Analysis of Cryptocurrencies Exchange Rates

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Mechanical Engineering

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To my Father, who inspired me all my life.

To my Mother, who helped me reach this moment.

To my two beautiful Sisters, with whom i share my childhood...

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I thank God for all the opportunities I have had throughout my life and for all the people who have passed through it.

Resumo

As Criptomoedas atrairam grande atenção nos mercados financeiros nos últimos anos.
Analisar as propriedades da distribuição e os factos estilizados dos retornos da criptomoeda é benéfico para os investidores avaliarem a carteira de activos e é relevante para os agentes reguladores avaliarem o risco do mercado das instituições financeiras.
Apesar disso, a pesquisa sobre as propriedades destas taxas de câmbio é relativamente limitada devido à sua recente manifestação. Espera-se que a natureza dos preços de criptomoedas, ou seja, as taxas de câmbio associadas, sejam diferentes das taxas de câmbio tradicionais.
O objetivo deste projeto é analisar as propriedades estatísticas das taxas de câmbio das criptomoedas por meio de uma nova abordagem de registo de movimentos de preços com base na magnitude da mudança do preço. Uma escala de tempo baseada em eventos que destaca atividades periódicas no mercado ajudando a destilar um conjunto de indicadores que recolhem informações importantes e demonstra que estes mesmos ajudam a construir perfis de mudanças de direção de mercados da criptomoeda, considerando que o uso de escalas de tempo físico para estudar séries financeiras corre o risco de perder atividades importantes.
O estudo confirma a utilidade da abordagem da análise do preço através do uso de um tempo intrínseco e os resultados corroboram com o facto deste método apresentar vantagens em relação á amostragem da série temporal com base num intervalo fixo de tempo.

Palavras-chave: Mudanças Direccionais, Tempo Intrínseco, Análse de Séries Temporais, Factos Estilizados, Mercado de Criptomoedas

Abstract

Cryptocurrencies have drawn tremendous attention in the financial markets over the past few years. Analyzing the distributional properties and stylized facts of cryptocurrency exchange rates is beneficial for investors to assess their portfolio and it is relevant for regulatory agents to assess the market risk of financial institutions.

Despite this, research on the properties of these exchange rates is relatively limited due to its recent manifestation. The nature of cryptocurrency prices, hence the associated exchange rates, are expected to be different from traditional currency exchange rates.

The purpose of this project is to analyze statistical properties of cryptocurrency exchange rates through a new approach of recording price movements.

An event-based time scale that captures periodic activities in the market helps to distillate a set of indicators capturing important information, and demonstrate that this indicators help construct directional change profiles of cryptocurrencies markets, considering that the use of physical time scales for studying financial time series runs the risk of missing important activities.

The study confirms the usefulness of the price analysis approach through the use of an intrinsic time and the results corroborate that this method has advantages over time series sampling based on a fixed time interval.

Keywords: Directional Changes, Intrinsic Time, Time-Series Analysis, Stylized Facts, Cryptocurrency Market.

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Nomenclature

DC Points

$\boldsymbol{DCC}$ Directional change confirmation point.

$\boldsymbol{EXT}$ Directional change extreme point.

P_c Current price of the market.

P_h Last high price of the trend.

P_l Last low price of the trend.

DC Indicators

$\boldsymbol{LenC}$ Length of the Coastline

$\boldsymbol{R_{DC}}$ Time-adjusted Return

$\boldsymbol{Sub - N_{DC}}$ Number of Directional Change Events with the Sub-threshold

$\boldsymbol{TM}$ Total Movement

$\boldsymbol{TT}$ Trend Time

$\boldsymbol{N_{DC}}$ Number of directional changes

$\boldsymbol{OSV}$ Overshoot value

Chapter 1

Introduction

In this first chapter, an overview of all the concepts used in this thesis are explained and a brief review of the current state of knowledge in this area is described.

The work developed links three main topics: the financial market, more specifically the cryptocurrency market, an event-based approach to observe the price movement as opposed to a fixed time interval normally used in time series and the concept of stylized facts.

During the research phase, it was found that some studies have coupled the world of the financial market, which includes not only the stock indexes but the also the forex market (foreign exchange market for trading currencies pairs), with the modern concept of directional changes. The application of this framework has yielded interesting results, therefore bringing people to analyse time series through the lens of the DC framework.

Likewise, the adoption of stylized facts, as opposed to bare facts, to explain a number of characteristics features common across stock indexes and exchange rates have been implemented as an instrument to expand the current knowledge in the field avoiding the numerous statistical descriptions.

Nevertheless, there is no academic study that blends the three topics all together. The idea with this endeavor is to analyse the statistical properties of the recently embraced cryptocurrency market within the scope of the directional change framework with the goal of extracting stylized facts that ”possibly” helps on the understanding of the proclaimed: ”coin of the future”.

1.1 Motivation

Despite the fact that the work developed during this past months seems to be outside the field of mechanical engineering, because the word cryptocurrency or exchange rate lead us towards the economic and financial filed, one cannot deny that at its core we are dealing with time series.

This is the tipping point that glues the two fields along with the mechanical engineering territory. A mechanical engineer do constantly face with loads of time series data from diverse applications as his main concern are dynamic systems (this means the study of systems that are time dependent), for example:

- Smart Grid Analysis: A future smart grid promises to use information about the small changes in magnitude, phase and frequency of the energy suppliers and appliances to improve efficiency, reliability and economics of electricity.

- Smart Farming: A solution for managing weather risk and crop health, delivering real-time, actionable insights directly from specific points on the field.

- Predictive Maintenance: The use of sensors placed at specific assets valuable to the company gathering data to determine a machine's likelihood of failure before that failure occurs, improving production efficiency and maintenance efficiency.

A more interesting argument is the fact that the cryptocurrency prices is a member of the high-frequency data family. This fact is the reflection of the enourmes quantity of data that by nature is inherently irregularly spaced in time. In other words, using a financial term, this is called tick-by-tick data, which comes from the fact that the data is a sequential record of transactions that can occur at any distinct point in time. Considerably this comes to our advantage by contemplating that the majority of the data that is retrieved from the sensors is actually sampled at high-frequency and generally not equally spaced.

Finally the concept of stylized fact comes in a convenient way. This is in reference to the soul purpose that this term was used as opposed to bare facts. The concept is going to be comprehensively explained in the following section but here is a brief description from Nicholas Kaldor, the economist who first introduced this concept in 1957:

"Since facts, as recorded by statisticians, are always subject to numerous snags and qualifdications, and for that reason are incapable of being accuratly summarized, the theorist, in my view, should be free to start off with a "stylized" view of the facts - i.e. concentrate on broad tendencies, ignoring individual detail, and proceed on the "as if" method, i.e. construct a hypothesis that could account for these "stylized" facts, without necessarily committing himself on the historical accuracy, or sufficiency, of the facts or tendencies thus summarized"

1.2 Cryptocurrencies

According to the traditional definition, a currency has three main purposes:

1. It serves as a medium of exchange
2. It is used as a unit of account
3. It allows to store value

In the beginning, coins were fabricated in precious metals. Therefore, the value of a coin was intrinsically interlinked by the value of the metal itself. Subsequently, money was printed in paper bank notes, but its value was linked somewhat to a quantity in gold, guarded in the vault of a central bank. In the twentieth century, a major shift in the direction currency policy: the abandonment of gold standard. The separation of the currencies from gold standard meant a acknowledgement that the value of a currency was not related to its intrinsic value or representation in gold, but rather to a broader concept as the confidence in the economy in which such currency is based.

Over the past few years, a new type of currencies, a synthetic one, emerged. It is named as 'synthetic' because it is not the resolution of a nation state, nor represents any underpinning asset or tangible wealth source. It appears as a new marketable asset resulting from a private agreement and encouraged by the anonymity of internet. Generically known as cryptocurrencies. Among them, the most widespread is Bitcoin.

One open issue today is if Bitcoin is in fact or may be thought as a currency. Until now, we cannot observe that Bitcoin satisfies the main properties of a standard currency. It is barely accepted as a medium of exchange, it is not employed as unit of account, and we can hardly believe that, given the great swings in price, anyone can consider Bitcoin as an appropriate option to store value. Given these characteristics, Bitcoin could be appropriated as an ideal asset for speculative purposes.

1.3 Stylized Facts

To discuss the possible contribution of stylized facts to Cryptocurrencies, it is required to clarify the meaning of the concept, which is not trivial regarding its diverse and sometimes superficial use in literature. Stylized facts promise a generalized description of social systems that is empirically grounded, but does not emphasize the claim for general validity like theories. Nevertheless, stylized facts are supposed to be reliable enough to support decision making.

1.3.1 How stylized facts emerged?

The first time the term was used was by Nicolas Kaldor, in an attempt to describe long-term economic growth. Since then, it went through a though path to prove it's value and it has resists some criticism from the scientific community. Soolow famously ridiculed that "There is no doubt that they are stylized, though it is possible to question whether they are facts". In a similar way, others seem to think that stylized facts are no different than other economic facts, and tend to puzzle over the sense in which they are "stylized".

In order to understand the reason behind stylized facts, a historical background should be taken into account. Everything started with Nicholas Kaldor, a notorious Cambridge economist in the post-war period. Kaldor was then a chief economic adviser to the Labour government in the United Kingdom. The problem of the day for economic policy in UK was the 13 wasted years where the rate of growth of the UK economy had been persistently lower than the main European countries: 2 per cent a year on average compared to 3-4 per cent for countries like Germany and France.

If existing theory could not explain the salient facts, new theory had to be invented. This event triggered the formulation of a methodology in science never performed before, going against the theoretical constructions of the neo-classical thought.

1.3.2 What are stylized facts?

In his work, Kaldor faced **data constrains** because it is clear that no worldwide dataset on economic growth was available in 1961. Most of the data on GDP were published in the late 1950's by the United Nations and only mentions two countries: USA and the UK. Even nowadays measurements errors is often a problem in developing countries, where statistical agencies lack resources and infrastructure to obtain the data required to improve accuracy and reliability. To address this issue, economist have resorted to indirect indicators such as measuring the light emanated by different countries using satellite imagery.

Kaldor's stylized facts offered two kinds of **methodological benefits**. First they provided more phenomena than the available data would license, in other words, the facts inferred from data was observed as 'plausible' as opposed to data-driven statements. The observations were not constrained by their statistical shortcomings. He defends himself by stating that "None of these 'facts' can be plausibly 'explained' by theoretical constructions of neo-classical theory". The second benefit, is that it broadens the range of theoretical options that were hold down by the, at the time, the restrict line of thought of the neo-classical theory.

Another characteristics of stylized facts is that they provide **methodological roles** in a four four-step process:

1. Start with a trivial theory
2. Determine the fact that, if true, the trivial theory would describe better than widely approved theories.
3. Of the phenomena in step 2, recognize those that are regarded as relevant by supporters of the widely accepted theories.
4. Any phenomena in the previous step that encounter data constrains are stylized facts.

As an example, one of the stylized facts stated by Kaldor declared that the per capita growth rate was positive in all economies. More recent empirical evidence provides interesting counterexamples to this stylized fact. For instance, Angola's GDP per capita was around 1100$ US in 1990 and dropped to 744$ by the end of the twentieth century. Another example is the infamous roller coaster growth of Argentina.

So Kaldor point is that stylizing facts makes sense when one's data are **constrained** and stylizing the fact plays a **methodological beneficial role**. Kaldor's facts do support mainly social-scientific facts, this is about human psychology and decision making. Aiming to understand all phenomenon that make up the natural and social world that humans live in, economists look for 'plausible' patterns: stylized facts.

1.3.3 Why stylized facts?

Why are stylized facts interesting in opposition to non-stylized or bare facts. Bare facts are kinds of facts that deserve no special title, e.g. well-confirmed statements about empirical regularities that are the typical objects of economic explanation.

Therefore, statement s is a **bare fact** if:

- s claims to describe a phenomenon: Phenomenon exhibit repeatable characteristics and is detectable by different procedures which allows for a statement to describe a phenomenon, the word used is purports because accounts for the fallibility of science.
- s is properly deduced from reliable data: To render such a scenario unlikely (fallibility of science), economist accurately measure the intended phenomenon and check if data is reliable with each other and proceed for an extensive inferential and empirical leg-work.
- s should be consistently described by a theory: Theory fundamental principles and assumption are able to derive statements that describe the properties and states on the phenomenon.

While, statement s is a **stylized fact** if:

1. s purports to explain a phenomenon.
2. s faces known and explicit data constrains, i.e. p is not validly inferred from reliable data.
3. s should be consistently described by a theory.
4. s performs a methodological beneficial role as well as being consistently described by a theory.

In one hand, stylized facts require less than bare facts in the sense that bare facts are detailed statistical description, and stylized facts may lack these details because they face known and explicit data constrains which make them not validly inferred from reliable data. On the other side, stylized facts require more than bare facts, that is, they must play a methodologically beneficial role, to summarize data working as building block for a theory building.

1.4 Topic Overview

Today cryptocurrencies have become a global phenomenon. Due to the nature and technology behind it, it has caught the attention of investors, governments, regulatory agents and academics.

Currently, the total market capitalization in cryptocurrencies is $\$183$ billion, to put this into perspective the apple market capitalization is $\$904$ billion, and Jeff Bezos (Amazon CEO) net worth is $\$133$ billion. To this date, there are more than 2080 forms of cryptocurrencies (`www.coinmarketcap.com`, November 2018). The most popular cryptocurrency and largest by market capitalization is Bitcoin $52,6\%$ of total market capitalization.

The exponential growth of Bitcoin has attracted considerable attention in recent years. At the end of 2017, the bitcoin price index reached the highest value of its recent history $\$20089,00$ in 17 December 2017, (`www.coinmarketcap.com`). Since then the price decrease to $\$5160,63$, a 74% drop in almost a year. To this date, 15 November 2018, Bitcoin has a market capitalization of $\$89$ billion.

Due to it's recent appearance (Bitcoin was created in 2009, but active trade only started in 2013), only a handful of studies have been carried out. Caporale et al. [1] showed signs of persistence, that implies predictability, and therefore evidence of market inefficiency which attracts investors looking for profits in the cryptocurrency market.

Emerging debates over the nature of cryptocurrency markets have been taking place all over social media and academic institutions. The first empirical analysis of eight forms of cryptocurrencies (70% of cryptocurrency market capitalization) Zhang et al. [2] concluded that: there are heavy tails, absence of autocorrelations, volatility clustering, leverage effect and long-range dependence in the returns of cryptocurrencies. There exists power-law correlation between price and volume.

Phillip et al. [3] The empirical data analysis shows Cryptocurrencies exhibit long memory, leverage effects, stochastic volatility and heavy tailedness.

Stylized facts refer to some important statistical properties of random variables of assets prices. Bariviera et al. [4] investigates some statistical properties of the bitcoin market and concluded that bitcoin presents a large volatility, it is reducing over time, long range memory is not related to market liquidity.

Recent efforts to find stylized facts and statistical properties of cryptocurrencies focused essentially on the analysis of price in a time series framework. This means, the asset's price is presented in fixed time intervals, which implies that our observations will depend on the chosen size of the interval (1 min, 5 min, hourly, monthly, yearly).

Recently, in the forex market of fiat currencies, a new approach has been adopted that revealed new insights. The concept of Directional Changes has allowed a new approach to summarize the price movements in financial markets, which consists of an event-based framework. The idea behind it focuses on the extracting a new intrinsic time unit, independent of the notion of physical time, defined by events. The directional change marks the market as downtrend or uptrend events based on a threshold defined the investor. The DC concept has been proved many times to be helpful in the study of the FX market, specially to establish new mathematical relations. Guillaume et al. [5] used the concept of DC to derive a scaling law that established a relation between the number of directional changes to the size of the threshold.

Glattfelder et al. [6] reported twelve new scaling laws by analysing 14 different currency pairs using the DC concept. This played an important role in describing complex systems, establishing invariance of scale in FX market.

Bisig et al. [7] measures the impact of political and economic events on the currency markets. Just like Richter Scale measures the intensity of earthquakes, the scale of market quakes (SMQ) quantifies the shock in the forex market caused by major economic and political events. DC concept has also helped created new indicators in the FX market as an alternative to common time indicators Tsang et al. [8] and Tsang and Ma [9].

Not only the DC concept was used to establish mathematical relationships and developing new indicators but also to generate new successful trading strategies and profitable forecasting. Ye et al. [10], Aloud et al. [11], Bakhach et al. [12], Kampouridis and Otero [13] developed trading strategies that joins the concept of DC concept with traditional indicators of technical analysis

Works done evaluating the risk and volatility of the FX market were also implemented Almeida et al. [14] and Peng et al. [15] respectively, using the concept of directional change as a framework. Almeida et al. [14] proposed a multi-output Probabilistic Fuzzy System (PFS) to forecast upwards and downwards price changes depending on current market conditions.

The most relevant studies and papers are very recent, which demonstrates that this new field is far from being understood. This project hopes to deepen the knowledge about Directional Changes, Cryptocurrencies and see how this different concepts may help us in comprehend the true value of cryptocurrency market.

1.5 Objectives

From the work developed here, the author intends to develop an higher understanding of the following concepts:

1. Analyzing cryptocurrencies exchange rate through directional changes framework.
2. Find some stylized facts that can contribute for a better understanding of the world of cryptocurrencies
3. Make the bridge between the mechanical engineering world and the financial field using the fact that both use as their foundations time series data for the explaining facts and build theories.

1.6 Thesis Outline

This previous section laid the foundation for the coming chapters. In the following paragraphs, the reader is going to be presented with the concepts used through out the work developed. Section 2, explains the necessary principles used in the financial world, introducing the differences between the physical and the intrinsic time, then comes the explanation of how directional changes work and the different characteristics it as. Also in this section a first approach is made with an spectral analysis to Bitcoin and the fist few conclusion of the employments of directional change framework are drawn.

Section 3, presents the underlying mechanism and the algorithm used for the detection of the events in the DC frameworks and also the indicators used in this study obtained from the profiling of the currency during a specific period. Then a required comparison is made to distinguish the usefulness and advantage of using the directional change approach as opposed to the traditional fixed-time intervals used to observe the price movements. Section 4, is the implementation of the work developed in three main areas: Bitcoin, Cryptocurrencies and Cross-Country exchanges. The idea is to profile using the indicators as a baseline for comparison and analyse the behaviour of the different assets. Then a brief study about the potential profit is also performed in this section and once again this perspective confirms the natural advantages of observing the time series in an event-based approach and not in an homogeneous sampled period. The last section is the conclusion, where the link is explained between the financial field and the mechanical engineering area. This thesis hopes give to an engineering a more efficient way to extract features from loads of time series data, this way reducing the number of points used in the analysis without compromising the relevant information in the data in itself, reducing complexity and accelerating the process of data.

Chapter 2

Background

2.1 Physical Time vs Intrinsic Time

A regular decision for an agent when looking at the financial market is to select the fixed time interval that he wishes to inspect the price, ranging from seconds through hourly, daily, monthly to annually changes. This is due to the inherent characteristics of a trade. A trade happens every time someone places an order and there is a consent on the present price of an asset. Therefore, the value is changing with time at an heterogeneous rate. This is commonly referred in the financial field as ”tick-by-tick” data, where ”tick” is a ”trade”. Consequently, the price is presented when a transaction is placed at a specific time.

The following figure, it is evident that there are considerable patterns being overlooked from the fact that the information is compacted by taking the mean value of the price during the time interval decided by the trader. This phenomenon is highlighted when working with high-frequency data. Hence, the point here is that with this analysis, there is actually a loss of information that may contain essential intelligence vital for the correct comprehension of the behaviour of the markets.

Figure 2.1: This graph shows the price curve of Bitcoin during one day: April 22, 2019 between 06:00 - 18:00. The blue line represents the value of the asset at an heterogeneous rate while the purple line illustrates the value of the stock averaged every hour and labelled to the right side. This second line typify the standard way an investor analyse the market, fixed-time interval

To deal with this issue, different solutions have been proposed among them is the study of price time series using intrinsic time.

In intrinsic time, time is defined by events. This event-based approach withdraws two single occurrences: uptrend and downturn events. An event is the basic unit of intrinsic time and characterized by a threshold θ of fixed magnitude, in contrast with the point-based system adopted by physical time scales. The physical time scale is homogeneous in which time scales equally spaced on any chosen time scale seconds, minute scale. In contrast, intrinsic time is inhomogeneous in time and independent of the notion of the physical time scales where any occurrence of an event represents a new intrinsic time.

Figure 2.2: This graph shows the price curve of Bitcoin during one day: April 22, 2019 between 06:00 - 18:00. The blue line represents the value of the asset at an heterogeneous rate while the other lines show the intrinsic time triggered only at periodic events across different magnitudes in the price curve.

2.2 Directional Changes

According to **?**] a directional-change (DC) event can take one of the two forms- a downturn event or an upturn event. An uptrend terminates when a Downturn event takes place. Similarly, a downtrend termintes an upturn C event takes place. Therefore, the DC event approach defines a price time series in FM as a sequence of:

Figure 2.3: This figure represents the sequence of events in directional change. That is to say that after every down trend there is an up trend and after this the occurrence of another down trend. This loop goes on, simplifying the price movements either in and up or down direction.

Each event is composed of two steps: a directional change event and an overshoot event.

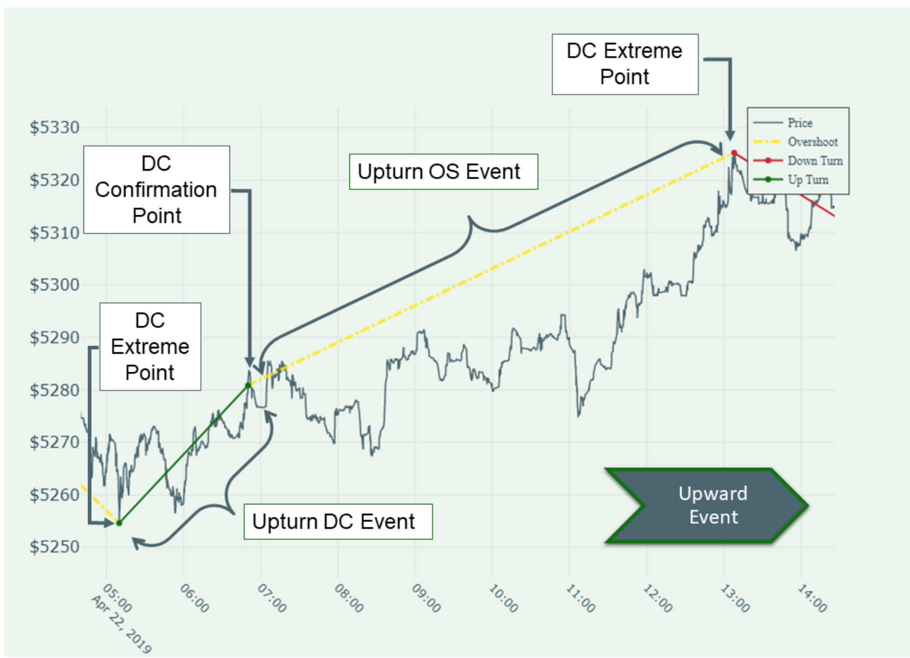


Figure 2.4: An upward event is characterized by an upturn directional change event and an upturn overshoot event. At the extremities a trend is confined by two extreme points and in the transition exists the directional change confirmation point.

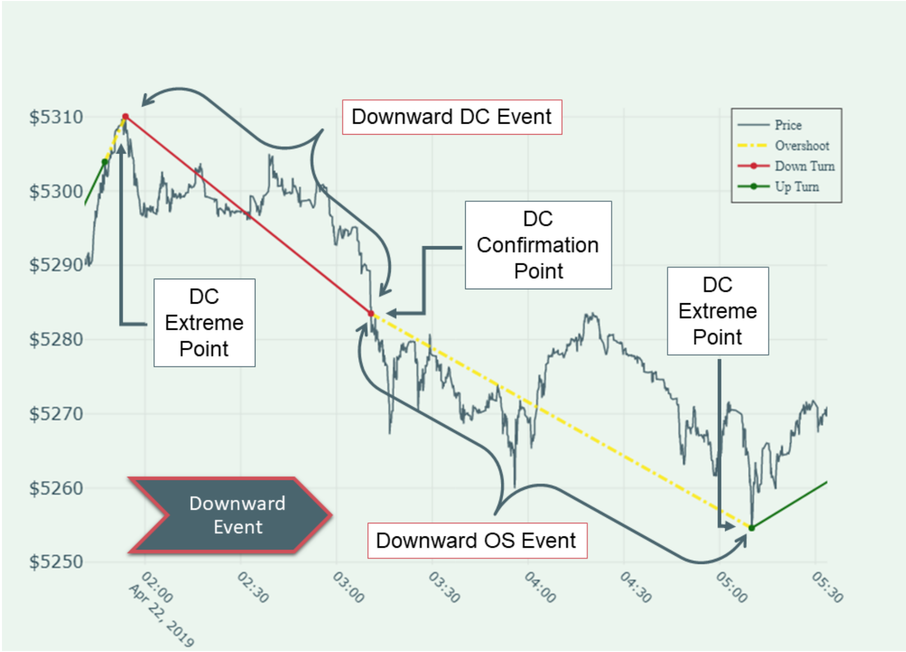


Figure 2.5: An downward event is also characterized by a downturn directional change event and a downturn overshoot event. At the extremities a trend is confined by two extreme points and in the transition exists the directional change confirmation point.

The directional change event is determined by a price variation considered by the observer. Here the threshold is a percentage that the user considers significant for the specific situation. One observer may consider 0.05% a significant change, while another observer may consider 5% is significant. Observers who use different thresholds will observe different DC events and trends.

2.3 Directional Changes Event Approach

2.3.1 Directional Change (DC) Event

In this section, it is going to be explained in a formal way the above definition. As a starting point let's consider the occurrence of a Downward event, represented in the following figure:

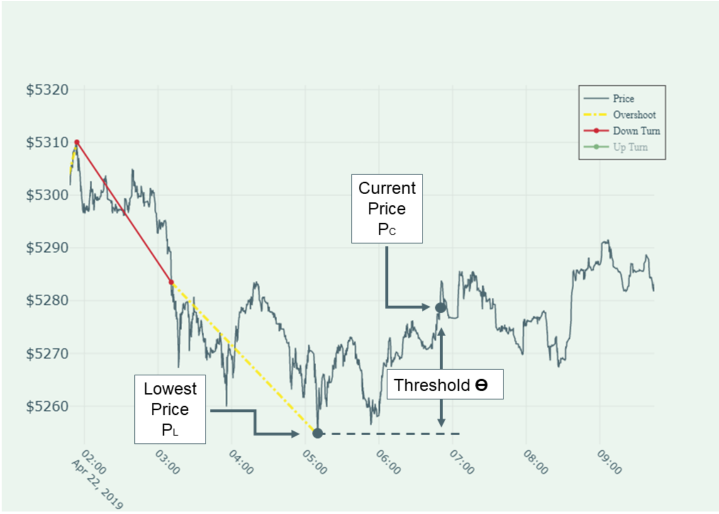


Figure 2.6: Illustration of the computation involved in the detection of an upward event. The figure highlights the two variables used to detect an upward event: the current price of the market and the last lowest price from the previous downward trend. Also the threshold defined by the user.

As explained before, the downward event comprises a DC event and an Overshoot event. The downturn DC event defines the beginning of a new downtrend and that means that there was a price drop where its magnitude was greater than the predefined threshold (following equation). This price change indicates the direction of the new trend and signals the point in time where the trend is confirmed.
The absolute price change is calculated between the current market price P_c and the last high price P_h:

$$P_c \leq P_h \times (1 - \theta) \tag{2.1}$$

So at this point, the previously equation is confirmed and the current price of the market P_c becomes the Directional Change Confirmation Point (DDC) and the last highest price P_h becomes the Directional Change Extreme Point (EXT). Is the point at which the downtrend DC event is confirmed. This also represents the commencement of the Downward Overshoot Event. As it will be explained in the following sections this overshoot event may contain a potential profit as long as the statistical properties of this specific market are properly analysed and the suitable stylized facts are well fetched.

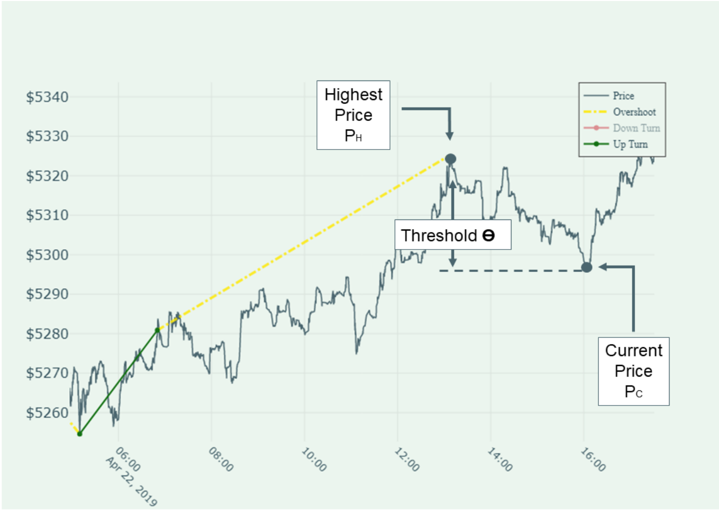


Figure 2.7: Illustration of the computation involved in the detection of an downward event. The figure highlights the two variables used to detect an downward event: the current price of the market and the last highest price from the previous upward trend. Also the threshold defined by the user.

During this Downward Overshoot Event, the lowest price within the current trend, P_l, is continuously updated. Additionally the current price market P_c is constantly feeding the following equation, taking the difference between the actual price P_c and the lowest value registered in the trend P_l:

$$P_c \geq P_l \times (1 + \theta) \tag{2.2}$$

If the price change is bigger than the user-defined threshold then an upturn DC event occurs. At this very moment the P_l becomes what is referred as a Directional Change Extreme Point (EXT) and the current price market is identified as a Directional Change Confirmation Point.

2.3.2 Spectral Analysis

Studying the price series under physically fixed time intervals require division of time into periods of equal length which have the drawback of missing major price movements. On the other hand, directional change events are significant events as they capture periodic major change in a price time series in which the magnitude of an event is defined by the observer. Therefore, diverse time periods in a price time series possibly will enclose a different number of DC (NDC) events of a different magnitude. If such statement hold, one can state that the price evolution is independent of physically fixed time changes. To verify this the following exercise was made:

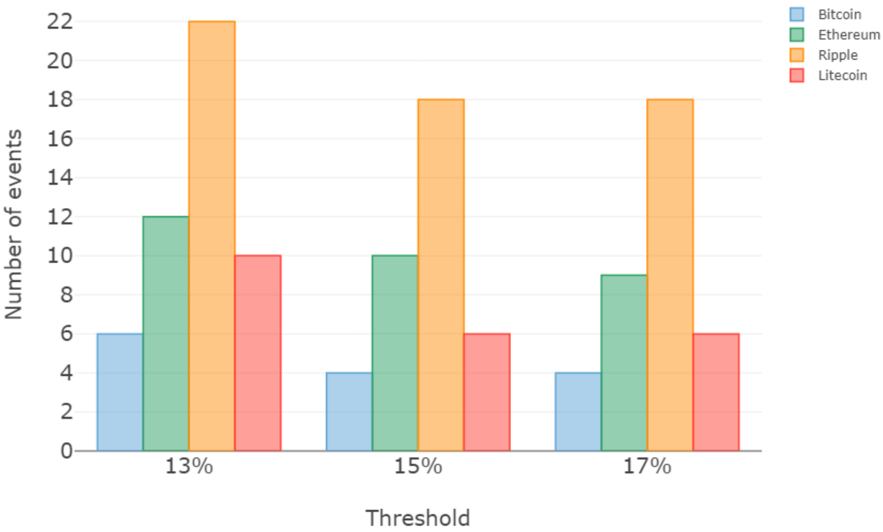


Figure 2.8: The bar graph represents the number of directional changes events using a threshold of 13%,15% and 17% during the month of January 2018

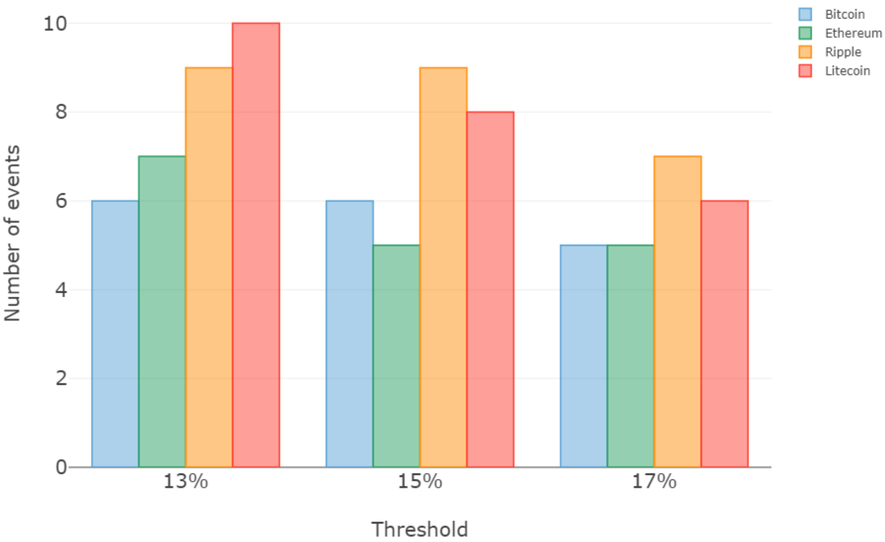


Figure 2.9: The bar graph represents the number of directional changes events using a threshold of 13%,15% and 17% during the month of February 2018

The reported results in figure 2.8 and 2.9 draw attention to two vital observations:

1. For different cryptocurrencies indices the same time periods with the same threshold magnitude on different days may possibly enclose a different NDC events

2. With the same threshold magnitude, some time periods on the same day have more DC events than others

These two observations point out those DC events of different magnitude are independent of physical time changes.

Chapter 3

Implementation

3.1 Data Set

The cryptocurrency data are from a website https://www.cryptodatadownload.com, which includes the timestamp and the close price every hour from July 2017 to May 2019 (not included). In particular, we focus on the top 4 cryptocurrencies (according to their market value) capitalization. The selected four forms of cryyptocurrencies account for 76,08% of the total capitalization, therefore the sample is an appropriate representation of the cryptocurrency market. The following cryptocurrencies were used in the study: Bitcoin (BTC), XRP (Ripple), ETH (Ethereum), LTC (Litecoin). The number of ticks is 15370. The data is filtered as missing data from certain timestamps get the median price of the previous and following consecutive prince.

3.2 Implementation of Directional Changes - Algorithm

Algorithm 1 Defining directional-change (DC) and overshoot (OS) events

Require: $initialise\ variables\ (event\ is\ Upturn\ Event,\ p^h = p^l = p(t_0),\ \Delta x_{dc}\ (Fixed) \geq 0,\ t_0^{dc} = t_1^{dc} = t_0^{os} = t_1^{os} = t_0)$

if $event\ is\ Upturn\ Event$ **then**
    if $p(t) \leq p^h \times (1 - \Delta x_{dc})$ **then**
        $event \leftarrow Downturn\ Event$
        $p^l \leftarrow p(t)$
        $t_1^{dc} \leftarrow t$ // End time for a Downturn Event
        $t_0^{os} \leftarrow t + 1$ // Start time for a Downward Overshoot Event
    else
        if $p^h < p(t)$ **then**
            $p^h \leftarrow p(t)$
            $t_0^{dc} \leftarrow t$ // Start time for a Downturn Event
            $t_1^{os} \leftarrow t + 1$ // End time for am Upward Overshoot Event
        end if
    end if
else
    if $p(t) \geq p^l \times (1 + \Delta x_{dc})$ **then**
        $event \leftarrow UpturnEvent$
        $p^h \leftarrow p(t)$
        $t_1^{dc} \leftarrow t$ // End time for an Upturn Event
        $t_0^{os} \leftarrow t + 1$ // Start time for an Upward Overshoot Event
    else
        if $p^l > p(t)$ **then**
            $p^l \leftarrow p(t)$
            $t_0^{dc} \leftarrow t$ // Start time for an Upturn Event
            $t_1^{os} \leftarrow t + 1$ // End time for an Upward Overshoot Event
        end if
    end if
end if

3.3 Indicators in Directional Change

Directional Changes is a new way of summarizing price changes. In this section, it is used a set of indicators proposed by **?**] which are useful for extracting information. With this indicators, the aim is to construct profiles for price changes summarized under the DC framework. Consequently this indicators can be used in different ways: financial decision makers can use the DC indicators as a toll to filter the significance of the price dynamics in a time series, analytical results can be used as an input to forecasting or automated trading models to identify investment opportunities and adjust the input factors. These DC indicators can be computed from Algorithm 1.

3.3.1 Number of Directional Changes: N_{DC}

N_{DC} is the total number of directional change events that happened over the profiled period, which includes the sum of the number of upturn and downturn DC price events with regard to a user defined threshold. Based on the same threshold, the time period which has higher N_{DC} value is more volatile than other time periods. It represents another way to assess the volatility of market price movements, it is a measure of frequency.

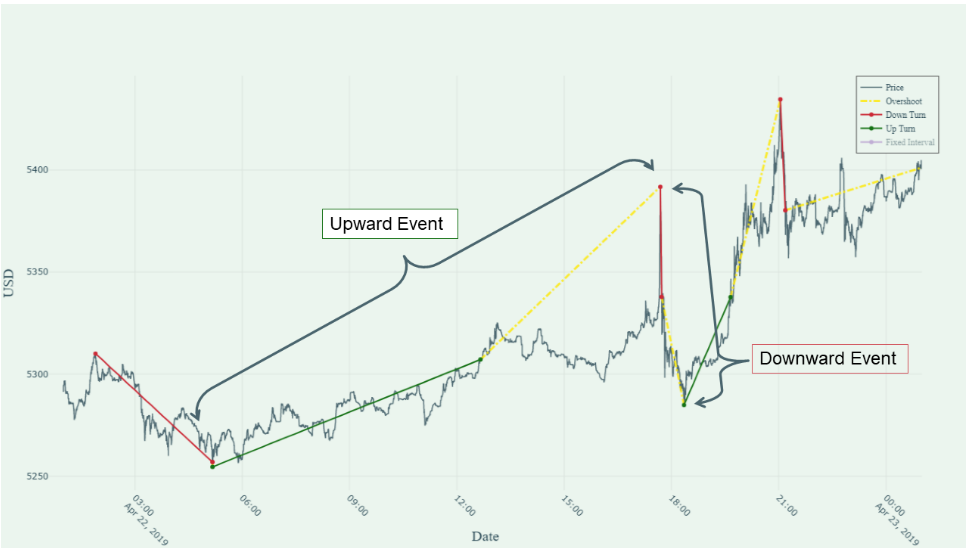


Figure 3.1: This graph shows the upward and downward events that are summed up to calculate the number of directional changes indicator. For the threshold and period this indicator can be a measure of frequency.

3.3.2 Overshoot Values: OSV

The overshoot value measures the magnitude of an overshoot event, which is the price change beyond the directional change event, in other words, it measures how far the overshoot goes from the directional change confirmation point (DDC) to the next extreme point (EXT). Figure 3.2 shows the price distance between these two points.

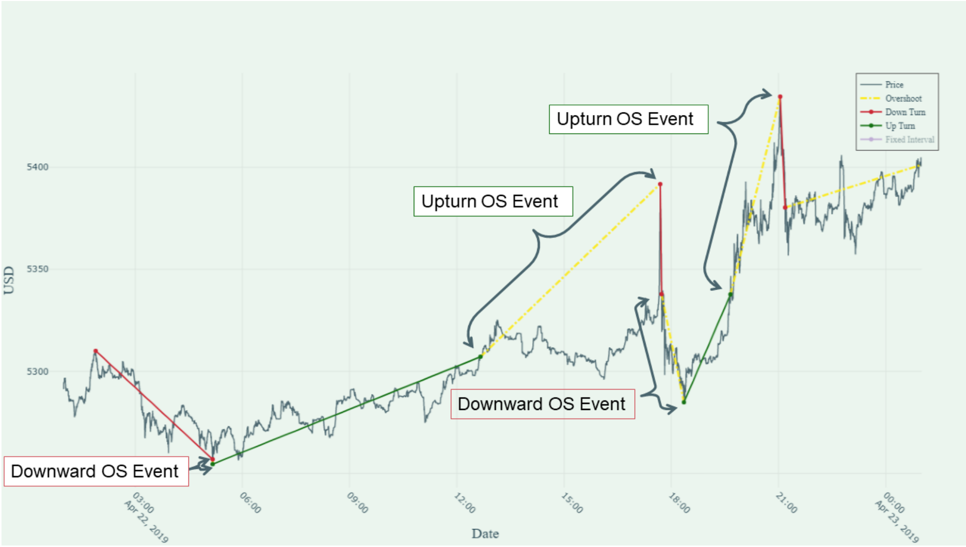


Figure 3.2: This graph shows the overshoot value at each event, described by the yellow dashed lines. As it is illustrated the magnitude of the overshoot may vary from almost non existent to long window of opportunity.

Instead of using the absolute value of the price change, one can measure relative to a certain threshold θ when comparison is made with different thresholds.

$$\boldsymbol{OSV} = \frac{\frac{(P_{EXT} - P_{DCC^*})}{P_{DCC^*}}}{\theta} \tag{3.1}$$

3.3.3 Trend Time: $\boldsymbol{TT}$

Directional change is defined based on events, so it uses intrinsic, as opposed to physical, time (Reference). However, that does not mean that it ignores physical time. The amount of physical time that a trend takes to complete is a significant piece of information. The price trend (complete price movement) is composed of a DC event, and an OS event follows and $\boldsymbol{TT}$ measures the average time in takes for a completion of a trend

$$\boldsymbol{TT} = \frac{t_{i+1} - t_i}{\boldsymbol{N_{DC}}} \tag{3.2}$$

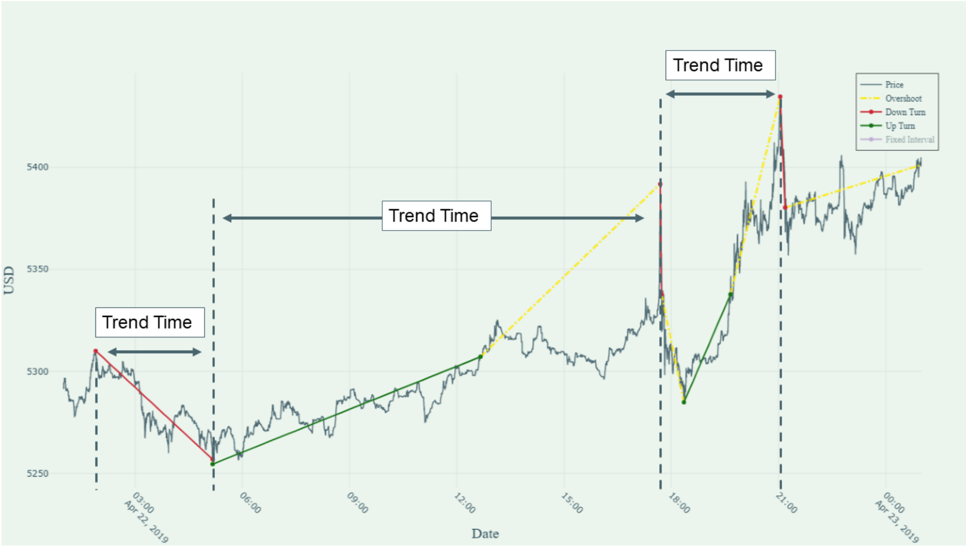


Figure 3.3: This graph shows the time it takes for a completion of a trend. Although it is an event based approach, the time is still used for extracting features complementing information of the events extracted.

3.3.4 Total Movement: TM

The total price movement value measures the price distance between the extreme points that begin and end a trend. It measures the maximum possible one can profit from each trend.

$$\boldsymbol{TM} = \frac{(P_{EXT_{i+1}} - P_{EXT_i})}{P_{EXT_i}} \tag{3.3}$$

Figure 3.4: This graph shows the magnitude between two consecutive directional change extreme points. In other words, is the sum of the threshold and the overshoot value

3.3.5 Time-adjusted Return: R_{DC}

The time-adjusted return is an indicator to measure the return in each trend per unit of time, in other words it measures how fast one could expect to see a price change either on an upturn or downturn event. A high R_{DC} means the profit can be earned in a short time period. It is defined as:

$$R_{DC} = \frac{TM}{TT} \tag{3.4}$$

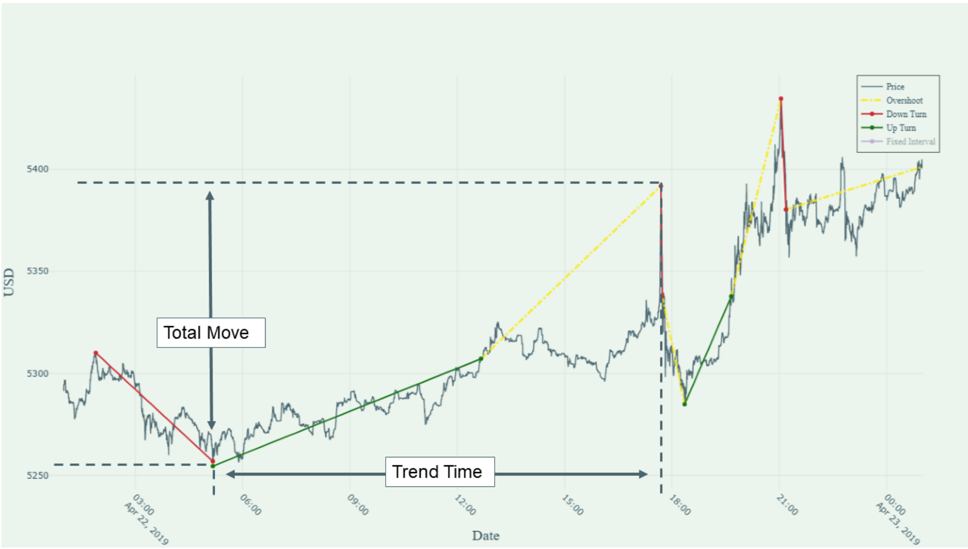


Figure 3.5: This graph shows the variables used in the calculation of the time adjusted-return. For each trend, it uses the total movement of the price and divides by the time it takes for the completion of it self.

3.3.6 Length of the Coastline: $LenC$

It represents the highest possible profit that one could make according to the DC profile. Assuming ideal foresight, the length of the Coastline over a defined period T, signify the profit potential. Under the intrinsic time, the PCC is defined in dynamic time intervals, which is established by price changes. The LenC indicator estimates the length of the PCC based on the price distance between extreme points as defined by intisic time.

The mean LeanC is an average magnitude of the upwards and downwards price trend of the DC event threshold (θ) over a time period T.

3.3.7 Number of Directional Change Events in Sub-threshold: $Sub - N_{DC}$

$Sub - N_{DC}$ measures the volatility of market price movements over the profiled period. This is because there still exist some price fluctuation in every DC trend. These price fluctuations are also important information of the market which is not able to be observed by N_{DC}. By choosing another smaller threshold, sub measures the total number of DC events that happened in each DC trend based on the smaller threshold. For example, as next figure 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-NDC value is more volatile than other DC trends.

Figure 3.6: This graph shows the last indicator that detects events in a trend using one fourth of the threshold value to extract the sub events in a trend.

3.4 Indicators Summary

Resuming the all the indicators presented in the previous section, the following table 3.1 dissects one possible way to feature extract information from the time series in directional changes.

Directional Change Indicator:	**Acronym:**	**Description:**
Number of directional change events	N_{DC}	measures the frequency of DCs
Overshoot Values at Extreme Points	OSV	measures the magnitude of an overshoot
Time for completion of a trend	TT	measures the time that it takes to complete a trend
Total Price Movements Value at Extreme Points	TM	measure the scale of prices changes
Number of directional change events in Sub-threshold	$Sub - N_{DC}$	measures the frequency of DCs in each DC trend
Undershoot Value at Extreme Points	USV	measures the scale price changes in each DC trend
Time independent Coastline	$LenC$	maximum possible returns over the profiled period
Time-adjusted return of DC	R_{DC}	measures the return in each upturn or downturn

Table 3.1: Directional change indicators summary

3.5 The Price Curve Coastline Comparison

With the aim of assessing the performance of the two different concepts: intrinsic time (directional-change events) and physical time changes (fixed time intervals), it is used a method for estimating the length of the price-curve coastline based on the price distance between fixed points. Basically, using the $LenC$ indicator explained in the previous section. Assuming perfect foresight (meaning the ability to predict future events), the length of the price-curve coastline over a define time period T, represents the potential profit. Glattfelder et al. [6] found that the length of the coastline defined by intrinsic time is long in the foreign exchange market.

It is therefore plausible to expect the same behaviour from the cryptocurrency market. Regarding this, it is used tick-by-tick data from www.suissebank.com of the bitcoin price in US dollars from April 22,2019.

The measurement of the length of the price-curve coastline over a time period T, as defined by intrinsic time, is the average upwards and downards price moves, considering the number of events. Both the upwards and the dowards price movements are defined by a fixed threshold size θ. Under the intrinsic time, the length of the price-curve coastline (PCC) is measured by:

$$\boldsymbol{PCC_\theta} = \frac{\sum_{i=1}^{\boldsymbol{N_{DC}}} |P_{EXT_{i+1}} - P_{EXT_i}|}{\boldsymbol{N_{DC}}} \tag{3.5}$$

where θ is a fixed threshold $(\%)$, $\boldsymbol{N_{DC}}$ is the total number of events on which the length of the price-curve coastline is measured. Hence, the number of events is determined by the threshold size, θ, that it is used. P_{EXT_i} is the price of the $i-th$ turning point, whether upturn or downturn point.

Figure 3.7: Price activities for BTC/USD on April 22, 2019. The blue line shows the tick-by-tick value of Bitcoin for that day. While the other line is the event-based summary using a threshold of 0.5%. This period is characterized by 13 events by the intrinsic time framework.

In opposition, the measurement of the length of the price-curve coastline defined by physical times changes at fixed time intervals is the average price movement between fixed points over a time period T, in which the time interval between these fixed points is equivalent. Under physical time, the length of the price-curve coastline $\boldsymbol{PCC_t}$ is measured by:

$$\boldsymbol{PCC_t} = \frac{\sum_{i=1}^{n} |P_{i+1} - P_i|}{n} \tag{3.6}$$

where P_i is the price at point i and n is the total number of fixed points which is equal to the number of events in the intrinsic time framework. For a better comparison it is used the same number of points both in the physical time and in the intrinsic time.

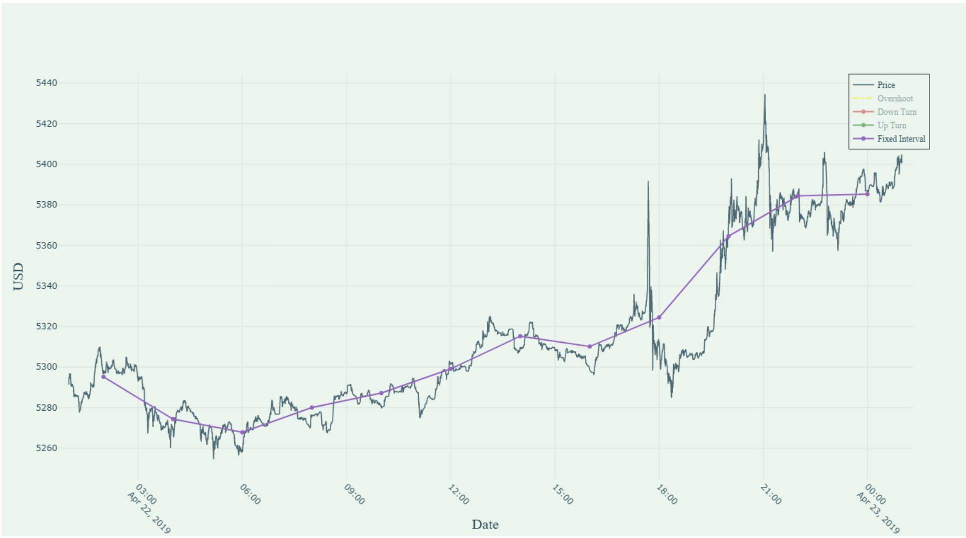


Figure 3.8: Price activities for BTC/USD on April 22, 2019. The blue line shows the tick-by-tick value of Bitcoin for that day. While the purple line is the fixed interval summary sampling the price value every two hours by means of averaging the asset value between a two hour window and stamping it to the right. This period is characterized by 11 intervals by the fixed physical time framework.

Taking into account the two possible ways to outline the price movements in the financial market, a conceivable question is raised: Which one, effectively, provides the foremost insights about future price evolution? Whether we are interpreting this question from the perpective of an investor, that is trying to asses the potential profit, from regulatory agents that try to reckon the risk of the financial institutions or an economics that is attempting yo evaluate the chance of a future big crises to help politician in their decision making

Figure 3.9: Price activities for BTC/USD on April 22, 2019. The blue line shows the tick-by-tick value of Bitcoin for that day. The purple line is the fixed interval summary sampling the price value every two hours. The other line is the event-based summary using a threshold of 0.5%. Both profiles have on average 12 events. The insight is that the usual way to observe the prices in the financial market culture overlooks important price activities. Look at what happens moments before 18:00 o'clock.

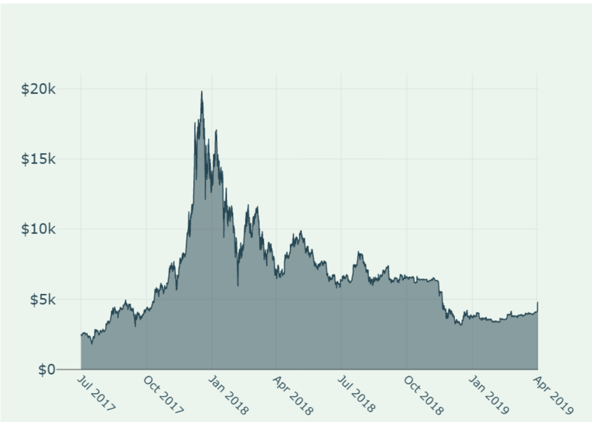
Intrinsic Time	**Physical Time**	**$\langle$Intervals$\rangle$**	**PCC(θ)**	**PCC(t)**
1%	$5H$	5	181.6%	50.45%
0.5%	$2H$	12	118.3%	26.63%
0.1005%	$10min$	144	28.64%	9.96%

Table 3.2: Comparison of the price curve coastline between the intrinsic time and physical time

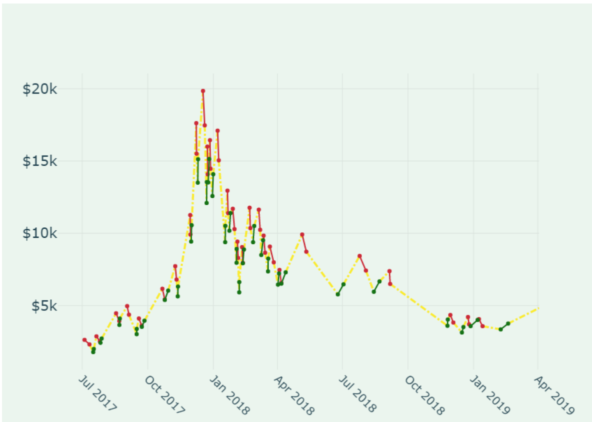
Chapter 4

Results

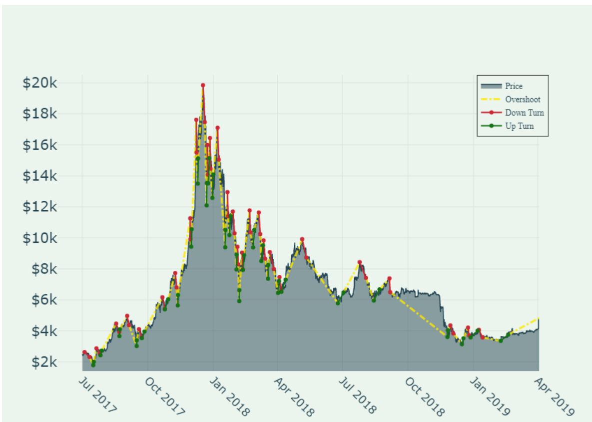
4.1 Profiling Bitcoin



(a) Physical Time



(b) Intrinsic Time: $Bitcoin12\%$

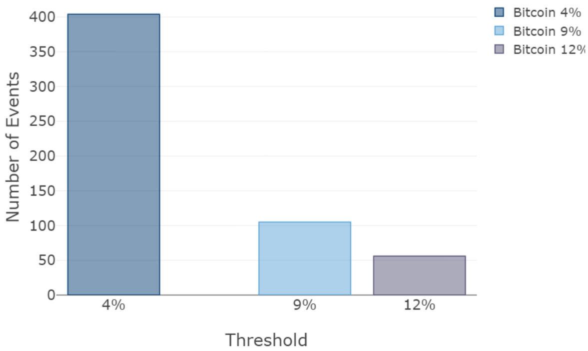


(c) Physical Time and Intrinsic Time: $Bicoin12\%$

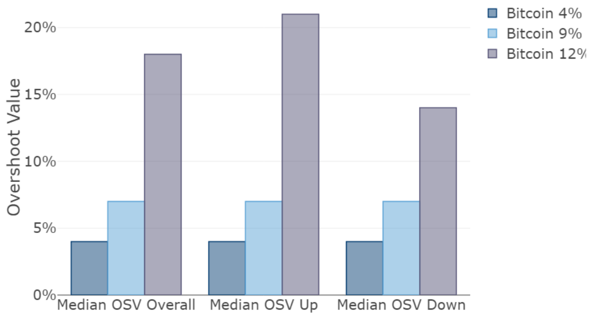
Figure 4.1: The price of Bitcoin from July 2017 to April 2019 seen through different frameworks

The preceding table 4.7 summarizes the DC observations under different thresholds on Bitcoin prices during the profiled period. These indicators were retrieved by Algorithm 1 varying the user-defined value among the following amounts: 4%, 9% and 12%.

Out of this, the first indicator that shows up is the number of directional changes $\boldsymbol{N_{DC}}$. The observer is able to readily access that as a result of the increase value of the threshold, the number of events identified diminishes: 404, 105 and 56, respectively . This situation is to be expected considering that the value of the threshold may be regarded as a way for the agent to define how relevant are the details in price evolution in his perspective. What is meant here is if the user is interested in the small variation of price changes then more events will be detected, on the contrary if the user thinks that the big changes are more relevant then a higher threshold is chosen and fewer events will be detected.



(a) $\boldsymbol{N_{DC}}$



(b) $\boldsymbol{OSV}$

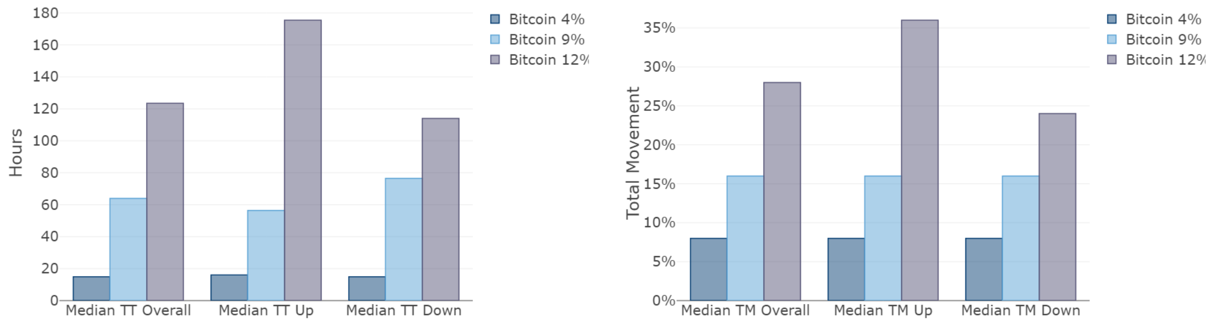
Figure 4.2: Number of directional changes and overshoot value information.

The second indicator is the median value of the overshoot $\boldsymbol{OSV}$. Accordingly, 4.11%, 7.15% and 18.04% is the median price change beyond the directional change event as the threshold increases. As an illustration, profiling the data with a 12% threshold it can be detected that from the 56 events generated, half of them produce an overshoot higher than 18%. It becomes apparent that as the threshold value rises the median overshoot of a trend also accentuates due to the fact that a trend only ceases when a major price changes takes place.

Furthermore, a notable characteristic is that at the 4% and 12% threshold there is a higher potential on the up trends than the down trends, this benefits results in a difference between the two directions of 3.5% and 52.2%, respectively. The opposite happens with the 9% threshold where the down trends have 9.1% more median overshoot than the up trends.

The third indicator is the trend time $\boldsymbol{TT}$. It measures the amount of physical time a trend takes to be completed. Given that, the trend time grows with the threshold: on median lasts for 15 hours (54000×3600), 64 hours (230400×3600) and 123.5 hours (444600×3600) in each instance. The finding in this case is the fact that the up trend time are higher in the case of the threshold 4% and 12% than the down trend time.

The $\boldsymbol{TM}$ indicator is pretty similar to the $\boldsymbol{OSV}$ indicator.

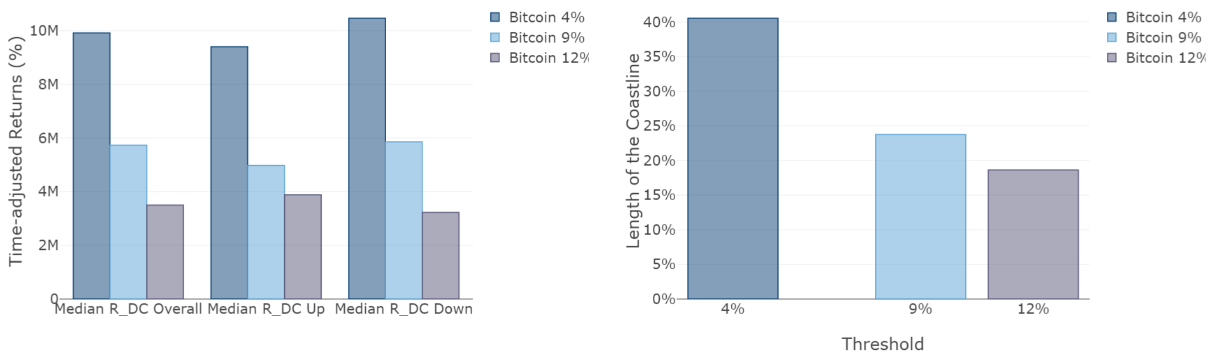


(a) $\boldsymbol{TT}$ (b) $\boldsymbol{TM}$

Figure 4.3: Trend time and total price movement information.

The profile extracts also the time-adjusted return ($\boldsymbol{R_{DC}}$), which is an indicator to measure how fast one could expect to see a price change.

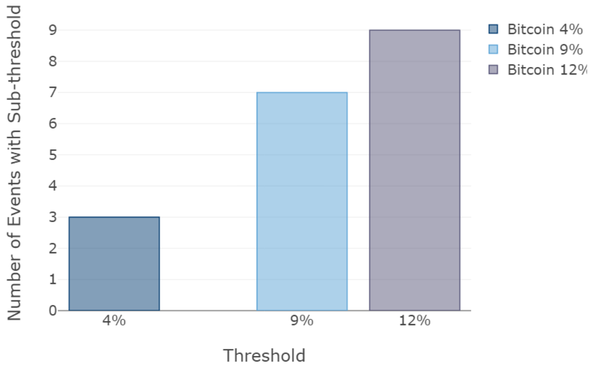
The length of the price-curve coastline is 40.54%,23.75% and 18.64%. It represents the highest possible profit that one cloud make according to the DC profile assuming perfect foresight.



(a) $\boldsymbol{R_{DC}}$ (b) $\boldsymbol{LenC}$

Figure 4.4: Time-adjusted return and length of coastline information.

The sub-threshold chosen is always a quarter of the threshold.



(a) $Sub_{N_{DC}}$

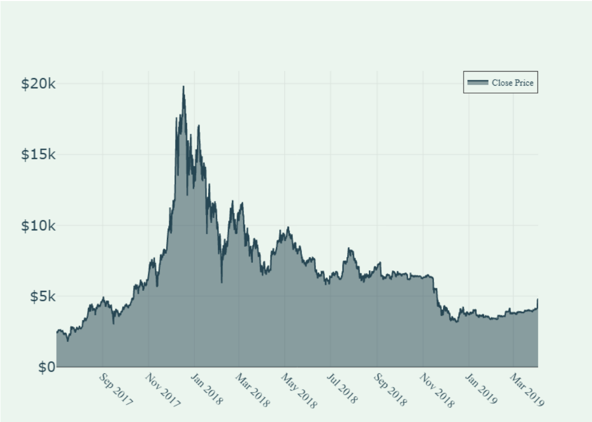
Figure 4.5: Number of directional changes with the sub-threshold information.

4.2 Profiling Cryptocurrencies

In this subsequent section, it is going to be given an overview of the cryptocurrency market through the use of the directional change frame of reference.

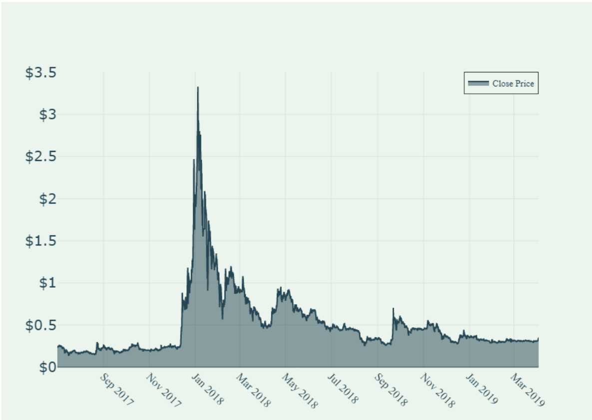
In this regard, historical prices of the top 4 cryptocurrencies by market capitalization (`www.cryptodatadownload.com`, 02 february 2019) are used to inspect the major characteristics of the recent crypto world. The four assets are Bitcoin, Ethereum, Ripple and Litecoin, all of which cover the period from July 1, 2017 to April 2, 2019. The dataset endorsed offers hour-by-hour price movements which accounts for 15373 points of information.

The following figure shows the time evolution of the four indices over the whole test period.

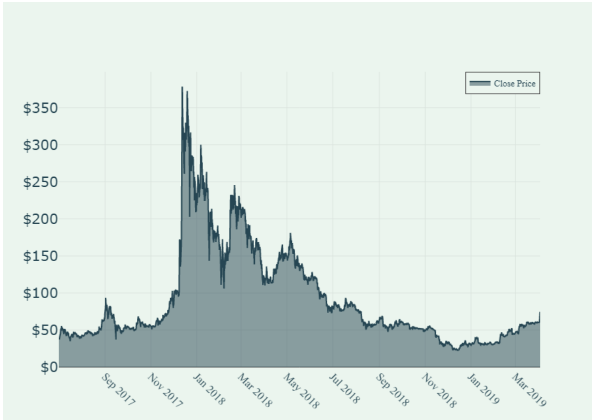


(a) $\boldsymbol{Bitcoin(BTC)}$

(b) $\boldsymbol{Ethereum(ETH)}$



(c) $\boldsymbol{Ripple(XRP)}$



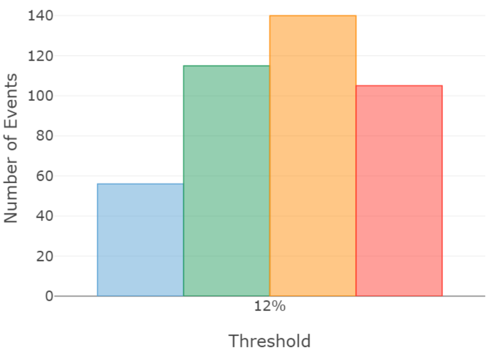
(d) $\boldsymbol{Litecoin(LTC)}$

Figure 4.6: The price of top 4 cryptocurrencies by market capitalization from July 2017 to April 2019.

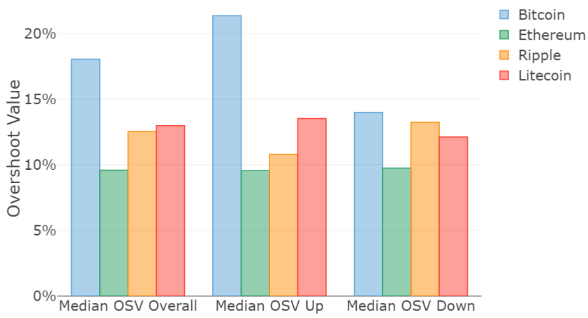
To the casual eye, it stands out that the four coins do share a comparable overall pattern, despite the fact that the magnitude per se are substantially distinct.

For this analysis, it is chosen a 12% threshold as the base line for comparison between the four cryptocoins.

As a starting point, the observation from the $\boldsymbol{N_{DC}}$ do indicate that for the profiled period $\boldsymbol{T}$, the asset that has the highest number of events is Ripple, followed by Ethereum, Litecoin and Bitcoin: 140, 115, 105 and 56, accordingly. As a result, it is clear that compared to Bitcoin, the other coins are more volatile when applying a user-defined threshold of 12%, in other words, the frequency at which upward and downward events occur at this threshold in this three coins is on average 53.3% higher than the events occurrence in Bitcoin. In general terms, when volatility increases, risk increases and returns decrease. This corroborates with the result of the second indicator.



(a) N_{DC}

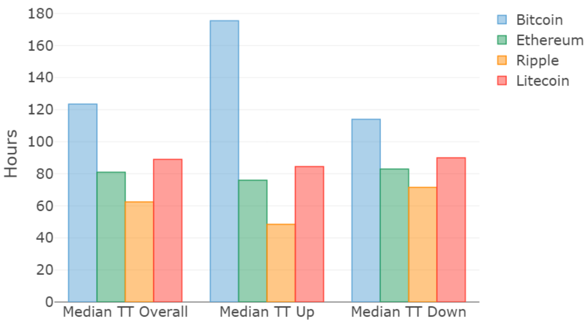


(b) OSV

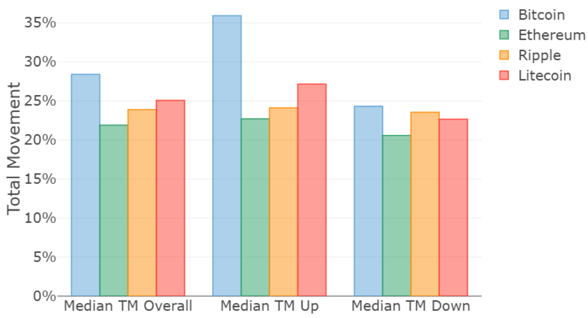
Figure 4.7: Number of directional changes and overshoot value information.

The Overshoot Value OSV indicates that on median the price change after a trend in both directions is detected is about 18.04%, 9.60%, 12.53% and 12.98% following a decreasing order in terms of capitalization market. The insight comes when the two directions are analysed separately. From the graph it stands out that the upward events do offer a better possibility of return than the downward events in the case of Bitcoin a difference of , Ethereum and Litecoin . This trait is not witnessed in Ripple where the overshoot is bigger in the downward events: .

In a 2011 report, Crestmont Research examined the historical relationship between stock market performance and the volatility of the market using the physical time framework. For this analysis, Crestmont used the average range for each day to measure the volatility of the Standard & Poor's 500 Index (S&P 500). Their research shed some light on the fact that higher volatility corresponds to a higher probability of a declining market, where a lower volatility corresponds to a higher probability of a rising market. The same pattern is identified here but now in the directional change framework and using a user-defined threshold.



(a) TT

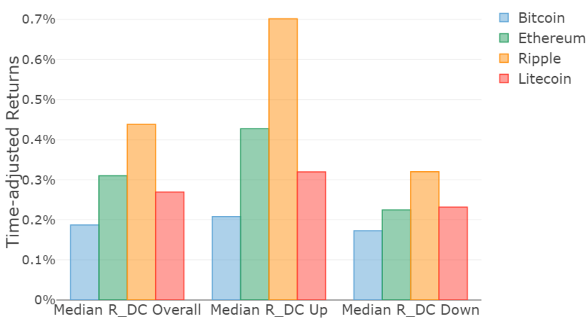


(b) TM

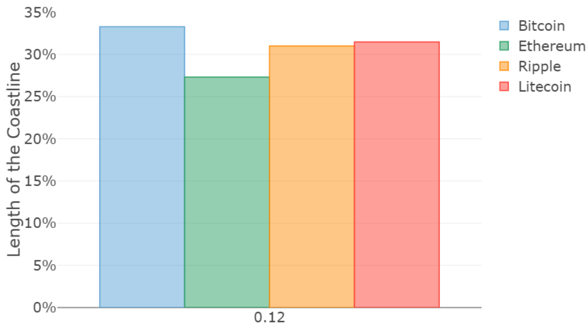
Figure 4.8: trend Time and total price movement information.

The third indicator is a close look at the time it takes for a trend to be completed TT. The bitcoin take on median 123.5 hours (seconds) for a completion of a trend, Ethereum require 81 hours (seconds), Ripple 62.5 hours (seconds) and Litecoin 89 hours (seconds). For example, a bitcoin trend last for more 49% than the time it takes the more volatile coin of the four assets, Ripple, to finish a trend. Moreover the difference in behaviour between the up and down direction also impacts this indicator, where the in general the upward events have a bigger timespan.

The total move indicator TM shows that with a threshold of 12% on median the price change magnitude of trend is about 25% for all assets.

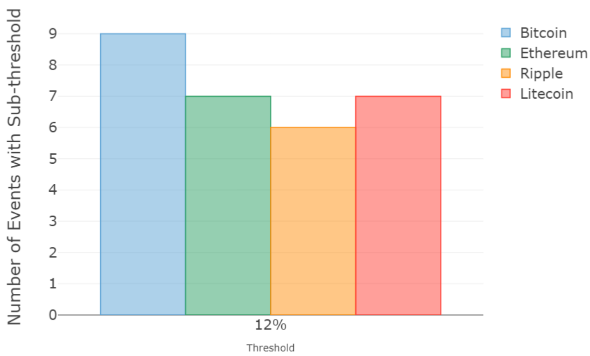


(a) R_{DC}



(b) $LenC$

Figure 4.9: Time-adjusted return and length of coastline information.



(a) $Sub_{N_{DC}}$

Figure 4.10: Number of directional changes with the sub-threshold information.

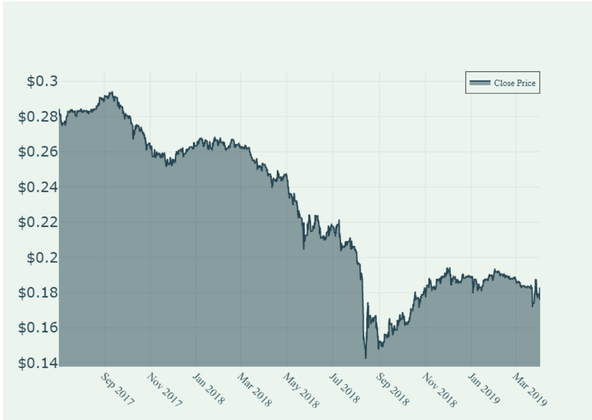
4.3 Profiling Cross Country

In this section, the analysis is going to be focused in profiling the forex market (country exchange rate pairs) and the cryptocurrency market in the directional change context.

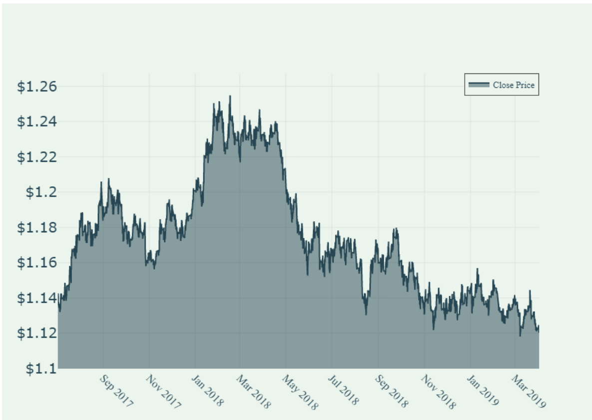
The idea is to investigate, armed with the lens of directional change, if there is any new insight or relation between the highly volatile cryptocurrency market and the counrrency pairs that do also behave in an unsteady way due to mainly their political and economic instability.

For this purpose, it is selected as a representation of the crypto world the bitcoin and to stand for the vulnerable country exchange rate pair it was choosen the Turkish Lyra (TRY/USD). As a baseline, it was also included in this study the EUR/USD pair because to set the reference and for being the most traded forex pair in the world holding the same status as Bitcoin in the cryptocurrency world.

(a) $\boldsymbol{Bitcoin(BTC)}$



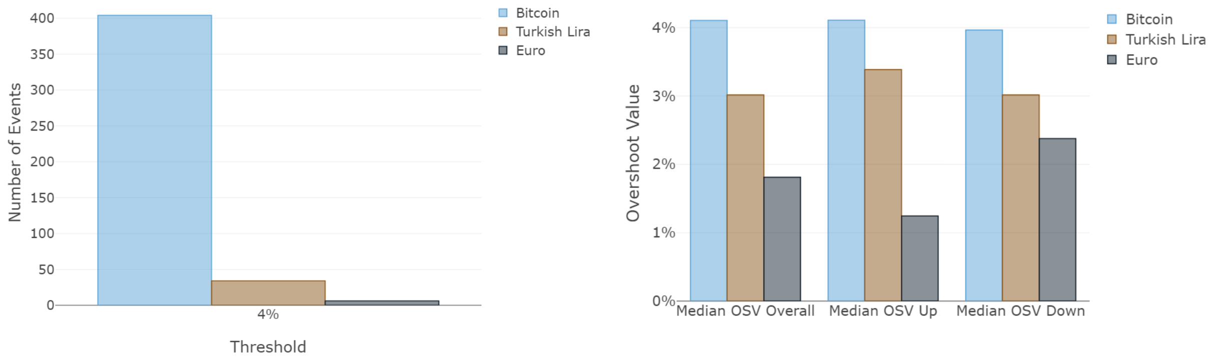
(b) $\boldsymbol{Turkish \quad Lira(TRY)}$



(c) $\boldsymbol{Euro(EUR)}$

Figure 4.11: The price of Bitcoin, an asset of the cryptocurrency market, and the Euro and the Turkish Lira assets from the forex market from July 2017 to April 2019.

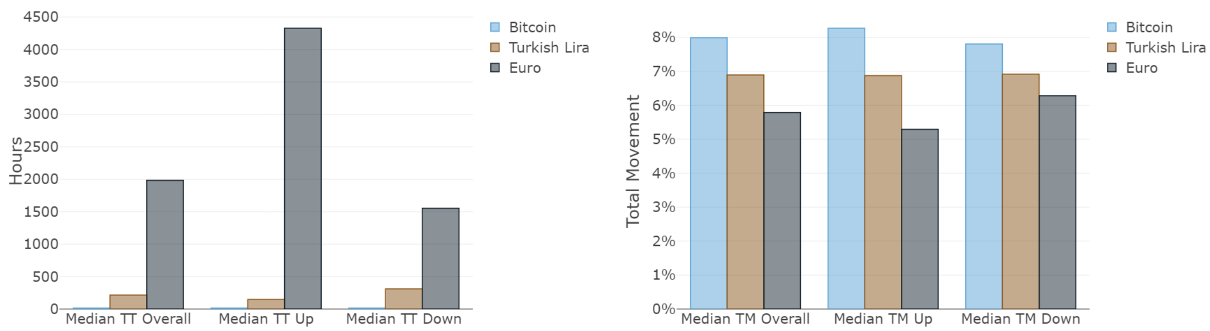
Beginning the research looking at the first indicator number of directional changes $\boldsymbol{N_{DC}}$, reminding that this feature can be interpreted as a measure of volatility, the result when applying a DC structures with a threshold of 4% is 404, 34, 6 for Bitcoin, Euro and Turkish Lira, respectively. This is, an increase of 1088% when directly comparing Bitcoin with Turkish Lira and a difference of 466% when contrasting Euro with a volatile country exchange Lira. So, it is clear that the magnitudes of price change frequency in the crypto world is much times higher, a fact that does not compromise the amount of investment held in this new synthetic coin.



(a) N_{DC} (b) OSV

Figure 4.12: Number of directional changes and overshoot value information.

The second indicator shows that the magnitude of the overshoot value for an investor is hoping to expect values of 4.11%, 3.01% and 1.81%, in the same order as before. Which confirms that when compared to the traditional forex exchanges, the cryptocurrency do present higher potential of profit or loss depending on the strategy of each agent. Also, in the profiled period it cleary observed that the in the case of Bitcoin and Lira there was more likehood to see higher price changes when facing an uptrend than compared to downtrend. This could not be detected in the EUR/USD pair, where the downtrend do represent an higher change of a bigger overshoot value.

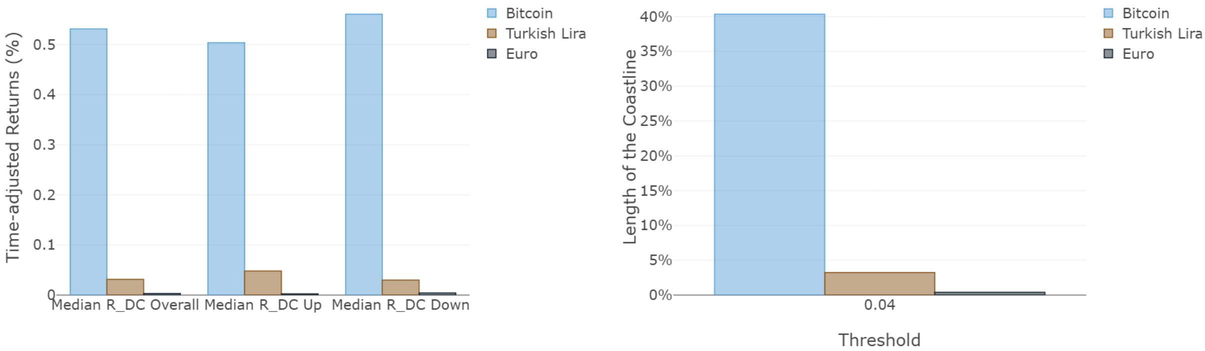


(a) TT (b) TM

Figure 4.13: Trend time and total price movement information.

The third indicator is the trend time TT, the bitcoin take on median 15 hours (54000 seconds /3600) for a completion of a trend, the Turkish Lira requires 215 hours (774000 seconds /3600) and Euro takes 1984.5 hours (7144200 seconds /3600). From the figure below it is obvious the difference a trend takes to be completed in the EUR/USD pair case, this discrepancy is due to the fact that this country pair do represent two of the most strong economic regions of the world.

The fourth indicator, total movement TM, reflects on median the total change in price there is in a trend and from the outcome of the algorithm the Bitcoin do appear to have the biggest price movement, not surprisingly as the same was established in the case of the OSV. On median the values recorded for the total movement were: 7.99%, 6.90% and 5.80%, accordingly.

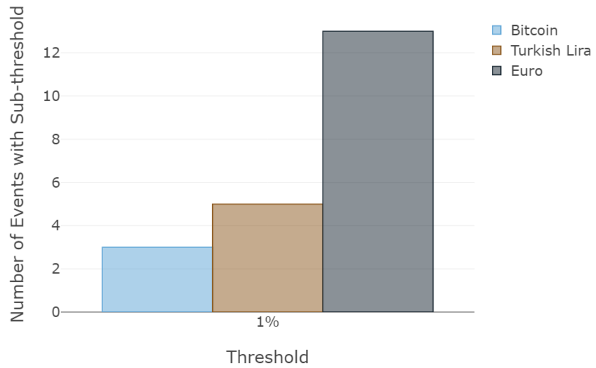


(a) $\boldsymbol{R_{DC}}$ (b) $\boldsymbol{LenC}$

Figure 4.14: Time-adjusted returns and length of coastline information.

The time adjusted return, $\boldsymbol{R_{DC}}$, evidently states that the Bitcoin do have a higher median on the return per unit of time. In this case, the time adjusted return for Bitcoin is 0.529% $(1.47 \times 10^{-4} \times 3600)$ this means that on median the price changes 0.529% per hour, for the Turkish Lira is 0.031% $(8.72 \times 10^{-6} \times 3600)$ and for the Euro is 0.0031% $(8.81 \times 10^{-7} \times 3600)$. This results explain why there is actually a big enthusiasm around the cryptocurrnecy market as in the perspective of an investor that is looking for a fast paced return (as we more than ever live in a fast-paced society), Bitcoin offers the answer as the price is changing in higher magnitudes per unit of time when compared to the traditional forex exchanges considered, before the appearance of the crypotocurrencies, as one of the fastest way to make money for skilled daily traders.

The other interesting indicator is the length of the coastline $\boldsymbol{Sub_{NDC}}$, as it represents the maximum potential profit that an agent can obtain considering the fact that he has perfect foresight of the movement of the market, which is impossible but nonetheless used as a measure of potential opportunity. The results obtained show that the bitcoin as a 40.54%, but also as the highest number of events so for a better comparison the value is divided by the number of directional changes: $40.54\% \div 404 = 0.1\%$ per trend, the Turkish Lira has on average: $3.24\% \div 34 = 0.095\%$ per trend, and the EURO/USD pair has an average length of coastline of: $0.39\% \div 6 = 0.065\%$ per trend.



(a) $Sub_{N_{DC}}$

Figure 4.15: Number of directional changes with the sub-threshold information.

From this final graph, the number of sub-thresholds of Bitcoin is 3, in the Turkish Lira is 5 and in the Euro is 13 . This shows that Euro has per trend more events with a threshold of one fourth of the initial threshold of 4%, which indicate us that the Bitcoin is more prone to big events while the Euro/USD and Turkish Lira pair is less predisposed to big events, this actually comes as expected confirming the stability of the exchange pairs, but also comes in great time to warn us for the fact that Bitcoin is characterized by big shifts and might be something that we have to accepted as it is, a completely new reality and there is no comparison that can be made with the traditional forex market.

4.4 Analysis of Returns in Directional Change

Additional investigation was conducted in dissecting the potential profit and risk an individual can expect between the use of a fixed-interval time frame and an event-based frame.

For this purpose, the Bitcoin price from July 7, 2017 to April 2, 2019 was submitted to the two different profile syntheses, while mindfully guaranteeing the same number of points of information for the sake of trustworthiness of comparison.

Taking this into account, it was found that using a threshold of 2.8% ensures the same number of intervals as the daily fixed interval for prices display: 642 points.

The following histogram, Figure 4.16, reveals that the probability of finding lower price changes is higher through the observation in daily returns, while with the use of a threshold of 2.8% the presence of returns lower than 2.2% is smaller. Accordingly, from the figure it is possible to recognize that from using the user-defined threshold, an agent contains an higher probability of assisting to larger returns both in positive or negative direction.

Apart from visual inspection, some statistics descriptors are presented in table so that a better understanding is performed. Kurtosis, Skewness and Jarque-Bera normality test were used:

Skewness measures the degree of asymmetry of a distribution around its mean value. Positive skewness indicates a distribution with an asymmetric tail extending toward more positive values, putting into the finance context this means there is more chances of an upside potential price change. While

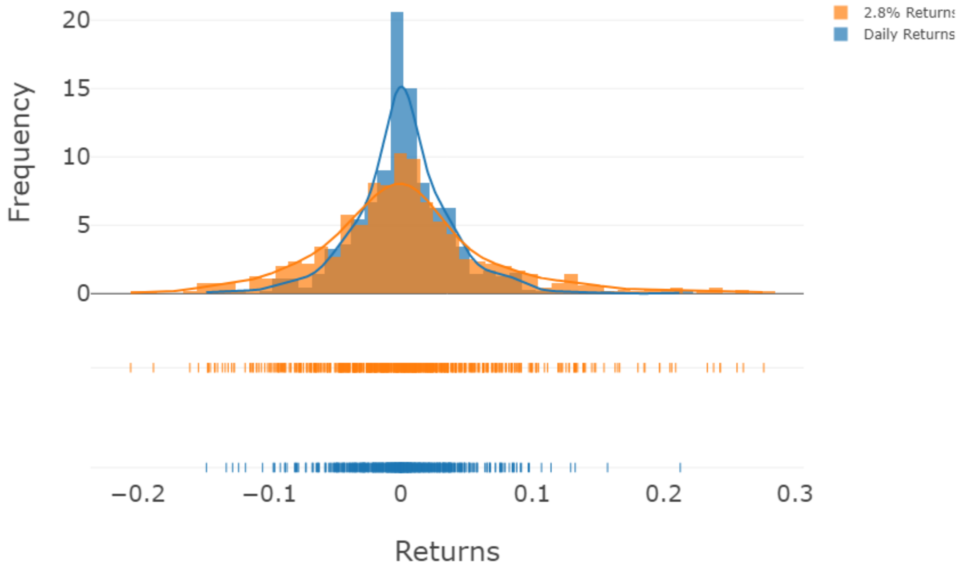


Figure 4.16: This graph displays the frequency at which different magnitudes of returns happen in the profiled period for Bitcoin price from July 7, 2017 to April 2, 2019. The comparison is performed summarizing the price daily and 2.8% return.

	⟨**Intervals**⟩	**Kurtosis**	**Skewness**	**Jarque-Bera**
Daily Returns	642	2.993	0.209	243.589
2.8% Returns	642	2.052	0.710	166.712

Table 4.1: Statistical descriptors to compare the returns obtain with physical time vs intrinsic time ensuring the same number of intervals.

negative skewness indicates a distribution with an asymmetric tail extending towards more negative values, which suggests that there is more probability of a downside potential price move. As consequence, zero skewness means the tail are symmetric.

The daily returns present a skewness value of 0.209 while the 2.8% returns have a value of 0.710, from this difference it is confirmed that using a threshold the agent has more chances of an upside potential price change than a downside price movement.

Kurtosis measures the 'tail-heaviness'. In other words, fat tails is a statistical phenomenon in which extreme values (low and high values) are more frequent than the Gaussian distribution. Therefore, a low kurtosis indicates fewer outliers whereas a high kustosis indicates greater presence of extreme values. With high kustosis, one will have 'fat' tails, higher frequency of outcomes at the extreme negative and positive ends of the distribution curve. Carrying this observation into finance, it means that for investors, high kurtosis of the return distribution implies that the investor will experience occasional extreme returns. This phenomenon is known as kurtosis risk.

The daily returns present a kurtosis value of 2.993 while the 2.8% returns have a value of 2.052, which indicates that there is a higher risk of extreme values with the use of daily returns compared to a threshold of 2.8%.

The Jarque-Bera Test is a test for normality. The test relies on the skewness and kustosis of the data to see if it matches a normal distribution. In general a large Jarque-Bera values indicate that the data is not normally distributed.

The results show that the daily returns are further way from being normal than the 2.8% threshold.

By way of conclusion, an important aspect of the financial market is that an agent can profit when prices are rising or are expected to rise (bull market), likewise there is also gain when the market is characterized by falling prices (bear market). The origin of these terms suggests that the use of "bull" and "bear" to describe markets comes from the way the animals attack their opponents. A bull thrusts its horns up into the air, while a bear swipes its paws downward. These actions are metaphors for the movement of a market. If the trend is up, it's a bull market. If the trend is down, it's a bear market.

The figure 4.17 highlights the fact using an event-based framework for the analysis of price can lead to a higher potential profit assuming perfect foresight.

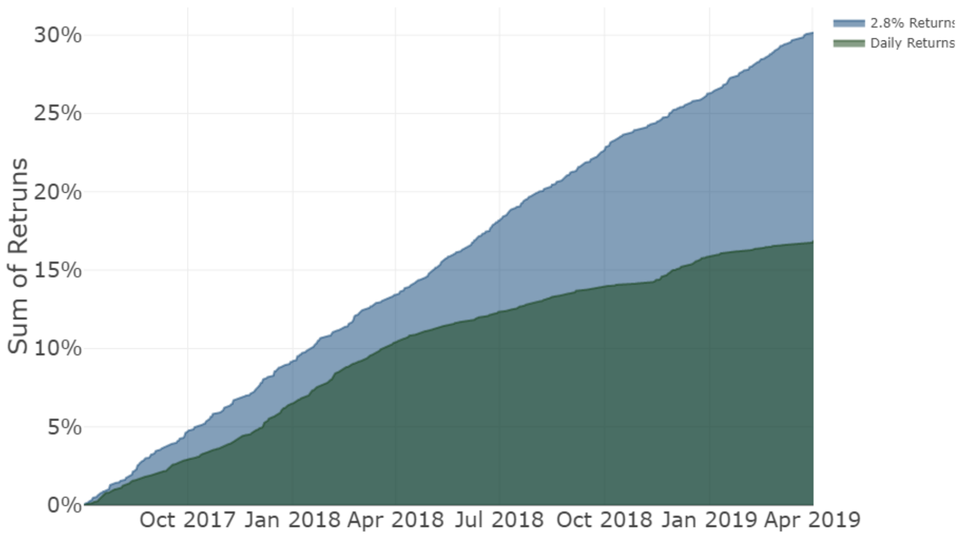


Figure 4.17: This graph displays the accumulation of returns for the profiled period. In other words can be seen as a maximum potential profit assuming perfect foresight.

Chapter 5

Conclusions

History recorded by events, not snapshots at fixed intervals, so should market prices too. Directional Change events capture 'significant changes' useful for summarising price movements and gives new perspectives in price movements. DC enables discovery of regularities not captures by interval-based summaries. It is different from the traditional time series It provides a different angle for capturing and analysing price changes. The coastline captures the potential profit in trading in a time period under the observed threshold. This is useful information that we do not often find in the time series analysis. This technique or framework can have important application in mechanics. For example, in predictive maintenance one can use the directional change to detect regularities and gain new insights. As market prices, machine operate and are damaged by events. Recording those events can be of major importance.

5.1 Achievements

The major achievements of the present work...

- Found some interesting statistical observations
- The coastlines measured by the DC framework are bigger than the coastlines measures with time-series
- The reported results in this paper emphasize the significance of considering DC and OS events in studying the price curve, rather than the physical fixed time intervals knowing the long coastline of price changes under the DC framework.

5.2 Future Work

Future deliberations may evolve in the direction of creating other indicators that can be extracted from the directional change framework. Therefore creating new useful insights that can be used for profiling a time series and a deeper understanding of the behaviour of any time signal. The more useful indicators one defines, the more information we can extract from the data. Another direction is to combine directional change analysis with the traditional time series analysis to explore synergy. Since they are two different methods to observe the same market, they may provide complementary market information.

Time series data as showed in this work, is also commonly encountered in the work of an Mechanical , for example, this framework can be used in predictive maintenance. Predictive maintenance is a method of preventing asset failure by analysing production data to identify patterns and predict issues before they happen. It is not a surprise therefore, that predictive maintenance has quickly emerged as a leading Industry 4.0. Implementing industrial IoT technologies to monitor asset health, optimize maintenance schedules, and gaining real-time alerts to operational risks, allows manufactures to lower service costs, maximize uptime, and improve production throughput. In addition, studying the time series under DC framework reduces the computational load and the complexity of time series known the small number of price points for evaluation. The computational costs (which consist of the cost of evaluating data rows) necessity not to be ignited. Therefore, computational costs have to be part of the criteria when it comes to choosing a method for studying price time series. The DC indicators can facilitate the construction of DC profiles from sensors data, because the sensors data displays diverse periodic patterns, revealed by the power of the data process in the high-frequency domain.

Potentially DC concept can be used to make feature extraction from high frequency data, reducing its complexity but maintaining characterizing patterns present in sequential time series. This can be used to feed the Machine Learning algorithms

In this paper offers purpose of this work was also to bring awareness to the field of Mechanical Engineering of the usefulness of Directional Change framework which can bring potential high benefits in the groundwork for the analysis of raw time series signals.

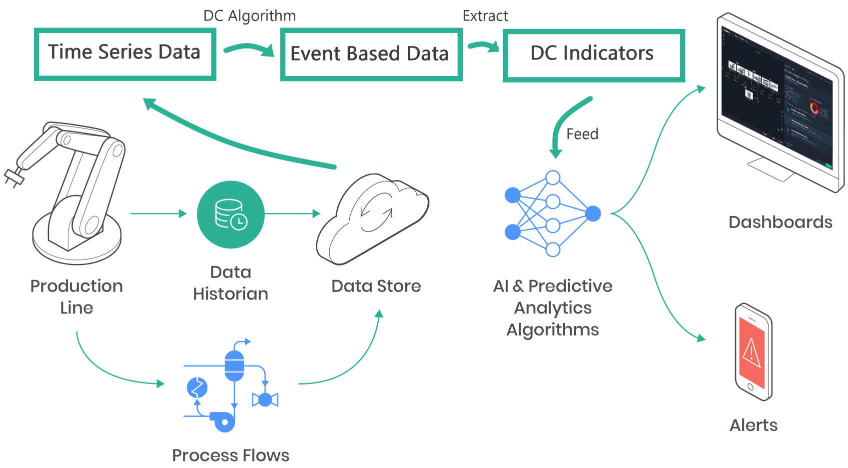


Figure 5.1: This figure presents a possible use of the directional change framework in the field of mechanic engineering. Concretely in predictive maintenance where big amounts of data from sensors could possibly be simplified to feed the machine learning algorithms without the loss of relevant information.

The DC indicators are different from traditional time series analysis indicators and the valuable tolls for risk management, volatility modelling and for creating automated trading models, the same ways these DC indicators can be good weapons to treat signal coming from sensors and be applied in mechanical engineering problems. I believe that the DC indicators can improve our study of dynamic behaviour of time signal, used a lot by mechanical engineering, and advance the quality of the predictions and inference we formulate regarding predictive maintenance.

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Appendix A

Tables with the results

A.1 Bitcoin Summary

DC Indicator	**Bitcoin 4%**	**Bitcoin 9%**	**Bitcoin 12%**
$\boldsymbol{Sub - threshold}$	1%	2.25%	3%
$\boldsymbol{N_{DC}}$	404	105	56
$\boldsymbol{OSV}$	4.11%	7.15%	18.04%
$\boldsymbol{OSV} \uparrow$	4.11%	6.82%	21.36%
$\boldsymbol{OSV} \downarrow$	3.97%	7.44%	13.99%
$\boldsymbol{TT}$	$54000s$	$230400s$	$444600s$
$\boldsymbol{TT} \uparrow$	$57600s$	$203400s$	$631800s$
$\boldsymbol{TT} \downarrow$	$54000s$	$275400s$	$410400s$
$\boldsymbol{TM}$	7.99%	16.03%	28.4%
$\boldsymbol{TM} \uparrow$	8.27%	16.43%	35.92%
$\boldsymbol{TM} \downarrow$	7.81%	15.77%	24.31%
$\boldsymbol{R_{DC}}$	$1.47 \times 10^{-4}\,\%/s$	$8.53 \times 10^{-5}\,\%/s$	$5.20 \times 10^{-5}\,\%/s$
$\boldsymbol{R_{DC}} \uparrow$	$1.39 \times 10^{-4}\,\%/s$	$7.41 \times 10^{-5}\,\%/s$	$5.78 \times 10^{-5}\,\%/s$
$\boldsymbol{R_{DC}} \downarrow$	$1.55 \times 10^{-4}\,\%/s$	$8.71 \times 10^{-5}\,\%/s$	$4.80 \times 10^{-5}\,\%/s$
$\boldsymbol{LenC}$	40.54%	23.75%	18.64%
$\boldsymbol{Sub_{NDC}}$	3	7	9

Table A.1: Directional changes indicators after profiling Bitcoin

A.2 Cryptocurrencies Summary

DC Indicator	**Bitcoin** BTC	**Ethereum** ETH	**Ripple** XRP	**Litecoin** LTC
$\boldsymbol{Threshold}$	12%	12%	12%	12%
$\boldsymbol{Sub-threshold}$	3%	3%	3%	3%
$\boldsymbol{N_{DC}}$	56	115	140	105%
$\boldsymbol{OSV}$	18.04%	9.60%	12.53%	12.98%
$\boldsymbol{OSV}\uparrow$	21.36%	9.56%	10.82%	13.53%
$\boldsymbol{OSV}\downarrow$	13.99%	9.75%	13.23%	12.12%
$\boldsymbol{TT}$	$444600s$	$291600s$	$225000s$	$320400s$
$\boldsymbol{TT}\uparrow$	$631800s$	$273600s$	$174600s$	$304200s$
$\boldsymbol{TT}\downarrow$	$410400s$	$298800s$	$257400s$	$324000s$
$\boldsymbol{TM}$	28.40%	21.91%	23.88%	25.08%
$\boldsymbol{TM}\uparrow$	35.92%	22.70%	24.12%	27.16%
$\boldsymbol{TM}\downarrow$	24.31%	20.58%	23.55%	22.67%
$\boldsymbol{R_{DC}}$	$5.21\times10^{-5}\,\%/s$	$8.62\times10^{-5}\,\%/s$	$12.17\times10^{-4}\,\%/s$	$7.48\times10^{-5}\,\%/s$
$\boldsymbol{R_{DC}}\uparrow$	$5.79\times10^{-5}\,\%/s$	$11.88\times10^{-4}\,\%/s$	$19.50\times10^{-4}\,\%/s$	$8.88\times10^{-5}\,\%/s$
$\boldsymbol{R_{DC}}\downarrow$	$4.80\times10^{-5}\,\%/s$	$6.24\times10^{-5}\,\%/s$	$8.90\times10^{-5}\,\%/s$	$6.44\times10^{-5}\,\%/s$
$\boldsymbol{LenC}$	33%	27%	31%	31%
$\boldsymbol{Sub_{N_{DC}}}$	9	7	6	7

Table A.2: Directional changes indicators after profiling Cryptocurrencies

A.3 Cross-Country Summary

DC Indicator	BTC/USD	TRY/USD	EUR/USD
$\boldsymbol{Threshold}$	4%	4%	4%
$\boldsymbol{Sub-threshold}$	1%	1%	1%
$\boldsymbol{N_{DC}}$	404	34	6
$\boldsymbol{OSV}$	4.11%	3.01%	1.81%
$\boldsymbol{OSV}\uparrow$	4.11%	6.82%	21.36%
$\boldsymbol{OSV}\downarrow$	3.97%	3.01%	2.38%
$\boldsymbol{TT}$	$54000s$	$774000s$	$7144200s$
$\boldsymbol{TT}\uparrow$	$57600s$	$529200s$	$15580800s$
$\boldsymbol{TT}\downarrow$	$54000s$	$1119600s$	$5590800s$
$\boldsymbol{TM}$	7.99%	6.90%	5.80%
$\boldsymbol{TM}\uparrow$	8.27%	6.87%	5.3%
$\boldsymbol{TM}\downarrow$	7.81%	6.91%	6.28%
$\boldsymbol{R_{DC}}$	$1.47\times10^{-4}\,\%/s$	$8.72\times10^{-6}\,\%/s$	$8.81\times10^{-7}\,\%/s$
$\boldsymbol{R_{DC}}\uparrow$	$1.39\times10^{-4}\,\%/s$	$1.34\times10^{-5}\,\%/s$	$7.08\times10^{-7}\,\%/s$
$\boldsymbol{R_{DC}}\downarrow$	$1.55\times10^{-4}\,\%/s$	$8.29\times10^{-6}\,\%/s$	$1.12\times10^{-6}\,\%/s$
$\boldsymbol{LenC}$	40.54%	3.24%	0.39%
$\boldsymbol{Sub_{NDC}}$	3	5	13

Table A.3: Directional changes indicators after profiling Cross-Country