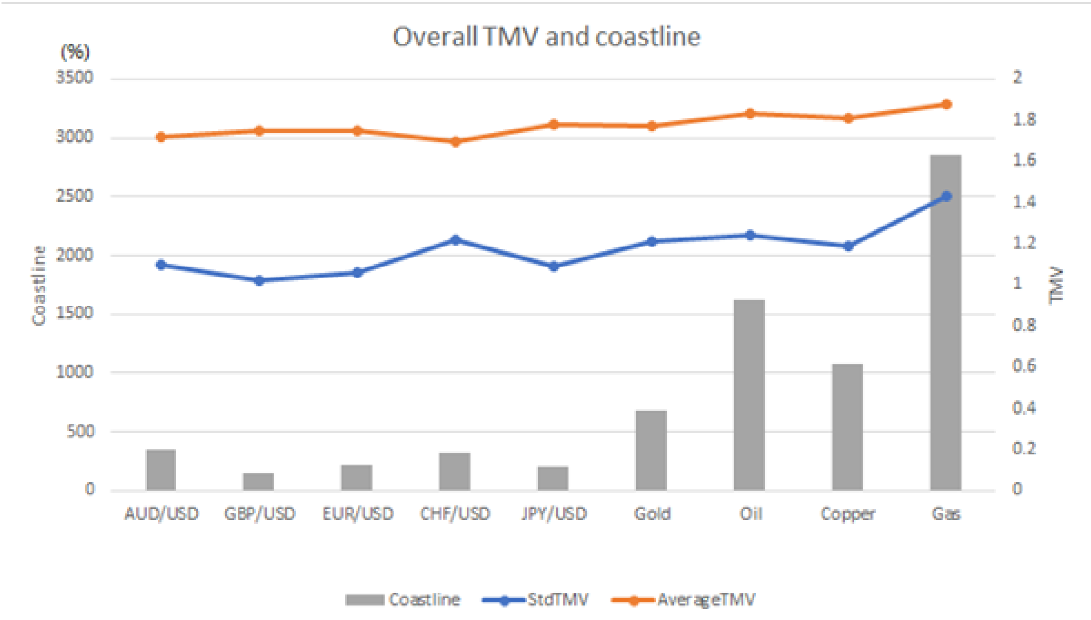



Figure 23: The average median TMV and standard deviation of TMV from DC profiles for nine assets between 2011 to 2015. Blue and orange line represents the median and standard deviation of TMV. Grey column stands for the coastline.

TMV measures the scale of price changes. It reminds us that everything being equal, the bigger the scale of changes, the more volatile one may consider the market to be. In Figure 23, we reported the median value of TMV as well as their standard deviations.

Figure 23 shows that all the median TMV values are comparable to each other in the range between 1.72 and 1.88. However, some assets show a lower standard deviation TMV values. For example, GBP/USD and JPY/USD markets in which the standard deviation TMV values are 1.02 and 1.09 respectively. This suggests that as far as TMV is concerned, the profiled periods showed similar volatilities and risks, except GBP/USD and JPY/USD markets, which showed a more volatile TMV values changes.

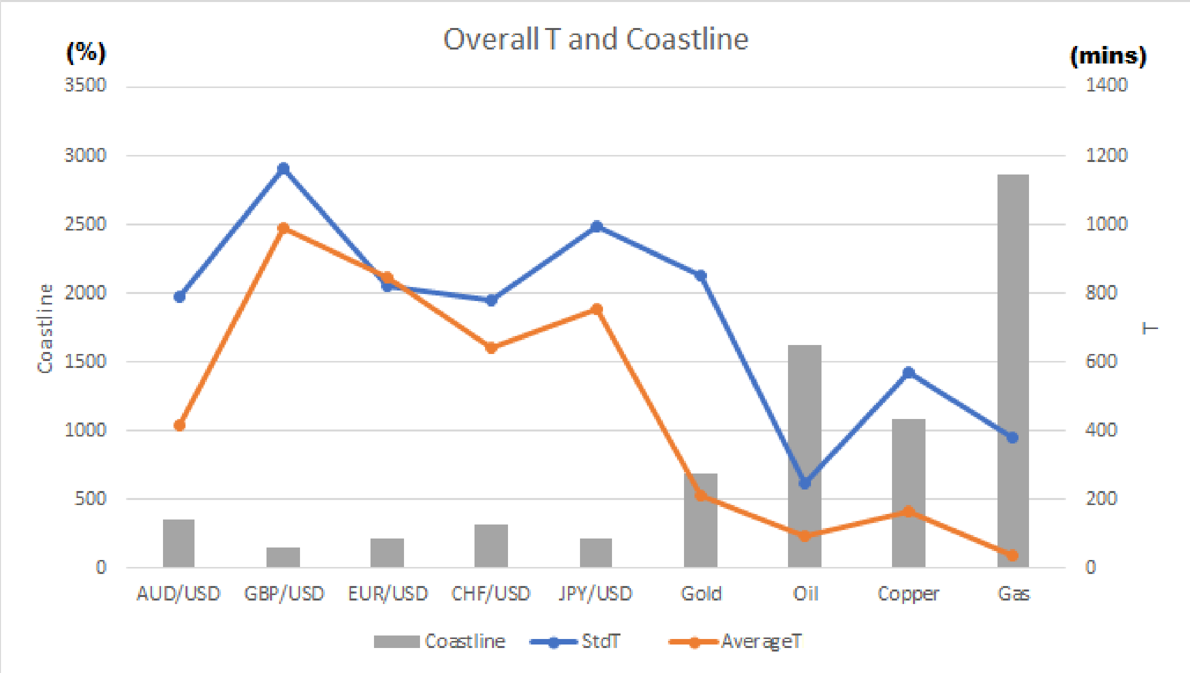



Figure 24: The average median T and standard deviation of T from DC profiles for nine assets between 2011 to 2015. Blue and orange line represents median and standard deviation of T. Grey column stands for the coastline.

Besides TMV, T also tells about volatility. From Section 3.2.3, T is the physical time that an up or a down trend takes to complete. Everything being equal, the longer time one trend takes to complete, the less volatile one may consider a market to be. In Figure 24, we have reported the average median and standard deviation T values of the nine assets. It shows that EUR/USD market presents a comparative high average median T value and lower average standard deviation T value. In other words, as far as T is concerned, the EUR/USD market has a lower volatility and risks in the profiled time period among all the assets. On the other hand, gold market presents comparative low average median and high average standard deviation T values, which showed a higher volatility and risks among all the assets.

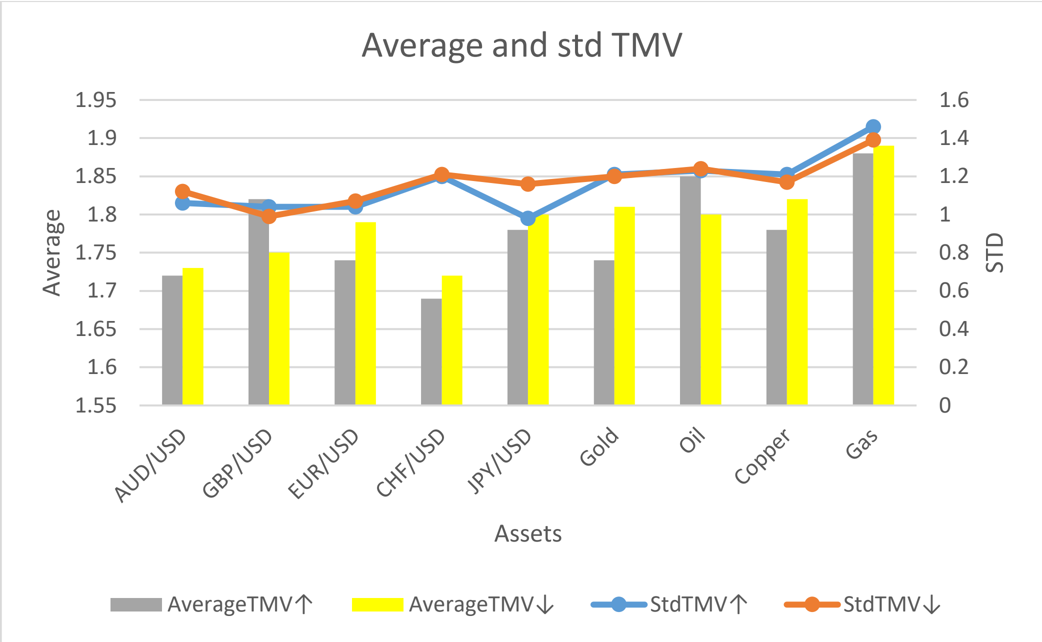



Figure 25: The average median TMV and standard deviation of TMV from DC profiles for nine assets between 2011, to 2015, which have been divided into uptrends and downtrends. Grey and yellow column represent average median values of TMV in uptrends and downtrends. Blue and orange line stands for average standard deviation of TMV in uptrends and downtrends.

As we mentioned in Chapter 3, in DC market analysis, the uptrend and downtrend are always consecutive to each other, which is different from time series analysis. So it can help market observers and traders to extract some new and useful information when they are analysing the difference between uptrends and downtrends in DC profiles. In Figure 25, we reported the average median value of uptrend and downtrend TMV as well as their standard deviations.

For average median TMV values, Figure 25 shows that all the average uptrend median TMV values are lower than the downtrend ones, except GBP/USD and the oil market. In other words, GBP/USD and the oil market are more volatile in the downtrends. Other assets are the opposite. Besides that, Figure 25 also shows that JPY/USD has big differences between uptrends and downtrends through the average standard deviation TMV values. JPY/USD market appears to be more volatile in the downtrends TMV values than uptrends. The volatility in the downtrends of JPY/USD fluctuates more than the uptrends.

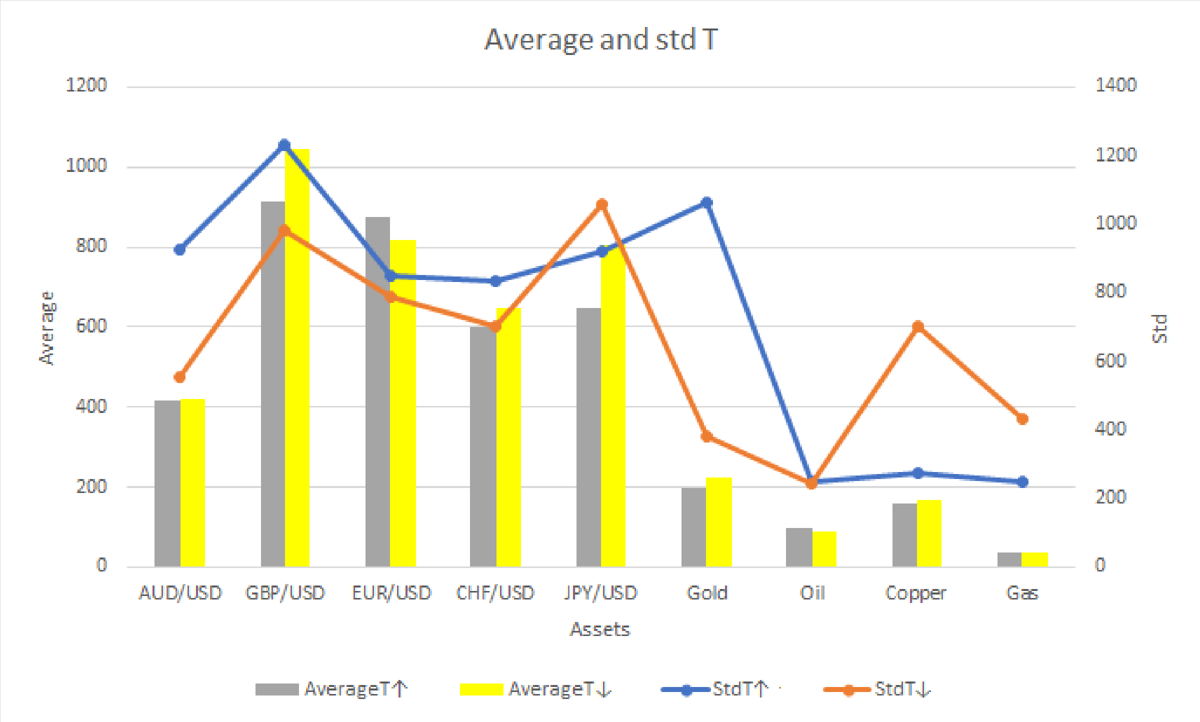



Figure 26: The average median T and standard deviation of T from DC profiles for nine assets between 2011, to 2015, which have been divided into uptrends and downtrends. Grey and yellow column represent average values of T in uptrends and downtrends. The blue and orange line stand for average standard deviation of T in uptrends and downtrends.

In Figure 26, we demonstrated the average median value of uptrend and downtrend T as well as their standard deviations. For average median T values, Figure 26 shows that all the average uptrend median T values are not apparently higher than the downtrend ones, except the EUR/USD market. In other words, EUR/USD market is more volatile in the downtrends when analysing T in DC profile. Other assets are the opposite. Besides that, Figure 26 also shows that JPY/USD has big differences between uptrends and downtrends through the average standard deviation T values. The JPY/USD market appears to be more volatile in the downtrends T values than in the uptrends. The volatility in the downtrends of JPY/USD changes more than the uptrends when concerning T values. To summarize the results in Figure 25 and 26, the JPY/USD market appears to be more volatile in the downtrends than uptrends. Trading in the JPY/USD market in downtrend event has more risks. We also mentioned that the average standard deviation T values in uptrends is much higher than downtrends in gold market, which means the high volatility and risk in uptrends for gold market.

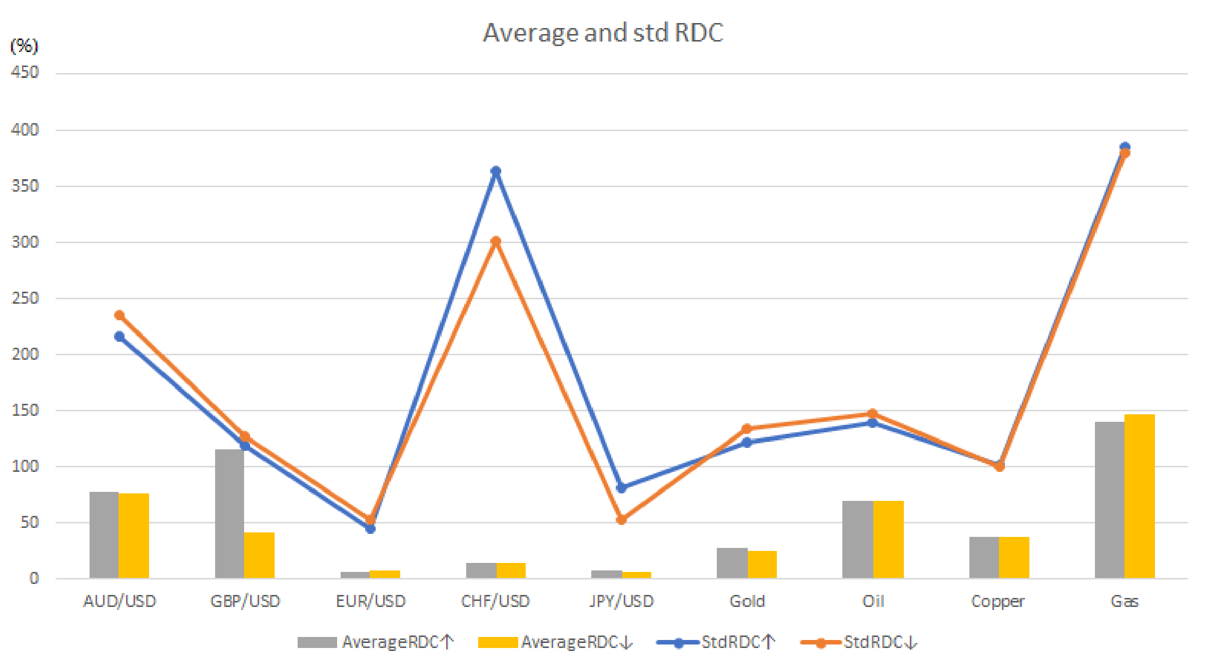



Figure 27: The average median $R_{DC}$ and standard deviation of $R_{DC}$ from DC profiles for the profiled assets between 2011 to 2015, which have been divided into uptrends and downtrends. Grey and yellow column represent average values of $R_{DC}$ in uptrend and downtrend events. Blue and orange line stand for average standard deviation of $R_{DC}$ in uptrends and downtrends.

As Chapter 3 introduced, $R_{DC}$ is the time adjusted return of each DC event. The returns that DC looks at ($R_{DC}$) are returns over directional change events, at irregular times. Figure 27 records the average median and standard deviation of $R_{DC}$ values from DC profiles. The details are also shown in Table 12 and Appendix 8.4.

Figure 27 shows that there is a big difference between uptrend and downtrend in $R_{DC}$ in GBP/USD market. The average median $R_{DC}$ values in the uptrend is 115.34% while the downtrend events $R_{DC}$ values is 41.3%. Considering the average standard deviation of $R_{DC}$ values is almost the same in the uptrends and downtrends, trading in the uptrend events will generate more return for traders in GBP/USD market through DC.

## 5.3 Summary

In this chapter, we showed the results of DC market profiles' applications in currency and commodity markets. To measure the potential profit through DC, we found that the energy assets, oil and gas markets have the longest coastline among the nine markets. In currency market, AUD/USD and CHF/USD showed the longer coastline against other three currencies. For market volatility, TMV values showed that GBP/USD and JPY/USD markets are more volatile in the magnitude of price changes in every trend. $T_{DC}$ values showed the gold market has a lower frequency of trend changes and risks in the profiled time period among all the assets.

Besides the potential profit and volatility, DC profiles also provides some useful information between the uptrends and downtrends. Through comparisons in TMV values between uptrends and downtrends, GBP/USD and the oil markets are more volatile in the downtrends. On the other hand, through comparisons in T values between uptrends and downtrends, EUR/USD market is more volatile in the downtrends than uptrends, which is different from other markets. TMV and T values also both showed that the volatility in the downtrends of JPY/USD fluctuates more than the uptrends. Trading in the JPY/USD market in downtrend event has more risks than uptrend event. What's more, in considering the returns ($R_{DC}$)in uptrends and downtrends, trading in the uptrend events will generate more return for traders in GBP/USD market.

# Chapter 6 Application and Discussion of DC profile comparisons in market information extraction

This chapter is the application of DC metrics in DC market profiles comparison.

## 6.1 Overview

After the application of DC profiling for DC market information extraction in Chapter 5. In Chapter 6 we apply DC market profiles comparison into a larger market data set. In this chapter we compare and analyse the DC currency and commodity market profiles from Chapter 5. In this chapter, we not only make comparisons between currency profiles or commodity profiles, but also make comparisons between different currency profiles and commodity profiles. Besides that, our comparisons are not limited in the same time period. We have also added comparisons between adjacent time period, for example, profiles of May 2012 to August 2012 and August 2012 to November 2012. On the other hand, we included comparisons between DC profiles year on year. For instance, there is a comparison of profiles between May 2012 to August 2012 and May 2013 to August 2013. By applying our DC metrics into more DC market profiles comparisons, our study shows some useful information about the differences between two markets profiles.

After this section, this chapter begins with the currency market profiles comparison in Section 6.2. We will include some comparisons between market profiles from the same time period, or same market from different time periods. In Section 6.3 we will continue to apply profile comparisons between different commodity market profiles. Section 6.4 will show the comparison results between different currency and commodity profiles. Then the chapter is summarized in Section 6.5.

## 6.2 Currency market comparison

We have five currency assets in our experiment tests. In DC metrics application, we used DC profiles of every three months for market comparison. Each of currency asset has been divided into 16 consecutive time periods. In this section, we present our DC metrics results of the assets in the currency market. The comparison pairs are shown in Table 13.

| File name | Comparison asset profiles |
|---|---|
| **AUD&GBP** | Profile comparison between AUD/USD and GBP/USD market |
| **AUD&EUR** | Profile comparison between AUD/USD and EUR/USD market |
| **AUD&CHF** | Profile comparison between AUD/USD and CHF/USD market |
| **AUD&JPY** | Profile comparison between AUD/USD and JPY/USD market |
| **GBP&EUR** | Profile comparison between GBP/USD and EUR/USD market |
| **GBP&CHF** | Profile comparison between GBP/USD and CHF/USD market |
| **GBP&JPY** | Profile comparison between GBP/USD and JPY/USD market |
| **EUR&CHF** | Profile comparison between EUR/USD and CHF/USD market |
| **EUR&JPY** | Profile comparison between EUR/USD and JPY/USD market |
| **CHF&JPY** | Profile comparison between CHF/USD and JPY/USD market |

Table 13: Ten DC profile comparison pairs for the same time period in currency market

### 6.2.1 Market comparison between different currency markets in the same time period

Comparison between different DC currency market profiles in the same time period in four years generates more than one hundred metrics files. We recorded the summarized results in Table 18 in the Appendix 8.5.

As we introduced in Chapter 4, $D_{P1}$ measures the differences in majority price changes between two DC profiles. $D_{P2}$ measures the differences in extreme price changes between two DC profiles. $D_T$ and $D_R$ measure the differences in time intervals and time adjusted returns of DC trends between two DC profiles respectively. $D_{TA}$ and $D_{RA}$ measure the differences in asymmetry of DC trends between two DC profiles respectively. We have demonstrated the results of average metric values for ten pairs of currency profile comparisons in Figure 28. The complete results are shown in Table 19 in the Appendix 8.5.

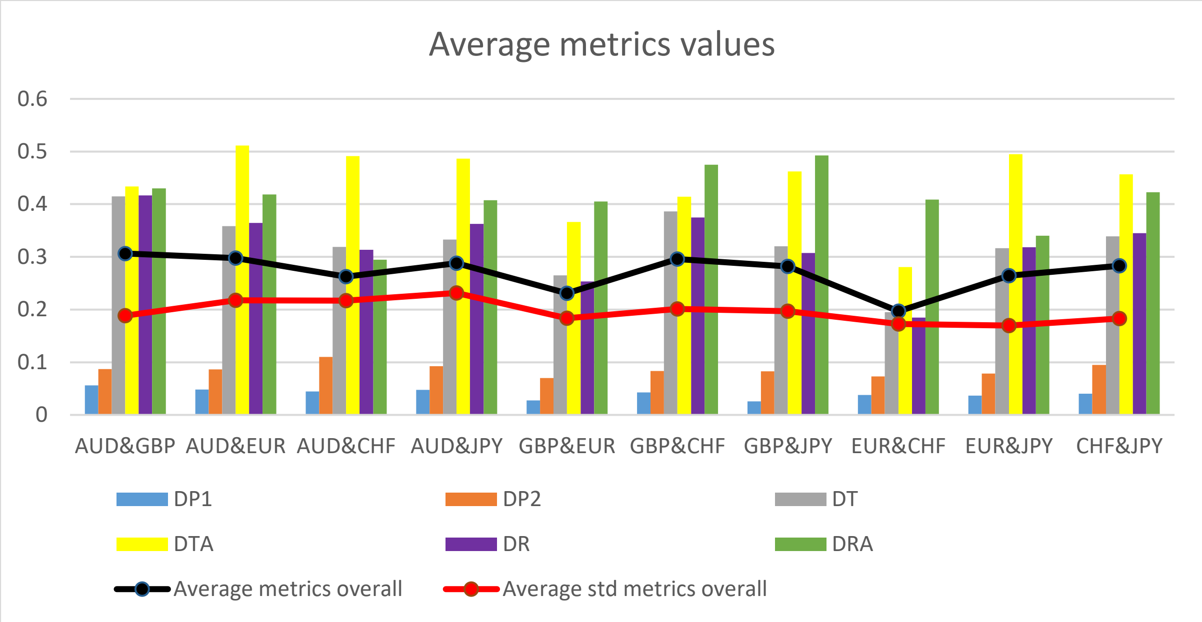



Figure 28: Average metric values for ten pairs of currency profiles comparisons. Blue and orange columns represent average $D_{P1}$ and DP2 values. Grey and yellow columns stand for average $D_T$ and $D_{TA}$ values. Purple and green columns are for average $D_R$ and $D_{RA}$ values. Black line stands for the average metrics overall and red line is for average standard deviation metric values overall.

From the average metrics overall in Figure 28, EUR/USD and CHF/USD markets (category EUR&CHF in Figure 28) showed the smallest differences from each other among all the comparisons, especially for $D_T$ and $D_R$ values. This means that EUR/USD and CHF/USD markets showed the most similarities in time intervals, and time adjusted returns of DC trends between each other. In other words, trading in DC events in these two markets may face similar risk and returns.

### 6.2.2 Market comparison in the same currency market between adjacent time periods

Apart from comparisons between currency market assets at the same time period, we also conducted comparisons in the same currency between different time periods. In Figure 29, we showed the comparisons results between adjacent time periods for the same currency market. The complete results are shown in Table 20 and Table 21 in Appendix 8.6.

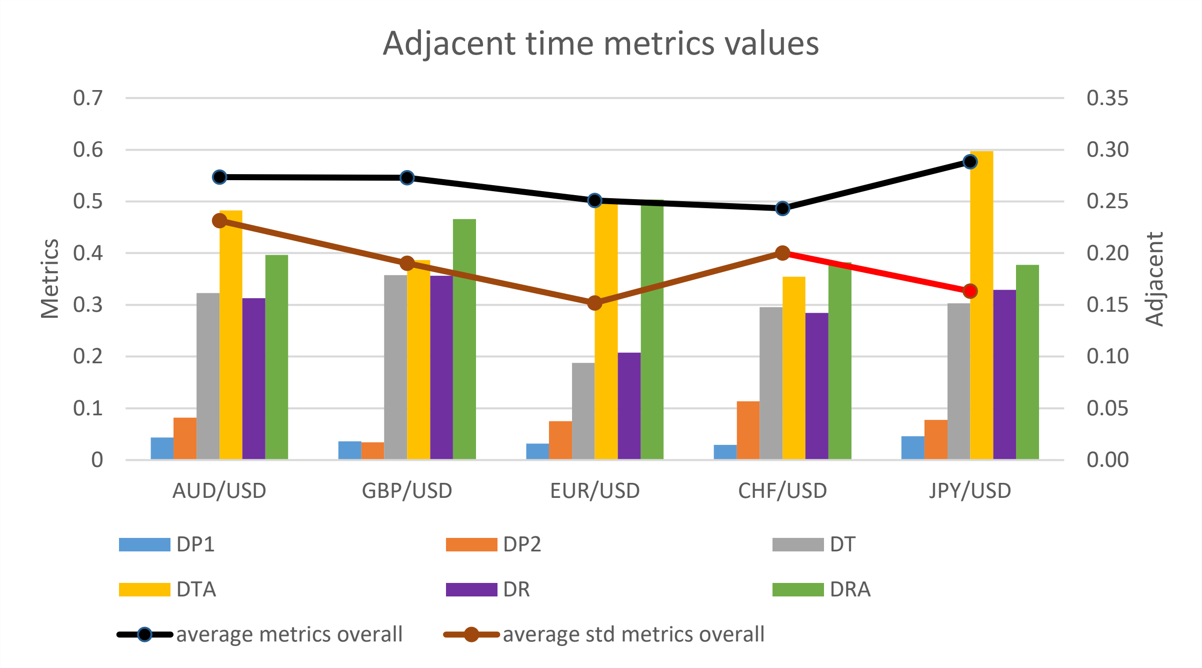



Figure 29: Average metric values for currency profiles comparisons between adjacent times in four years. Blue and orange columns represent average $D_{P1}$ and $D_{P2}$ values. Grey and yellow columns stand for average $D_T$ and $D_{TA}$ values. Purple and green columns are for average $D_R$ and $D_{RA}$ values. Black line stands for the average metrics overall and red line is for average standard deviation metric values overall.

From Figure 29, EUR/USD market shows the smallest value in $D_{P1}$, $D_{P2}$, $D_T$ and $D_R$ in average overall metrics. It also shows the lowest average standard deviation metric values. In other words, the EUR/USD market has a comparable steady performance in volatility changes among all the five currencies. However, EUR/USD market contains big values in $D_{TA}$ and $D_{RA}$, which means the differences between uptrends and downtrends changed a lot. In our view, traders in EUR/USD market may adopt similar trading strategies across the time but the asymmetry between uptrends and downtrends is worthy of attention. On the other hand, CHF/USD market shows the smallest value in $D_{TA}$ and $D_{RA}$ and the lowest average overall metrics value at the same time. So CHF/USD market may be a less risky market for the traders who adopt similar trading strategies season over season in DC market analysis.

### 6.2.3 Market year-on-year comparison in the same currency market

In addition, to make comparisons between adjacent time periods of DC profiles in the same currency market, we also added comparisons between seasonal DC profiles year on year. The results are displayed in Figure 30 and Figure 31. The complete results are shown in Table 22 and Table 23 in Appendix 8.7.

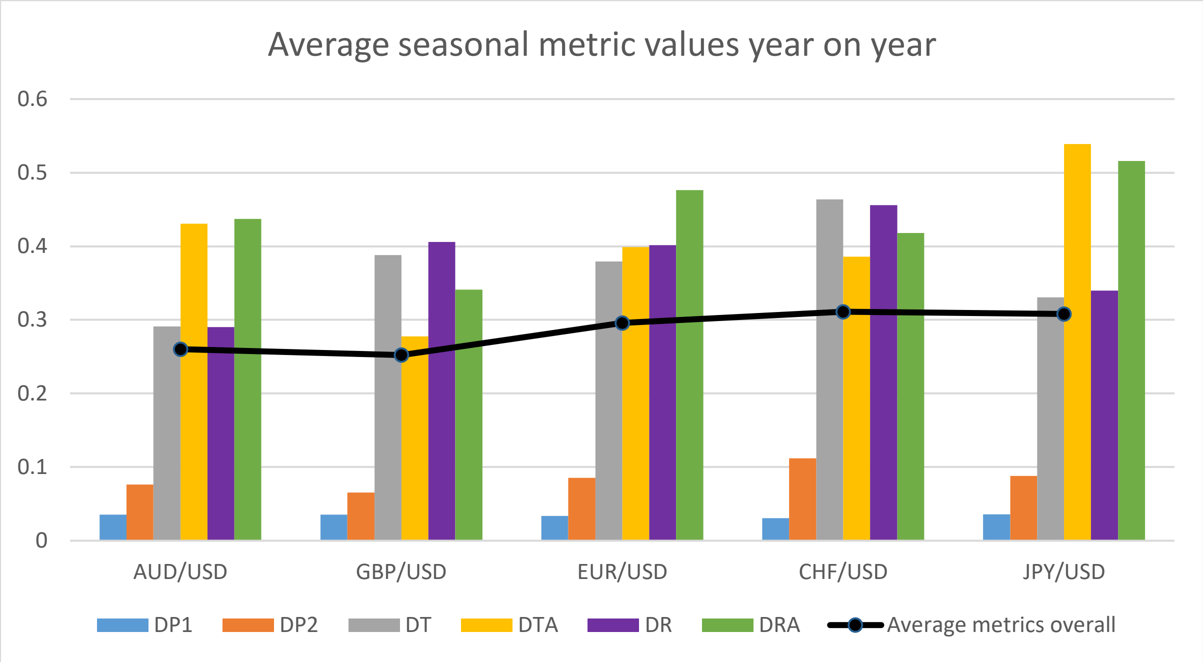



Figure 30: Average metric values for currency profiles comparisons between year-on-year seasonal time in four years. Blue and orange columns represent average $D_{P1}$ and $D_{P2}$ values. Grey and yellow columns stand for average $D_T$ and $D_{TA}$ values. Purple and green columns are for average $D_R$ and $D_{RA}$ values. Black line stands for the average metrics overall and red line is for average standard deviation metric values overall.

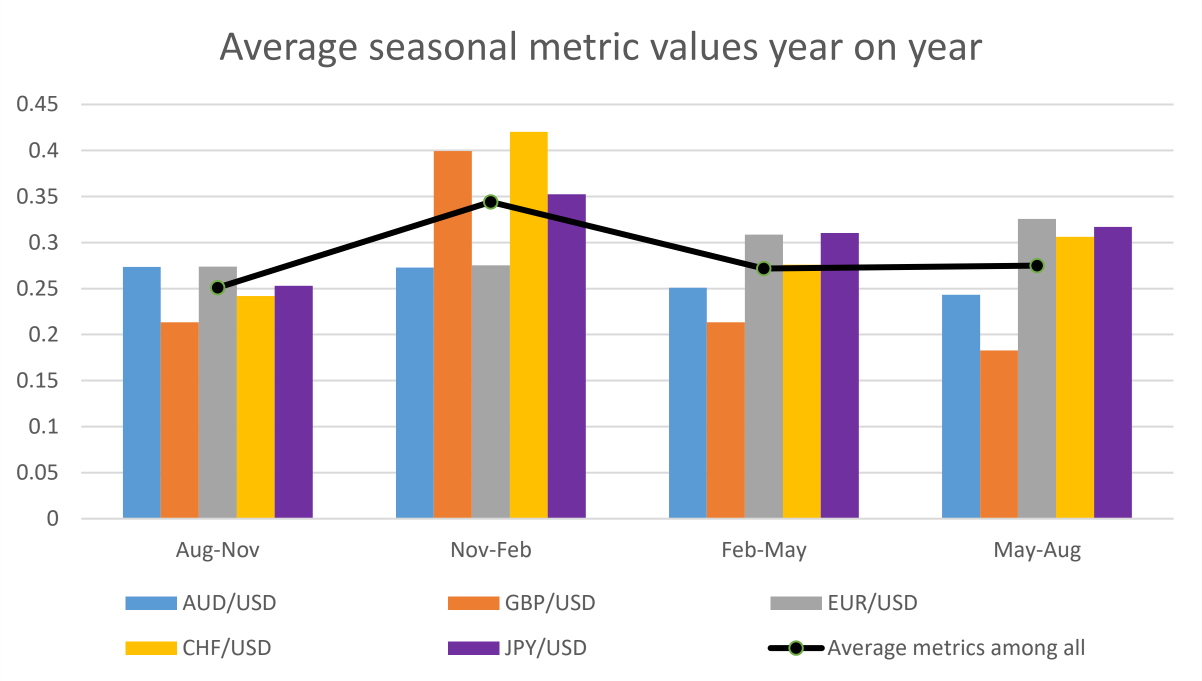



Figure 31: Average overall metric values for currency profiles comparisons between year-on-year seasonal times in four years. Blue and orange columns represent average overall AUD/USD and GBP/USD metrics values. Grey and yellow columns stand for average overall EUR/USD and CHF/USD metrics values. Purple column is for average overall JPY/USD metrics values. Black line stands for the average metrics among all currencies.

Figure 30 demonstrated the average metric values for currency profile comparisons between year-on-year seasonal time in four years in six metrics factors. GBP/USD market has the lowest average metrics value among all, as the black line in Figure 30 showed. Figure 31 is another angle to show the comparison results. It demonstrated the average overall metric values for currency profile comparisons between year-on-year seasonal time in four years in five currencies factors. From Figure 31, GBP/USD market also showed the lowest average overall metrics values among all, except the second quarter of the year. In other words, GBP/USD market may be a less risky market for the traders who adopt similar trading strategies year on year in most time periods. Another interesting phenomenon for market observers is the second quarter in Figure 31, which is November to February in next year, shows a significant difference among all. The average overall metrics value in GBP/USD, CHF/USD and JPY/USD markets all rise significantly. While AUD/USD and EUR/USD markets shows a more stable performance year on year.

### 6.2.4 Summary of currency market comparison

The comparison results in Section 6.2 can be divided into three parts. For comparisons between different market profiles in the same time period, EUR/USD and CHF/USD markets showed the most similarities in time intervals, and time adjusted returns of DC trends between each other, which means trading in DC events in these two markets may face similar risk and returns. For comparisons between adjacent time periods in same market, CHF/USD market shows the smallest value in $D_{TA}$ and $D_{RA}$ and the lowest average overall metrics value at the same time. CHF/USD market may be a less risky market for the traders who adopt similar trading strategies season over season in DC market analysis. For year-on-year profiles comparisons in the same market, GBP/USD market may be a less risky market for the traders who adopt similar trading strategies year on year in most time periods.d

## 6.3 Commodity market comparison

We have four commodity assets in our experiment tests. In DC metrics application, we used DC profiles of every three months for market comparison. Since each commodity asset lasts four years, each of them has been divided into 16 consecutive time periods. In this section, we present our DC metrics results of the assets in commodity market. The comparison pairs are shown in Table 14.

| **File name** | **Comparison asset profiles** |
|---|---|
| **Gold&Oil** | Profile comparison between Gold and Oil market |
| **Gold&Copper** | Profile comparison between Gold and Copper market |
| **Gold&Gas** | Profile comparison between Gold and Gas market |
| **Oil&Copper** | Profile comparison between Oil and Copper market |
| **Oil&Gas** | Profile comparison between Oil and Gas market |
| **Copper&Gas** | Profile comparison between Copper and Gas market |

Table 14: Ten DC profile comparison pairs for the same time period in commodity market

### 6.3.1 Market comparison between different commodity markets in the same time period

Comparison between different DC commodity market profiles in the same time period in four years generates more than one hundred metrics files. We recorded the summarized results in Table 24 in the Appendix 8.8.

As the same way we introduced currency market DC profiles comparison in Section 6.2.1, we have demonstrated the results of average metric values for six pairs of currency profiles comparisons in Figure 32. The complete results are shown in Table 25 in Appendix 8.8.

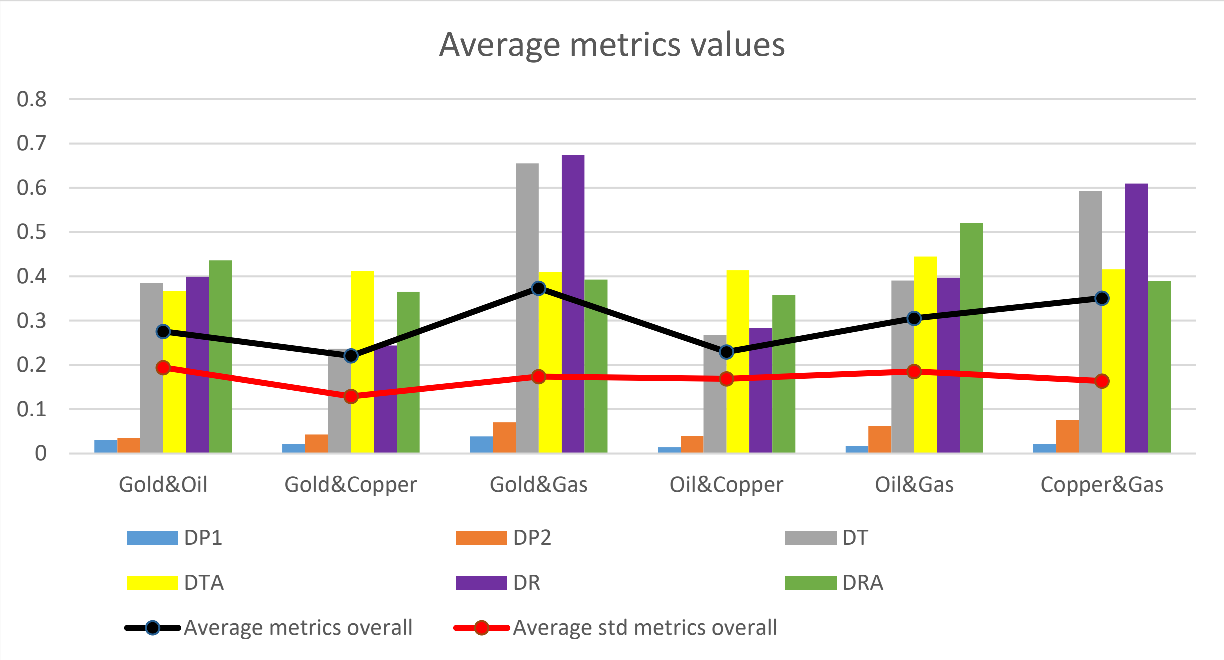



Figure 32: Average metric values for six pairs of commodity profiles comparisons. Blue and orange columns represent average $D_{P1}$ and $D_{P2}$ values. Grey and yellow columns stand for average $D_T$ and $D_{TA}$ values. Purple and green columns are for average $D_R$ and $D_{RA}$ values. Black line stands for the average metrics overall and red line is for average standard deviation metric values overall.

From the average metrics overall in Figure 32, gold and copper markets showed the smallest differences from each other among all the comparisons, especially for $D_T$ and $D_R$ values. This means that gold and copper markets showed the most similarities in time intervals, and time adjusted returns of DC trends between each other. These two markets also have the lowest standard deviation values for the metrics. In other words, trading in DC events in these two markets may face similar risk and returns. On the other hand, $D_T$ and $D_R$ values between gold and gas market are markedly higher than others, which reflects the significant difference in volatility and returns between these two markets.

### 6.3.2 Market comparison in the same commodity market between adjacent time periods

As the same way in currency market profiles comparison in Section 6.2.2, apart from comparisons between commodity market assets at the same time period, we also conducted comparisons in the same commodity between different time periods. In Figure 33, we showed the comparison results between adjacent time periods for the same commodity market. The complete results are shown in Table 26 and Table 27 in Appendix 8.9.

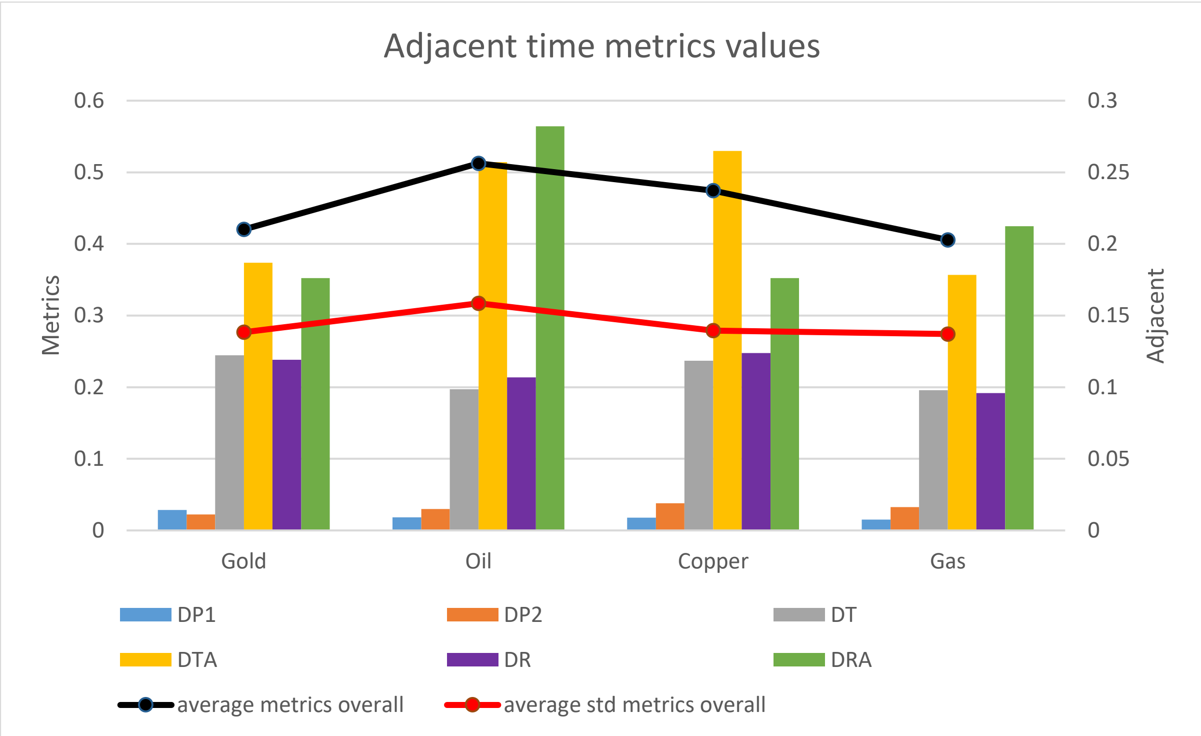



Figure 33: Average metric values for commodity profiles comparisons between adjacent times in four years. Blue and orange columns represent average $D_{P1}$ and $D_{P2}$ values. Grey and yellow columns stand for average $D_T$ and $D_{TA}$ values. Purple and green columns are for average $D_R$ and $D_{RA}$ values. Black line stands for the average metrics overall and red line is for average standard deviation metric values overall.

From Figure 33, the gas market shows the smallest value in $D_{P1}$, $D_T$, $D_{TA}$ and $D_R$ in average overall metrics. It also shows the lowest average standard deviation metric values. In other words, the gas market has a comparable steady performance in volatility changes among all the four commodities. In our view, traders in the gas market may adopt similar trading strategies across time. On the other hand, the oil market shows comparatively small values in $D_{P1}$, $D_{P2}$, $D_T$ and $D_R$ in average overall metrics but contains big values in $D_{TA}$ and $D_{RA}$, which means the differences between uptrends and downtrends changed a lot. In our view, traders in the oil market may adopt similar trading strategies across the time but the asymmetry between uptrends and downtrends is worthy of attention.

### 6.3.3 Market year-on-year comparison in the same commodity market

In addition, to make comparisons between adjacent time periods of DC profiles in the same commodity market, we also added comparisons between seasonal DC profiles year on year. The results are displayed in Figure 34 and Figure 35. The complete results are shown in Table 28 and Table 29 in Appendix 8.10.

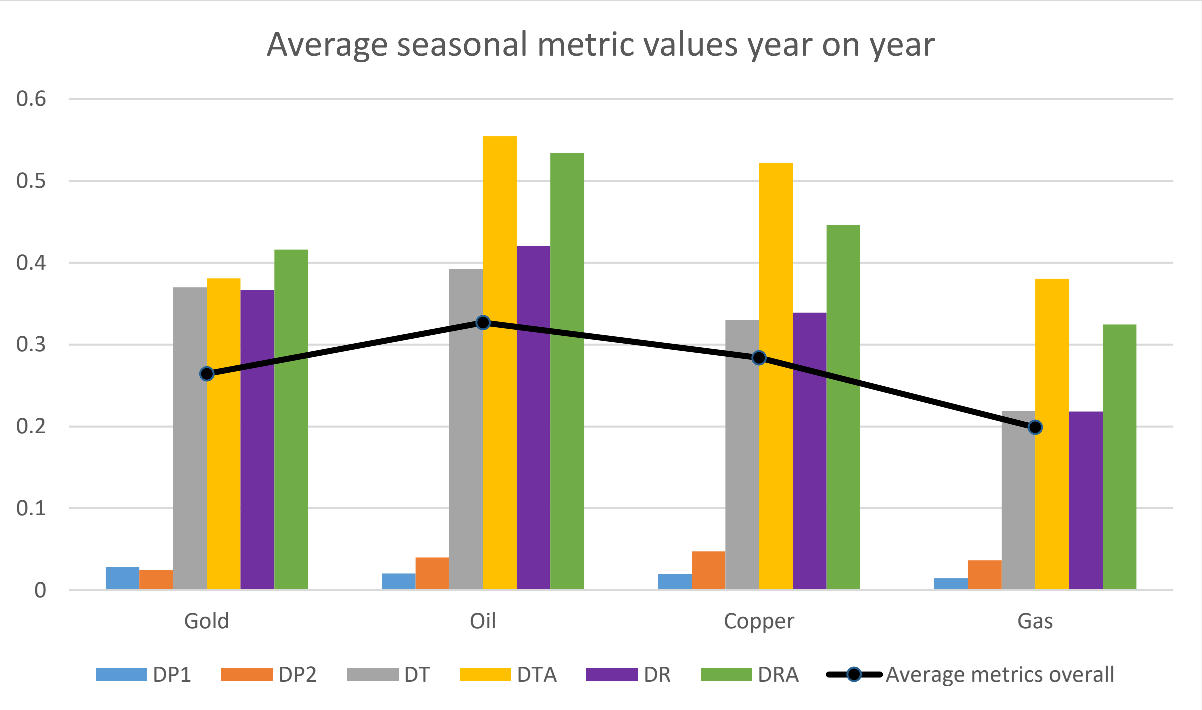



Figure 34: Average metric values for commodity profiles comparisons between year-on-year seasonal times in four years. Blue and orange columns represent average $D_{P1}$ and $D_{P2}$ values. Grey and yellow columns stand for average $D_T$ and $D_{TA}$ values. Purple and green columns are for average $D_R$ and $D_{RA}$ values. Black line stands for the average metrics overall and red line is for average standard deviation metric values overall.

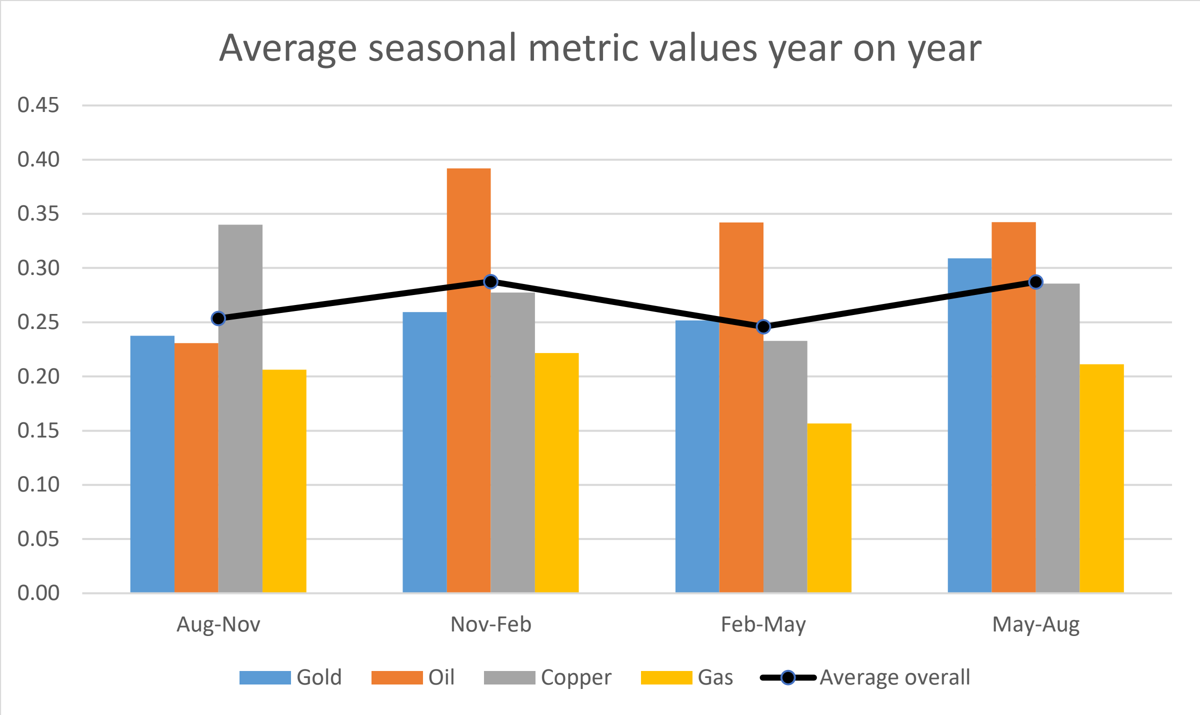



Figure 35: Average overall metric values for commodity profiles comparisons between year-on-year seasonal times in four years. Blue and orange columns represent average overall Gold and Oil metrics values. Grey and yellow columns stand for average overall Copper and Gas metrics values. Black line stands for the average metrics among all currencies.

Figure 34 demonstrated the average metric values for commodity profile comparisons between year-on-year seasonal time in four years in six metrics factors. The gas market has the lowest average metrics value among all, as the black line in Figure 34 showed. Figure 35 demonstrated the average overall metric values for commodity profile comparisons between year-on-year seasonal time in four years in four commodities factors. From Figure 35, the gas market also showed the lowest average overall metrics values among all. In other words, the gas market may be a less risky market for the traders who adopt similar trading strategies year on year in most time periods.

On the other hand, the oil market presents a more volatile performance. In Figure 34, the oil market shows the highest average metrics value among all, especially in $D_{TA}$ and $D_{RA}$ values, or in other words, the asymmetry between uptrends and downtrends. From Figure 35, the oil market also has great changes in the average metrics values in four quarters time periods. So we conclude that compared with other three commodity assets, trading in the oil market using similar trading strategy year-on-year is riskier for market traders.

### 6.3.4 Summary of commodity market comparisons

The comparison results in Section 6.3 can also be divided into three parts. For comparisons between different market profiles in the same time period, gold and copper markets showed the most similarities in time intervals, and time adjusted returns of DC trends between each other. These two markets also have the lowest standard deviation values for the metrics. Trading in DC events in these two markets may face similar risk and returns. For comparisons between adjacent time periods in the same market, gas market shows the smallest value in $D_{P1}$, $D_T$, $D_{TA}$ and $D_R$ in average overall metrics. It also shows the lowest average standard deviation metric values. So the gas market has a comparable steady performance in volatility changes among all the four commodities. Traders in the gas market may adopt similar trading strategies across time. For year-on-year comparisons in the same market, gas market has the lowest average and median metrics value among all. So gas market may be a less risky market for the traders who adopt similar trading strategies year on year in most time periods. On the other hand, the oil market presents a more volatile performance. Trading in the oil market using similar trading strategy year-on-year is riskier for market traders.

## 6.4 Contrast between currency market and commodity market

We have presented our DC profile comparison results in currency and commodity market respectively in last two sections. However, currency and commodity markets are related with each other (Agrawal 2010, Change 1999, Shenbagaraman 2003, Wang 2007). In this section, we apply DC metrics to make contrast between Currency market and commodity market in the same time period and try to extract some new information about the relations between currency and commodity market. As the same in the last two sections, we used DC profiles of every three months for market comparison. In this section, we present our DC metrics results of between currency and commodity market. The comparison pairs are shown in Table 15.

| File name | Comparison asset profiles |
|---|---|
| **AUD&Gold** | Profile comparison between AUD/USD and Gold market |
| **AUD&Oil** | Profile comparison between AUD/USD and Oil market |
| **AUD&Copper** | Profile comparison between AUD/USD and Copper market |
| **AUD&Gas** | Profile comparison between AUD/USD and Gas market |
| **GBP&Gold** | Profile comparison between GBP/USD and Gold market |
| **GBP&Oil** | Profile comparison between GBP/USD and Oil market |
| **GBP&Copper** | Profile comparison between GBP/USD and Copper market |
| **GBP&Gas** | Profile comparison between GBP/USD and Gas market |
| **EUR&Gold** | Profile comparison between EUR/USD and Gold market |
| **EUR&Oil** | Profile comparison between EUR/USD and Oil market |
| **EUR&Copper** | Profile comparison between EUR/USD and Copper market |
| **EUR&Gas** | Profile comparison between EUR/USD and Gas market |
| **CHF&Gold** | Profile comparison between CHF/USD and Gold market |
| **CHF&Oil** | Profile comparison between CHF/USD and Oil market |
| **CHF&Copper** | Profile comparison between CHF/USD and Copper market |
| **CHF&Gas** | Profile comparison between CHF/USD and Gas market |
| **JPY&Gold** | Profile comparison between JPY/USD and Gold market |
| **JPY&Oil** | Profile comparison between JPY/USD and Oil market |
| **JPY&Copper** | Profile comparison between JPY/USD and Copper market |
| **JPY&Gas** | Profile comparison between JPY/USD and Gas market |

Table 15: Twenty DC profile comparison pairs for the same time period between currency and commodity market

Comparison between different DC commodity market profiles in the same time period in four years generates more than one hundred metrics files. We recorded summarized results in Table 30 in the Appendix 8.11 to 8.15.

In the same way we introduced DC market profiles comparisons in the last two sections, we have demonstrated the results of average metric values for twenty pairs of profile comparisons between five currencies and commodity market in Figure 36. The complete results are shown in tables in Appendix 8.11 to 8.15.

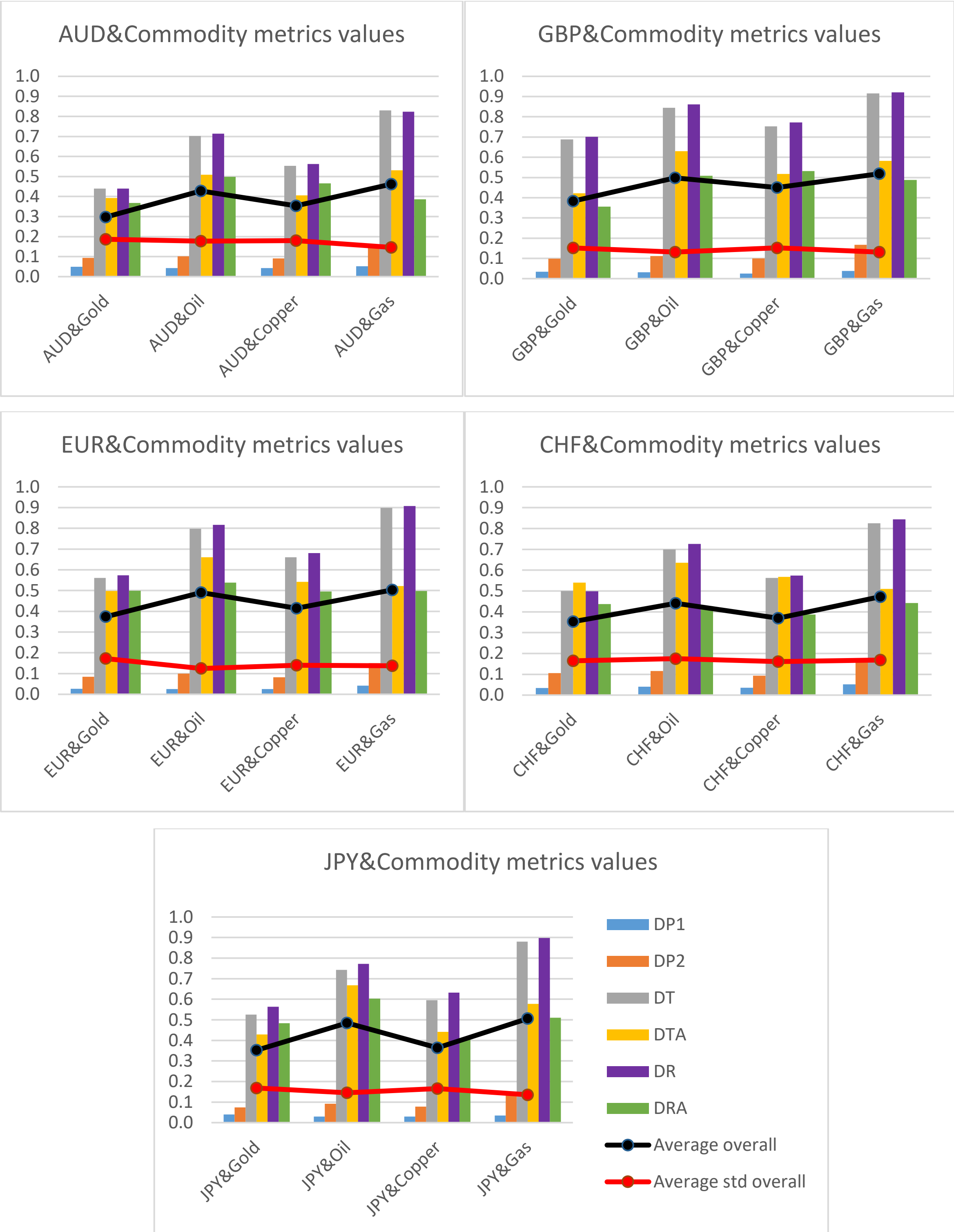



Figure 36: Average metric values for profile comparisons between five currencies and commodities in the same time period in four years. Blue and orange columns represent average $D_{P1}$ and $D_{P2}$ values. Grey and yellow columns stand for average $D_T$ and $D_{TA}$ values. Purple and green columns are for average $D_R$ and $D_{RA}$ values. Black line stands for the average metrics overall and red line is for average standard deviation metric values overall.

By comparing the average metrics value overall (black line) in Figure 36, we found there was some interesting information in common. Firstly, the overall average metrics value is always lower than another two when comparing gold and copper with any currencies. In other words, gold and copper markets showed less differences with the five currency assets. If we see gold and copper market as representatives of metal assets in commodity market, we may conclude that metal assets show more similarities with five currency markets than energy assets in the same time period through DC market analysis.

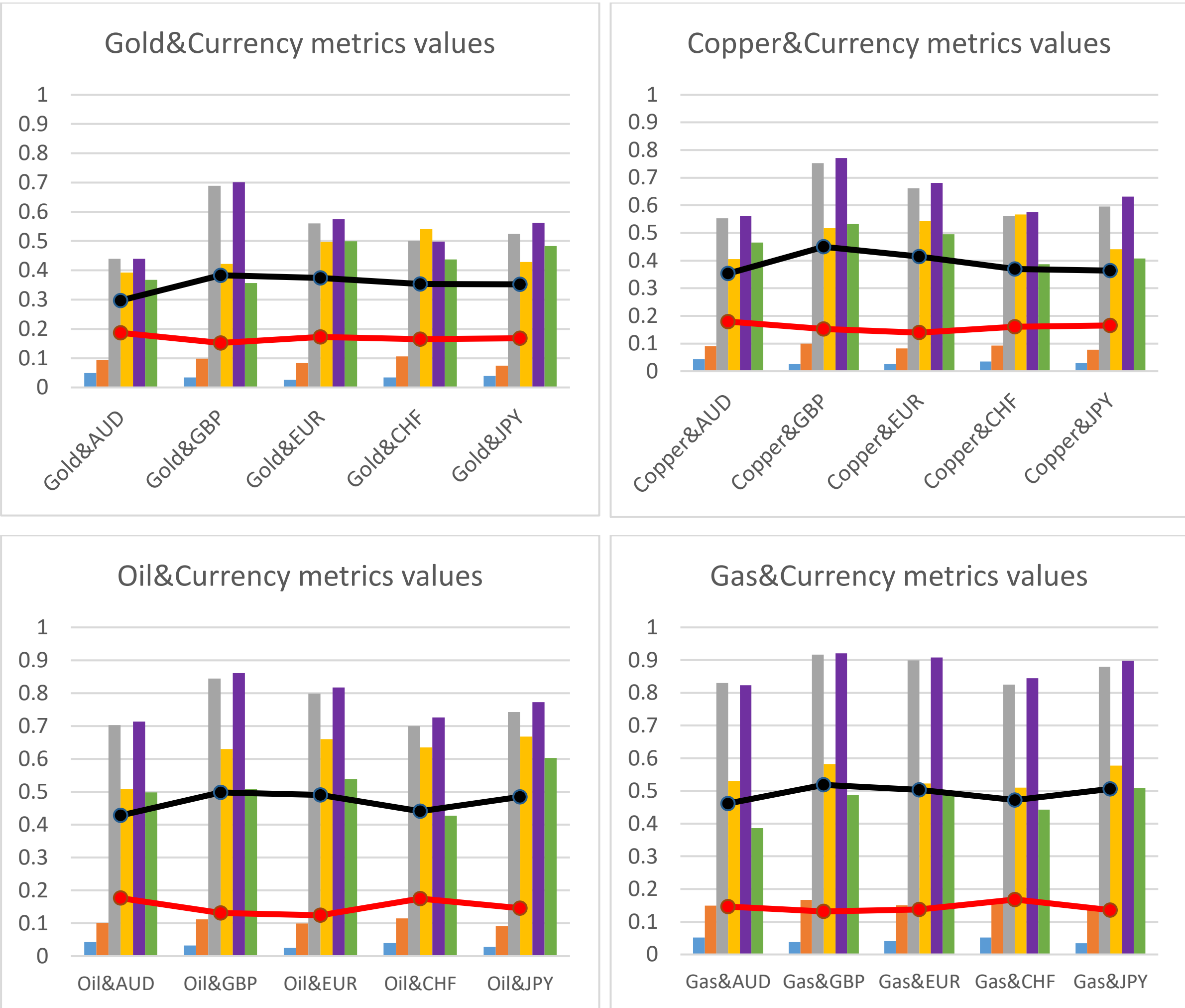



Figure 37: Average metric values for profiles comparisons between four commodities and currency in the same time period in four years. Blue and orange columns represent average $D_{P1}$ and $D_{P2}$ values. Grey and yellow columns stand for average $D_{T}$ and $D_{TA}$ values. Purple and green columns are for average $D_{R}$ and $D_{RA}$ values. Black line stands for the average metrics overall and red line is for average standard deviation metric values overall.

Figure 36 looks at differences between commodities and each currency. Figure 37 provides us another angle, which looks at differences between currencies and each commodity. The four Figures in Figure 37 shows that AUD/USD market always presents the smallest differences between four commodity assets. As the black lines in Figure 36 show. AUD/USD market and the gold market showed the smallest average overall metrics values among all. Traders may adopt similar trading strategies when trading in these two markets through DC market analysis.

In addition, amongst all of the metrics values in four figures in Figure 36 and 37, gas always shows the greatest difference with five currencies, especially GBP/USD market. $D_T$ and $D_R$ values both close to 1 between Gas and GBP/USD market, which means a significant difference in time interval and time adjusted return, or in other words, volatility and trend return, between these two markets in the same time period. Therefore, the performance of the gas market can be a significant signal for traders who are trading in the five currency markets, especially for GBP/USD market.

## 6.5 Summary

In this chapter, we showed the results of DC market profiles comparisons in currency and commodity markets. For the comparisons between different market profiles in the same time period, EUR/USD and CHF/USD markets showed the most similarities in time intervals, and time adjusted returns of DC trends between each other, which means trading in DC events in these two markets may face similar risk and returns. For commodity market, comparison results between gold and copper market profiles also showed the same conclusion. On the other hand, we should mention that the differences in time intervals and time adjusted returns between gold and gas market are markedly higher than others, which reflects the significant difference in volatility between these two markets. In addition, for comparison between currency and commodity market profiles, gold and copper markets showed less differences than the other two commodity markets with the five currency assets. If we see gold and copper market as representatives of metal assets in commodity market, we may conclude that metal assets show more similarities with currency market than energy assets in the same time period.

For the comparisons between same market profiles in different time periods, we divided them into two kinds of comparisons. One is comparisons between profiles from adjacent time periods. For example, CHF/USD market shows the smallest value in $D_{TA}$ and $D_{RA}$ and the lowest average overall metrics value at the same time. So CHF/USD market may be a less risky market for the traders who adopt similar trading strategies season over season in currency market. It may lead the same conclusion for gas market after analysing the comparison results among the commodity markets. Another way of comparison is between year-on-year market profiles. We found that GBP/USD and gas markets may be less risky markets for the traders who adopt similar trading strategies year on year among the currency and commodity markets in most time periods. On the other hand, compared with other three commodity assets, trading in the oil market using similar trading strategy year on year is riskier for market traders. We have also found another interesting phenomenon for market observers. The market profiles in time period from November to February in next year shows a significant difference among all. The average overall metrics value in GBP/USD, CHF/USD and JPY/USD markets all rise significantly. While AUD/USD and EUR/USD markets shows a more stable performance year on year.

# Chapter 7 Conclusions

This chapter provides a summary of the thesis, points out the contributions being made, and goes on to discuss possible future direction of the research work.

## 7.1 Summary

As the thesis title implied, our work is concerned with introducing directional change (DC) as a new way for information extraction and analysis from financial market data. The changing nature of the financial market has led to the need for new and different ways to analyse data, and the trend is for market efficiency to rely on being informationally efficient. The survey of the literature in Chapter 2, revealed that financial researchers have begun searching for different ways of analysing market behaviour, rather than using that of the usual method of time series, because of the drawbacks associated with market data being recorded at fixed time intervals. As, in time series, using sampled data from a fixed time interval has the disadvantage that it can miss the moment of extreme points in market price movement. And it is these extreme points that can provide significant market information for market observers and traders. On the other hand, as compared to traditional time series analysis, DC uses fixed price change intervals, called thresholds, to sample market data points. Some researchers have also applied DC in defining scaling laws and analysing market patterns. As an empirical, data-driven approach, DC shows its advantages in capturing market extreme points and maximizing potential profit, compared with time series analysis. Therefore, DC provides market researchers with a new way to understand market dynamics and brings an insight into the market price movement.

Based on this idea, we carried out three steps in this thesis aimed at building a new approach to data analysis, using DC to help us extract useful information from the financial market. The first step, which was presented in Chapter 3, is to define our DC indicators for describing DC-based market summaries. These indicators made up the first part of the vocabulary to help us establish DC market profiles to extract different market information. We have written our own program called TR1 to help us produce these indicators and profiles. The profiles give us insight into the market, such as a different angle to see the market volatility and the potential profit of trading within a certain time period. This useful information is not observable with time series analysis but is a complement to it.

After the invention of DC indicators and establishment of DC market profiles, our second step in the research is to create DC metrics for comparison of different aspects between two DC market profiles. The detailed description of DC metrics is in Chapter 4. These DC metrics advanced DC indicators and profiles in market information extraction. Since they made DC profiles from different market data comparable with each other and built a quantitative measurement to measure the differences between them. They made up the rest of the part of our vocabulary of DC market summaries. In this step, we have also written a program called TR2 to help us batch processing the metrics results. By comparing DC profiles between different markets in the same time period, or DC profiles between two time periods of the same market, we can extract significant new market information, which has not been captured before.

Since this vocabulary has been created, we applied it to real financial markets data in our third step of research. This part of work is presented in Chapter 5. The database in this thesis has been provided by Thomson Reuters and Kibot. Because of the limitation of data and the purpose of profile comparisons, we used minute-by-minute open price data from five main currencies and four representative commodities from 2011 to 2015. In this step, DC indicators and profiles helped us demonstrate the high volatile time period and the assets which contain the maximum potential profit. They also showed the volatile assets and trends among all. For example, as far as T is concerned, the gold market has a high volatility and risks in the profiled time period among all the assets.  The JPY/USD market appears to be more volatile in the downtrends than in uptrends. Thus, trading in JPY/USD market in the downtrend event has more risks.

Apart from DC indicators and profiles, DC metrics have been applied as well. In our research, we made comparisons between different markets in the same time period, or the same markets between different time periods, which generated almost one thousand comparison pairs. DC metrics helped us extract significant market information through DC profile contrasts. Some markets showed a great similarity between each other through DC metrics in certain time periods, or in certain aspects. For example, gold and copper markets showed the most similarities in time intervals, and time adjusted returns of DC trends between each other. On the other hand, $D_T$ and $D_R$ values between gold and gas market are markedly higher than others, which reflects the significant difference in volatility between these two markets. We may also conclude that metal assets show more similarities with the currency market than with energy assets in the same time period, through comparisons between currency and commodity DC markets profiles. DC market analysis not only defined volatility in a new way, but also revealed the asymmetry between uptrends and downtrends events. This information is not observable through time series analysis, but through DC market analysis only.

## 7.2 Contributions

The major contributions of this thesis are as follows:

1. We have proposed DC as a new method to help us extract useful market information by defining DC indicators and build DC market profiles. We invented ten DC indicators to help us analyse market volatility in DC. Compared with the standard deviation used in time series analysis, DC market analysis can summarize market volatility by looking at the magnitude of price change in every DC trend and the frequency of price changes. Besides that, DC also provides insight into volatility in every DC trend, which indicates the trading risks in every DC trend. What's more, in a DC profile, the uptrend and downtrend are always consecutive to each other, which is different from time series analysis. DC profile provides us with indicators to analyse the asymmetry between uptrends and downtrends. The production of the DC indicators is a major contribution for future research in DC market information extraction.

2. We have proposed a method to quantitatively measure the differences between two markets summarized in DC profiles. We introduced DC metrics as a quantitative way to measure the differences between two DC profiles in different aspects. The value of DC metrics is always between 0 and 1, which makes DC metrics results comparable with each other. To the best of our knowledge, no one has been able to make comparisons between different markets in the same time period, or the same markets between different time periods in DC. In Chapter 4, we demonstrated that DC metrics is an advanced way to help us extract some useful information that time series

analysis cannot capture. For instance, USD/CHF market and USD/JPY market showed great similarity between each other in DC metrics values but performs differently through time series analysis. The information can lead to different trading strategies for traders.

3. We have provided empirical evidence for DC indicators application in real financial markets in Chapter 5. By looking at DC profiles of nine financial assets, we concluded that there was a highly volatile time from November 2012 to May 2013. The energy assets, oil and gas, have the longest coastline. And in currency market, AUD/USD and CHF/USD markets showed the longer coastline against the other three currencies. Besides that, by looking at the difference between uptrends and downtrends, it is possible to conclude that the EUR/USD market is more volatile in the downtrends when analysing T in DC profile. Trading in JPY/USD market in the downtrend event has more risks.

4. We have also provided empirical evidence for DC metrics application in the real financial market in Chapter 6. By making contrasts in the same markets between different time periods, Trading in DC events in EUR/USD and CHF/USD markets may face similar risk and returns.

## 7.3 Future work

This thesis adopts DC as a new approach for financial market information extraction. Unlike time series analysis, DC market analysis is based on the market points sampled at irregular time intervals, which provides a new angle for market observers and traders. The ways to measure market volatility and potential profit in DC market analysis can provide extra market information for traders, in addition to the traditional time series analysis, and help them to make better decisions. These two approaches will complement each other. By combining the market information extracted through these two approaches to explore synergy, they may provide complementary market information for the researchers.

DC market analysis is in its infancy. We may revise our current DC indicators and metrics to define some new ones in the future according to continuing research. For example, to simplify the DC metrics application process, we have not applied all the indicators in DC profiles in profile comparisons, such as Sub-NDC. The more useful are the indicators to be applied in profile comparisons, the more accurate market information we may then extract from it. Besides that, a richer data set may also bring us more insight and information about the financial market.

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# Appendix

## 8.1 Specification of TR1

TR1 is a program that reads in time-stamped prices (which we call the Input Data File) and output a profile of the input data. The profile includes two parts. First, TR1 outputs a file that contains all the data points at extreme points and directional change confirmation points. We call this the DC-Data File. Secondly, TR1 outputs a summary of the profile. We call it the Profile Summary File. In reality the threshold that user used may be too big or too small, which may affect the effectiveness of DC profiling. So, the program will warn the user under these situations.

Following is the specification of TR1.

**Input Data File**

This is a csv file with one record per data point, where each record comprises the following fields:

- TimeStamp: Time stamp, which could include the date and time of a Trade
- TradePrice: Price of a trade
- Threshold: The program will ask user the threshold to be used. The sub-threshold used in the program equals to a quarter of the threshold.

**Output**: The program will produce two files: (1) “DC-Data File” and (2) “Profile Summary File”.

**Output 1: DC-Data File**

This is a csv file with two parts:

(**Header**, **Body**)

**Header:** it contains information that enables other researchers to reproduce the results:

- Program_ID: Program and version: e.g. TR1.0 v.1.0
- Author: Ran Tao
- Date on which the DC-Data File was produced
- File_input: Name of the Input Data File
- Theta: Threshold used to run the program

- Sub-Threshold: A quarter of the Threshold
- Tstart: First $T_{Trade}$ displayed in the Input Data File; i.e. start of the data series
- Tfinal: Final $T_{Trade}$ displayed in the Input Data File; i.e. end of the data series
- Link to the Working Paper <Edward will give you a link>

**Body:** it is a table with one record per extreme point; each record comprises the following fields:

- $T\_{EXT}$: Date_Time at extreme point
- $P_{EXT}$: Price at extreme point
- $T_{DCC}$: Date_Time at DC Confirmation (DCC) point
- $P_{DCC}$: Price at DCC point
- DCC*:  Minimum price at DCC point
- $OSV_{EXT}$: The OSV at extreme point $T_{EXT}$
- T: The time taken by the current trend, i.e. the difference between the current $T\_{EXT}$ and the next $T\_{EXT}$ (If T = 1, which means that $P_{DCC}$ and $P_{EXT}$ become the same spot, then the program will warn the user “Warning: The threshold is too small”)
- TMV: Total Price movements value at extreme point $T\_{EXT}$
- $R_{DC}$: (= $TMV_{EXT} \div T$ ) the time-adjusted return of the trend
- Sub-$N_{DC}$: The total number of directional changes in each TM event based on the sub-threshold
- $USV_{EXT}$: The USV at extreme point $T_{EXT}$

**Output 2: Profile Summary File**

This is a csv file with name-value pairs. It contains three parts: (1) Header, (2) Profile for the whole period; and (3) Snapshot Profile.

**Part 1: Header**: it contains information that provides information for reproducing the results:

- Program and version: e.g. TR1.4
- Author: Ran Tao
- Date on which the DC-Data File was produced
- File_input: Name of the Input Data File

- Threshold: Theta
- Sub-Threshold: A quarter of the Threshold
- Tstart: First $T_{Trade}$ displayed in the Input Data File; i.e. start of the data series
- Tfinal: Final $T_{Trade}$ displayed in the Input Data File; i.e. end of the data series

**Part 2: Profile for the whole period:**

- TL: Length of the time period covered by the Input Data File, also represents the time units in total, e.g. minutes.
- $N_{DC}$: The total number of directional changes over the profiled period (If $N_{DC}$ is smaller than 30, which may affect the effectiveness of the indicators in the profile, then the program will warn the user “Warning: The threshold is too big”)
- PC: Price change – the spot percentage increase/decrease in price at the last extreme point (EXT) from the first extreme point in the DC-Data File
- MedianOSV = (MedianOSV_overall, MedianOSV_up, MedianOSV_down)
  - MedianOSVoverall: median of absolute value of $OSV_{EXT}$ collected in the DC-Data File
  - MedianOSVup: median value of $OSV_{EXT}$ collected for the up-trends only
  - MedianOSVdown: median of absolute value of $OSV_{EXT}$ collected for the down-trends only
- Median$T_{DC}$ = (MedianT_overall, MedianT_up, MedianT_down)
  - The median value of $T_{DC}$ collected, the median value of $T_{DC}$ in the up trends and in the down trends
- Median$R_{DC}$ = (Median$R_{DC}$_overall, Median$R_{DC}$_up, Median$R_{DC}$_down)
  - The median value of $R_{DC}$ collected, the median value of $R_{DC}$ in the up trends and in the down trends
- $C_{DC}$ = Length of Coastline defined by directional change events ($\sum_{i=1}^{N(\theta)} TMV_{EXT_i}$ )
  - the median value of TMV collected in the DC-Data File
- MedianSub-$N_{DC}$: The median value of Sub-$N_{DC}$ collected in the DC-Data File
- Median$USV_{EXT}$: The median of absolute value of $USV_{EXT}$ collected in the DC-Data File

**Part 3: Snapshot profile**: information at T_final

- $T_{final}$: Final TimeStamp displayed in the Input Data File; i.e. the date and time at the end of the data series
- $P_{final}$: Final TradePrice displayed in the Input Data File; i.e. price at the end of the data series
- SPC: Price change – the spot percentage increase/decrease in price at the current point from the beginning of the period covered by the Input Data File
- SOSV: The Spot OSV at the final trend of the period
- STMV: The Spot TMV at the final trend of the period
- ST: The Spot time taken in the current trend
- $SR_{DC}$: The Spot $R_{DC}$ at the current point

## 8.2 Example: DC-Data File

DC-Data file is a file that contains all the data points at extreme points and directional change confirmation points. It also includes the indicators, such as $OSV_{EXT}$, which is calculated from the data points. The DC-Data file is machine readable for testing the correctness of the Summary Profile and calculating new indicators if needed.

Table 16 shows a sample DC-Data File. This file contains two parts: the Header and the Body. The Header starts from the beginning to end of the row that starts with "Tfinal" (the first eight lines in Table 16). It contains sufficient information to reproduce the results. Table 16 it shows the version of the program run (which is TR1.3) and the date and time (2016.03.03 22:20:37, which reads 3rd March 2016 at time 22:22:37) at which the program was executed. It shows the name of the Input Data File ("EURUSD-Oct2009sec") and the threshold being used (0.004, i.e. 0.4%, as shown in row 5 column 2). The sub-threshold is 0.001. i.e. 0.1% (row 6 column 2). It also shows the time of the first transaction and the final transaction recorded in the Input Data File (01/10/2009,00:00:00and 30/10/2009,16:58:58, respectively).

The Body is the table that starts with "T_EXT" (row 10 in this example) and finishes at the end of the file. Each row records a Directional Change event. For example, the first extreme point recorded is at "01/10/2009, 01:24:56". The transaction price recorded was 1.4629(column 2). At "01/10/2009, 01:49:28" (row 10, column 3), the transaction price was 1.457 (column 4). Since this price is 0.4% higher than the extreme price (1.4629), it confirmed an upward directional change from the extreme point. The table also records the minimum price that must be reached before one could confirm an upward directional change. This is called $P_{DCC*}$ (column 5). In the first event (row 11), $P_{DCC*}$ is 1.4629× (1-0.4%) = 1.457048.

With $P_{EXT}$ and $P_{DCC*}$, we calculate overshoot value at extreme points. $OSV_{EXT}$ = ((1.4521-1.457048) ÷ 1.457048) ÷ 0.004 = - 0.84905 (column 6, row 11). With $P_{EXT}$ and $P_{DCC}$, we calculate total price movements at extreme points. TMV = ((1.4521-1.4629) ÷ 1.4629) ÷ 0.004 = - 1.84565 (column7, row 11). Time interval (column 8) records the time units between each T_EXT, such as 25740 (column 8, row 11). The next column is $R_{DC}$, which measures the time-adjusted return of upturn/downturn trend. $R_{DC}$ = |TMV| × threshold / $T_{DC}$ = 1.84565 × 0.004 ÷ 25740 = 2.87× $10^{-7}$ (column 10, row 11). Sub_$N_{DC}$ (column 11, row 11) records that there are 23 DC events happened in first trend based on sub-threshold 0.1% (row 6 column 2). The last column records the undershoot value at extreme points ($USV_{EXT}$) in each trend.

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Program_ID:TR1.3 | | | | | | | | | | |
| Author: Ran Tao | | | | | | | | | | |
| Date | 2016.03.03 22:20:37 | | | | | | | | | |
| File_input | EURUSD-Oct2009sec | | | | | | | | | |
| Threshold(Theta) | 0.004 | | | | | | | | | |
| Sub-Threshold | 0.001 | | | | | | | | | |
| Tstart | 01/10/2009,00:00:00 | | | | | | | | | |
| Tfinal | 30/10/2009,16:58:58 | | | | | | | | | |
| | | | | | | | | | | |
| T_EXT | PEXT | T_DCC | PDCC | PDCC* | OSVEXT | TMV | T | R_DC | sub_NDC | USV |
| 01/10/2009,01:24:56 | 1.4629 | 01/10/2009,01:49:28 | 1.457 | 1.457048 | -0.84905 | -1.84565 | 25740 | 2.87E-07 | 23 | 0 |
| 01/10/2009,08:33:56 | 1.4521 | 01/10/2009,10:55:30 | 1.4582 | 1.457908 | 0.084299 | 1.084636 | 8496 | 5.11E-07 | 3 | 0.257218 |
| 01/10/2009,10:55:32 | 1.4584 | 01/10/2009,11:35:24 | 1.4525 | 1.452566 | -0.40728 | -1.40565 | 33300 | 1.69E-07 | 19 | 0 |
| 01/10/2009,20:10:32 | 1.4502 | 02/10/2009,02:21:42 | 1.4561 | 1.456001 | 0.051374 | 1.051579 | 31129 | 1.35E-07 | 13 | 0.154533 |
| 02/10/2009,04:49:22 | 1.4563 | 02/10/2009,08:32:52 | 1.4504 | 1.450475 | -0.39208 | -1.39051 | 13484 | 4.12E-07 | 9 | 0.12065 |
| 02/10/2009,08:34:06 | 1.4482 | 02/10/2009,09:03:04 | 1.454 | 1.453993 | 1.858194 | 2.865626 | 7320 | 1.57E-06 | 13 | 0.481433 |
| 02/10/2009,10:36:06 | 1.4648 | 02/10/2009,11:21:52 | 1.4589 | 1.458941 | -0.40111 | -1.39951 | 19054 | 2.94E-07 | 15 | 0.222764 |
| 02/10/2009,15:53:40 | 1.4566 | 04/10/2009,20:34:46 | 1.4625 | 1.462426 | 0.525428 | 1.52753 | 37650 | 1.62E-07 | 17 | 0.153854 |
| 05/10/2009,02:22:24 | 1.4655 | 05/10/2009,08:54:52 | 1.4596 | 1.459638 | -0.05789 | -1.05766 | 24070 | 1.76E-07 | 7 | 0.13702 |
| 05/10/2009,09:03:34 | 1.4593 | 05/10/2009,12:02:24 | 1.4652 | 1.465137 | 1.887673 | 2.895224 | 94725 | 1.22E-07 | 43 | 0.085316 |
| 06/10/2009,11:22:20 | 1.4762 | 06/10/2009,20:26:22 | 1.4702 | 1.470295 | -0.88336 | -1.87983 | 96693 | 7.78E-08 | 35 | 0.289058 |
| 07/10/2009,14:14:04 | 1.4651 | 07/10/2009,19:29:18 | 1.471 | 1.47096 | 1.553339 | 2.559552 | 67407 | 1.52E-07 | 23 | 0.152961 |
| 08/10/2009,08:57:34 | 1.4801 | 08/10/2009,09:21:12 | 1.4741 | 1.47418 | -0.36963 | -1.36815 | 4180 | 1.31E-06 | 7 | 0.152627 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 08/10/2009,10:07:14 | 1.472 | 08/10/2009,11:10:18 | 1.4779 | 1.477888 | 0.644839 | 1.647418 | 8710 | 7.57E-07 | 17 | 0.16916 |
| 08/10/2009,12:32:24 | 1.4817 | 08/10/2009,20:05:32 | 1.4757 | 1.475773 | -0.89329 | -1.88972 | 37106 | 2.04E-07 | 13 | 0.118582 |
| 08/10/2009,22:50:50 | 1.4705 | 09/10/2009,07:28:40 | 1.4764 | 1.476382 | 0.155448 | 1.156069 | 31249 | 1.48E-07 | 1 | 0.304799 |
| 09/10/2009,07:31:42 | 1.4773 | 09/10/2009,09:04:50 | 1.4713 | 1.471391 | -0.69506 | -1.69228 | 17996 | 3.76E-07 | 13 | 0.067963 |
| 09/10/2009,12:31:38 | 1.4673 | 11/10/2009,17:28:26 | 1.4732 | 1.473169 | 0.174929 | 1.175629 | 22843 | 2.06E-07 | 7 | 0.220613 |
| 11/10/2009,18:53:30 | 1.4742 | 11/10/2009,21:17:10 | 1.4683 | 1.468303 | -0.11973 | -1.11925 | 8822 | 5.07E-07 | 9 | 0.204317 |
| 11/10/2009,21:20:32 | 1.4676 | 12/10/2009,05:02:40 | 1.4736 | 1.47347 | 2.397334 | 3.406923 | 124182 | 1.1E-07 | 33 | 0.0509 |
| 13/10/2009,07:50:28 | 1.4876 | 13/10/2009,09:30:16 | 1.4816 | 1.48165 | -0.31208 | -1.31084 | 9276 | 5.65E-07 | 9 | 0.21935 |
| 13/10/2009,10:25:04 | 1.4798 | 13/10/2009,13:46:58 | 1.4858 | 1.485719 | 1.847725 | 2.855116 | 143276 | 7.97E-08 | 49 | 0.168269 |
| 15/10/2009,02:13:04 | 1.4967 | 15/10/2009,05:46:58 | 1.4907 | 1.490713 | -1.05875 | -2.05452 | 21322 | 3.85E-07 | 7 | 0.268328 |
| 15/10/2009,08:08:26 | 1.4844 | 15/10/2009,09:36:26 | 1.4906 | 1.490338 | 1.067275 | 2.071544 | 46296 | 1.79E-07 | 19 | 0.419368 |
| 15/10/2009,21:00:02 | 1.4967 | 16/10/2009,02:30:54 | 1.4907 | 1.490713 | -0.99167 | -1.98771 | 41007 | 1.94E-07 | 25 | 0.134164 |
| 16/10/2009,08:23:38 | 1.4848 | 16/10/2009,11:06:00 | 1.4908 | 1.490739 | 0.194669 | 1.195447 | 38227 | 1.25E-07 | 9 | 0.218013 |
| 18/10/2009,19:02:10 | 1.4919 | 18/10/2009,20:16:58 | 1.4859 | 1.485932 | -0.49336 | -1.49139 | 5612 | 1.06E-06 | 3 | 0.504734 |
| 18/10/2009,20:35:42 | 1.483 | 19/10/2009,01:30:48 | 1.489 | 1.488932 | 1.757636 | 2.764666 | 92893 | 1.19E-07 | 55 | 0.100743 |
| 19/10/2009,22:24:00 | 1.4994 | 20/10/2009,10:17:12 | 1.4933 | 1.493402 | -0.85416 | -1.85074 | 48119 | 1.54E-07 | 9 | 0.133922 |
| 20/10/2009,11:46:04 | 1.4883 | 20/10/2009,16:56:20 | 1.4943 | 1.494253 | 1.731099 | 2.738023 | 94421 | 1.16E-07 | 39 | 0.200769 |
| 21/10/2009,13:59:58 | 1.5046 | 21/10/2009,23:37:22 | 1.4985 | 1.498582 | -0.69759 | -1.6948 | 53215 | 1.27E-07 | 15 | 0.13346 |
| 22/10/2009,04:46:54 | 1.4944 | 22/10/2009,08:18:00 | 1.5006 | 1.500378 | 0.920168 | 1.923849 | 55998 | 1.37E-07 | 17 | 0.166625 |
| 22/10/2009,20:20:12 | 1.5059 | 23/10/2009,02:34:38 | 1.4998 | 1.499876 | -0.12941 | -1.12889 | 22561 | 2E-07 | 7 | 0.16668 |
| 23/10/2009,02:36:14 | 1.4991 | 23/10/2009,05:48:48 | 1.5051 | 1.505096 | 0.000598 | 1.0006 | 11554 | 3.46E-07 | 13 | 0.099661 |
| 23/10/2009,05:48:48 | 1.5051 | 23/10/2009,15:39:06 | 1.499 | 1.49908 | -0.16337 | -1.16271 | 51565 | 9.02E-08 | 5 | 0.033354 |
| 25/10/2009,20:14:40 | 1.4981 | 25/10/2009,22:00:18 | 1.5041 | 1.504092 | 0.350311 | 1.351712 | 7464 | 7.24E-07 | 13 | 0.232698 |
| 25/10/2009,22:19:04 | 1.5062 | 26/10/2009,10:53:08 | 1.5001 | 1.500175 | -2.62889 | -3.61838 | 58753 | 2.46E-07 | 17 | 0.099988 |
| 26/10/2009,14:38:18 | 1.4844 | 27/10/2009,02:06:56 | 1.4904 | 1.490338 | 0.396286 | 1.397871 | 44389 | 1.26E-07 | 7 | 0.301945 |
| 27/10/2009,02:58:10 | 1.4927 | 27/10/2009,05:11:10 | 1.4867 | 1.486729 | -1.61919 | -2.61272 | 38186 | 2.74E-07 | 39 | 0.100893 |
| 27/10/2009,13:34:36 | 1.4771 | 28/10/2009,02:53:28 | 1.4831 | 1.483008 | 0.184018 | 1.184754 | 48033 | 9.87E-08 | 7 | 0.370868 |
| 28/10/2009,02:55:16 | 1.4841 | 28/10/2009,05:34:02 | 1.4781 | 1.478164 | -1.65131 | -2.6447 | 62842 | 1.68E-07 | 37 | 0.033826 |
| 28/10/2009,20:22:38 | 1.4684 | 29/10/2009,03:48:18 | 1.4743 | 1.474274 | 1.95459 | 2.962408 | 65891 | 1.8E-07 | 43 | 0.237405 |
| 29/10/2009,14:40:52 | 1.4858 | 30/10/2009,07:54:40 | 1.4798 | 1.479857 | | | | | | 0.219616 |

Table 16: DC Data File produced by TR1 (see specification in Chapter 3 section 3 or Appendix 8.1) based on second-by–second data in EUR/USD market from October 1, 2009 to October 30, 2009 (Threshold 0.4%, Sub-Threshold 0.1%)

## 8.3 Specification of TR2

TR2 is a program that reads two DC data files (a DC data file could be the result from TR1, which is the profile of a period in a market summarized under DC (Tsang 2016)) and outputs a metrics file about their similarities and differences. The metrics file includes six metrics we defined so far. The value of each metric is always between 0 and 1. The closer to 0 means the less differences between two DC data files. These six DC metrics are able to quantitatively measure six different aspects between two DC data files.

Following is the specification of TR2.

**Input DC-Data File**

**DC-Data File 1, DC-Data File 2**

These are csv files that produced from TR1.

The format of each file contains these series of indicators below:

- $T_{\_EXT}$: Date and time at each DC extreme point
- $P_{EXT}$: Price at the time of each DC extreme point ($T_{\_EXT}$)
- $T_{DCC}$: Date and time at each DC Confirmation (DCC) point
- $P_{DCC}$: Price at each DCC point
- $T_{DC}$: The time taken by the current trend, i.e. the time intervals between the current $T_{EXT}$ and the next $T_{EXT}$
- TMV: Total Price movements value at extreme point $T_{EXT}$
- $R_{DC}$: Annualised return of each DC event

**Output**: The program will produce a DC metrics file.

This is a csv file with name-value pairs. It contains two parts: (1) Header, (2) metrics of the DC profiles.

**Part 1: Header** – it contains information that provides information for reproducing the results:

- Program and version: e.g. TR2.0
- Author: Ran Tao
- Date on which the DC-Data File was produced
- File_input: Name of the Input Data File
- Theta: Threshold
- Tstart: First $T_{Trade}$ displayed in the Input Data File; i.e. start of the data series
- Tfinal: Final $T_{Trade}$ displayed in the Input Data File; i.e. end of the data series

**Part 2: DC metric:**

This part of the csv file contains the metrics values of the two DC-Data Files. There are six metrics now. These six metrics values are quantitative ways to measure six different aspects between two DC data files. The value of each metric is always between 0 and 1. The closer to 0 means the less differences between two DC data files in the certain aspect.

- $D_{P1}$: measure the difference in majority prices changes (e.g. the median value of the TMV series).
- $D_{P2}$: measure the difference in extreme prices changes (e.g. the average value of the top 5% of the TMV series).
- $D_{T}$: measure the difference in time intervals of trends. (e.g. the median value of the $T_{DC}$ series)
- $D_{TA}$: measure the difference in time intervals asymmetry between up and down trends. (e.g. the median values of the uptrend $T_{DC}$ series and downtrend $T_{DC}$ series)
- $D_{R}$: measure the difference in annualised returns of trends (e.g. the median value of the $R_{DC}$ series).
- $D_{RA}$: measure the difference in in annualised returns asymmetry between up and down trends. (e.g. the median values of the uptrend $R_{DC}$ series and downtrend $R_{DC}$ series)

## 8.4 Profiles of currency and commodity markets' assets (average standard deviation)

| Average(Std) | AUD/USD | GBP/USD | EUR/USD | CHF/USD | JPY/USD | Gold | Oil | Copper | Gas |
|---|---|---|---|---|---|---|---|---|---|
| TMV | 1.10 | 1.02 | 1.06 | 1.22 | 1.09 | 1.21 | 1.24 | 1.19 | 1.43 |
| TMV↑ | 1.06 | 1.04 | 1.04 | 1.20 | 0.98 | 1.21 | 1.23 | 1.21 | 1.46 |
| TMV↓ | 1.12 | 0.99 | 1.07 | 1.21 | 1.16 | 1.20 | 1.24 | 1.17 | 1.39 |
| $T_{DC}$ | 790.64 | 1166.07 | 818.29 | 780.27 | 993.25 | 851.09 | 247.54 | 569.63 | 380.32 |
| $T_{DC}$↑ | 924.65 | 1229.76 | 848.54 | 832.19 | 922.95 | 1065.04 | 248.32 | 273.06 | 247.74 |
| $T_{DC}$↓ | 553.57 | 983.07 | 787.02 | 702.44 | 1060.03 | 380.38 | 245.09 | 703.47 | 431.85 |
| $R_{DC}$ | 233.63 | 124.27 | 56.19 | 338.57 | 71.97 | 130.68 | 145.13 | 102.26 | 389.74 |
| $R_{DC}$↑ | 216.22 | 118.84 | 45.24 | 363.53 | 81.45 | 121.00 | 139.85 | 100.85 | 384.98 |
| $R_{DC}$↓ | 235.22 | 126.53 | 52.22 | 301.19 | 52.24 | 134.46 | 146.73 | 100.61 | 379.41 |
| $C_{DC}$ | 353.49 | 150.07 | 213.03 | 321.17 | 205.98 | 680.46 | 1625.14 | 1081.80 | 2862.18 |

Table 17: Summarized average standard deviation values of DC profiles with a threshold of 0.4% on nine assets from currency and commodity markets with minute-by-minute open prices, 2011 to 2015.

## 8.5 Market comparison between different currency markets in the same time period

| Average | AUD&GBP | AUD&EUR | AUD&CHF | AUD&JPY | GBP&EUR | GBP&CHF | GBP&JPY | EUR&CHF | EUR&JPY | CHF&JPY |
|---|---|---|---|---|---|---|---|---|---|---|
| $D_{P1}$ | 0.0563 | 0.0479 | 0.0445 | 0.0477 | 0.0277 | 0.0429 | 0.0254 | 0.0377 | 0.0369 | 0.0405 |
| $D_{P2}$ | 0.0872 | 0.0861 | 0.1101 | 0.0924 | 0.0699 | 0.0836 | 0.083 | 0.073 | 0.0785 | 0.0948 |
| $D_T$ | 0.4149 | 0.3587 | 0.319 | 0.3327 | 0.2646 | 0.3861 | 0.3199 | 0.1953 | 0.3168 | 0.3392 |
| $D_{TA}$ | 0.4336 | 0.5116 | 0.4913 | 0.4864 | 0.366 | 0.4142 | 0.4621 | 0.2807 | 0.4951 | 0.4566 |
| $D_R$ | 0.4168 | 0.3642 | 0.3136 | 0.3626 | 0.2533 | 0.3746 | 0.3071 | 0.1847 | 0.3186 | 0.3451 |
| $D_{RA}$ | 0.4299 | 0.4183 | 0.2946 | 0.4074 | 0.4054 | 0.4752 | 0.4923 | 0.409 | 0.34 | 0.4229 |

Table 18: Summarized average median DC metrics values between DC profiles from five currency market assets in the same time period (every three months), 2011 to 2015.

| Std | AUD&GBP | AUD&EUR | AUD&CHF | AUD&JPY | GBP&EUR | GBP&CHF | GBP&JPY | EUR&CHF | EUR&JPY | CHF&JPY |
|---|---|---|---|---|---|---|---|---|---|---|
| DP1 | 0.069 | 0.0602 | 0.052 | 0.0671 | 0.0248 | 0.0246 | 0.0231 | 0.024 | 0.0282 | 0.0282 |
| DP2 | 0.0947 | 0.0957 | 0.1341 | 0.1042 | 0.0526 | 0.1135 | 0.052 | 0.1143 | 0.0474 | 0.1196 |
| DT | 0.195 | 0.2957 | 0.3143 | 0.321 | 0.2414 | 0.2744 | 0.2466 | 0.2039 | 0.1751 | 0.2198 |
| DTA | 0.2935 | 0.2947 | 0.2772 | 0.3232 | 0.2886 | 0.2757 | 0.3111 | 0.2375 | 0.2824 | 0.2781 |
| DR | 0.2 | 0.2852 | 0.311 | 0.306 | 0.2423 | 0.271 | 0.2484 | 0.2033 | 0.1716 | 0.2119 |
| DRA | 0.2769 | 0.2734 | 0.2115 | 0.2673 | 0.252 | 0.2466 | 0.3004 | 0.2544 | 0.313 | 0.2386 |

Table 19: Summarized average standard deviation DC metrics values between DC profiles from five currency market assets in the same time period (three months), 2011 to 2015.

## 8.6 Market comparison in the same currency market between adjacent time periods

| Average | AUD/USD | GBP/USD | EUR/USD | CHF/USD | JPY/USD |
|---|---|---|---|---|---|
| DP1 | 0.0438 | 0.0364 | 0.0319 | 0.0292 | 0.0459 |
| DP2 | 0.0821 | 0.0341 | 0.0751 | 0.1135 | 0.0774 |
| DT | 0.323 | 0.3578 | 0.1876 | 0.2959 | 0.3031 |
| DTA | 0.4825 | 0.3867 | 0.4996 | 0.3542 | 0.5975 |
| DR | 0.3127 | 0.3561 | 0.2076 | 0.2847 | 0.3288 |
| DRA | 0.3964 | 0.4662 | 0.504 | 0.3826 | 0.3775 |
| Average metrics overall | 0.2734 | 0.2729 | 0.2510 | 0.2434 | 0.2884 |

Table 20: Summarized average DC metrics values between DC profiles from five currency market assets in adjacent time periods (every three months), 2011 to 2015.

| Average std | AUD/USD | GBP/USD | EUR/USD | CHF/USD | JPY/USD |
|---|---|---|---|---|---|
| DP1 | 0.0718 | 0.0233 | 0.0225 | 0.0155 | 0.0345 |
| DP2 | 0.1283 | 0.0347 | 0.0481 | 0.1695 | 0.0588 |
| DT | 0.3069 | 0.2916 | 0.1446 | 0.2556 | 0.1712 |
| DTA | 0.3538 | 0.2212 | 0.2726 | 0.2223 | 0.2658 |
| DR | 0.3051 | 0.2961 | 0.1436 | 0.2643 | 0.1737 |
| DRA | 0.2227 | 0.2749 | 0.2802 | 0.274 | 0.2752 |
| Average std metrics overall | 0.2314 | 0.1903 | 0.1519 | 0.2002 | 0.1632 |

Table 21: Summarized average standard deviation DC metrics values between DC profiles from five currency market assets in adjacent time periods (every three months), 2011 to 2015.

## 8.7 Market year-on-year comparison in the same currency market

| Average | AUD/USD | GBP/USD | EUR/USD | CHF/USD | JPY/USD |
|---|---|---|---|---|---|
| DP1 | 0.0353 | 0.0355 | 0.0335 | 0.0307 | 0.0357 |
| DP2 | 0.0762 | 0.0655 | 0.0852 | 0.1121 | 0.0881 |
| DT | 0.2911 | 0.3880 | 0.3795 | 0.4638 | 0.3307 |
| DTA | 0.4308 | 0.2774 | 0.3990 | 0.3857 | 0.5389 |
| DR | 0.2903 | 0.4060 | 0.4017 | 0.4559 | 0.3398 |
| DRA | 0.4373 | 0.3412 | 0.4765 | 0.4182 | 0.5159 |
| Average metrics overall | 0.2602 | 0.2522 | 0.2959 | 0.3111 | 0.3082 |

Table 22: Summarized average DC metrics values between DC profiles from five currency market assets in the same quarter year time periods (every three months), 2011 to 2015.

| Average metrics values | Aug-Nov | Nov-Feb | Feb-May | May-Aug |
|---|---|---|---|---|
| AUD/USD | 0.2734 | 0.2729 | 0.2510 | 0.2434 |
| GBP/USD | 0.2134 | 0.3994 | 0.2135 | 0.1827 |
| EUR/USD | 0.2738 | 0.2754 | 0.3088 | 0.3256 |
| CHF/USD | 0.2418 | 0.4203 | 0.2761 | 0.3062 |
| JPY/USD | 0.2529 | 0.3525 | 0.3103 | 0.3170 |
| Average overall | 0.2511 | 0.3441 | 0.2719 | 0.2750 |

Table 23: Summarized average overall DC metrics values between DC profiles from five currency market assets in four quarters year on year (every three months), 2011 to 2015.

## 8.8 Market comparison between different commodity markets in the same time period

| Average | Gold&Oil | Gold&Copper | Gold&Gas | Oil&Copper | Oil&Gas | Copper&Gas |
|---|---|---|---|---|---|---|
| $D_{P1}$ | 0.0300 | 0.0216 | 0.0383 | 0.0142 | 0.0168 | 0.0216 |
| $D_{P2}$ | 0.0350 | 0.0432 | 0.0708 | 0.0404 | 0.0621 | 0.0755 |
| $D_{T}$ | 0.3854 | 0.2368 | 0.6553 | 0.2674 | 0.3906 | 0.5930 |
| $D_{TA}$ | 0.3677 | 0.4116 | 0.4092 | 0.4135 | 0.4449 | 0.4156 |
| $D_{R}$ | 0.3995 | 0.2442 | 0.6736 | 0.2829 | 0.3970 | 0.6097 |
| $D_{RA}$ | 0.4359 | 0.3655 | 0.3926 | 0.3575 | 0.5209 | 0.3892 |

Table 24: Summarized average median DC metrics values between DC profiles from four commodity market assets in the same time period (every three months), 2011 to 2015.

| Average Std | Gold&Oil | Gold&Copper | Gold&Gas | Oil&Copper | Oil&Gas | Copper&Gas |
|---|---|---|---|---|---|---|
| DP1 | 0.0189 | 0.0186 | 0.0271 | 0.0122 | 0.0150 | 0.0194 |
| DP2 | 0.0264 | 0.0266 | 0.0490 | 0.0283 | 0.0381 | 0.0387 |
| DT | 0.2530 | 0.1277 | 0.2248 | 0.2026 | 0.2348 | 0.1926 |
| DTA | 0.3364 | 0.2289 | 0.2578 | 0.3056 | 0.3357 | 0.2552 |
| DR | 0.2621 | 0.1387 | 0.2238 | 0.2118 | 0.2460 | 0.1915 |
| DRA | 0.2686 | 0.2337 | 0.2588 | 0.2518 | 0.2420 | 0.2855 |

Table 25: Summarized average standard deviation DC metrics values between DC profiles from four commodity market assets in the same time period (three months), 2011 to 2015.

## 8.9 Market comparison in the same commodity market between adjacent time periods

| Average | Gold | Oil | Copper | Gas |
|---|---|---|---|---|
| DP1 | 0.0287 | 0.0182 | 0.0177 | 0.0152 |
| DP2 | 0.0224 | 0.0299 | 0.0381 | 0.0328 |
| DT | 0.2447 | 0.1971 | 0.2371 | 0.1956 |
| DTA | 0.3739 | 0.5142 | 0.5298 | 0.3568 |
| DR | 0.2383 | 0.2137 | 0.2478 | 0.1919 |
| DRA | 0.3523 | 0.5643 | 0.3524 | 0.4246 |
| Average metrics overall | 0.2101 | 0.2562 | 0.2372 | 0.2028 |

Table 26: Summarized average DC metrics values between DC profiles from four commodity market assets in adjacent time periods (every three months), 2011 to 2015.

| Average std | Gold | Oil | Copper | Gas |
|---|---|---|---|---|
| DP1 | 0.0186 | 0.0115 | 0.0135 | 0.0107 |
| DP2 | 0.0162 | 0.0205 | 0.0402 | 0.03 |
| DT | 0.1619 | 0.1528 | 0.1554 | 0.1369 |
| DTA | 0.2105 | 0.3599 | 0.2495 | 0.3161 |
| DR | 0.1599 | 0.16 | 0.1567 | 0.1465 |
| DRA | 0.2625 | 0.2467 | 0.222 | 0.1826 |
| Average std metrics overall | 0.1383 | 0.1586 | 0.1396 | 0.1371 |

Table 27: Summarized average standard deviation DC metrics values between DC profiles from four commodity market assets in adjacent time periods (every three months), 2011 to 2015.

## 8.10 Market year-on-year comparison in the same commodity market

| Average | Gold | Oil | Copper | Gas |
|---|---|---|---|---|
| DP1 | 0.0282 | 0.0202 | 0.0201 | 0.0146 |
| DP2 | 0.0247 | 0.0398 | 0.0475 | 0.0365 |
| DT | 0.3700 | 0.3922 | 0.3300 | 0.2190 |
| DTA | 0.3809 | 0.5543 | 0.5215 | 0.3803 |
| DR | 0.3667 | 0.4205 | 0.3390 | 0.2183 |
| DRA | 0.4158 | 0.5340 | 0.4460 | 0.3247 |
| Average metrics overall | 0.2644 | 0.3268 | 0.2840 | 0.1989 |

Table 28: Summarized average DC metrics values between DC profiles from four commodity market assets in the same quarter year time periods (every three months), 2011 to 2015.

| Average metrics values | Aug-Nov | Nov-Feb | Feb-May | May-Aug |
|---|---|---|---|---|
| Gold | 0.2377 | 0.2593 | 0.2518 | 0.3089 |
| Oil | 0.2307 | 0.3920 | 0.3422 | 0.3424 |
| Copper | 0.3401 | 0.2774 | 0.2329 | 0.2857 |
| Gas | 0.2062 | 0.2217 | 0.1566 | 0.2111 |
| Average overall | 0.2536 | 0.2876 | 0.2458 | 0.2870 |

Table 29: Summarized average overall DC metrics values between DC profiles from four commodity market assets in four quarters year on year (every three months), 2011 to 2015.

## 8.11 Contrast between AUD/USD market and commodity market

| Average | AUD&Gold | AUD&Oil | AUD&Copper | AUD&Gas |
|---|---|---|---|---|
| $D_{P1}$ | 0.0497 | 0.0431 | 0.0432 | 0.0515 |
| $D_{P2}$ | 0.0933 | 0.1017 | 0.0909 | 0.1492 |
| $D_{T}$ | 0.4399 | 0.7024 | 0.5532 | 0.8297 |
| $D_{TA}$ | 0.3922 | 0.5091 | 0.4051 | 0.5308 |
| $D_{R}$ | 0.4398 | 0.7138 | 0.5619 | 0.8229 |
| $D_{RA}$ | 0.368 | 0.4984 | 0.4651 | 0.3858 |
| Average overall | 0.2972 | 0.4281 | 0.3532 | 0.4617 |

Table 30: Summarized average DC metrics values between AUD/USD market profiles and four commodity market assets in the same time periods (every three months), 2011 to 2015.

| Average std | AUD&Gold | AUD&Oil | AUD&Copper | AUD&Gas |
|---|---|---|---|---|
| DP1 | 0.0688 | 0.0680 | 0.0707 | 0.0696 |
| DP2 | 0.0776 | 0.0617 | 0.0794 | 0.0556 |
| DT | 0.2345 | 0.1608 | 0.2098 | 0.1070 |
| DTA | 0.2649 | 0.3022 | 0.3069 | 0.2507 |
| DR | 0.2152 | 0.1498 | 0.2035 | 0.1276 |
| DRA | 0.2583 | 0.3170 | 0.2076 | 0.2659 |
| Average std overall | 0.1865 | 0.1766 | 0.1797 | 0.1461 |

Table 31: Summarized average standard deviation DC metrics values between AUD/USD market profiles and four commodity market assets in the same time periods (every three months), 2011 to 2015.

## 8.12 Contrast between GBP/USD market and commodity market

| Average | GBP&Gold | GBP&Oil | GBP&Copper | GBP&Gas |
|---|---|---|---|---|
| DP1 | 0.0336 | 0.0321 | 0.0255 | 0.0377 |
| DP2 | 0.0983 | 0.1116 | 0.0997 | 0.1666 |
| DT | 0.6886 | 0.8444 | 0.7530 | 0.9163 |
| DTA | 0.4216 | 0.6303 | 0.5179 | 0.5819 |
| DR | 0.7011 | 0.8614 | 0.7717 | 0.9207 |
| DRA | 0.3563 | 0.5083 | 0.5319 | 0.4877 |
| Average overall | 0.3833 | 0.4980 | 0.4500 | 0.5185 |

Table 32: Summarized average DC metrics values between GBP/USD market profiles and four commodity market assets in the same time periods (every three months), 2011 to 2015.

| Average std | GBP&Gold | GBP&Oil | GBP&Copper | GBP&Gas |
|---|---|---|---|---|
| DP1 | 0.0322 | 0.0228 | 0.0198 | 0.0295 |
| DP2 | 0.0497 | 0.0520 | 0.0542 | 0.0750 |
| DT | 0.1660 | 0.0677 | 0.1429 | 0.0526 |
| DTA | 0.2308 | 0.2860 | 0.3179 | 0.2536 |
| DR | 0.1557 | 0.0589 | 0.1189 | 0.0616 |
| DRA | 0.2781 | 0.3008 | 0.2597 | 0.3165 |
| Average std overall | 0.1521 | 0.1314 | 0.1522 | 0.1315 |

Table 33: Summarized average standard deviation DC metrics values between GBP/USD market profiles and four commodity market assets in the same time periods (every three months), 2011 to 2015.

## 8.13 Contrast between EUR/USD market and commodity market

| Average | EUR&Gold | EUR&Oil | EUR&Copper | EUR&Gas |
|---|---|---|---|---|
| DP1 | 0.027 | 0.0256 | 0.0259 | 0.0413 |
| DP2 | 0.0846 | 0.0997 | 0.0826 | 0.1504 |
| DT | 0.5608 | 0.7986 | 0.6611 | 0.899 |
| DTA | 0.4975 | 0.6604 | 0.5425 | 0.5224 |
| DR | 0.5741 | 0.817 | 0.6808 | 0.9079 |
| DRA | 0.4994 | 0.5388 | 0.4959 | 0.4983 |
| Average overall | 0.3739 | 0.4900 | 0.4148 | 0.5032 |

Table 34: Summarized average DC metrics values between EUR/USD market profiles and four commodity market assets in the same time periods (every three months), 2011 to 2015.

| Average std | EUR&Gold | EUR&Oil | EUR&Copper | EUR&Gas |
|---|---|---|---|---|
| DP1 | 0.0254 | 0.0222 | 0.0168 | 0.0284 |
| DP2 | 0.0737 | 0.0689 | 0.0596 | 0.0844 |
| DT | 0.2237 | 0.0510 | 0.1232 | 0.0569 |
| DTA | 0.2792 | 0.2479 | 0.2838 | 0.3099 |
| DR | 0.2152 | 0.0453 | 0.1091 | 0.0576 |
| DRA | 0.2162 | 0.3111 | 0.2450 | 0.2910 |
| Average std overall | 0.1722 | 0.1244 | 0.1396 | 0.1381 |

Table 35: Summarized average standard deviation DC metrics values between EUR/USD market profiles and four commodity market assets in the same time periods (every three months), 2011 to 2015.

## 8.14 Contrast between CHF/USD market and commodity market

| Average | CHF&Gold | CHF&Oil | CHF&Copper | CHF&Gas |
|---|---|---|---|---|
| DP1 | 0.0342 | 0.0406 | 0.0357 | 0.0517 |
| DP2 | 0.1061 | 0.1154 | 0.0933 | 0.1611 |
| DT | 0.5005 | 0.6997 | 0.5624 | 0.8253 |
| DTA | 0.5404 | 0.6353 | 0.5673 | 0.5097 |
| DR | 0.4985 | 0.7263 | 0.5746 | 0.8444 |
| DRA | 0.4374 | 0.4269 | 0.3865 | 0.4427 |
| Average overall | 0.3529 | 0.4407 | 0.3700 | 0.4725 |

Table 36: Summarized average DC metrics values between CHF/USD market profiles and four commodity market assets in the same time periods (every three months), 2011 to 2015.

| Average std | CHF&Gold | CHF&Oil | CHF&Copper | CHF&Gas |
|---|---|---|---|---|
| DP1 | 0.0232 | 0.0311 | 0.0287 | 0.0290 |
| DP2 | 0.0936 | 0.0862 | 0.0968 | 0.0840 |
| DT | 0.1872 | 0.1429 | 0.1407 | 0.1648 |
| DTA | 0.2713 | 0.3064 | 0.2813 | 0.3463 |
| DR | 0.2081 | 0.1214 | 0.1498 | 0.1464 |
| DRA | 0.2070 | 0.3623 | 0.2684 | 0.2380 |
| Average std overall | 0.1651 | 0.1751 | 0.1610 | 0.1681 |

Table 37: Summarized average standard deviation DC metrics values between CHF/USD market profiles and four commodity market assets in the same time periods (every three months), 2011 to 2015.

## 8.15 Contrast between JPY/USD market and commodity market

| Average | JPY&Gold | JPY&Oil | JPY&Copper | JPY&Gas |
|---|---|---|---|---|
| DP1 | 0.0394 | 0.0291 | 0.0292 | 0.0341 |
| DP2 | 0.0744 | 0.0919 | 0.0783 | 0.1359 |
| DT | 0.5249 | 0.7423 | 0.5954 | 0.8801 |
| DTA | 0.4287 | 0.6683 | 0.4413 | 0.5775 |
| DR | 0.5630 | 0.7724 | 0.6317 | 0.8983 |
| DRA | 0.4831 | 0.6028 | 0.4081 | 0.5096 |
| Average overall | 0.3523 | 0.4845 | 0.3640 | 0.5059 |

Table 38: Summarized average DC metrics values between JPY/USD market profiles and four commodity market assets in the same time periods (every three months), 2011 to 2015.

| Average std | JPY&Gold | JPY&Oil | JPY&Copper | JPY&Gas |
|---|---|---|---|---|
| DP1 | 0.0309 | 0.0205 | 0.0242 | 0.0230 |
| DP2 | 0.0607 | 0.0714 | 0.0563 | 0.0713 |
| DT | 0.1855 | 0.1694 | 0.2271 | 0.0870 |
| DTA | 0.2828 | 0.1956 | 0.2153 | 0.2397 |
| DR | 0.1742 | 0.1601 | 0.2250 | 0.0792 |
| DRA | 0.2761 | 0.2565 | 0.2458 | 0.3138 |
| Average std overall | 0.1684 | 0.1456 | 0.1656 | 0.1357 |

Table 39: Summarized average standard deviation DC metrics values between JPY/USD market profiles and four commodity market assets in the same time periods (every three months), 2011 to 2015.