SCHOOL OF ECONOMICS AND FINANCE
FACULTY OF COMMERCE, LAW AND MANAGEMENT

Price Discovery, Technical Analysis and Weak-Form Efficiency: Evidence from Cryptocurrencies

Shaad Ismail (1430980)

Supervisor: Dr.Yudhvir Seetharam

A research report submitted to the Faculty of Law, Commerce and Management, University of the Witwatersrand in partial fulfilment of the requirements for the degree of Master of Commerce (50%) in Finance.

Johannesburg, South Africa

February 2021

Price Discovery, Technical Analysis and Weak-Form Efficiency: Evidence from Cryptocurrencies

Abstract

The continued prevalence of Bitcoin and other cryptocurrencies in the media, in online forums, and even casual conversation continue to add to the buzz of this controversial asset class. What adds to the controversy around cryptocurrencies is that they do not have fundamental value, so we can only observe the price of the cryptocurrency. The question thus arises as to whether we can discover the price of a cryptocurrency, and whether this means that the market is predictable. The present study explores the price discovery process in the cryptocurrency market. This is achieved by using state space modelling, via the Kalman filter, and technical analysis. The sample period covers 2010 to 2020 and consists of the top 30 cryptocurrencies based on market capitalisation. The Kalman filter is passed through all 30 cryptocurrencies and used to generate the efficient equilibrium price level which is further utilised to yield buy and sell opportunities. Additionally, the ability of a family of five technical trading rules (Moving Average (MA), trading range breakout, Moving Average Convergence, Divergence (MACD), Relative Strength Index (RSI), and Bollinger Bands (BB)) to generate returns in excess of the passive buy and hold benchmark is explored. The results show superior performance of the technical trading rules and the Kalman filter across the full sample as well as in the sub samples even after including transaction costs. Overall the results provide strong evidence in favour of the ability of the Kalman filter and technical analysis to "time" the market.

Declaration

I, Shaad Ismail, declare that this research paper is my own work and that I have correctly acknowledged the work of others. It is submitted to fulfil the requirements for the degree of Master of Commerce in Finance at the University of the Witwatersrand, Johannesburg. I declare that this research paper has not been submitted for any other degree or examination in this or any other institution.

Shaad Ismail

February 2021

Acknowledgements

I take this opportunity to express my respectful appreciation on the help, guidance and supervision made by my supervisor Dr Yudhvir Seetharam.

I would like to acknowledge everyone who played a role in my academic accomplishments. A big thank you for the fruitful discussions, scrutiny and moral support.

A special mention to my parents, Ayesha and Munier, to whom I am indebted. Your unwavering support, guidance and understanding has always encouraged me towards higher levels in my career progression and achievement.

Table of Contents

List of figures

List of Tables

Definition of abbreviations, terms and symbols

BB (Bollinger Bands): are counter-trend indicators defined by a set of trend lines plotted two standard deviations away from a simple moving average of a security's price.

Bitcoin: is a type of cryptocurrency that was created in 2009. It is an electronic payment system based on cryptographic "proof" instead of traditional trust.

Bitcoin being the "**leader**" in the cryptocurrency market: Bitcoin was the first cryptocurrency to be launched (known as the original cryptocurrency) and remains the leader of the space. Bitcoin has the highest market capitalisation, user base, and popularity.

CCI30 (The Cryptocurrencies Index 30): is a rules-based index designed to measure the overall growth, daily and long-term movement of the block chain sector. This index tracks the 30 largest cryptocurrencies by market capitalisation.

Efficient Market Hypothesis (EMH): asserts that prices at all times reflect relevant available information. This implies that no consistent abnormal profits can be made in financial markets.

Efficient price level: can be described as the equilibrium price, descriptive of the balance of demand and supply for the cryptocurrency in question. This efficient price level reflects the equilibrium relationship between buyers and sellers and reflects all the available information, and thus can be regarded as the efficient price.

Equilibrium Price: refers to the price of a security when there is a balance between demand and supply for that security. The present study uses the term equilibrium price to refer to the efficient price level of a share.

Fundamental value: is a measure of what an asset is worth. This value may differ from the market values of the asset.

Market Efficiency: the traditional definition of market efficiency is given by the EMH (discussed above) where the current price reflects all available information such that no abnormal profits can be sustained in the long term.

Moving Average (MA): is a type of technical trading rule that issue a buy (sell) signal when the actual price, or a relatively recent average price, is greater (below) a longer-term average of the share price.

Price efficiency: refers to the concept that the price of an asset reflects all public supply and demand information pertaining to it.

Price discovery: is a process culminating in a price for an asset. It depends on market structure, liquidity and information flow other than demand and supply. Important to note is that price does not equal fundamental value when the market is inefficient. In efficient markets, prices reflect fundamental values of securities. Therefore when the term price discovery is utilised it is a reference to price estimation in the context of the study.

Random Walk: theory contends that share price changes have the same distribution and are independent of each other, implying that past movement cannot be used to predict its future movement

Relative Strength Index (RSI): is a technical trading rules that compares the upward movement of price with the downward movement over a certain period. The RSI is a bounded counter-trend indicator that oscillates between 0 and 100.

Technical analysis: The broad term technical analysis refers to a large array of trading techniques. More specifically, technical analysis includes making investment decisions based on the predictions of past trading data only (Brock, Lakonishok, and LeBaron, 1992).

Trading indicator: refer to mathematical calculations that are plotted as lines on a price chart. These help traders identify overbought/oversold levels in the form of buy and sell trading signals.

The Kalman filter: is an iterative mathematical process that uses a set of equations and consecutive data inputs to quickly estimate the true value of the object being measured, when the measured values contain uncertainty or variation.

The Moving Average Convergence Divergence (MACD): is a technical trading rule formed using moving averages, more specifically it is calculated by subtracting the longer exponential moving average (EMA) from the shorter EMA.

Trading Range Breakout: is a technical trading rule that signals maximum and minimum prices for a security that has traded over the past n days. The trading range breakout indicator identifies both a support and resistance level of the assets price, and uses these levels to generate buy and sell signals.

Weak form efficiency: states that future prices cannot be predicted by analysing past price.

1. Introduction

1.1 Background

Price discovery determines the spot price of an asset through the interactions of buyers and sellers. The agreed upon price between buyers (who drive demand) and sellers (who drive supply) is a common and effective indicator of demand and supply in the marketplace (Yoon, 2013). Any fluctuation in demand and supply will therefore influence prices, at times causing the price to be considered unattractive relative to its fundamental (or perceived) value. Therefore, the price discovery process can help gauge whether an asset is currently overbought or oversold relative to its perceived value, and whether buyers or sellers are dominant in any one particular market (Kambeu, Mpofu & Muchochoma, 2017). The price discovery process (which involves market structure, liquidity and information flow) in inefficient markets often leads to the discovery of patterns or trends in historical and publicly available information exploitable through technical and fundamental analysis. This study focuses on information flow, specifically, historical information and whether technical analysis can be applied to exploit price discovery inefficiencies (over and under valuation of securities). Exploitation of such securities implies the market is weak form inefficient.

Share prices change because of changes in the demand and supply of said shares. When there are more buyers than sellers at a particular price level, the price will increase until the buying pressure subsides. Similarly, when there are more sellers than buyers at a particular price level, the price will fall. A share price that has been driven down is a favourable buying opportunity when traders sense that the downward momentum has stopped. Therefore, the price discovery process is determined by the volume of supply-side and demand-side of traders. However, the price of a particular share does not necessarily indicate the value of the share in question. Price however does indicate the current/market value, but the fundamental value could arguably be higher or lower. Consequently, the share price is not always the best indicator of the fundamental value of a company. Therefore, a share could be worth more (or less) than what its current price indicates.

Traders try to identify shares that are undervalued in order to make a profit from the movements of the market price of that share. More specifically, this involves identifying prices that do not reflect their true value. This includes an element of predictability, whereby individuals try to forecast undervalued or overvalued share prices. The broad term *"technical analysis"* refers to a large array of trading techniques. More specifically, technical analysis includes making investment decisions based on the predictions of past trading data only (Brock, Lakonishok, and LeBaron, 1992). This involves attempting to search for recurrent and predictable patterns in share prices. The fundamental idea is to forecast equity prices by examining past prices. Therefore, technical analysis assists traders in identifying undervalued/overvalued levels of a particular share.

The assumptions of technical analysis directly oppose the notion of efficient markets. The belief patterns of price adjustment directly contradict the Efficient Market Hypothesis (EMH). Keynes (1937) note that the market value of any good or service is determined by the interaction of supply and demand. Additionally, supply and demand are governed by factors such as economic variables which the market weighs in automatically. Additionally, Keynes (1937) notes that if one disregards minor fluctuations, the prices for individual securities and the overall value of the market tend to move in trends, which persist for appreciable lengths of time. These trends react to shifts in supply and demand functions. Lastly, these shifts can be detected in the price action of the market itself.

Before moving on to the more recent approaches to anticipating share performance one should mention the more traditional approach to determining fundamental values of firms and shares, which was based on fundamental analysis. Fundamental analysis uses financial data (for example balance sheets and income statements) as an investment device, estimating the fundamental value of the security. The fundamental analysis approach thus determines whether the security is under-priced and therefore profitable, this being if the security price is trading below its fundamental value.

In the financial market context, technical trading indicators also provide signals as to when a share is overbought or oversold through buy and sell signals based on past trading data (Drake and Downs, 2003). In contrast to fundamental analysis, which was promptly taken on by academics, Lo, Mamaysky, and Wang (2000) describe technical analysis as being an "orphan from the start". Despite technical analysis being around for many decades, it still has not received the same level of academic acceptance as the more traditional approaches

Since the seminal work of Fama (1970), the EMH has dominated the field of finance for years. However, the assumptions upon which the EMH are built are ones of a world in which investors are rational and fully informed. If one is able to use technical analysis to generate abnormal returns, it implies that the weak form EMH does not hold. According to the weak form of the EMH, all the information used to construct technical trading rules should already be reflected in the share price. Therefore, using technical analysis should not allow one to consistently outperform the passive benchmark of the market index.

The predictive power of technical analysis has repeatedly been examined, by testing the weak form of the EMH. This involves the application of technical trading rules and testing their ability to generate returns above that of a simple buy and hold strategy or using past price information to establish predictability of returns by testing their randomly generated behaviour. The question as to whether or not technical trading rules predictive ability is able to consistently generate excess profits greater than that of a passive buy and hold strategy thus becomes a direct violation of the weak form of the EMH. In addition to the price discovery process, the present study examines if the weak form of EMH will be violated if the overbought and oversold levels recommended by the buy and sell signals of the technical trading rules are able to yield returns greater than that of a simple buy and hold strategy.

Despite the recent practical success of numerous technical trading rules, there are still studies that highlight technical trading rule failures. Thus, the question as to whether technical analysis can generate consistent profits, as opposed to simply “being lucky”, continues to be an ongoing debate. Nevertheless, practitioners continue to devote significant resources and time to technical trading. However, technical analysis still remains in the shadow of the EMH. Attempts to beat the market with trading rules is still met with much scepticism amongst academics, despite the ongoing popularity and success of numerous technical trading rules used in markets throughout the world.

The continued prevalence of Bitcoin and other cryptocurrencies in the media, in online forums, and even amongst the common man continue to add to the buzz of this controversial asset class. Bitcoin’s significant rise highlighted the relevance of cryptocurrencies within finance, technology and in government. Some describe cryptocurrencies such as Bitcoin as digital gold and argue that they are the next wave of the democratisation of finance, while others contend that cryptocurrencies are in a bubble and is simply an unfortunate hype that a large number of investors have been caught up in. What is clear is that the cryptocurrency market continues to receive significant attention and remains particularly relevant within the world’s financial sphere. In its most complex form, the revolutionary technologically innovativeness of cryptocurrencies could arguably challenge political, economic and social ideas of society.

The unique make-up of cryptocurrencies adds to the uncertainty and hesitancy that many investors approach this subject with. The lack of understanding and research, as well as the temperamental nature of cryptocurrencies all adds to the uncertainty within the cryptocurrency market. However, this does not deter investors from attempting to understand cryptocurrencies or trying to gain a return from both this popular, technologically advanced and innovative digital asset. In a way, cryptocurrencies satisfied investors never ending search for new ways to invest and new assets to invest in. The attempt to time the market and generate significant returns became a reality for some cryptocurrency investors. Consequently, this resulted in much attention around Bitcoin and other cryptocurrencies. Despite this many do not fully understand the cryptocurrency universe. This aspect of cryptocurrencies adds to the motivation of this study. More specifically, the use of technical analysis within cryptocurrencies. The question arises as to whether technical analysis is beneficial within the cryptocurrency market and what the implications of this are in terms of weak-form market efficiency within the cryptocurrency market. Technical analysis is an active strategy that better equips investors that are looking to time the market. The present study explores this by determining whether a family of five common technical trading rules are able to generate returns greater than that of a passive buy and hold strategy.

The difficulty with cryptocurrencies is that they have very little underlying value. The question thus arises as to what determines the value of cryptocurrencies and how this is associated to the corresponding cryptocurrency price. This speaks to the price discovery process in the cryptocurrency market, which is addressed in the present study. The value of a particular cryptocurrency emanates from the extent to which the market is willing to accept the certain cryptocurrency in question. The more established the cryptocurrency is within the market, and the more widespread use of the cryptocurrency, the higher the price will be. Put simply, cryptocurrencies get their value based on the scale of the community involved, which include demand, scarcity or the coins utility. For example Athey, Parashkevov, Sarukkai, and Xia (2016), Bolt and van Oordt (2016), and Pagnotta and Buraschi (2018) all provide models in which the value of cryptocurrencies depends on some combination of (1) usage and the degree of adoption, (2) the scarcity of the cryptocurrency, and (3) the value of anonymity.

Since the launch of Bitcoin in 2009 numerous other cryptocurrencies have emerged, resulting in a rapidly developing cryptocurrency market throughout the world. Despite Bitcoin occupying the largest market share, other cryptocurrencies have slowly begun to erode Bitcoin's dominance. Bitcoin originated as a medium of exchange in the form of a virtual currency. For example, people are able to send and receive Bitcoin via their digital wallet in exchange for goods or services. However, cryptocurrencies do not act solely as a medium of exchange. There are various cryptocurrencies with many applications. Ethereum, the second largest digital token, allows for the building of Smart Contracts and a range of decentralised applications, while Ripple acts as a global settlement network.

Understanding the underlying asset allows one to determine how the asset in question derives its value. This basic rule has allowed investors to generate returns from particular financial assets. This has allowed investors to determine whether an asset is efficiently priced or whether this asset is under or overvalued. Despite this simple rule, many investors were able to generate returns from Bitcoin and other cryptocurrencies without truly understanding what they were investing. This all falls under the Bitcoin craze where many investors were able to yield significant returns. Ever since the emergence of the Efficient Market Hypothesis in the mid-1960, the question that has been constantly asked is whether markets are efficient and whether prices are random and unpredictable. This has paved the way as to how financial markets should operate. The question comes to mind as to whether this applies to the fairly new cryptocurrency market. Does this volatile and controversial market abide by the norms put forth by the efficient market hypothesis? The present study explores this question, with a focus on the price discovery process within the cryptocurrency market.

Despite the developing literature on cryptocurrencies, the cryptocurrency market is still in its infancy, and much is still unclear about the cryptocurrency universe. Over the last decade, and through the emergence of the cryptocurrency market the question as to whether investors understand the way cryptocurrency markets operate has arisen. This provides an opportunity to better understand cryptocurrencies. One significantly important aspect of cryptocurrencies is their price. Consequently, the "value" of cryptocurrencies is not determined using the fundamental valuation approach (for example the use of financial statements in determining the value of companies), but is rather equivalent to its price, which is arguably driven by non-fundamental factors, such as investor sentiment (Pagnotta & Buraschi, 2018).

The price of a cryptocurrency is determined by the price discovery process. The lack of information on the cryptocurrency universe and the supposedly purely price driven market speaks to the price discovery process within the cryptocurrency universe. The present study thus looks to add to the limited amount of literature examining the price discovery process of the cryptocurrency universe. Cryptocurrencies do not have fundamental value, so we can only observe the price of the cryptocurrency. The question thus arises as to whether we can discover the price of a cryptocurrency? If we do, does this mean that the market is predictable? The present study also adds value to existing literature as it covers both bull and bear markets in cryptocurrencies, as the former often dominates these type of studies, especially for the earlier studies.

1.2 Research gap and objectives

The main objective of this study is to explore the price discovery process in the cryptocurrency market and determine whether this means that the market is predictable. The objective of using the Kalman filter is to estimate asset prices (similar to the Capital Asset Pricing Model or the Fama-French models) of the cryptocurrency in question. Additionally, the present study explores whether the technical trading rules can generate returns greater than that of a simple buy and hold strategy, speaking to the weak form efficiency of the cryptocurrency market. The corresponding hypotheses from the above objectives are detailed in Chapter 3.

1.3 Contribution of the study

The present study examines an alternative asset class, cryptocurrencies, and provides a unique perspective into the price discovery process of the cryptocurrency market, through the use of both the Kalman filter and technical trading rules. This study will thus contribute towards the research that focusses on the price discovery process, technical analysis and weak form of market efficiency.

The cryptocurrency market is still fairly immature and there is a lack of information around the cryptocurrency universe (Bouri, Shahzad, & Roubaud 2019). This makes it difficult to determine the value of cryptocurrencies. Unlike traditional asset classes, where financial statements or fundamental factors are used to determine the value of said assets, the cryptocurrency market lacks these underlying precepts. This essentially means that the value of cryptocurrencies is not determined using the fundamental approach, but rather that the price of the cryptocurrency has a much larger weighting of importance. Consequently, the price of a cryptocurrency provides the only information needed to base decisions on whether to buy or sell a cryptocurrency. This highlights the importance of the price discovery process within the cryptocurrency market and motivates the objective of this study.

There is wide coverage of technical analysis and the use of technical trading rules, but this study goes further, by looking at the conceptual link between the price discovery process and technical analysis, which much of the literature fail to consider. In exploring the price discovery process the Kalman filter is utilised, in identifying the efficient price level. Five technical trading rules are examined, resulting in the outcome of buy and sell signals generated from each of these trading rules. The efficient price level, recommended by the Kalman filter, is compared to cryptocurrency prices and then compared to the overbought and oversold levels generated by the technical trading rules. This comparison has implications on the price discovery process in the cryptocurrency market. Additionally, this study examines the weak form of the EMH by comparing the buy and sell signals to the passive buy and hold benchmarks (the CCI30 and an artificially constructed market index).

Existing literature on cryptocurrencies is relatively new, but constantly growing. Giudici and Polinesi (2019), state that understanding price interconnectedness is important to describe relationships between different asset classes, and to understand whether prices in different markets quickly react to each other (whether markets are efficient or not). Brandvold, Molnár, Vagstad, and Valstad (2015) were the first to study the price discovery process in Bitcoin, by means of econometric methodologies of Hasbrouck (1995) and Gonzalo and Granger (1995). While more literature has been since published on the price discovery process in the cryptocurrency market, the literature is still in its infancy. Additionally, much of the literature looks at the price discovery process across different exchanges. There remains a gap in the literature addressing the price discovery process and technical analysis in cryptocurrencies, and the implications of these two spheres in the cryptocurrency market.

Despite the body of research on technical analysis and its implications on weak form market efficiency, including Fama and Blume (1966), Jensen and Benington (1970), Sweeney (1988), Ratner and Leal (1999), Metghalchi, Chang and, Marcucci (2008), Bajgrowicz and Scaillet (2012), Wang, An, Liu, and Huang (2016) and Jiang, Tong, and Song (2019) to name a few, there remains a gap in the literature addressing the use of technical analysis and its implications on weak form market efficiency in alternative asset classes, such as cryptocurrencies. A unique contribution of this study is to look at the combination of price discovery and technical analysis in the cryptocurrency market. Lastly, this study contributes to the limited amount of literature looking at the combination of the price discovery process and technical analysis.

The present study thus aims to add to the body of literature by addressing the price discovery process and technical analysis, specifically in the cryptocurrency market, by analysing the top 30 cryptocurrencies as of *30 September 2020*. Additionally, this study aims to add to the literature by examining the profitability of technical analysis in relation to a simple buy and hold strategy. Although the focus of this study is on the learning ability of investors (through the Kalman filter) and technical analysis, it could open further avenues for research which could include using other types of state space models and technical trading indicators in other asset classes. However, the results of this study can provide insights into the price discovery process, technical analysis and weak form efficiency in the cryptocurrency market. Lastly, the unique approach of this study provides an alternative view into the topics at hand.

The potential benefits of this research are to academics, investment professionals and the ordinary investor. This research presents an opportunity to better understand the potential application of technical analysis and the price discovery process within the cryptocurrency market. Through the application of state space modelling and technical analysis, the weak form of the EMH is also explored in the cryptocurrency market. Accordingly, this study will clarify whether there is value to technical analysis and what implications this has for weak form efficiency in the cryptocurrency market. Additionally, this study assesses whether the price discovery process and technical trading signals derived from popular technical trading rules are related to dimensions of market quality, and efficient price levels. Despite technical analysis' widespread historical and current use, it remains something of a black sheep in academic literature. However, technical analysis continues to be popular among investors and remains present in academic literature.

The present study provides a unique approach in exploring the price discovery process. The Kalman filter together with technical analysis provides a distinctive methodology in exploring the price discovery process in the cryptocurrency market. Technical analysis may not have a fit within academic literature, but it cannot be ignored as it is a common tool used in many markets. This study's results will shed light on the price discovery process in the cryptocurrency market as well as the weak form efficiency of the cryptocurrency market.

1.4 Structure of the study

The remainder of this research is structured in five chapters and will proceed as follows: Chapter 2 reviews the literature on the price discovery process, the EMH, technical analysis, cryptocurrencies and the Kalman filter. Chapter 3 describes the data, variables, hypotheses and methodology of the Kalman filter and the technical trading rules. Chapter 4 shows the empirical results around the Kalman filter and the use of technical trading rules in the cryptocurrency market. Finally, the concluding remarks are presented in Chapter 5.

2 Literature review

The below literature review first explores the literature around the determination of an asset's price through the price discovery process. Next the literature around the Efficient Market Hypothesis is surveyed. This involves exploring the inherent conflict between the weak form market efficiency and technical analysis and the opposing ideas behind these two spheres. Literature on technical analysis, including the failures and success of technical analysis over the years, are then explored. This includes how some technical trading rules have been able to beat the buy and hold strategy in some markets, while in other markets the profitability of technical analysis is found to be illusionary, thus supporting the Efficient Market Hypothesis. Finally, literature surrounding the distinctive cryptocurrency universe is explored before ending the literature review by exploring the Kalman filter and its use within finance.

2.1. The price discovery process

The price discovery process refers to the process of determining the price of an asset through the interactions of buyers and sellers (Kambeu, Mpofu & Muchochoma, 2017). In other words, price discovery is the means through which an asset's price is set by matching buyers and sellers according to a price that both sides are willing to accept Kambeu, Mpofu and Muchochoma (2017) refer to the price discovery process as the determination of prices, while Schreiber and Schwartz (1986) describe price discovery as the search for an equilibrium price. Since price discovery involves the incorporation of information into price, Baillie, Booth, Tse and Zabotina (2002) define the price discovery process as the incorporation of the information implicit in investor trading into market prices. The aspect of incorporating new information implies that price discovery is a process that is dynamic in nature and relies on a dynamic information flow process that eventually triggers price movements (Kambeu, *et al.,*2017). Price discovery involves market structure, liquidity and information flow. The present study specifically focuses on information flow.

Gusev, Kroujiline, Govorkov, Sharov, Ushanov and Zhilyaev (2015) state that the price of shares generally change when investors buy or sell securities. An investor's decision to buy or sell securities is based on the information they hold regarding a certain share. Thus, when investors receive meaningful information about a particular share they act according to this information and trade to alter their trading positions, which results in a change of price.

Therefore, the arrival of new information affects investors' beliefs about a particular security thereby causing a change in the price.

Yoon (2013) notes that the price of a security is determined when there is a balance between demand and supply for that security (equilibrium price). This implies that the fundamental principles of demand and supply determine the price in financial markets (Hanousek & Kočenda, 2009). When the market shifts away from the equilibrium price, a market mechanism will ensure that the price reverts back to an equilibrium. In accordance with the EMH, prices of securities fully reflect available information. This suggests that the last price of a security contains all relevant information (Fama, 1970). This implies that the price of a share changes when new information about the security is revealed. Zhang and Jaffy (2015) state that it is thus plausible to assume that the current market price, which is based on all past information, represents an equilibrium relationship between buyers and sellers. In other words, the current equilibrium should fully reflect all available information. Once new information flows into the market, the old equilibrium price adjusts and moves to a new equilibrium price (Zhang & Jaffy, 2015).

Technical analysis predicts the future price based on historical trading information, which is inconsistent with the weak form of EMH (Fama, 1970). As already stated, the adjustment of the equilibrium price to a new equilibrium is a result of the security's discovery process. If some technical analysis signals suggest rising prices and a large amount of people trade on this signal, prices will eventually rise due to excess demand (Fritz & Weinhardt, 2016). On the other hand, market participants could identify price movements which do not reflect price relevant information, for example caused by uninformed traders, and trade in the opposite direction which upholds efficient prices. Fritz and Weinhardt (2016) thus state that technical analysis has an influence on trading with respect to liquidity, supply and demand and price efficiency. Technical analysis thus has the ability to affect the equilibrium price, and thus the price discovery process, as well as the efficiency of markets. Important to note is that the present study considers the equilibrium price as being the efficient price level. More specifically, the efficient price level reflects the equilibrium relationship between buyers and sellers.

2.2. The Efficient Market Hypothesis and technical analysis

The (EMH) has paved the way for how financial markets should operate and has been substantially applied to theoretical models and empirical studies. This has resulted in a vast amount of literature on the efficiency of markets and the price discovery process. The EMH is based on the notion of random walk theory which states if the flow of information is free flowing and immediately reflected in share prices, then tomorrow's price change will reflect only tomorrow's news and will be independent of the price changes today (Darolles, Gourieroux, & Le Fol, 2000).

The origins of the EMH and its first formation can be independently traced back to two individuals, specifically Samuelson (1965) and Fama (1965). Samuelson (1965) provided evidence that correctly anticipated prices fluctuate randomly and Fama (1965) defined and introduced the EMH, which can be encapsulated as prices fully reflecting all available information. Fama (1965)'s data consisted of daily prices for each of the thirty stocks of the Dow-Jones Industrial Average, and the sample period covered included 1957 to 1962. Fama (1965) looked to explore the random walk model in more detail and test the model's empirical validity. Two basic assumptions were made when testing the random walk model, (1) successive price changes are independent, and (2) the price changes conform to some probability distribution. The main finding was in strong support of the random walk model, implying that chart reading (formally known as technical analysis today) is of no real value to the share market investor. In summary, the random walk theory contends that share price changes have the same distribution and are independent of each other, implying that past movement cannot be used to predict its future movement (Fama, 1965). However, the weak form market efficiency implies that one is unable to beat the market as share prices incorporate and reflect all relevant information available.

Fama (1965) described an efficient market as one in which all price changes are completely random and unpredictable, and fully reflect all available information. Therefore, an efficient market can be described as a market where share prices are random and unpredictable and where price changes follow no patterns and have no predictable nature. However, Fama (1965) importantly argues that the EMH is applicable in a rationalised and idealised world of frictionless markets, costless trading by all market participants and the absence of informational exclusivity among investors. However, a frictionless market in which all information is freely available and investors agree on its implications is, of course, not descriptive of markets in practice.

In contrast to the EMH assumptions, Fisal (2017) acknowledges the traditional assumptions around technical analysis. Firstly, the current share price and the trade frequency of a particular share encompasses all available information about the security. This therefore represents the fundamental value of the security. Secondly, price movements can be charted in order to identify trends or make future price predictions. This allows an investor to identify short term and long term trends allowing them to make better or more accurate future price predictions. The final assumption of technical analysis is that history repeats itself. This assumption is made with regards to human behaviour. This implies that traders will behave in the same manner to similar conditions that occurred in the past and are currently repeated (Fisal, 2017). The impact of this behaviour is assumed to be reflected in the share price's behaviour, resulting in the expectation that past price behaviour follows the same behaviour pattern in the future. Fisal (2017) thus acknowledges the implication of this final assumption being that investors can use the understanding of how past traders reacted to profit when those conditions arise again.

A seminal publication around the EMH is that of Cowles (1933) who investigated the forecasting ability of professional investors within the United States. He aimed to analyse investment professionals' performance through their ability to predict future prices or their ability to select shares that dominated over others. He concluded that the ability of stock markets to forecast accurately was imperfect. More specifically, the ability of the market to predict into the future was minimal. The findings of this study gave rise to discussions around determining whether share prices change in a random manner.

The EMH is used to characterise a price series where all subsequent price changes represent random departures from previous prices. Kendall (1953) examined the properties of returns by examining 22 price-series (ranging from 486 terms ay weekly intervals to 2387 terms at weekly intervals) and concluded that the pattern of events in price series is less structured than was originally assumed. More specifically, price changes follow a random walk and are thus independent and it is near impossible to reliably predict share prices (which in their case was one week ahead) without additional information. Overall, Kendall (1953) argued that share price fluctuations are independent of each other and have the same probability distribution. Put simply, the random walk proposes that share prices have an unpredictable path.

Additionally, the random walk model supports the idea that the current price is not a reliable indicator for the future as the flow of information is unrestricted and is immediately reflected in share prices, making tomorrow's price change independent of the price changes today. Moreover, information in the form of news is unpredictable and thus price changes are unpredictable and random. Roberts (1959) demonstrated that an actual share price series is notably similar to that of a random walk model, and indicated that there is an equal possibility of acquiring a negative change to that of obtaining a positive change.

Van Horne and Parker (1967) state that the theory of random walks in the movement of share prices implies that share price fluctuations are independent over time and can be considered a random process. This further implies that the use of technical trading rules or charting procedures will not yield profits greater than a simple buy and hold strategy. Van Horne and Parker (1967) empirically test the random walk theory relative to certain decision rules based upon past share price movements on the New York Stock Exchange over the period 1960 to 1966. The results indicate an inability to profit from technical trading rules, even when transaction costs are ignored, supporting the idea that fluctuations in share prices essentially are random. Van Horne and Parker (1968) extend their previous study using an exponential weighted moving average. The authors once again conclude that it is not possible to realize a consistent profit by trading securities with the weighted moving average decision rules tested.

Under the EMH (weak form) investors are unable to outperform the market and thus cannot achieve higher returns as information is not exclusive but available to everyone. Additionally, new information cannot lead to abnormal profits, as it is directly available to markets and is easily reflected on share prices. The weak form EMH promotes the efficiency of the financial market concerning information. Fama (1970) describes an efficient market as being one "where large amounts of rational profit maximizers actively compete with each trying to predict future market values of individual securities and where important current information is almost freely available to all participants".

Fama (1970), distinguishes market efficiency into three different forms, specifically the weak form, semi-strong form and strong form of market efficiency. Weak form efficiency is where all past share prices are integrated into current share prices, meaning that these past share prices cannot be used for future predictions. The weak form of market efficiency form thus contends that technical analysis cannot be used by investors for future prediction and does not generate higher returns. The semi-strong form is where share prices reflect all public information. If a market is efficient in the weak form, then all relevant publicly available information will be reflected in the market price. The semi-strong form entails that the market reacts quickly to new information and this is assimilated into the price and thus reflected in the new price equilibrium. This asserts that investors cannot gain an upper hand by using publicly available information. Lastly, the strong form of market efficiency states that all information (public or private) is entirely accounted for in current share prices, preventing investors from gaining a competitive advantage.

Fama (1965) proposes that competition in an efficient market will result in the effects of new information on fundamental values to instantaneously be reflected in actual prices. This leaves no room for active managers as they are unable to generate performance by means of exploiting available information. Overall, under the EMH foundation, specifically the weak form, technical analysis cannot be employed for generating future abnormal returns over time. The traditional view is that the arrival of new information spreads swiftly and is quickly incorporated into the prices of securities, making technical analysis futile in helping investors earn above normal returns. Consequently, technical analysis, the study of trends and past share prices or graph representation analysis, should not produce extra profits for investors as past pricing is integrated in current prices (Gupta, Bedi, & Lakra, 2014).

However, the validity of the EMH, specifically the weak form, has been called into question as several studies have uncovered evidence that some technical trading rules have significant predictive ability (Levy 1967a, Lukac, Brorsen & Irwin 1988, Caginalp & Laurent, 1998, Neely, Rapach, Tu, & Zhou, 2014 and Fisal, 2017). The evidence from these studies generally indicate that some trading strategies based on exploiting apparent trends in historic share price data yield returns that are superior to a buy and hold strategy, even before transaction costs are taken into account. The overall dominance of the weak form EMH has been questioned as some investors believe that share prices are at least partially predictable. Behavioural and psychological principles have emerged which include elements of share price determination.

Essentially, the weak form EMH is an encumbrance for forecasters and thus technical analysts. Simply put, the speculative returns investors try and foresee are unforecastable. The logic is that if returns were forecastable, they would be used to generate unlimited profits. Timmermann and Granger (2004) state that the EMH is unique in the sense that investors' current and future predictions influence their current and future trades which in turn affect returns. There are likely to be short-lived gains to the users of new financial prediction methods but once these methods become more widely used, their information may get incorporated into prices and they will cease to be successful. This race for innovation coupled with the market's adoption of new methods is likely to give rise to many new generations of financial forecasting methods (Timmermann & Granger, 2004).

Despite the evidence that security prices follow random walks, and that security markets are at least weak form efficient, individuals and financial institutions spend much time and resources, attempting to predict future prices. There have been numerous studies that have found the ability of technical trading rules to generate superior returns to that of a simple buy and hold strategy, implying value in technical analysis (Levy 1967a, Lukac, Brorsen & Irwin 1988, Caginalp & Laurent, 1998, Neely, Rapach, Tu, & Zhou, 2014 and Fisal, 2017). However, many of these studies fail to consider data snooping biases or transaction costs, which greatly affect the validity of these studies and their claimed inconsistency with the EMH. Nonetheless, some studies still do not find any support for the weak form market efficiency even when transaction costs are considered, and even after making adjustments for data snooping. These studies certainly question the weak form and ideas surrounding the EMH. Contrastingly, as will be discussed below, there have been numerous studies that have used technical analysis and have failed to find any forecasting power, or significant profitability resulting from the use of technical analysis. These studies all support the weak form EMH, specifically the weak form, and brand technical analysis as being futile.

2.3 The success of technical analysis through time

Technical analysis involves looking at the history of past price patterns, trends or other evidence that is suggestive of future price movements. At the time, Neely (1997) acknowledged the increasing popularity of the use of technical analysis by financial practitioners to make investment decisions. Over the years technical analysis has become more commonly used, with more traders adopting technical analysis techniques, in aiding them in identifying favourable trades (Drake & Downs, 2003).

Drake and Downs (2003) describe a technical indicator as a mathematical calculation, using price or volume data, designed to “indicate” when a condition exists or when a condition has been met. Some indicators try and identify a trend direction, while others look at determining the speed at which the price is changing. However, the type of indicator is indifferent as they all try to determine the future price direction. Senanedsch (2012) stated that one should be careful when linking data and the type of technical trading strategy simulated.

The roots of basic forms of technical analysis can be traced back to the Japanese rice trading on the Dojima Rice Exchange in Osaka as early as the 1600s (Moss & Kintgen, 2009). Since then technical analysis has evolved into an extensive universe of technical trading rules. This evolution has been aided by the rapid growth of technology and machine learning which has accelerated the rate at which technical analysis has developed, as well as the probability of success of technical analysis. Computers have become more common and more powerful which has allowed analysts to combine fundamental economic data with price and volume data, producing new indicators. Additionally, the ordinary investor is able to utilise a diverse range of technical trading rules within their trading strategies.

The role of technical analysis and its predictive merit remains a controversial topic in academic literature. The majority of the early literature on technical analysis are in full support of the weak form EMH and regard technical analysis as being futile. Overall, these studies have concluded that technical analysis and the use of technical trading rules, is useless. However, since around the late 1980's there has been an increasing amount of evidence that has indicated strong support of simple forms of technical analysis. This evidence is presented in the influential work of Sweeney (1986), Lukac, Brorsen and Irwin (1988), and Brock, *et al.*, (1992). These articles led to academics further questioning the weak form EMH through the use of technical trading rules in attempting to beat the market, as opposed to random walk testing. Additionally, the more recent work of Neely, Rapach, Tu, and Zhou (2014), Wang, An, Liu, and Huang (2016), and Jiang, Tong, and Song (2019) also find support in favour of technical analysis. These studies have found evidence in favour of technical analysis indicating significant forecasting power and profitability of numerous technical trading rules in different markets around the word (Brock, *et al.*, 1992).

The investment of securities is a financial activity that is influenced by many factors such as politics, the economy, and the psychology of investors. With the rapid development of the financial markets, many professional traders use technical indicators to analyse the stock market. As a result, technical analysis has an extensive history of use by participants in various markets around the world. However, there are sharp opposing views of many practitioners and academics as they tend to be sceptical about technical analysis. However, in contrast to much of the earlier studies, recent empirical studies tend to be in favour of the value of technical trading rules. To begin, the pioneering work of Smidt (1965) surveys amateur traders in US commodity futures markets and finds that a significant amount of the respondents use charts in order to identify trends or patterns in prices.

Levy (1967a) and Levy (1967b) report the results of empirical tests of technical trading rules (the relative strength selection and portfolio upgrading rules purely based on past price series of common shares) using data from the New York Stock exchange from 1965, and find that some of the trading rules notably outperform the buy and hold strategy. By reason of this evidence Levy (1967a) conclude and refute the theory of random walks.

Jensen and Bennington (1970) replicate Levy's (1967a) trading rules on 29 independent samples of 200 securities each over successive 5-year time intervals in the period 1931 to 1965. The results are not in support of Levy (1967a) and Levy (1967b). After considering transaction costs the trading rules did not generate significantly superior returns to that of the simple buy and hold strategy. The results with respect to Levy's trading rules indicate that security prices on the New York Stock Exchange are exceptionally close to that predicted by efficient market theories. Finally, Levy's (1967a) conclusion that the theory of random walks has been refuted is not substantiated (Jensen & Benington, 1970).

Sweeney (1988) develop a test of statistical significance of filter rule profits and implements this test by re-examining some of the results of Fama and Blume (1966), who found no profits for the best trading rule after adjusting for transaction costs. The test involves selecting a subset of Fama and Blume's (1966) most promising stocks and then following these stocks from 1970 to 1982. The results indicate that for this sample, it appears that significant profits can be generated by investors with low but feasible transaction costs.

The seminal work, and one of the most comprehensive studies on technical trading rules is that of Brock, *et al*., (1992), who argue that the conclusion reached by earlier studies that found technical analysis to be useless might have been premature. Brock, *et al*., (1992) data include a collection of 90 years of daily data which is the Dow Jones Industrial Average from the first trading day in 1897 to the last trading day in 1986. They proceed to explore two of the simplest and most popular trading rules, specifically the moving average-oscillator and the trading-range break (resistance and support levels). The trading rule's used are evaluated by their ability to forecast future price changes. Overall, Brock, *et al.*, (1992) results provide strong support in favour of the technical trading and their predictive power. Nevertheless, the authors still affirm that transactions cost should still be thoroughly considered before such strategies can be put into action.

Caginalp and Laurent (1998) reveal for the first-time scientific tests that show statistical validity of any price pattern. They use two sets of data which include daily prices of all S&P500

stocks between 1992 and 1996 and perform a statistical test of the predictive capability of candlestick patterns. The out-of-sample tests indicate a profit of almost 1% during a two-day holding period. The non-parametric test makes use of three-day candlestick patterns and removes conditions on magnitude. The results indicate that traders are influenced by price behaviour.

The statistical validation of the various candlestick patterns used by Caginalp and Laurent (1998) implies that experience in observing the behaviour of prices has a different effect on the profitability of traders, which traditionally was thought to have no trading value since that information has already been incorporated into market prices. Therefore, the analysis of these trading patterns that offer basic clues to the structural mechanism of the market are of fundamental value, and could possibly result in profitability gains.

Ratner and Leal (1999) apply ten variable length moving average technical trading rules to ten emerging equity markets in Asia and Latin America from 1982 through to 1995. The effectiveness of these trading rules are examined in the following emerging markets; Argentina, Brazil, Chile, India, Korea, Malaysia, Mexico, the Philippines, Taiwan and Thailand. The authors then take into account transaction costs for each trading rule in each country and then compare this to a simple buy and hold strategy. These technical trading rules are only found to be profitable in the markets of Taiwan, Thailand, Mexico and the Philippines. Even though the results indicate that the trading rule profitability is limited to those 4 countries, the trading rules applied to practically all emerging markets in this study present forecasting ability.

Sullivan, Timmermann, and White (1999) reassess the results of Brock, *et al*., (1992) and find them to be robust, and in support of the profitability of some trading rules on the Dow Jones Industrial Average. The authors contend that it is possible that historically, the best trading rules were able to produce superior performance, but more recently this superior performance and profitable opportunities arising from these technical trading rules could have disappeared due to the markets becoming more efficient.

Kwon and Kish (2002) investigate the simple price moving average, the momentum, and the trading volume technical trading rules using the New York Stock Exchange value-weighted index over the period 1962 to 1996. In addition to the full sample period, three sub-periods (1/7/62-31/12/ 72), (1/1/73-31/12/84), and (1/1/85-31/12/96) are tested to determine if the value of the trading rules dissipate over time. The results indicate that the technical trading rules utilised have the potential to generate profitable opportunities over a buy and hold strategy. However, the authors also find that when the trading rules are applied to different samples, the results are in fact weaker, which could possibly imply that the market is getting efficient in information over the years because of technological improvements.

Wong, Manzur, and Chew (2003) use test statistics to test the performance of moving average and relative strength index trading rules using Singapore data for the period January 1974 to December 1994, a total of 21 years. The authors divide the full sample period into three sub-periods of seven years each and test each of the trading rules in each sample period, as well as the full sample. In general, the findings conclude that technical analysis can be useful in timing stock market entry and exit points. Moreover, applying the technical indicators can generate substantial profits on the Singapore Stock Exchange (SES). The authors note that many firms in the SES tend to generate excess profits by applying technical trading rules, resulting in may member firms of the SES have their own technical trading teams that rely heavily on technical analysis. However, Wong *et al.,* (2003) did not consider transaction costs in their analysis.

Fifield, Power, and Donald Sinclair (2005) examine the forecasting power of the filter rule and the moving average oscillator rule using index data for eleven European stock markets (Finland, France, Germany, Greece, Hungary, Ireland, Italy, Portugal, Spain, Turkey and the UK) over a 10-year period from January 1991 to December 2000. This study therefore analyses the predictive ability of technical trading rules and examines their implications for market efficiency. The findings reveal that the emerging markets studied in this paper are informationally inefficient, as they display some degree of predictability in their share returns, while the developed markets did not.

Menkhoff (2010) acknowledges that technical analysis is not an area that is well understood by financial market professionals and proceeds to conduct a survey in 2003/2004 on 692 fund managers in 5 countries (the US, Germany, Switzerland, Italy and Thailand) in which a large majority of these participants rely on technical analysis. Firstly, the author finds that technical analysis is decidedly important as an information class and a vast majority of fund managers use it to some extent. Secondly, technical analysis is used in preference as a complement to fundamental analysis. Lastly, within technical, psychological influences are an important pricing determinant in financial markets as technicians tend to believe that herding is beneficial and thus rely on trend-following behaviour. However, important to note is that technical analysis does not dominate the decision-making process of fund managers. Finally, the most significant result that is found is with technical analysis and the view that prices are heavily determined by psychological influences. As a result, technicians apply trend-following behaviour.

Neely, Rapach, Tu, and Zhou (2014) note the extensive of use of macroeconomic variables to forecast US equity risk premium and the limited attention paid to technical indicators, despite being widely employed by investors. The authors thus seek to fill this gap by utilising technical indicators to forecast the equity risk premium and compare their performance with that of macroeconomic variables. The data span from December 1950 to December 2011 for 14 well-known macroeconomic variables and 14 technical indicators, which include moving average, momentum and volume-based rules. The results reveal that the technical indicators have significant in-sample and out-of-sample forecasting power, on par or surpassing that of macroeconomic variables. Additionally, technical indicators and macroeconomic variables are able to identify different types of information, which assist in the prediction of the equity risk premium. More specifically, technical indicators are able to recognise the decline in the equity risk premium near business-cycle peaks. Lastly, the authors state that better equity premium forecasts are derived when information from both technical indicators and macroeconomic variables are used.

Fisal (2017) uses technical analysis to determine whether future price movements can be predicted to make profitable returns in the stock market. The results indicate that technical analysis does generally assist in the prediction of future price movements despite the false signals that can occur. However, the author points out that technical analysis in no way guarantees stock return, but rather aids investors in maximising returns or minimising losses by knowing when to enter or exit a stock position. This study involved using candlestick, chart patterns and a range of technical indicators, including support and resistance, moving averages, moving average convergence divergence, momentum and relative strength index to conclude whether a certain stock or market index is heading towards bullish or bearish territory.

Alhashel, Almudhaf, and Hansz (2018) examine a range of popular technical trading rules across nine major real estate markets in the Asia-Pacific region over the period 1995-2015 to explore the profitability of these rules. The results support the predictive power and profitability of trading rules in the markets of Indonesia, Malaysia, Taiwan, and Thailand but not in the markets of China, Hong Kong, Japan, the Philippines, and Singapore. The study's results are robust to the including of transaction costs, adjustments for risk, and data snooping. The results for the markets in which technical trading rules are beneficial, in its predictive power and profitability, indicate that buy and sell signals resulting in returns that are significantly different from those achieved by a buy and hold strategy can be generated, which contradicts the weak-from market efficiency.

Jiang, Tong, and Song (2019) analyse the profitability of a large number of technical trading rules in the Chinese stock market. The authors consider five of the most commonly used categories of technical, which include channel breakout, filter rules, moving average, oscillator rules and support resistance. The sample period included daily data on the Chinese aggregate stock exchange over the period 1997 to 2015. The results indicate that there are large profitability gains when using technical trading rules, measures by market timing ability or Sharpe ratio gain. Moreover, the results remain in support of the technical trading rules when tested in different sub periods as well as when transaction costs are considered.

The literature reviewed indicates that technical analysis is relevant and does have its place amongst finance literature. The weak form efficient market hypothesis has been rejected successfully by the profitability of trading rules with a variety of indicators in several relatively developed countries and different markets. However, as will be seen below, the amount of literature on technical analysis within the cryptocurrency market is limited and still in its infancy. The present study seeks to fill this gap by exploring technical analysis and the price discovery process within the cryptocurrency market.

2.4 Technical analysis failures

The wide application of technical analysis in financial markets over the decades has led to much debate around the value of technical analysis and where technical analysis fits within the theoretical framework of finance literature. Despite technical trading rules being widely used by practitioners in financial markets, their profitability still remains controversial. Thus, the use of technical analysis remains an inconclusive debate with its supporters fiercely arguing its prevalence and credibility within financial theory and in practice, while its adversaries continue to dismiss its feasibility. Despite this one cannot fail to notice the popular usage of various trading rules.

Despite the widespread acceptance and adoption of technical analysis by many practitioners, academics have traditionally treated technical analysis with disdain and disregard. It has been described by Malkiel (2005) as an “anathema to the academic world” due to its conflict with market efficiency, one of the central pillars of academic finance. After numerous years of debate, the profitability and implications of technical trading rules still remains puzzling. If markets are weakly efficient, rational investors should quickly arbitrage away the profits, implying that technical trading rules are of no value (Kuang, Schröder, & Wang, 2014). However, if technical trading rules cannot generate persistent profits, the vexing question as to why so many experienced and amateur traders continue to use technical trading rules still arises.

One of the best-known and most influential works on technical analysis is that of Fama and Blume (1966), where they intensively test Alexander's filter rules on daily closing prices of 30 individual securities in the Dow Jones Industrial Average from 1956 to 1962. The results indicate that across all 30 securities, only three small filter rules generated greater returns than those of the buy-and-hold strategy. Lastly, the authors conclude that the excess profits generated from the long transactions over the buy-and-hold strategy may be negative in practice if brokerage fees, operating expenses and clearing house fees are taken into account. Other studies (Van Horne and Parker, 1967, 1968; James, 1968; Jensen and Benington, 1970) on stock markets also show that trading rules based on moving average or relative strength indicators are not profitable.

Bessembinder and Chan (1998) re-examine Brock, *et al*., (1992) finding that technical analysis has forecasting power for US equity index returns and reveal that the forecasting ability documented by Brock, *et al*., (1992) is in part due to return measurement errors that originate from nonsynchronous trading. Hudson, Dempsey and Keasey (1996) try to determine whether Brock *et al*., (1992)'s findings, that simple trading rules (moving average rules and trading-range breakout rules) have predictive ability, are applicable on UK data using the Financial Times Industrial Ordinary Index from 1935 to 1994. The authors find that although the trading rules are significant, in the presence of trading costs, the rules are unlikely to make returns over and above a buy and hold strategy. Consequently, the authors argue that in contrast to Brock, *et al*., (1992)'s results that provide strong support for technical trading rule strategies, their findings are seen as supporting the weak form efficiency of financial markets.

Chang, Lima, and Tabak (2004) find evidence that emerging market indices' returns do not resemble a random walk. However, for developed country indices such as Japan and the US, the Random Walk Hypothesis cannot be dismissed. These findings suggest that there is a level of predictability in emerging market equity returns. Similarly, Chong, Ng, and Liew (2014) determine the performance of the MACD and the RSI trading rules in the stock markets of five other Organization for Economic Cooperation and Development (OECD) countries (non-us). The results indicate that the MACD and RSI trading rules are able to consistently generate superior abnormal returns in the Italian (Milan Comit General Index) and Canadian (S&P/TSX Composite Index) stock markets. The authors argue that this could be a result of the Italian stock market being less developed compared to other major OECD countries, making it relatively inefficient.

Neely and Weller (2003) examine the out-of-sample performance of intraday technical trading strategies and note that trading rules are able to recognise stable patterns in data. However when transaction costs and trading hours are considered, no evidence of excess returns are found. Neely and Weller (2003) thus conclude that their results are consistent with market efficiency. Similarly, Chen, Huang, and Lai (2009) find, for the eight Asian stock markets examined (Hong Kong, Indonesia, South Korea, Malaysia, Singapore, Taiwan, Thailand and Japan), strong support for the EMH, indicating that technical analysis is highly unlikely to generate superior profits in these Asian stock markets. Additionally, the authors conclude that data snooping, non-synchronous trading and transaction costs have a significant impact on the overall performance of technical analysis

Yen and Hsu (2010) investigated the profitability of 8061 technical trading rules in ten futures markets, which include five financial and five commodity underlying assets. The results suggest market efficiency in nine out of the ten future markets. The authors note that although the results tend to deny the profitability of the tested technical trading rules in the majority of the futures markets, it is not conclusive to the implication that technical analysis is completely futile in the futures market. Chen and Metghalchi (2012) confirm the validity of the weak form EMH in the Brazilian stock index (BOVESPA) over the period 1996 to 2011 by analysing the predictive power of various trading rules. The results indicate that all buy and sell differences generated by the trading rules are insignificant, and none of them are able to outperform the passive buy and old strategy, thus the results strongly support the weak form of market efficiency for the Brazilian stock market in the long period.

Shynkevich (2012) examine technical trading rules in a set of technology industry and small cap sector portfolios over the period 1995 to 2010 and find that for the first half of the sample period the trading rules are able to generate significant predictability even when transaction costs are assumed to be of small to moderate size. However, the results from the second half of the sample period indicate that technical analysis is unable to outperform the buy and hold strategy. Shynkevich (2012) argues that as a result of the more recent period being characterised by weaker shot-term predictability, elements of the equity market have become more efficient over time.

Zhu, Jiang, Li, and Zhou (2015) examine moving average and trading range break rules using the Shanghai Stock Exchange Composite Index (SHCI) from 1992 to 2013 and the Shenzhen Stock Exchange Component Index (SZCI) from 1991 to 2013. The authors find that the best trading rule outperforms the buy-and-hold strategy when transaction costs are not taken into consideration however, once transaction costs are considered, trading profits are eliminated completely. The conclusion that moving average and trading break rules cannot outperform the standard buy and hold strategy for the Chinese stock exchange indexes is achieved.

2.5 Cryptocurrency

Hudson and Urquhart (2019) note that cryptocurrencies are a new type of financial instrument that have received a great amount of interest both from the media and investors in the recent past. The first cryptocurrency created was Bitcoin, proposed by Nakamoto (2008), as a peer-to-peer electronic cash system which allows online payments to be sent directly from one party to another without going through financial institutions. Since then, the academic literature around Bitcoin and other cryptocurrencies has continued to grow. However, the finance literature regarding Bitcoins and other cryptocurrencies is limited and in its infancy, since they are fairly new financial assets.

Despite the scepticism and lack of understanding of Bitcoin, Urquhart (2016) acknowledge all the attention that this cryptocurrency has received in the media by investors in recent years. Urquhart (2016) thus proceed to examine the market efficiency of Bitcoin, recognising the influential role that Fama's (1970) Efficient Market Hypothesis has played in finance. The data consist of the first aggregated Bitcoin price index that aggregates rate from all available Bitcoin exchanges around the world resulting in a volume weighted average Bitcoin price. The sample period covers August 2010 to July 2016.

The methodology employed involves employing a range of powerful tests for randomness in order to avoid spurious results and to capture all the dynamics of Bitcoin. These tests include examining autocorrelations via the Ljung-Box test, employing the runs test and Bartels test to determine whether returns are independent, the variance ratio test, the BDS test of Brock, *et al*., (1996), which is a common non-parametric test for serial dependence in share returns, and finally the rescaled Hurst exponent for long memory of share returns is employed. Urquhart's (2016) results show that the Bitcoin market is not weakly efficient over the full sample period, with this inefficiency being particularly strong. However, the results show that Bitcoin may be becoming more efficient (evident by some tests for market efficiency of Bitcoin returns being random) and the author argues that Bitcoin may become more efficient over time as more analysis and trading of Bitcoin occurs.

Nadarajah and Chu (2017) extend Urquhart's (2016) analysis and show that a simple power transformation of Bitcoin returns and the use of eight different tests do in fact yield results that indicate market efficiency in Bitcoin returns. The data included in their study is as that used in Urquhart (2016)

Detzel, Liu, Strauss, Zhou, and Zhu (2018) examine the predictability of Bitcoin returns. The sample period covered includes July 2010 to June 2018. The results find that while Bitcoin returns may be unpredictable by macroeconomic variables, they are in fact predictable by 1 to 20 week moving averages of daily prices, both in and out of sample. The results show that trading strategies based on moving averages generate substantial alpha, utility and Sharpe ratio gains, and significantly reduce the severity of drawdowns relative to a buy and hold position in Bitcoin. Overall, these results indicate that technical analysis is beneficial in Bitcoin and does indeed have advantages.

Hudson and Urquhart (2019) carry out a comprehensive analysis of technical trading rules in cryptocurrency markets. The analysis includes daily data from four different cryptocurrencies, the most liquid and profitable cryptocurrencies, (Bitcoin, Litecoin, Ethereum and Ripple) with the data ranging from around July 2010 to December 2017. Similar to Hsu, Taylor, and Wang (2016), Hudson and Urquhart (2019) study five classes of technical trading rules that are commonly used by traders and examined in the literature. The rules include moving averages, filter rules, support-resistance rules, oscillator trading rules and channel breakout rules. The results show that technical trading rules have significant predictive power in cryptocurrencies. However Bitcoin does not offer any predictability in the out of sample period. Hudson and Urquhart (2019) paper fits into the literature supporting the application of technical trading rules, specifically in the cryptocurrency market, suggesting that technical trading rules are profitable within these financial markets.

Corbet, Eraslan, Lucey, and Sensoy (2019) develop the work of Brock, *et al.*, (1992) by testing whether two of the most popular technical trading rules (the moving average and the trading range break) hold for the Bitcoin market using high-frequency data. The data consist of dollar denominated Bitcoin closing prices at one minute intervals over the period January 2014 through to June 2018. Overall the results are in strong support of moving average strategies. Important to note is that the authors failed to consider transaction costs and how this would affect the performance of the moving average trading rule.

Giudici and Polinesi (2019) explore the dynamics of cryptocurrency asset prices. More specifically how price information is channelled among different Bitcoin market exchanges, and between Bitcoin markets and traditional ones. The data sample consist of daily data from May 2016 through to April 2018. The methodology employed involves clustering Bitcoin prices from different exchanges. This is achieved by enriching the correlation based minimum spanning tree method with a preliminary filtering method based on the random matrix approach. The main results conclude that Bitcoin price exchange are positively related with each other, with the largest exchanges driving the prices. Additionally, the results show that Bitcoin exchange prices are not affected by classic asset prices, but their volatilities are.

The more recent work of Grobys, Ahmed, and Sapkota (2020) employ simple moving average trading rules on daily data on the eleven most frequently traded cryptocurrencies, which at the time included including Ripple, Litecoin, Ethereum, Dogecoin, Peercoin, Bitcoins, Steller Lumen, Nxt, MaidSafeCoinand Namecoin and Bitcoin, during the period 2016 to 2018. The study finds that the simple moving strategy with a 20 day moving average can generate returns in excess of the average market return, suggesting that the cryptocurrency market is inefficient. In contrast to this finding Anghel (2020) investigate the relevance of machine learning and technical analysis in the cryptocurrency market and find that their trading performance is not different from the more traditional financial markets. Overall, the results imply that cryptocurrencies are more efficient than originally thought as statistically significant returns are rarely achieved.

Shynkevich (2020) explores the market efficiency of Bitcoin prices through the use of technical analysis. The results find that the use of technical trading rules in in Bitcoin prices yields significant return predictability. However, this return predictability is short lived as it disappears once the introduction of Bitcoin futures on the regulated derivatives exchanges in December 2017. The author concludes that that the predictability of Bitcoin prices documented in literature may be attributed to the market inefficiency in Bitcoin prices prior to the emergence of Bitcoin futures on the regulated derivatives exchanges, which had a significant impact on the market efficiency of Bitcoin.

2.6 The Kalman filter

The Kalman filter was first introduced by Kalman (1960), describing a recursive solution to the discrete linear filtering problem. Due to the rapid advancements in digital computing, the Kalman filter has been the subject of extensive research and application. Peeperkorn and Seetharam (2016) describe the Kalman filter as a set of mathematical equations that provide an efficient computational method to estimate the state of a process, in a way that minimises the mean of the squared error. The major strength of this model is that it can approximate investor learning in a complex environment, even when the precise nature of the modelled system is unknown (Welch and Bishop, 2004). Despite the increased use of the Kalman filter since its introduction in 1960, the application of a Kalman filter is still relatively new in an emerging market context. For example, Chen and Lai (2013) use a Kalman filter in predicting a volatility index and find that it produces superior results to that of a linear model.

Fritz and Weinhardt (2016) acknowledge the role technical analysis plays in the decision-making process of some investors. If technical analysis traders act as uninformed noise traders and generate a relevant amount of trading volume, market quality could be affected. The authors examine moving average trading signals and support and resistance levels with regards to market quality and price efficiency. In their analysis, Fritz and Weinhardt (2016) apply the state space methodology introduced by Menkveld, Koopman and, Lucas (2007) to obtain a decomposition of observed prices into an efficient price component and pricing errors (transitory component). The results indicate that pricing errors increase significantly in the direction of MA signals and the direction of active support or resistance levels, respectively.

Peeperkorn and Seetharam (2016) note that the use of the Kalman filter is still relatively new territory for South African financial research, with little published work on the methodology to date. The authors thus proceed and explore the application of the Kalman filter in South Africa utilising equities listed on the Johannesburg Stock Exchange (the data sample covers December 1996 to December 2012). More specifically, the authors examine the appropriateness of estimating a share’s beta via a learning algorithm, in order to contrast this method against the popular method of estimating beta. This is conducted in both a short run and long run context, to provide robustness to the results. Through application of state-space modelling, the authors thus re-explore the asset pricing model. The result is an asset pricing model which tracks the evolution of investor probability beliefs and learning through a Kalman filter. The results show that the behaviourally inspired model exhibits an improvement over a traditional asset pricing model. The pricing errors are reduced by as much as 41% over the 16-year period.

2.7 Summary of literature review

This extensive literature review highlights the success and failures of technical analysis through time. Most of the early literature on technical analysis are in full support of the weak form EMH and regard technical analysis as being futile. Overall, these studies have concluded that the use of technical trading rules is useless. However, as seen above, there has been numerous studies that have found evidence in favour of technical analysis. This not only highlights the success of technical analysis but also questions weak form efficiency. It is important to note that caution should be taken when assessing whether a study has found a market to be inefficient or not. Many factors could affect the trading rules used to prove the efficiency of a market. For example, the impact of transaction costs and data snooping have significant effects on the profitability of technical trading rules which in turn affects the overall results of whether a trading rule is able to truly produce returns in excess of a passive buy and hold strategy. Overall, technical analysis remains a black sheep in financial literature and amongst academics. For example, Lo, Mamaysky, and Wang (2000) state that the separation that exists between technical analysis and academic critics has created one of the greatest gulfs between academic finance and industry practice.

The literature reviewed also highlights the opportunity to further explore technical analysis and the price discovery process in the cryptocurrency market. The above reviewed literature supports the decision to explore the price discovery process in the cryptocurrency market, specifically through the use of the Kalman filter and technical analysis. This adds to the growing amount of literature around cryptocurrencies and technical analysis. The unique approach of exploring the price discovery process through the Kalman filter adds to the motivation of the present study and provides a distinctive angle to exploring the price discovery process in the cryptocurrency market. This essentially speaks to the learning ability of investors in the cryptocurrency market over time. The incorporation of technical trading rules adds to the existing debate around the value in technical analysis and the implications this has on the

Efficient Market Hypothesis with specific reference to the cryptocurrency market. Overall, the literature review highlights the validity of the present study and motivates exploring the price discovery process and technical analysis in the cryptocurrency market.

3. Data and Methodology

The overall objective of this study is to explore the price discovery process of cryptocurrencies using the Kalman filter and technical analysis. The Kalman filter is also used as a simple trading strategy based on an efficient price level reference point, which is compared to the more simple family of technical trading rules. Additionally, this study addresses the weak form of the EMH, by determining whether the buy and sell signals generated by the technical trading rules are able to generate returns greater than that of the "passive[1]" buy and hold benchmark.

The main idea in addressing the weak form of market efficiency is not necessarily to mark which trading rule performs better, but rather to examine if the trading rules are able to outperform the passive buy and hold benchmark on a consistent basis, that is over the full sample period and over the sub-periods, and with the inclusion of transaction costs. The remainder of Chapter 3 looks at the data used, the hypotheses testing followed by the methodology employed in terms of the price discovery process, the technical trading rules used and the performance metrics. Finally the robustness checks in the form of the data snooping, transaction costs and data frequency are explained.

3.1. Data

The data included in this study consist of the top 30 cryptocurrencies based on market capitalisation as of 25 November 2020. These cryptocurrencies are explored through the Kalman filter and technical analysis. Analysing the top 30 cryptocurrencies will provide a fair and accurate representation of the entire cryptocurrency market, as the top 30 cryptocurrencies capture a very high percentage of the cryptocurrency market capitalisation. Daily closing cryptocurrency prices of the top 30 cryptocurrencies were obtained from CoinLore and Yahoo! finance. All prices are denominated in US dollars. Market capitalisation data over the same time period was obtained from coinmarketcap.com. The data covers a 10-year sample period, from July 2010 to November 2020. The sample period was chosen based on the availability of data.

The top 30 cryptocurrencies represent the cryptocurrency market with a confidence level of 99% and a confidence interval of 1.11, indicating that the margin of error of the top 30

[1] Traditionally, a passive benchmark is considered to be the market index.

cryptocurrencies as an indicator of the market is 1.11% (Cryptocurrencies Index 30, 2020). The daily returns of the cryptocurrencies and the market index for the cryptocurrencies (the CCI30, as well as an artificially constructed market index) were calculated using continuous returns, and the returns were annualised for ease of interpretation.

The performance of the buy and sell signals were compared to the two passive buy and hold benchmarks, which are the CCi30 and an artificially constructed market cap index[2], which are discussed in more detail below. This CCi30 one of the oldest Crypto indexes and was launched on January 2015. The index reflects the top 30 cryptocurrencies adjusted by market capitalisation to get a broader representation of the market. However, the market cap is not computed randomly at any given moment but calculated by an exponentially weighted moving average of the market capitalization, which reduces the effects of the high volatility present in the cryptocurrency market (Cryptocurrencies Index 30, 2020). Additionally, the CCi30 is the most accurate tool for measuring the cryptocurrency market, and the blockchain sector in general. The CCi30 provides a useful instrument for investors, a benchmark for traders, as well as a replicable index for Exchange Traded Fund's (ETF's) of passive funds. The CCi30 is considered the industry standard benchmark for cryptocurrencies (Rivin & Scevola, 2018).

In addition to the CCi30, the present study includes another artificially constructed passive buy and hold market cap index. The reason for including this additional market index is due to the lack of data for the CCi30 for the entire sample period (2010 to 2020). Unfortunately, data for the CCi30 was only available from the start of 2015. Consequently, the present study creates a market index based on the individual cryptocurrencies that make up 80% or more of the market since the start of the sample period. This results in an "artificial" market index over the entire sample period. The performance of the strategies can thus be evaluated over the entire sample period using the artificial market index, as well as during the sub-sample (2015-2020), using the CCi30.

3.2 Hypothesis testing

The hypotheses explored in the present study are as follows:

H1: A Kalman filter can identify the permanent and transitory price of the cryptocurrency in question.

[2] This index is constructed due to the lack of data for the CCi30 for the entire sample period (2010 to 2020).

H1a: A Kalman filter cannot identify the permanent and transitory price of the cryptocurrency in question.

H2: The use of a Kalman filter as a cryptocurrency trading tool will generate statistically and economically greater returns than that of the technical trading rules, net of transaction costs.

H2a: The use of a Kalman filter as a cryptocurrency trading tool will not generate statistically and economically greater returns greater than that of the technical trading rules, net of transaction costs.

H3: The buy and sell signals from the technical trading rules generate statistically and economically greater returns in excess of the passive buy and hold benchmark (either the artificial market index or the CCI30), net of transaction costs.

H3a: The buy and sell signals from the technical trading rules do not generate statistically and economically greater returns in excess of the passive buy and hold benchmark (either the artificial market index or the CCI30), net of transaction costs.

3.3 Methodology

The methodology employed in the present study consists of three parts. The first includes the price discovery process through the use of the Kalman filter. The second part of the methodology generates buy and sell signals based on a family of five technical trading rules, which are discussed in more detail below. The third part of the methodology relates to the comparison between the outcomes of the first two steps. This involves analysing the price discovery process of the cryptocurrencies by determining whether the referenced efficient price level recommended by the Kalman filter can outperform the technical trading rules.

Additionally, the present study examines whether the technical trading rules are able to outperform the passive buy and hold benchmark. This comparison is based on returns as well as the risk adjusted performance of the technical trading rules. Tests of the trading rules will be conducted over the full sample period (2010 to 2020), as well as in two sub-periods (2010 to 2014 and 2015 to 2020). This approach is similar to Chong and Ng (2008) who address data snooping using this method. The performance of the technical trading rule strategies will be compared to the two passive buy and hold benchmarks (the CCi30 and the artificially constructed market index) as well as through the use of the Sharpe, Treynor, and Sortino measures. Lastly, the robustness checks are explored in the form of transaction costs, data snooping and reviewing the performance of the technical trading rules using a different frequency of data. Therefore, in order to beat the passive buy and hold benchmark, a technical trading rule strategy will have to generate returns above the benchmark, net of transaction costs. Furthermore, an additional frequency of data (weekly) will be included, and tests will be conducted for each strategy on both daily and weekly frequencies, so to analyse several time intervals.

One of the main drivers of volatility in the cryptocurrency market is the speculation of traders (Pagnotta & Buraschi, 2018). Consequently, it is not uncommon for traders to enter or exit trades of the same cryptocurrency more frequently in the cryptocurrency market. Therefore, the present study will implement a hold between signals strategy as opposed to a predefined holding period. More specifically, if a buy signal is generated from a particular trading rule on day 1 and a subsequent sell signal is generated on day 6, the trader will sell their position on day 6. Furthermore, if the next buy signal is generated 12 days after the sell signal the trader will then buy the particular cryptocurrency in question. Therefore, as opposed to having a 10 day holding period the present study will hold the particular cryptocurrency between buy and sell signals.

3.3.1 The Kalman filter and price discoery

Utilising the Kalman filter, part one of the methodology explores the price discovery process in the cryptocurrency market. The Kalman filter was used to generate an efficient price level. This efficient price level can be described as the equilibrium price, descriptive of the balance of demand and supply for the cryptocurrency in question. This efficient price level reflects the equilibrium relationship between buyers and sellers and reflects all the available information, and thus can be regarded as the efficient price. The Kalman filter effectively describes to the learning ability of investors (Fritz & Weinhardt, 2016). The filter applies a regression function that is expected to capture the behavioural profile of a typical investor that trades actively. Given that technical traders are uninformed noise traders, (Fritz and Weinhardt, 2016), this study looks at the effect of transitory and permanent price components when technical trading rule signals are generated.

The Kalman filter's efficient price level is essentially used as a reference point, representing the equilibrium price. This reference point is used to determine whether a particular cryptocurrency is overbought or oversold. If the Kalman filter's modelled price is higher than the actual price in the market, a buy opportunity is signalled, indicating that the specified cryptocurrency is oversold and trading below its perceived value. However, a sell signal is generated if the model price is lower than the actual price on the market, indicating that the cryptocurrency is overbought and selling for more than its perceived value. This simple trading strategy based on the Kalman filter and its ability to generate an efficient price level (or reference point) is then compared to the technical trading rule strategies, which include the Moving Average (MA), trading range breakout, Moving Average Convergence, Divergence (MACD), Relative Strength Index (RSI), and Bollinger Bands (BB). The returns of these six trading strategies are then compared to determine whether the Kalman Filter is able to outperform the other technical trading strategies.

The Kalman methodology utilised in this study is similar to that of Fritz and Weinhardt (2016). Menkveld, *et al.,* (2007) note that state space models through the Kalman filter are natural tools in modelling the efficient price as an unobservable state variable.

Foster (1996) states that the Kalman filter permits the regression parameters to progress through time according to a stochastic process, assumed to be a random walk on the premise that information arrives randomly. However, it should be noted that the Kalman filter assumes randomness, but the present study tests the weak form EMH and not the random walk hypothesis. The random walk theory contends that share price changes have the same distribution and are independent of each other, implying that past movement cannot be used to predict its future movement (Fama, 1965). However, the weak form market efficiency implies that one is unable to beat the market as share prices incorporate and reflect all relevant information available.

The general form of the Kalman filter consists of two parts expressed in state space form; (1) the measurement equation which describes how the data series under consideration is generated from the state variables, and (2) the transition equation which describes the evolution of these state variables. The intuition underlying the Kalman filter model can be explained with a simple regression model containing time-varying parameters:

$$Y_t = X_t\alpha_t + \varepsilon_t \quad (1)$$

Where Y_t is the $\boldsymbol{n}$ x $\mathbf{1}$ vector of endogenous variables, X_t is an $\boldsymbol{n}$ x $\boldsymbol{m}$ matrix of predetermined variables and ε_t is an $\boldsymbol{n}$ x $\mathbf{1}$ vector serially uncorrelated errors with zero mean and constant variance matrix, H_t. α_t represents the $\boldsymbol{m}$ x $\mathbf{1}$ vector of time-varying parameters. Equation 1 represents the measurement equation. The elements of α_t will not be observable, but they are generated by a first-order Markov process defined as:

$$\alpha_t = T_{\alpha_{t-1}} + u_t \quad (2)$$

Where T is a known $\boldsymbol{m}$ x $\boldsymbol{m}$ matrix and u_t is a vector of serially uncorrelated errors with zero mean and constant variance matrix, Q_t.

In conceptually addressing the volatility of the cryptocurrency market the Kalman filter takes into account both the observed values, which in this case is the actual price of the cryptocurrency in question, and the predicted values, which are those generated by the Kalman filter. The Kalman filter utilises the observed prices, which ensures that the filter does not disregard what is actually happening in the cryptocurrency market. The Kalman takes the weighted sum aggregation between the observed price and the predicted price. The Kalman filter will thus encompass all the volatility within the share price of the cryptocurrency in question and use this to generate a new estimate. This iterative process thus allows one to capture the volatility in the cryptocurrency market and the resulting price output generated from the Kalman filter will narrow down on the errors within each new estimate resulting in a final value. This final value represents the equilibrium price of the cryptocurrency in question. This follows the idea that the Kalman filter predicts information based on its current belief, then updates its belief with new information.

In exploring the price discovery process this study adopts a similar approach to that of Fritz and Weinhardt (2016), more specifically, a state space model (the Kalman filter) is applied. The previous Chapters highlighted evidence that trading with regards to technical analysis can affect supply and demand as well as informational efficiency, which arguably could be exploited by some technical trading rules. As a result, the Kalman filter effectively speaks to the learning ability of investors, which is linked to the price discovery process (Fritz & Weinhardt, 2016). Additionally, Peeperkorn and Seetharam (2016) incorporate state space modelling into an asset pricing model with the outcome being a model which tracks the evolution of investor probability beliefs and learning through a Kalman filter.

Similar to Fritz and Weinhardt (2016), the present study applies a state space model to analyse permanent and transitory price changes in relation to the technical analysis signals generated by the technical indicators. The present study expects price effects to be increasingly transitory around technical analysis signals. This expectation is based on the belief that technical analysis traders are uninformed noise traders who possibly trade on the same side as the market. As per an adopted approach of the state space model methodology, in a similar way to Menkveld *et al.,* (2007), Brogaard, Hendershott and, Riordan (2014) and Hendershott and Menkveld (2014), this study decomposes prices into transitory and permanent parts.

The basic state space model is defined as follows. The observed (log-) price, $p_{i,t}$, for cryptocurrency i at time t is modelled as:

$$p_{i,t} = m_{i,t} + s_{i,t} \quad (3)$$

Where $m_{i,t}$ is the unobservable efficient price and $s_{i,t}$ is the transitory price component (pricing error). The efficient price follows a random walk:

$$m_{i,t} = m_{i,t-1} + n_{i,t} \quad (4)$$

Where n is a normally distributed error term with zero- mean and variance σ_n^2. This study follows Brogaard, Hendershott and, Riordan (2014) and Hendershott and Menkveld (2014) and assumes an autoregressive process for the pricing error:

$$s_{i,t} = \emptyset s_{i,t} + \varepsilon_{i,t} \quad (5)$$

Where ε is a Gaussian error term independent of n with zero mean and variance σ_ε^2. The three model parameters $\emptyset, \sigma_n$ and σ_ε are estimated from daily (log-) price observations per day. The unobserved efficient price, which is part of the state vector in the State Space Model (SSM) notation, is obtained through the Kalman filter. To fit the model, this study optimises the diffuse likelihood function based on the Kalman filter output, where the initial conditions of the unknown variables are assumed to have infinite variance (Fritz & Weinhardt, 2016). The transitory error term variance parameter is restricted to 90% of the unconditional variance of $p_{i,t}$. The auto-correlation parameter $\emptyset$ is allowed to take values between -0.9 and +0.9 in order to avoid non-stationary boundary solutions.

The time series of prices for the cryptocurrency in question is regressed against the SSM trend, which denotes the state predictions one-step ahead of the actual series. The unconstrained time-invariant covariance estimates are set to a default value of 0.01. The present study utilises an unscented Kalman filter, where a number of "sigma" points, as opposed to one point, are used. This results in a high resolution belief and typically better results. The overall idea behind the unscented Kalman filter is to produce numerous sampling points (Sigma points) around the current state estimate based on its covariance. These points are then propagated through the nonlinear map to get more accurate estimation of the mean and covariance of the mapping results. The unobserved efficient price, which is part of the state vector in the state space model connotation, is obtained through the Kalman smoother, through the use of the Kalman filtering output in a backwards recursion. The smoothing output is used to determine all the components of the model (estimates are obtained for the efficient price and the pricing error).

Three additional tests will be conducted on the Kalman filters output. More specifically, the Jarque-Bera test, the Brock–Dechert–Scheinkman (BDS) test, and the Hurst exponent will be performed on the returns of the Kalman filter (the actual, permanent and transitory prices). These three tests are carried out on the 30 cryptocurrencies over the full sample period (2010 to 2020). The normality, linearity, and the chaos of each of the returns (the actual, permanent and transitory prices) are examined using the Jarque-Bera test, the BDS (Brock–Dechert–Scheinkman) test, and the Hurst exponent respectively. The Jarque-Bera test is a normality test that matches the skewness and kurtosis of the data to determine whether the returns match a normal distribution. The BDS test is a test for time based dependence in a series. This involves determining whether the returns fluctuated over the sample and has indirect implications of the structural break. Finally, the Hurst exponent determines whether the returns are chaotic (non-deterministic) or deterministic.

3.3.2. Technical trading rules

The second part of the methodology involves the use of a family of five technical trading rules, which include the Moving Average (MA), Trading Range Breakout, Moving Average Convergence, Divergence (MACD), Relative Strength Index (RSI), and Bollinger Bands (BB). These trading rules are used to generate signals in the form of buy and sell opportunities. These signals can then be compared to determine the overbought or oversold levels of the cryptocurrencies. Each technical trading rule is applied to all thirty cryptocurrencies, generating buy and sell signals for each cryptocurrency across the full sample period (2010 to 2020). Additionally, Cooper and Gulen (2006) suggest that a valid efficiency test cannot be carried out with a technical strategy that did not exist during the time period over which the data for the test are taken. All the technical trading rules used in this study thus cover the time period over which the data is tested.

Similar to Gerritsen, (2016) and Gerritsen, Bouri, Ramezanifar, and Roubaud (2020), this study utilises five trading rules which were all well-known prior to the start of the trading of cryptocurrency and can also limit the potential for data snooping bias according to Brock, *et al.,* (1992). Although there is an extensive universe of available technical trading rules, this study focuses on the most popular and commonly used technical trading rules in academic literature. These technical trading rules are also common in cryptocurrency markets and their common use is based upon their success in generating buy and sell signals that result in greater returns. Additionally, the popularity in using the present studies technical trading rules is that these technical trading rules perform well in different stock markets, exchange markets and even futures markets (Park & Irwin, 2007). A description of each of the technical trading rules utilised in this study are given below:

3.3.2.1 Moving Average

Moving Average (MA) rules are arguably one of the most popular trading rules applied in practice (Brock *et al.,* 1992). Gerritsen *et al.,* (2020) state that MA rules issue a buy (sell) signal when the actual price, or a relatively recent average price, is greater (below) a longer-term average of the share price. Following Gerritsen *et al.,* (2020), this paper uses the Simple Moving Average (SMA), defined as follows:

$$MA(A)_{t,n} = \frac{1}{n}\sum_{j=t-n+1}^{t} A \quad (7)$$

$$= (A_t + A_{t-1} + \cdots + A_{t-n+2} + A_{t-n+1)/n} \quad (8)$$

Equation 1 is the Simple *n*-day Moving Average for an asset (A) at time t, and A_t is the closing price of the asset at time t. Drake and Downs (2003) note that long term and short term Moving Averages can be constructed using an infinite number of combinations.

Similar to Brock, *et al.,* (1992) and Gerritsen *et al.,* (2020), this study uses the 1-day, 2-day and 5-day averages for the short-term and the 50-day, 150-day and 200-day averages for the long-term. These parameters are chosen based on their popularity and will be denoted as follows; 1-50, 1-150, 5-150, 1-200 and 2-200, where the first number is the short-term average (STA) and the second number in the long-term average (LTA). Since this study will be looking at cryptocurrencies such as Bitcoin, which are traded on all calendar days of the year, these rules will involve the returns for a period of approximately one-week, half a quarter, one-and-a-half quarters and half a year. For the purpose of defining trading rules, let *k* be the number of periods for STA and l the number of periods for LTA. The trading rule can thus be summarised as follows: Buy if $STA(A)_{t,k}$ crosses $LTA(A)_{t,k}$ from below, provided that $STA(A)_{t,k}$ >$LTA(A)_{t,k}$. A sell signal is generated if $LTA(A)_{t,k}$ crosses $STA(A)_{t,k}$ from above, provided that $STA(A)_{t,k}$ <$LTA(A)_{t,k}$.

3.3.2.2 Trading range breakout

The trading range breakout (support and resistance levels) indicator signals maximum and minimum prices for a security that has traded over the past n days. A breakout is thus a share moving outside a designated support or resistance level with increased volume. The trading range breakout indicator identifies both a support and resistance level of the assets price. These levels are defined as:

$$\text{Support (A)}_{\text{t}} = \text{MIN}(\text{A}_{\text{t}-1,}\ \text{A}_{\text{t}-2,\ldots,}\text{A}_{\text{t}-\text{n}-1)} \quad (9)$$

$$\text{Resistance (A)}_{\text{t}} = \text{MAX}(\text{A}_{\text{t}-1,}\ \text{A}_{\text{t}-2,\ldots,}\text{A}_{\text{t}-\text{n}-1)} \quad (10)$$

Following Brock *et al.,* (1992) and Gerritsen *et al.,* (2020), the present study applies 50, 150 and 200 days for n. For example, the 150-day resistance level for share *i* on day *t* is the maximum share price during the past 150 trading days. The implications of the trading range breakout rule is that if the share price increases above the resistance level, this will indicate a bullish signal and the opposite holds for the support level. The trading range breakout rule can thus be summarised as follows: Buy if A_t > $\text{Resistance (A)}_{\text{t}}$ and sell if A_t<$\text{Support (A)}_{\text{t}}$.

3.3.2.3 The Moving Average Convergence Divergence

The Moving Average Convergence Divergence (MACD) is formed using moving averages, more specifically it is calculated by subtracting the longer exponential moving average (EMA) from the shorter EMA. This study uses the conventional parameters, a 12-period EMA and a 26-period EMA, which are the most commonly used long and short-period EMAs (Murphy, 1999). Similar to Auret and Sayed (2020) the EMA is defined as:

$$EMA_{k,t} = K\left(P_t - EMA_{k,t-1}\right) + EMA_{k,t-1} \quad (11)$$

where $K = \frac{2}{k+1}$ for a chosen parameter k, with P_t acting as the closing price for a share on day t.

The MACD line represents the difference between a long-run EMA and a short-run EMA and is defined as follows:

$$MACD_{s,l,t} = EMA_{s,t} - EMA_{l,t} \text{ with } l > s \geq l \quad (12)$$

where s represents 12 days and l representing 26 days. The crossing of 0 of the MACD line can be interpreted as a change in momentum or the beginning of a new trend. However, Auret and Sayed (2020) state that one criticism of the MACD line is that it overweights recent price information. Consequently, a signal line is applied which is a 9-period EMA of the MACD line. Similar to Auret and Sayed (2020) this signal line is defined as:

$$Signal_{\,kt} = K\left(MACD_{s,l,t} - Signal_k t - 1\right) + Signal_{k,t-1} \quad (13)$$

A buy signal is generated when the MACD line crosses the signal line to the upside. This can be viewed as a bullish crossover as the trend is seen as taking momentum in the upward direction. In contrast, a sell (short) signal occurs when the MACD line crosses below the signal line, signifying a bearish crossover. However, it is important to note that the signal crossovers do not indicate the duration or amplitude of a trend. Therefore, a MACD histogram can be employed, which displays the difference between the MACD line and the signal line as a histogram, and is defined as:

$$HIST_{s,l,k,t} = MACD_{s,l,t} - Signal_{kt} \quad (14)$$

If the histogram is above the zero line, it indicates an upward trend, with strong bullish momentum, indicated by large positive values. On the contrary, if the histogram is below the zero line, it indicates a downward trend, with strong bearish momentum. Drake and Downs (2003) point out that the MACD histogram is an effective instrument when confirming short term trading opportunities. However, two criticisms of the MACD histogram is that it is at times unable to recognise extremes in trends and momentum, and is also flawed in identifying changes in trends and momentum with a delay. The buy/ sell signals can be summarised as Buy if $\mathrm{MACD(A)_t}$ > 0, or if MACD $\mathrm{SIGNAL(A)_t}$ > 0, or if MACD $\mathrm{HISTOGRAM(A)_t}$ > 0 and sell if $\mathrm{MACD(A)_t}$ < 0, or if MACD $\mathrm{SIGNAL(A)_t}$ < 0, or if MACD $\mathrm{HISTOGRAM(A)_t}$ < 0.

3.3.2.4 The Relative Strength Index

Relative Strength Index (RSI) compares the upward movement of price with the downward movement over a certain period. The RSI is a bounded counter-trend indicator that oscillates between 0 and 100. A share can be considered as fairly priced if its RSI is at the centreline 50. An RSI value above 50 is indicative of a bullish market, while a bearish market will have and RSI below 50. More specifically, an RSI value greater than 70 will indicate the overbought level, and less than 30 the oversold level. The 14-day RSI is used in this study as it is a popular length of time utilised by traders (Chong and Ng, 2008). The RSI is defined as:

$$RSI_{k,t} = 100 * \frac{G_{k,t}}{G_{k,t} + L_{k,t}} \quad (15)$$

where $G_{k,t}$ is the average gain and $L_{k,t}$ is the average loss at time t, by exponential smoothing over the last 14 days (*k=14*). Lastly, when RSI < 30 it signals that the market is oversold indicating that a buy trade can be placed, and when RSI > 70 it suggests that the market is overbought indicating that a sell trade can be placed.

3.3.2.5 The Bollinger Band method

The Bollinger Band method (BB) is a counter-trend indicator defined by a set of trend lines plotted two standard deviations away from a simple moving average of a security's price. According to Lento, Gradojevic, and Wright, (2007), the BB (20,2) is the traditional method, and is utilised in this study. This parameter refers to a 20-day moving average where the distance between the MA and the bands is twice the standard deviation of the assets price measured over the most recent 20-day period, $\sigma_{A,20}$. At time t the upper and lower bands can be defined respectively as:

$$BBUPPER(A)_t = MA(A)_{t,20} + 2\sigma_{A,20} \quad (16)$$

$$BBLOWER\ (A)_t = MA(A)_{t,20} - 2\sigma_{A,20} \quad (17)$$

One can interpret an actual share price exceeding one of the bands as the share price returning to the moving average. The BB method can thus be summarised as follows: Buy on condition that A < $BBLOWER\ (A)_t$, and sell on condition that A >$BBUPPER(A)_t$.

3.3.3 Performance metrics

The third part of the methodology involves analysing the performance of the technical trading rules and Kalman filter. More specifically, the risk-adjusted performance measures (discussed below) are used to evaluate the performance of the Kalman filter and whether the filter outperforms the technical trading rules. Additionally, the performance of the Kalman filter and the technical trading rules evaluated in terms of being able outperform the passive buy and hold benchmark. This involves analysing the returns generated by the buy and sell signals recommended by each of the technical trading rules by comparing them to the passive buy and hold benchmark (either the CCI30 or the artificial market cap index). This speaks to the weak form market efficiency of the cryptocurrency market.

The risk-adjusted measures utilised in the present study include the Sharpe ratio, Treynor ratio and Sortino ratio. This performance methodology is similar to Sullivan *et al*., (1999) and Metghalchi *et al*., (2008) who also evaluate certain technical trading rules under both mean returns and the Sharpe ratio criteria, however, this study utilises two additional measures, the Treynor and Sortino measures. The present study calculates the rolling Sharpe, Treynor and Sortino ratios as this provides insights on the time-varying performance of a strategy. A description of each measure is given below:

3.3.3.1 Sharpe ratio

The Sharpe ratio, also called the reward-to-variability ratio, was developed by Sharpe (1966) and measures the average excess return per unit risk. This ratio is thus the average return earned in excess of the risk-free rate per unit of total risk. The Sharpe ratio is calculated as follows:

$$S_p = \frac{R_p}{\sigma_p} \qquad (18)$$

Where R_p is the average is return of portfolio and σ_p is the standard deviation of the rate of return for portfolio$p$. A greater Sharpe ratio is usually interpreted as greater risk-adjusted performance.

3.3.3.2 Treynor ratio

The Treynor ratio, developed by Treynor (1965), is a portfolio performance measure incorporating a risk factor, more specifically, it is a performance metric for determining how much excess return is generated for each unit of risk taken on by a portfolio. This ratio consists of risk produced by the market as well as unique risk from a share or returns of assets in general. The Treynor ratio is known as the risk premium per unit of risk. The ratio is calculated as follows:

$$T_i = \frac{\overline{R_i}}{\beta_i} \qquad (19)$$

Where $\bar{R}_i$ is the average rate of is return for Portfolio i and β_i is the slope of the Portfolio's characteristic line.

3.3.3.3 Sortino ratio

Sortino and Price (1994) developed the Sortino ratio, a variation of the Sharpe ratio that differentiates harmful volatility from total overall volatility by using the asset's downside deviation as opposed to the total standard deviation of portfolio returns. The Sortino ratio differs from the Sharpe ratio is two fundamental ways; (1) it measures the excess returns of a portfolio's average return to a minimum threshold of acceptable returns selected by an investor and (2) this ratio captures the downside risk of a share or asset. Consequently, the Sortino ratio does not punish shares or assets for being volatile on the upside. A higher Sortino ratio can be interpreted as signalling superior performance. The Sortino ratio is calculated as follows:

$$ST_i = \frac{\bar{R}_i}{DR_i} \quad (20)$$

Where $\bar{R}_i$ is the average rate of return for Portfolio i and DR_i is the downside risk coefficient for Portfolio i. Downside risk refers to the volatility of returns below a specific hurdle rate of the investors choice. This study uses a hurdle rate of 0% performance, indicating that all negative returns will be considered as downside risk. As per Harlow (1991), in order to measure downside risk below a minimum threshold, the semi-standard deviation measure will be utilised:

$$Semi - Deviation = \sqrt{\frac{1}{n}\sum_{R<\bar{R}}(R_{it} - \bar{R}_i)^2} \qquad (21)$$

Where n is the number of portfolios returns that are negative, R_{it} is the return of portfolio i at time t and $\bar{R}_i$ is the average expected returns for portfolio i.

3.4 Robustness checks

The present study makes use of three robustness checks in the form of accounting for data snooping, transaction costs and testing the same trading rules using weekly data. The robustness measures are aimed at yielding more reliable results, adding to the validity of the present study. Each of the robustness checks are discussed in more detail below.

3.4.1 Data snooping

The potential impact of data snooping on the performance of technical trading rules has been recognised by Jensen and Benington (1970) who make mention of selection bias and explain that over time, one will surely be able to find a trading rule that is profitable on a set of random numbers, provided that the testing of the trading rule can be done on the same set of numbers which was used to discover the rule. Data snooping can thus arise from a survivorship bias functioning on the entire universe of technical trading rules that have been assessed historically.

Bajgrowicz and Scaillet (2012) note that data snooping is widely recognised as a significant issue in finance. In addition, Sullivan *et al.*, (1999) note that data snooping is an important issue that is often encountered, but seldom confronted when evaluating technical trading rules. Data snooping occurs when a given data set is used more than once for the purpose of inference or model selection. The concern when reusing data in this manner is that there is a possibility that any satisfactory or notable findings may be due to chance as opposed to the fundamental value of the method in yielding results.

In order to prevent a data snooping bias, Senanedsch (2012) proposes dividing the data sample into sub-periods. Splitting the data sample and testing the strategies in each sample prevents data snooping bias as it reduces the probability of any notable findings being due to chance. Testing the strategies over split sub-periods allows one to accurately determine whether the strategies are able to yield significant or satisfactory findings in each sub-period, as opposed to a single period which could result in a significant finding when there is none.

Therefore, in order to avoid data snooping bias, the full sample is split into two sub-samples and tests are conducted on the full sample as well as the two additional sub-samples. More specifically, the full sample (2010 to 2020) is divided into 2010 to 2014 and 2015 to 2020. Each technical trading rule is then examined in each period. This approach is similar to Kwon and Kish (2002), Wong, Manzur and Chew (2003), and Chong and Ng (2008). The two benchmarks used in the present study (the CCi30 and the artificial market index) will be examined in the different time periods according to the available data for the benchmarks. For example, the CCi30 only has data from 2015 onwards. More specifically, over the full sample (2010 to 2020) the artificial market index will be used, over the first sub period (2010 to 2014), the artificial market index will also be used, and over the last sub period (2015 to 2020) the CCi30 will be used and the artificial market index will be used.

3.4.2 Transaction costs

Shynkevich (2012) indicates that superior predictability should not immediately be regarded as evidence of abnormal profitability of technical analysis or a complete refuting of the weak EMH. Greater predictability does not necessarily indicate superior profitability as transaction costs can considerably impact the true value of predictability and profitability. It has been maintained that abnormal profits generated by technical trading rules in early studies are deceiving, as many of these studies failed to consider transaction costs (Shynkevich, 2012). For example, studies have pointed out that once transaction costs are considered, the abnormal profitability of trading rules seems to disappear (Fama and Blume, 1966; Bessembinder & Chan, 1998; Bajgrowicz & Scaillet, 2012). Transaction costs are an important input into the present study, and can therefore have a material impact on the conclusion reached.

Previous literature considers that the average transaction costs should be equal to 1% of the value of the transaction applied on a buy or sell signal (Levy, 1967a, 1967c; Marney, Tarbert & Fyfe, 2000). However, as recommended by Senanedsch (2012), and applied in this study, a rate of 0.25% is used. Using 0.25% is a more practical and realistic rate, as online brokers and institutional investors normally have access to a lower rate (Corrado & Lee, 1992; Neely & Weller, 2003). This rate is a general rate and not specific to cryptocurrencies.

Transaction costs for each strategy are thus calculated in order to evaluate the return of a strategy, as well as the return used as an input in the Sharpe, Treynor and Sortino ratios. This allows the evaluation of a trading strategy considering the market impact cost of trading. It is first necessary to generate the technical trading rules signal. These signals allow one to find the buying and selling price of the cryptocurrency in question. As per Senanedsch (2012), for each buy signal the strategy is debited with the purchase price plus transaction costs, and for each sell signal the strategy is credited with the sale price minus the transaction cost. The return is the result of the sum of these movements from all the signals under the specific technical trading rule strategy. Transaction costs are set to equal 0.25% of the value of the transaction applied on a buy and sell opportunity.

3.4.3 Data frequency

Initially, the methodology employed utilises daily data of the top 30 cryptocurrencies. However, in order to account for robustness, this study employs the same methodology on a different frequency of data, weekly data. Therefore, each strategy is tested using different parameters and on daily and weekly data.

The overall objective of this study is to explore the price discovery process of cryptocurrencies using the Kalman filter and technical analysis. The above methodology highlights the process the present study goes through in order to achieve this objective. In exploring the price discovery process the Kalman filter is passed through all 30 cryptocurrencies generating the efficient price level (a permanent and transitory price) of each cryptocurrency. This efficient price level can be regarded as the equilibrium price of the cryptocurrency in question. A simple strategy is formed using the efficient price level as a reference point and generating buy and sell opportunities. Similarly, a family of five technical trading rules (the Moving Average, Moving Average Convergence Divergence, Rate of Change, Relative Strength Index and Bollinger Bands) are used to generate buy and sell signals on the same set of cryptocurrencies. The returns of the Kalman filter 'strategy' and the technical trading strategies are then compared.

The present study utilizes risk-adjusted performance measures, which include the Sharpe, Tryenor and Sortino ratios. In an additional analysis the technical trading rules are examined in terms of their ability to generate returns in excess of the passive buy and hold benchmark. The CCI30 and an artificially constructed market cap index are used as the passive buy and hold benchmarks. This analysis speaks to the weak form market efficiency of the cryptocurrency market. Finally, three robustness checks are include in the present study. These include accounting for data snooping by testing the technical trading rules in the full sample and across two sub samples, accounting for transaction costs and re-examining the technical trading rules using both daily and weekly frequencies of data.

4. Results

In this Chapter the findings of the present study are discussed. Firstly, the price discovery process is explored in the cryptocurrency market by analysing the performance of the Kalman filter. This involves analysing the Kalman filter's output in the form of the permanent price (the efficient/equilibrium price) and the transitory price (which is the pricing error). The Kalman filter is then used as a trading strategy to generate buy and sell opportunities based on using the efficient/equilibrium price as a reference point. The performance of the Kalman filter is then analysed in terms of its ability to generate return in excess of the technical trading strategies, as well as on a risk-adjusted basis (using the Sharpe, Treynor and Sortino ratios).

Next the performance of the technical trading rules are examined. This includes analysing each of the technical trading rules in the full sample period as well as in the two sub-periods. Additionally, the performance of the technical trading rules is examined both before and after transaction costs are considered. The ability of the technical trading rules to generate returns in excess of the passive buy and hold benchmark is examined using traditional test statistics and risk-adjusted measures (Sharpe, Treynor and Sortino ratios). Finally, the same technical trading rules are examined after converting the daily data into weekly data.

4.1 Performance of the Kalman filter

In this Chapter the results around the price discovery process are examined. More specifically, the output from the Kalman filter is first explored. This involves exploring the permanent and transitory prices generated from the Kalman filter across all 30 cryptocurrencies. Additionally, the present study examines the Kalman filter output through three additional tests which include the BDS test, the Jarque-Bera test and the Hurst exponent. The Kalman filters performance against the family of five technical trading rules, and the passive buy and hold benchmark, is then examined in the second part of this Chapter.

4.1.1 The Kalman filter and the Cryptocurrency market

The Kalman filter is used to generate the efficient price level for each of the 30 cryptocurrencies in the full sample period 2010 to 2020. This efficient price level is assumed to be the recommended efficient price of the particular cryptocurrency in question. This means that the recommended Kalman price follows a random walk and contains all relevant past information. The Kalman filter is passed through all 30 cryptocurrencies in the full sample period (2010 to

2020) and the output in terms of the permanent price (efficient recommended price) and the transitory price (pricing error) is achieved.

Figure 1 below displays the actual Bitcoin price plotted against the Kalman price from 2016 to 2020. Bitcoin, being the leader in the cryptocurrency market, provides unique perspective into the volatile nature of cryptocurrencies. The plot captures Bitcoin's extreme spikes throughout the sample. One is able to see Bitcoin's historic price jump in 2017 and then crash in 2018. The efficient Kalman price is also seen in Figure 1 below. The Kalman price closely follows the actual price of Bitcoin, sometimes exceeding the actual price and at other times being slightly below the actual price. What is noticeable is that the Kalman price does not exceed the actual price by any significant amount nor fall below the actual price by a large margin.

Figure 1: Kalman vs actual price (Bitcoin)

Figure 1 displays the Actual price and the Kalman filter's efficient price of Bitcoin from 2016 to 2020.

Overall, the permanent (efficient price) is very close to the actual price throughout a large majority of the 30 cryptocurrencies. However Table 1 displays that *Bitcoin, Wrapped. Bitcoin* and *yearnfinance* had the greatest pricing errors. This means that Bitcoin, Wrapped Bitcoin and yearn finance have the greatest discrepancy between the actual price and the Kalman filter's efficient price. A possible reason for the deviation from the Kalman filter's efficient price could be the 'hype' around these cryptocurrencies, especially around *Bitcoin*. Arguably, the hype around *Bitcoin* could possibly cause its price to deviate as large amounts of traders could buy or sell *Bitcoin* at a specific time. Additionally, *yearnfinance* listed fairly recently, on the 30th September 2020, and this could be causing its actual price to differ from the Kalman filter's efficient price.

Table 1: The Kalman filter output

Table 1: The Kalman Filter output				
Cryptocurrency		Actual Price	Permanent price	Transitory price
1	BCH	267.556	265.626	1.930
2	BTC	13737.109	13668.678	68.432
3	ETH	396.358	392.410	3.949
4	XRP	0.240	0.240	-0.001
5	LINK	10.798	11.029	-0.232
6	LTC	53.817	54.039	-0.221
7	CARDANO	0.092	0.094	-0.002
8	BINANCE.COIN	27.884	28.137	-0.253
9	POLKADOT	4.030	4.095	-0.065
10	BSV	158.672	160.990	-2.318
11	EOS	2.431	2.465	-0.034
12	MONERO	118.734	121.511	-2.776
13	TRON	0.0244	0.0249	-0.0005
14	Wrapped.Bitcoin	13606.960	13673.216	-66.256
15	Crypto.com.coin	0.081	0.082	-0.002
16	Steller	0.076	0.077	-0.001
17	Tezos	1.897	1.926	-0.030
18	UNUS.SED.LEO	1.280	1.276	0.004
19	NEO	15.220	15.094	0.125
20	Cosmos	4.610	4.644	-0.034
21	NEM	0.100	0.099	0.001
22	Huobi.Token	4.150	4.170	-0.020
23	MIOTA	0.246	0.249	-0.003
24	Ve.Chain	0.01007	0.01016	-0.0001
25	DASH	65.124	66.582	-1.458
26	Theta	0.589	0.597	-0.008
27	Zcash	55.062	56.196	-1.135
28	Aave	0.517	0.518	-0.001
29	Ethereum.Classic	4.957	5.063	-0.106
30	yearnfinance	10074.160	10308.620	-234.460

Table 1 displays the results of the Kalman filter when it is passed through each of the 30 cryptocurrencies in the full sample period (2010 to 2020). The actual price refers to the most recent price within the sample period of the cryptocurrency in question. The permanent price refers to the unobserved efficient price recommended by the Kalman filter for each cryptocurrency. The transitory price is the pricing error for the particular cryptocurrency *in question. The permanent and transitory price values are at the same date stamp as the actual price (2nd November 2020).*

The results from Table 1 therefore show that a Kalman filter can identify the permanent and transitory price of the cryptocurrency in question. In summary, the Kalman filter was able to generate the permanent (efficient price) and the transitory price (pricing error) for the cryptocurrencies in the 2010 to 2020 sample period. However, the question now arises as to how "well" the Kalman filter was able to identify the permanent and transitory pricing errors.

Figure 2 below confirms the above findings. We are able to see that the actual cryptocurrency price and the Kalman filter's generated "efficient" price are similar. Figure 2 below shows that there is no large difference between the actual price or the Kalman filter's efficient price of the cryptocurrency in question.

Figure 2: Actual price vs the Kalman price for 11 cryptocurrencies

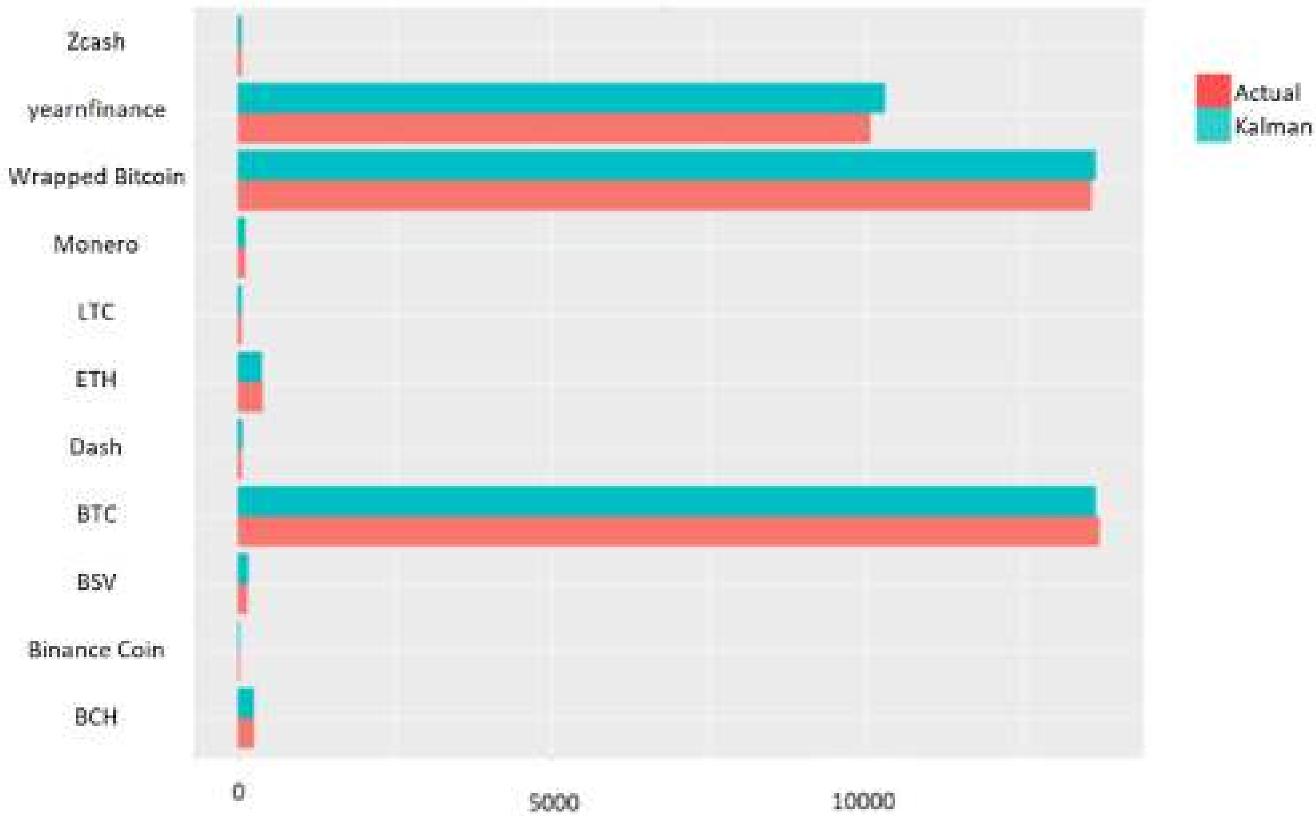

Figure 2 displays the most current actual price in the data set against the Kalman filter's "efficient" price for 11 cryptocurrencies over the full sample period 2010 to 2020. For viewing purposes the cryptocurrencies that have an actual closing price of less than 16 (chosen empirically) are excluded from the figure.

In determining how "well" the Kalman filter is able to identify the permanent and transitory pricing errors the test-statistic is computed for each cryptocurrency to determine whether each of the permanent price series has differences that are statistically indistinguishable from zero when compared to the actual price of the cryptocurrency in question. Table 2 below displays these results.

Table 2: Actual price vs Kalman filter efficient price

Table 2: Actaul Price vs Kalman Fiter Efficient Price	
Cryptocurrency	**T-stat**
BCH	0.04992
BTC	0.07963
ETH	0.06616
XRP	0.00774
LINK	0.12676
LTC	0.06550
CARDANO	-0.0881
BINANCE.COIN	0.13824
POLKADOT	0.57118
BSV	0.40586
EOS	0.06179
MONERO	0.06299
TRON	-0.64543
Wrapped.Bitcoin	0.26019
Crypto.com.coin	-0.44043
Steller	-0.08389
Tezos	0.08511
UNUS.SED.LEO	0.06580
NEO	0.04562
Cosmos	0.24899
NEM	-0.03280
Huobi.Token	0.11749
MIOTA	0.01442
Ve.Chain	-0.97998
DASH	0.02975
Theta	-0.02095
Zcash	-0.03865
Aave	0.00285
Ethereum.Classic	0.05444
yearnfinance	0.78139

Table 2 displays the t-stat for all 30 cryptocurrencies. The t-stat represents the statistical significance of the difference between the actual price and the Kalman filter's generated efficient price of the cryptocurrency in question.

Graphically, we stated that the Kalman filter was able to identify the permanent and transitory price. When looking at the test-statistics in Table 2, this result is confirmed. The Kalman filters efficient price across the 30 cryptocurrencies was statistically indistinguishable from the actual cryptocurrency price 100% of the time. This is seen in Table 2 where none of the t-stats are significant. This means that all the cryptocurrencies were priced efficiently in terms of the Kalman filter. Overall, we can conclude that the Kalman filter was effectively able to generate the efficient price of the cryptocurrency in question. Therefore, we fail to reject hypothesis 1 in that the Kalman filter is able to identify the permanent price (the efficient price) and the transitory price (pricing error) with a reasonable amount of accuracy.

We noted that based on Table 1, *Bitcoin*, *Wrapped.Bitcoin* and *yearnfinance* had the greatest pricing errors. When looking at Table 2 it can be seen that for the majority of the cryptocurrencies efficient Kalman price are insignificantly different from the actual price of the corresponding cryptocurrency, which indicates that across majority of the cryptocurrencies the actual price is very similar to the equilibrium/efficient price of the cryptocurrency in question. This has possible implications on market efficiency. More specifically, this could imply that the market is inefficient for the cryptocurrencies with the largest pricing errors (*Bitcoin*, *Wrapped.Bitcoin* and *yearnfinance).*

Next, this Chapter looks at the results of the BDS test, the Jarque-Bera test and the Hurst exponent when applied to the actual price and the Kalman filter output (the permanent and transitory price) of the cryptocurrencies. The Jarque-Bera test looks at the normality of the returns, the BDS test examines the linearity of return, and finally the Hurst exponent determines whether returns are chaotic (non-deterministic) or deterministic. The null hypothesis of the Jarque-Bera test is a joint hypothesis of the skewness and the excess kurtosis being zero. Table 3 indicates that the p-value of the Jarque-Bera test is both below 0.05 for the actual price and the permanent price, therefore we reject the null hypothesis, suggesting that these series are non-normal distributions. For the transitory price we accept the null hypothesis of a normal distribution.

Table 3: Analysis of the Kalman filter output

Table 3: Analysis of the Kalman Filter output			
Test	**Actual Price**	**Permanent Price**	**Transitory Price**
Jarque-Bera test	0.00010***	0.0000***	0.05415**
BDS test	0.01087***	0.00296***	0.07476**
Hurst Exponent	0.55153	0.55137	0.46290

*Table 3 displays the averages of the 3 tests for the actual price, permanent price and the transitory price across the 30 cryptocurrencies. The values presented for the Jarque-Bera test and the BDS test are in the form of p-values. P-values are reported where * denotes significance at the 10% level, ** at the 5% and *** at the 1% level of significance.*

The BDS p-values for the actual price and the transitory price are insignificant at the 5% level, indicating that the series for the actual price and transitory price are non-linear. However, the permanent price series are linear in terms of the BDS test. Finally, the Hurst exponents for the actual and permanent prices are greater than 0.5, indicative of a persistent (deterministic) time series. This provides a good signal on the modelling of these two series. This roughly translates to a trending market. However, the Hurst exponent of the transitory price indicates that the series is anti-persistent, which roughly translates to a sideways (random) market. This indicates that it is difficult to predict the future.

4.2 Application of the Kalman filter and the technical trading rules

The next part of the analysis involves using the efficient price level as a reference point. This reference point is taken as the true and "efficient" value of the cryptocurrency and used to determine buy or sell signals for the given cryptocurrency. The Kalman filter is passed through each of the 30 cryptocurrencies and the efficient price generated is compared to the actual price of the cryptocurrency in question. If the actual price is less than the Kalman filter's efficient price (reference point), this indicates that the cryptocurrency in question is oversold as it is trading below its perceived value and thus a buy opportunity is generated. Conversely, if the actual price is greater than the Kalman filters efficient price level, an overbought indication is generated. This indicates that the particular cryptocurrency is selling for more than its perceived value, resulting in a sell opportunity. The outcome results in buy and sell opportunities generated from the Kalman filter. This simple trading strategy based on the reference point (efficient price) of the Kalman filter is then compared to the more technical trading rules of the Moving Average (MA), Moving Average Convergence Divergence (MACD), Rate of Change (ROC), Relative Strength Index (RSI) and Bollinger Bands (BB). The final analysis determines whether the buy and sell opportunities generated by the Kalman filter are able to outperform the technical trading rules. The performance of the Kalman filter against the buy–and-hold strategy will be examined in Chapter 4.3.

Table 4 below displays the average buy and sell returns, standard deviation and number of each buy and sell signal for each technical trading strategy, as well as the Kalman filter strategy, over the full sample period 2010 to 2020, gross of transaction costs. When looking at the average buy returns in Table 4 one can see that the Kalman filter has the highest return of 0.0915% when compared to the technical trading rules. This refers to around 0.1% a year. The same can be seen in the average sell returns, where the average return for the Kalman filter is 1.3577%, which is considerably higher than the other sell returns of the technical trading rules.

This result indicates that the Kalman filter, when used as a trading strategy, can yield greater returns than the technical trading rules (used in this study) in the cryptocurrency market. The standard deviation of both the sell and buy averages of the Kalman filter are also considerably higher than those of the technical trading rules. When looking at the average number of buy and sell signals, it can be seen that those of the Kalman filter strategy are not considerably different to those of the technical trading rules. Finally it can be seen that both the average buy and sell returns of the Kalman filter are greater than the passive buy and hold index (the artificial market index based on the cryptocurrencies that make up 80% or more of the market during the full sample period 2010 to 2020). These results are similar to that of Hudson and Urquhart (2019) who find siginificant predictability and profitability of technical trading rules in the cryptocurrency market.

Overall, the below results questions the effectiveness of the technical trading rules used in the present study. However, when analysing the performance of the technical trading rules against the benchmark we can see that the technical trading rules all outperform the passive buy and hold benchmark. This is seen by all the t-statistics being significant for all the technical trading rules buy and sell signals. This indicates that the technical trading rules were able to outperform the passive buy and hold benchmark. Overall, we can conclude that a simple strategy such as using the Kalman filter to generate buy and sell opportunities is able to outperform all of the technical trading rules used in the present study.

Table 4: The Kalman filter vs Technical analysis (2010 to 2020)

Table 4: Full Sample			**Kalman filter vs Technical Trading Rules**				
Strategy	**X(B)-X(H)**	**X(S)-X(H)**	**X(B)-X(S)**	**SD(B)**	**SD(S)**	**N(B)**	**N(S)**
MA 1-50	0.04831 (19.7599)	0.0524 (17.6926	-0.00408 (1.97352)	0.06103	0.07216	623	594
MA 1-200	0.05197 (17.3190	0.04979 (17.6657	0.00218 (0.90802)	0.07413	0.06940	610	606
MA 1-150	0.04910 (18.0433	0.05173 (17.7566	-0.00263 (2.37405)	0.06748	0.07147	615	602
MA 2-200	0.05454 (17.3716	0.04765 (17.5356	0.00689 (1.86878)	0.07772	0.06678	613	604
MA 5-150	0.05462 (17.3962	0.04752 (17.5282	0.00711 (2.40359)	0.07792	0.06645	616	601
MACD	0.05469 (17.6667	0.04705 (17.2040	0.00764 (4.62319)	0.07799	0.06596	635	582
MACD SIGNAL	0.05523 (17.8167	0.04676 (17.1425	0.00846 (4.57283)	0.07818	0.06572	636	581
MACD HISTOGRAM	0.05059 (17.8245	0.0500 (17.9849	0.00059 (0.31076)	0.07002	0.06855	609	608
ROC	0.04889 (20.1334	0.05129 (17.6876	-0.00239 (2.23819)	0.06137	0.06970	639	578
RSI	0.04402 (5.36682)	0.123712 (7.94593)	-0.07969 -	0.06032	0.17686	54	129
BOLLINGER BANDS	0.05667 (3.95497)	0.14053 (9.47601)	-0.08385 -	0.08522	0.16933	35	130
KALMAN FILTER	0.09074 (1.32101)	1.35691 (21.8096	-1.2662 -	1.71153	1.52879	621	604

Table 4 displays X(B) and X(S) which are the mean returns of the buys and sells. X(H) is the mean return for the buy and hold strategy (the artificially constructed market index). SD(B) and SD(S) are the standard deviation of the buy and sell days and N(B) and N(S) are the number of buy and sell signals. The values in parentheses are the t-statistics testing the difference of the mean buy and mean sell from the mean buy and hold, and buy-sell from zero. '-' indicates the square root of a negative number which is not a real number.

Table 5 below displays the average Sharpe ratios of the buy and sell opportunities for the technical trading rules and the Kalman filter over the full sample period, 2010 to 2020. In the first column showing the average buy Sharpe ratios, the Kalman filter's Sharpe ratio is the only negative value, resulting in the Kalman filter having the worst risk adjusted performance in terms of the Sharpe ratio (the passive buy and hold benchmark has a higher buy Sharpe ratio than the Kalman filter). The highest average Sharpe ratio is that of the Rate of Change technical trading indicator. When looking at the average sell Sharpe ratios one can see that the Kalman filter has a Sharpe ratio of 0.0828. The average sell Sharpe ratio of the Kalman filter is however greater than the passive buy and hold benchmark.

Overall, the results indicate that the ability of the Kalman filter as a simple trading strategy is viable against the technical trading rules used in the present study.

Table 5:Sharpe ratios (2010 to 2020)

Table 5: Full Sample Sharpe Ratios		
Strategy	**BUY**	**SELL**
MA 1-50	2.2776	0.7774
MA 1-200	1.1452	0.9867
MA 1-150	1.6883	0.8552
MA 2-200	0.9078	1.1926
MA 5-150	0.9090	1.1888
MACD	0.9593	1.0924
MACD SIGNAL	0.9256	1.1752
MACD HISTOGRAM	1.7288	0.8420
ROC	2.5072	-0.6660
RSI	2.3503	3.0947
BOLLINGER BANDS	1.4100	2.8629
KALMAN FILTER	-0.0160	0.0828
Artificial index	0.0214	

Table 5 displays the BUY and SELL are the average Sharpe ratios.

Thus, the conclusion is reached that there is value in using the Kalman filter as a trading strategy in the cryptocurrency market. The results provide evidence of technical trading rules and the Kalman filter's ability to recognise whether a cryptocurrency is either overbought or oversold. For the technical trading rules, in some cases the sell signals outperformed the buys and in other instances the buy signals outperformed the sell signals. This shows that over time the cryptocurrency market went through periods where buyers were more dominant than sellers and vice versa. However, both the buy and sell signals were able to generate returns greater than that of the passive buy and hold benchmark. The overall conclusion is that the technical trading rules were able to recognise overbought/oversold levels better than the passive buy and hold benchmark. The Kalman filter was also able to effectively recognise overbought/oversold levels of the cryptocurrencies analysed in this study. In fact, the Kalman filter yielded greater returns than the benchmark and the technical trading rules. Therefore, we fail to reject Hypothesis 2. That is, a Kalman filter will generate returns greater than that of the technical trading rules. Additionally, the Kalman filter is able to outperform the technical trading rules on a risk-adjusted basis. The results indicate that the price discovery process is driven by investor sentiment, specifically the abundance of buyers or sellers at any point in time in the cryptocurrency market.

4.3 Performance of the Technical Trading rules
4.3.1 Full Sample

Tables 6, 7 and 8 present the results of the technical trading rules for the full sample period (2010 to 2020) as well as the two sub-periods (2010 to 2015 and 2015 to 2020) across all 30 cryptocurrencies. The tables below analyse the technical trading rules mean returns, mean standard deviations and average number of buys and sells across all 30 cryptocurrencies. The results in Table 6 indicates that all the technical trading rules, which include the Moving Average (MA), Moving Average Convergence Divergence (MACD), Rate of Change (ROC), Relative Strength Index (RSI) and Bollinger Bands (BB) are all able to generate returns greater than the passive buy and hold benchmark within the full sample period. Importantly to note is that Table 6 includes the effect of transaction costs and thus differs to Table 4 in that sense. Columns 1 and 2 in Table 6 display the differences of mean returns between buy and sell days and the benchmark; column 3 displays the difference between the buy and sell signals; columns 4 and 5 report the mean standard deviations of the returns on buy and sell days. Finally, columns 6 and 7 show the total number of buy and sell days for the particular technical trading rule.

Table 6: Performance of the technical trading rules (2010 to 2020)

Table 6: Full Sample			**Post- Transaction costs**				
Strategy	**X(B)-X(H)**	**X(S)-X(H)**	**X(B)-X(S)**	**SD(B)**	**SD(S)**	**N(B)**	**N(S)**
MA 1-50	0.04791 (19.83866)	0.05241 (17.90914)	-0.00451 (2.65311)	0.06050	0.07104	628	589
MA 1-200	0.05190 (17.38928)	0.04965 (17.89706)	0.00225 (1.19644)	0.07388	0.06815	613	604
MA 1-150	0.04899 (18.12257)	0.05155 (17.98094)	-0.002567 (3.47924)	0.06714	0.07021	617	600
MA 2-200	0.05454 (17.44703)	0.04753 (17.78728)	0.00701 (2.09724)	0.07749	0.06555	615	602
MA 5-150	0.05460 (17.45096)	0.04740 (17.78503)	0.00720 (2.45337)	0.07773	0.06523	617	599
MACD	0.05457 (17.72454)	0.04689 (17.44898)	0.00768 (4.48935)	0.07775	0.06468	638	579
MACD SIGNAL	0.05513 (17.82429)	0.04673 (17.10612)	0.00839 (5.20518)	0.07813	0.06575	638	579
MACD HISTOGRAM	0.05014 (17.89022)	0.04997 (18.19330)	0.000164 (0.27704)	0.06949	0.06744	615	603
ROC	0.04811 (20.19666)	0.05114 (17.73519)	-0.00303 (3.65804)	0.06089	0.06863	654	567
RSI	0.04401 (5.36166)	0.12335 (7.96201)	-0.07934 -	0.06035	0.17598	54	129
BOLLINGER BANDS	0.05661 (3.94988)	0.13964 (9.46178)	-0.08303 -	0.08527	0.16849	35	130

Table 6 displays X(B) and X(S) which are the mean returns of the buys and sells. X(H) is the mean return for the buy and hold strategy, which in this period is the artificial market index based on the cryptocurrencies that make up 80% or more of the market. N(B) and N(S) are the number of buy and sell days. SD(B) and SD(S) are the standard deviation of the buy and sell days. The values in parentheses are the t-statistics testing the difference of the mean buy and mean sell from the mean buy and hold, and buy-sell from zero. '-' indicates the square root of a negative number which is not a real number.

In order to illustrate the meaning of the numbers in Table 6, let us choose the row of MA 1-50, which reports the results of the moving average, with a short term average of 1 day and a long term average of 50 days. We will be in the market (buy days) if the artificial market index is greater than MA 1-50 and out of the market (sell days) if the artificial market index is less than or equal to MA 1-50. The mean return difference between the buy days and the passive buy and hold benchmark for MA 1-50 is 0.04791. This indicates that the MA1-50 technical trading rule is able to beat the passive buy and hold benchmark as it generates returns in excess of the benchmark. The same conclusion can be reached for the mean return difference between sell days and the passive benchmark, since the resulting value is positive 0.05241. Columns 5 (SD(B)) and 6 (SD(S)) report the standard deviation of buy and sell days. Because SD(S) (0.07104) is greater than SD(B) (0,0650), it implies that the artificial market index is more volatile when the market is going down. Finally the average number of buy and sell days (628 and 589 respectively) are reported in the last two columns.

Additionally, Table A1 in appendix A provides the results for the technical trading rules before transaction costs are considered. These results provide strong support of the technical trading rules' ability to generate returns greater than that of the passive buy and hold benchmark. It is evident from Table 6 that the effect of transaction costs on the mean returns of the buy and sell signals has a trivial effect on the ability of the technical trading rules average return in excess of the passive buy and hold benchmark.

The results in Table 6 shows strong support of the technical trading rules' ability to generate returns greater than the passive buy and hold market index. This is evident by all the t-statistics for the technical trading rules' excess returns to that of the benchmark being significant. This includes the t-statistics being significant for the net position (buys–sells). All five technical trading rules yield returns greater mean buy and sell returns than that of the market index despite the inclusion of transaction costs. The Bollinger Bands trading rule yields the highest excess return to the passive buy and hold benchmark in both the buy and sell days. However, the average sells (0.13964) in excess of the benchmark are fairly larger than the average buys (0.05661). The RSI's average excess sell returns to the passive benchmark are also impressive, being noticeably higher than the rest of the technical trading rules (0.1233), with the exception of the Bollinger Bands. Similar to Table 4A, the numbers of buys and sells in Table 4B indicate that the number of buy days are higher than the sell days, with the exception of the BB and RSI trading rules.

4.3.2 2015 to 2020 sub-period

Table 7 presents the results of the technical trading indicators in the sub-sample 2015 to 2020 with the inclusion of transaction costs. Again, the results reported indicate significant support for the technical trading rules' ability to produce returns greater than that of the passive buy and hold benchmark. Despite the inclusion of transaction costs, the technical trading rules are still able to beat both passive buy and hold benchmarks. This is evident in all the technical trading rules being able to yield positive mean buy and sell returns in excess to both the passive benchmarks (the artificial market index and the CCi30 index). The statistically significant t-statistics also indicate that all the technical trading rules have significantly different average returns than that of the passive buy and hold benchmark. This is also evident in the net positions of the technical trading rules (buys-sells). Table A2 in Appendix A displays the results of the technical trading rules before transaction costs are considered. The results are in strong support of the technical trading rules and provide evidence of the technical trading rules' ability to generate statistically significant returns in excess of the passive buy and hold benchmark.

The Bollinger Bands and RSI trading strategies are once again the two strategies yielding the highest returns, particularly for the mean sell returns. In terms of the buy signals, the MA 1-50 yields the lowest return, although this return is still greater than both market indices, and in terms of the sell signals, the MACD Signal generates the lowest mean return. Overall, the highest returns are generated from the Bollinger Band strategy. The standard deviations for the trading strategies are fairly high if one compares them to the standard deviation of normal shares. This result is expected due to the data consisting of cryptocurrencies, which are known to be naturally volatile. The number of buys and sells amongst the trading rules is fairly even except for the RSI and Bollinger Band trading rules, which both have a significantly lower number of buys than sells. In general, the results are in strong support of the technical trading rules and their ability to beat the benchmark even with the inclusion of transaction costs.

Table 7: Performance of the technical trading rules (2015 to 2020)

Table 7: 2015 to 2020			**Post- Transaction costs**						
Strategy	**X(B)-X(H)**	**X(S)-X(H)**	**X(B)-X(H*)**	**X(S)-X(H*)**	**X(B)-X(S)**	**SD(B)**	**SD(S)**	**N(B)**	**N(S)**
MA 1-50	0.04701 (19.46772)	0.05214 (17.39553)	0.04766 (19.73846)	0.05280 (17.61362)	-0.00514 (1.94792)	0.05820	0.07082	581	558
MA 1-200	0.05115 (17.04596)	0.04917 (17.30672)	0.05180 (17.26383)	0.04983 (17.53681)	0.00198 (1.31410)	0.07187	0.06757	574	566
MA 1-150	0.04821 (17.96124)	0.05112 (17.25710)	0.04887 (18.20477)	0.05177 (17.47779)	-0.00290 (2.32196)	0.06460	0.07009	579	560
MA 2-200	0.05377 (17.08488)	0.04708 (17.19985)	0.05443 (17.29259)	0.04774 (17.43867)	0.00669 (2.13775)	0.07547	0.06499	575	564
MA 5-150	0.05385 (17.18763)	0.04696 (17.10436)	0.05450 (17.39628)	0.04761 (17.34248)	0.00689 (2.80451)	0.07533	0.06498	578	560
MACD	0.05431 (17.38456)	0.04592 (16.93410)	0.05496 (17.59384)	0.04658 (17.17516)	0.0083 (4.84976)	0.07655	0.06292	600	538
MACD SIGNAL	0.05479 (17.38046)	0.04584 (16.70621)	0.05544 (17.58784)	0.04649 (16.94447)	0.00895 (5.02713)	0.07702	0.06393	597	543
MACD HISTOGRAM	0.04848 (17.31676)	0.05042 (17.83810)	0.04914 (17.055027)	0.05107 (18.06938)	-0.00194 -	0.06636	0.06795	562	578
ROC	0.04768 (20.24534)	0.05025 (16.97129)	0.04833 (20.52294)	0.05090 (17.19208)	-0.00257 (3.92346)	0.05932	0.06671	635	508
RSI	0.04663 (5.15397)	0.11613 (7.33756)	0.04728 (5.22623)	0.11679 (7.37887)	-0.06951 -	0.06627	0.16713	54	112
BOLLINGER BANDS	0.06029 (4.95845)	0.14888 (8.57759)	0.06095 (5.01221)	0.14954 (8.61525)	-0.08859 -	0.09012	0.17438	55	101

Table 7 displays X(B) and X(S) which are the mean returns of the buys and sells. X(H) is the mean return for the buy and hold strategy, which in this period is the artificial market index based on the cryptocurrencies that make up 80% or more of the market. X(H) is the mean return for an additional benchmark, the CCi30 index which contains the top 30 cryptocurrencies. The reason for the inclusion of the CCi30 in this sub- period and not the other sub periods is due to the CCi30 index only having data available from 2015 onwards. N(B) and N(S) are the number of buy and sell days. SD(B) and SD(S) are the standard deviation of the buy and sell days. The values in parentheses are the t-statistics testing the difference of the mean buy and mean sell from the mean buy and hold, and buy-sell from zero. '-' indicates the square root of a negative number which is not a real number.*

4.2.3 2010 to 2014 sub-period

Table 8 presents the average results of the technical trading rules for the sub-period 2010 to 2014 across all 30 cryptocurrencies. Importantly to note in this sub-period is that it only consisted of approximately 6 cryptocurrencies. This is because many of the cryptocurrencies in the full sample period launched fairly recently, for example some cryptocurrencies launched in 2017 while others even launched in 2020. This resulted in a lack of data across this sub-sample (2010 to 2014). Consequently, this sub-sample only had data for 6 cryptocurrencies. The average return of the artificial market index is higher than in the previous samples, sitting at 0.001. Despite the higher average return for the market index, the technical trading rules still stand out. Similar to the results in the previous tables, the findings displayed in Table 8 clearly indicate the superior performance of the 5 technical trading rules. Each trading rule is able to produce positive returns in excess of the passive buy and hold benchmark.

Table 8: Performance of the technical trading rules (2010 to 2014)

Table 8: 2010 to 2014			**Post-Transaction costs**				
Strategy	**X(B)-X(H)**	**X(S)-X(H)**	**X(B)-X(S)**	**SD(B)**	**SD(S)**	**N(B)**	**N(S)**
MA 1-50	0.05385 (10.86759)	0.04830 (9.91728)	0.00556 (4.95175)	0.07078	0.06518	204	179
MA 1-200	0.05261 (10.18992)	0.04870 (10.59880)	0.00392 (1.44638)	0.07286	0.06232	199	184
MA 1-150	0.05346 (9.72053)	0.04770 (11.13546)	0.00575 -	0.07570	0.05959	190	194
MA 2-200	0.05236 (10.15638)	0.04880 (10.61810)	0.00356 (1.33145)	0.07273	0.06231	199	184
MA 5-150	0.05418 (9.78571)	0.04732 (11.10183)	0.00686 -	0.07591	0.05949	188	195
MACD	0.05574 (10.95556)	0.04609 (9.93912)	0.00965 (4.59155)	0.07422	0.06055	213	171
MACD SIGNAL	0.05567 (11.21293)	0.04666 (9.62005)	0.00901 (6.43877)	0.07248	0.06336	213	171
MACD HISTOGRAM	0.05322 (10.75181)	0.04842 (10.01609)	0.00480 (3.99318)	0.06892	0.06672	194	191
ROC	0.05531 (11.51259)	0.04436 (9.22249)	0.01095 (7.43056)	0.07279	0.06021	230	157
RSI	0.05847 (4.60942)	0.13218 (6.13374)	-0.07371 -	0.06987	0.16270	30	57
BOLLINGER BANDS	0.07850 (4.45705)	0.25144 (4.49980)	-0.17295 (1.69143)	0.09179	0.27375	27	24

Table 8 displays X(B) and X(S) which are the mean returns of the buys and sells. X(H) is the mean return for the buy and hold strategy, which in this period is the artificial market index based on the cryptocurrencies that make up 80% or more of the market. N(B) and N(S) are the number of buy and sell days. SD(B) and SD(S) are the standard deviation of the buy and sell days. The values in parentheses are the t-statistics testing the difference of the mean buy and mean sell from the mean buy and hold, and buy-sell from zero. '-' indicates the square root of a negative number which is not a real number.

The results displaying the performance of the technical trading rules over the same sub-sample (2010 to 2014) but before considering transaction costs are presented in Table A3 in Appendix A. The results provide evidence in favour of the technical trading rules and once again depict the value in technical analysis. Table 8 displays the average results for all the technical trading strategies across all 30 cryptocurrencies with the inclusion of transaction costs. Once again the power of the technical trading rules can be seen. Despite the inclusion of transaction costs, each trading rule is able to generate greater returns than that of the simple buy and hold benchmark.

This result holds for both the buy and sell signals across all five trading rules. The t-statistics for all the technical trading rules, for both buys and sells are statistically significant. This indicates that the technical trading rules were able to convincingly outperform the passive buy and hold benchmark. The same can be seen in the net position (buys-sells), once again showing the superior ability of the technical trading rules.

As seen in the previous results, the RSI and Bollinger Bands trading rules generate the highest mean buy and sell returns in excess of the passive buy and hold benchmark. The average number of buy and sell days for the RSI and BB strategies are considerably lower when compared to the other technical trading strategies. This indicates that on average a trader will be trading (buying and selling) at a much lower frequency when compared to the other trading rules. The results reported in Table 6B provide strong support for the ability of technical trading rules to generate returns in excess of the passive buy and hold benchmark.

The results presented in the above tables prove clear and unwavering support of the ability of technical trading rules. In the full sample period (2010 to 2020) and in each sub-sample (2010 to 2015 and 2015 to 2020) the chosen technical trading rules consisting of the Moving Average (MA), Moving Average Convergence Divergence (MACD), Rate of Change (ROC), Relative Strength Index (RSI) and Bollinger Bands (BB) are all able to generate returns in excess of the passive buy and hold benchmarks (either the artificial market index or the CCi30 or both). This was evident by the statistically significant t-statistics for the individual buy and sell signals as well as for the net positions (buys-sells) across all five technical trading rules in the full sample periods and in the two sub-periods.

The inclusion of transaction costs has shown to be trivial in the ability of the technical trading rules ability to produce greater returns than the benchmark. In each sample period the technical trading rules are still able to beat the passive benchmark when transaction cost are considered. Overall, the RSI and Bollinger Bands technical trading rules perform the best, generating the highest returns in excess of the passive buy and hold benchmark. The above results, for the full sample and sub-periods, fail to reject Hypothesis 3. More specifically, the buy and sell signals from the technical trading rules generate returns in excess of the passive buy and hold benchmark (either the artificial market index or the CCI30), net of transaction costs. In summary the above results provide convincing evidence of the superior ability of technical analysis within the cryptocurrency market. The above results have implications that support the use of technical trading rules in the cryptocurrency market to achieve returns greater than that of a passive buy and hold benchmark.

4.4 Risk-adjusted performance of the technical trading rules

4.4.1 Full sample

Table 9 below depicts the performance ratios for each of the technical trading rules, as well as the artificial market index, over the period 2010 to 2020. The performance ratios include the Sharpe, Treynor and Sortino ratios, and each ratio is analysed in terms of the average buy and sell days across all 30 cryptocurrencies. Importantly to note is that these ratios are based on the returns of the technical trading rules once transaction costs have been considered. In order for the technical trading rule to outperform the passive buy and hold benchmark on a risk adjusted basis, the difference between the average Sharpe ratio, for example, between the technical trading rule in question and the artificial market index must be positive. This same analysis is followed throughout each sub-period (Tables 10 and 11) in order to determine the risk adjusted performance of each technical trading rule in the full sample period (2010 to 2020) and the two sub-samples (2015 to 2020 and 2010 to 2015).

Table 9: Performance ratios (full sample)

Table 9: Full Sample-Post transaction costs						
Strategy	**Sharpe Ratio**		**Sortino ratio**		**Treynor Ratio (Artificial market index)**	
	BUY	**SELL**	**BUY**	**SELL**	**BUY**	**SELL**
MA 1-50	2.2776	0.7774	0.9187	0.5940	0.7812	0.2703
MA 1-200	1.1452	0.9867	0.7638	0.6962	0.4011	0.3253
MA 1-150	1.6883	0.8552	0.8658	0.6368	0.5823	0.2900
MA 2-200	0.9078	1.1926	0.6876	0.7651	0.3211	0.3833
MA 5-150	0.9090	1.1888	0.6880	0.7640	0.3172	0.3903
MACD	0.9593	1.0924	0.7065	-0.7486	0.3297	0.3710
MACD SIGNAL	0.9256	1.1752	0.6943	0.7603	0.3145	0.4059
MACD HISTOGRAM	1.7288	0.8420	0.8708	0.6311	0.5958	0.2857
ROC	2.5072	-0.6660	0.9314	-0.5767	0.8329	0.2330
RSI	2.3503	3.0947	0.9230	0.9524	0.8457	0.5914
BOLLINGER BANDS	1.4100	2.8629	0.8234	0.9447	-0.6137	1.1937
Artificial Index	0.0214		0.0569			

Table 9 displays the BUY and SELL averages of the Sharpe, Treynor and Sortino ratios for the buy and sell days for each technical trading rule over the period 2010 to 2020. Note that the artificial index refers to the artificial market index based on the cryptocurrencies that make up 80% or more of the market over the full sample period (2010 to 2020).

Table 9 starts with some well-known moving average rules and ends off with the final technical trading rule used in the present study, Bollinger Bands. It can be seen from Table 9 that the buy Sharpe ratios for the technical trading rules are all greater than that of the passive artificial market index. The same can be seen for the sell Sharpe ratios with the exception of Rate of

Change which has a negative Sharpe ratio of -0.666. The MA 1-50 technical trading strategy has the highest average Sharpe ratio for the buy days, while the RSI and Bollinger Bands have the highest average Sharpe ratios for the sell days.

When looking at the Sortino ratios the ROC indicator yields the highest buy Sortino ratio while the RSI trading strategy has the highest average sell Sortino ratio. The Moving Average Convergence Divergence and the ROC have negative average sell Sortino ratios and are thus not able to outperform the artificial market on a risk-adjusted basis. On a risk-adjusted basis all the sell Sortino ratios of all the technical trading rules are greater than that of artificial market Sortino ratio. RSI has the highest average buy Treynor ratio and the Bollinger Bands have the lowest average buy Treynor ratio. However, the Treynor ratio for the Bollinger Bands for the average sell days is the highest (1.1937). Overall, the performance measures indicate that the technical trading rules are able to outperform the passive benchmark on a risk adjusted basis.

4.4.2 Sub-period 2015 to 2020

Table 10: Performance ratios (2015 to 2020)

Table 10: 2015 to 2020-Post transaction costs								
	Sharpe Ratio		Sortino ratio		Treynor Ratio (CCi30)		Treynor Ratio (Artificial market index)	
Strategy	BUY	SELL	BUY	SELL	BUY	SELL	BUY	SELL
MA 1-50	2.1986	0.7744	0.9135	0.5924	0.2587	0.2849	5.5871	-3.7776
MA 1-200	1.1250	0.9773	0.7583	0.6926	3.3109	0.8678	-2.6249	3.8305
MA 1-150	1.6471	0.8486	0.8604	0.6337	0.4130	0.4313	-3.0338	4.3449
MA 2-200	0.8936	1.1800	0.6820	0.7616	-0.6187	2.3976	-2.2315	2.8624
MA 5-150	0.8947	1.1766	0.6824	0.7606	-0.5535	-1.6486	-2.1237	2.5099
MACD	0.9547	1.0652	0.7048	0.7404	-0.6122	-1.4155	-6.7850	5.9378
MACD SIGNAL	0.9198	1.1489	0.6922	0.7528	-0.6146	-1.4033	-5.9371	-7.1632
MACD HISTOGRAM	1.6370	0.8514	0.8590	0.6355	0.2799	0.3049	-4.2677	7.5844
ROC	2.4690	0.6505	0.9295	0.5681	0.1955	0.2059	4.2850	-2.6400
RSI	2.4170	2.7335	0.9268	0.9400	0.2585	0.1212	-0.6834	-1.3881
BOLLINGER BANDS	1.4877	2.8293	0.8372	0.9434	3.9127	0.3506	-0.3455	1.9113
Artificial Index	0.0237		0.0605					
CCi30 Index	0.0195		0.0363					

Table 10 displays the BUY and SELL averages of the Sharpe, Treynor and Sortino ratios for the buy and sell days for each technical trading rule over the period 2015 to 2020. Both the CCi30 and the artificial market indices are analysed in this time period. This is due to the CCi30's available data corresponding to this sub-period. Therefore, this sub-period allows the performance comparison of the technical trading rules against two benchmarks.

Table 10 above shows the Sharpe, Treynor and Sortino ratios of all the technical trading rules and the passive buy and hold benchmarks (the artificial market index and the CCi30) for the sub-period 2015 to 2020. Table 8 provides evidence of the dominant performance of the technical trading rules against two passive buy and hold benchmarks. The average Sharpe ratios of all the technical trading rules in both the buy and sell columns are greater than that of both the artificial market index and the CCi30. Even the lowest buy and sell average Sharpe ratio, 0.8947 (MA 2-200) and 0.6505 (ROC), respectively, are greater than that of the two passive buy and hold benchmarks. The RSI and BB trading strategies have the highest Sharpe ratios. The ROC, RSI and MA 1-50 trading rules all stand out due to their high Sortino ratios for the buy signals, and the RSI and BB's have the highest Sortino ratios in the sell signals. However, the ROC has the lowest average Sortino ratio in the sell signals, but this ratio is still greater than both the passive buy and hold benchmarks.

Overall, the results from the Sortino ratios also indicate the superior performance of the technical trading rules in comparison to the two passive buy and hold benchmarks. When the CCi30 is used as the benchmark in the calculation of the Treynor ratio the Bollinger bands technical trading rule generates the highest buy Treynor ratio (3.9127). However, in the sell column, using the CCi30 index for the Treynor ratio, the MA 2-200 technical trading rule yields the highest Treynor ratio (2.3976). When the artificial market index is used as the benchmark in the Treynor ratio the MA 1-50 technical trading generates that highest Treynor ratio followed by the ROC strategy within the buy signals. When looking at the sell signals when the artificial market index is used the MACD histogram performs the best, with the greatest Treynor ratio of 7.5844. Overall, in this sub-period (2015 to 2020) the technical trading rules are once again proven to have superior performance than that of the two passive buy and hold benchmarks.

4.4.3 Sub-period 2010 to 2014

Table 11: Performance ratios (2010 to 2014)

[illegible]						
[illegible]	[illegible]		[illegible]		[illegible]	
	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]		[illegible]			

Table 11 displays the BUY and SELL averages of the Sharpe, Treynor and Sortino ratios for the buy and sell days for each technical trading rule over the period 2010 to 2014. The passive buy and hold benchmark in this period is the artificial market index, which refers to the artificial market index based on the cryptocurrencies that make up 80% or more of the market over the sub-period (2010 to 2014).

Table 11 above displays the performance ratios for each of the technical trading rules, as well as the artificial market index, over the sub-period 2010 to 2014. Over this sub-period (2010 to 2014) the limited data resulted in a total of six cryptocurrencies being analysed due to the availability of data. The performance ratios include the Sharpe, Treynor and Sortino ratios, and each ratio is analysed in terms of the average buy and sell days across the six cryptocurrencies in this sub-sample. The results indicate that the average Sharpe ratios for all the technical trading rules, for both the buy and sell signals, are greater than that of the passive buy and hold benchmark, except for the sell signals based on the MA 1-50 technical indicator. The MACD histogram generates the highest average Sharpe ratio for the buy signals and the ROC produces the highest average Sharpe ratio for the sell signals. In terms of the Sortino ratios the technical trading rules are able to generate higher average ratios, for both the buy and sell signals, than the artificial index. The Treynor ratios for the buy signals are negative across all the technical trading rules, while the sell signals are all positive, with the MA 2-200, MA 1-200 and the Bollinger Bands having the greatest Treynor ratios. Overall, the technical trading rules are once again able to beat the passive buy and hold benchmark within this sub-period. The Treynor ratio for the sell signals are the only negative ratios in this sub-period.

The results from the performance measures across the full sample and the sub-periods indicate that the technical trading rules are able to outperform the passive buy and hold benchmarks on a risk adjusted basis. This finding is does not support that of Nadarajah and Chu (2017) who find no value in technical analysis within Bitcoin prices. In the full sample and in the two sub-periods the Sharpe ratios of the technical trading rules indicate a greater risk adjusted performance than the passive buy and hold benchmark. These results support those in the previous analysis that looked at whether the technical trading rules were able to outperform the benchmark on a return basis. More specifically, the present results support that of Hudson and Urquhart (2019) and Shynkevich (2020), who find that the use of technical trading rules in Bitcoin prices and other cryptocurrencies yield significant return predictability.

Overall, the results are convincing of the dominant ability of the technical trading rules to generate greater performance than that of the passive buy and hold benchmark. The findings of the present study are similar to that of Corbet, *et al.,* (2019) and Grobys, *et al.,* (2020) whose findings support the superior performance of the moving average trading rules in the cryptocurrency market. When looking at these results it is very easy to question the weak form efficiency of the cryptocurrency market. The question now arises as to whether these results provide new evidence against the market efficiency of the cryptocurrency market. The results certainly show that the profitability of specific technical trading rules, particularly the RSI and Bollinger Bands can exceed that of a buy and hold strategy for the full sample and for the sub-periods by a significant amount. This shows that technical analysis is valuable to traders within the cryptocurrency market.

The question now arises as to what these results imply for weak form market efficiency in the cryptocurrency market. The significant performance of the technical trading rules against the passive benchmark certainly questions the weak from efficiency of the cryptocurrency market. Based on these results one could easily conclude that the profitability of technical trading rules is certainly no myth and in fact far superior to that of a simple buy and hold strategy. This could allow one to easily conclude and label the cryptocurrency market as not being weak form market efficient. However, despite the assumptions of the EMH (that are not always realistic), this is still a bold statement to make even in light of the above findings.

One could argue that markets go through periods of clear market efficiency and periods where market efficiency almost vanishes. There are limitations in the present study, for example the severe lack of data throughout the entire sample period and the inclusion of the transaction costs at 0.25%. These greatly affects the ability of the technical trading rules against the benchmark. Therefore, one is not able to irrefutably conclude that the cryptocurrency market is not weak form efficient. However, the above results certainly indicate that there is definitely value in technical trading rules and that their use in the practical trading world is beneficial.

In conclusion, the results from this analysis clearly indicate the value in using technical analysis in cryptocurrency trading. The results support those of Hudson and Urquhart (2019) who show that technical trading rules offer substantially higher risk-adjusted returns than the simple buy and hold strategy. There has been much scepticism about technical analysis amongst the academic world due to its conflict with the efficient market hypothesis. However, the above results clearly indicate that despite technical analysis being somewhat of a black sheep, this by no means discredits the actual ability and value of technical in the cryptocurrency market. The implications of the above findings support the use of technical trading rules and their use within the cryptocurrency market.

4.5 Data frequency

The robustness checks in the present study consisted of accounting for data snooping, transaction costs and analysing the same technical trading rules using weekly data. The first two robustness checks were already explored in the previous Chapter. Therefore, the final robustness check conducted in this Chapter involves using weekly data as opposed to daily data. The final robustness check involved converting the daily data into weekly data and running the technical trading rules on this data. The same technical trading rules are applied on the weekly data, which include the Moving Average (MA), Moving Average Convergence Divergence (MACD), Rate of Change (ROC), Relative Strength Index (RSI) and Bollinger Bands (BB).

The performance of the technical trading rules are thus examined using weekly data and the robustness of the results are examined. Converting the data to weekly data resulted in a significant decrease in the amount of data points available in the sample. The lack of data even before converting to weekly data was a limitation of the present study. Consequently, the last sub-period (2010 to 2015) did not yield enough weekly data points in order to explore this robustness check in this sub-period. As a result this robustness check were carried out on the full sample (2010 to 2020) and one sub-sample (2015 to 2020).

Table 12 below displays the results for the full sample (2010 to 2020) using weekly data. The results confirm that even after transaction cost are considered the technical trading rules generate higher returns than the passive buy and hold benchmark. Converting the data into weekly data results in a decrease in the number of buy and sell signals for the technical trading strategies. Additionally, the Bollinger Bands strategy yield the greatest returns in excess of the passive buy and hold benchmark. This result is similar to that when daily data was used. Overall, the results from Table 12 support the earlier findings.

Table 12: Performance of the technical trading rules over 2010 to 2020 (weekly data)

Table 12: Full Sample (weekly data)				**Post- Transaction costs**		
Strategy	**X(B)-X(H)**	**X(S)-X(H)**	**SD(B)**	**SD(S)**	**N(B)**	**N(S)**
MA 1-50	0.1079	0.0847	0.1323	0.0872	85	83
MA 1-200	0.1090	0.0840	0.1335	0.0871	83	85
MA 1-150	0.1092	0.0837	0.1337	0.0864	83	85
MA 2-200	0.1087	0.0844	0.1337	0.0872	82	86
MA 5-150	0.1083	0.0844	0.1332	0.0871	83	85
MACD	0.1060	0.0864	0.1310	0.0897	85	83
MACD SIGNAL	0.1089	0.0858	0.1358	0.0898	86	83
MACD HISTOGRAM	0.1019	0.0878	0.1233	0.0975	87	81
ROC	0.1040	0.0854	90.6207	0.0937	91	78
RSI	0.1229	0.2670	0.1789	0.3392	11	23
BOLLINGER BANDS	0.2398	0.3093	0.4510	0.3487	7	19

Table 12 displays X(B) and X(S) which are the mean returns of the buys and sells. X(H) is the mean return for the buy and hold strategy, which in this period is the artificial market index based on the cryptocurrencies that make up 80% or more of the market. N(B) and N(S) are the number of buy and sell days. SD(B) and SD(S) are the standard deviation of the buy and sell days.

Table 13 below displays the performance measures of the technical trading rules over the full sample (2010 to 2020). The results in terms of the Sharpe ratio indicate superior risk adjusted performance of the technical trading rules to that of the passive buy and hold benchmark. The average buy and sell Sharpe ratios of all the technical trading rules are greater than that of the passive buy and hold benchmark. This is seen for both the buy and sell signals. The technical trading rules also have higher Sortino ratios than the benchmark for both the buy and sell signals. The Treynor ratios of the technical trading rules are very high when using weekly data. The MA 1-50 trading rule has the highest average buy Treynor ratio of 12.8240, while the lowest belongs to that of the MACD signal which is -7.0820. The results from the performance measures over the full sample support the superiority of the technical trading rules over the passive buy and hold benchmark. The results for this sample period are in support of the earlier findings that used daily data.

Table 13: Performance ratios over 2010 to 2020 (weekly data)

Table 13: Full Sample (weekly data)			**Post-transaction costs Performance Measures**			
Strategy	**Sharpe Ratio**		**Sortino ratio**		**Treynor Ratio (Artificial market index)**	
	BUY	**SELL**	**BUY**	**SELL**	**BUY**	**SELL**
MA 1-50	2.3570	4.0797	0.9400	0.9886	12.8240	3.8099
MA 1-200	2.4798	3.6172	0.9466	0.9813	11.5887	3.7222
MA 1-150	2.4747	3.6942	0.9463	0.9827	10.7301	3.7486
MA 2-200	2.4750	3.6031	0.9464	0.9810	11.6575	3.6801
MA 5-150	2.4629	3.7052	0.9457	0.9829	12.6174	3.9180
MACD	2.2884	4.2144	0.9359	0.9907	7.6376	4.8427
MACD SIGNAL	2.1155	4.0046	0.9242	0.9876	-7.0820	4.8407
MACD HISTOGRAM	2.4389	4.0815	0.9444	0.9887	8.8724	3.0259
ROC	2.3475	3.7385	0.9394	0.9839	8.7650	3.1041
RSI	1.1935	1.7837	0.7958	0.8747	-1.0384	4.4390
BOLLINGER BANDS	1.1902	2.4041	0.8453	0.8897	-0.1333	4.1743
Artificial Index	0.0877		0.0266			

Table 13 displays the BUY and SELL averages of the Sharpe, Treynor and Sortino ratios for the buy and sell days for each technical trading rule over the period 2015 to 2020. Both the CCi30 and the artificial market indices are analysed in this time period. This is due to the CCi30's available data corresponding to this sub-period. Therefore, this sub-period allows the performance comparison of the technical trading rules against two benchmarks.

The results in Table 14 are for the sub-period 2015 to 2020. The average returns, for both the buys and sells, based on the technical trading rules are all greater than that of the passive buy and hold benchmark. This includes both the artificial market index and the CCi30 index that are used in this sub-period. This result holds for both the buy and sell signals. Once again the average number of buy and sell days are noticeably lower when weekly data is used. The highest standard deviation belongs to that of the average buy of the Rate of Change technical trading rule. These results are once again in support of the earlier findings in the present paper that found technical trading rules to be able to yield greater returns to that of the passive buy and hold strategy.

Table 14: Performance of the technical trading rules over 2015 to 2020 (weekly data)

Table 14: 2015 to 2020 (weekly data)			**Post- Transaction costs**					
Strategy	**X(B)-X(H)**	**X(S)-X(H)**	**X(B)-X(H*)**	**X(S)-X(H*)**	**SD(B)**	**SD(S)**	**N(B)**	**N(S)**
MA 1-50	0.1090	0.0869	0.1173	0.0952	0.1280	0.0900	80	78
MA 1-200	0.0995	0.0970	0.1078	0.1053	0.1077	0.1096	81	75
MA 1-150	0.1032	0.0918	0.1115	0.1001	0.1151	0.0998	77	79
MA 2-200	0.0994	0.0971	0.1077	0.1054	0.1072	0.1098	80	76
MA 5-150	0.1032	0.0917	0.1115	0.1000	0.1161	0.0989	77	80
MACD	0.1078	0.0873	0.1161	0.0956	0.1278	0.0883	82	75
MACD SIGNAL	0.1096	0.0884	0.1179	0.0967	0.1315	0.0918	82	77
MACD HISTOGRAM	0.1020	0.0911	0.1103	0.0994	0.1180	0.1005	82	76
ROC	0.1064	0.0858	0.1147	0.0941	0.8638	0.0913	86	72
RSI	0.1305	0.2507	0.1388	0.2590	0.1934	0.3319	10	22
BOLLINGER BANDS	0.3505	0.5725	0.3588	0.5808	0.4472	0.5538	8	13

Table 14 displays X(B) and X(S) which are the mean returns of the buys and sells. X(H) is the mean return for the buy and hold strategy, which in this period is the artificial market index based on the cryptocurrencies that make up 80% or more of the market. X(H) is the mean return for an additional benchmark, the CCi30 index which contains the top 30 cryptocurrencies. The reason for the inclusion of the CCi30 in this sub- period and not the other sub periods is due to the CCi30 index only having data available from 2015 onwards. N(B) and N(S) are the number of buy and sell days. SD(B) and SD(S) are the standard deviation of the buy and sell days.*

Table 15 displays the performance ratios of the technical trading rules in the sub-period 2015 to 2020. The average Sharpe and Sortino ratios for the buy and sell signals are greater than that of the passive buy and hold benchmark. This result is once again in support of technical trading rules over this sub-period. The Treynor ratios of the buy signals when the CCi30 is used as the benchmark are all negative. Additionally the Treynor ratios of the sell signals when the artificial market index is used are very high. However, the results do support those observed when daily data is used. The results are all robust to the earlier findings and provide significant support in favour of the technical trading rules used. The results support that of Hudson and Urquhart (2019) and Shynkevich (2020) who highlight the superior performance technical trading rules in Bitcoin and other cryptocurrencies.

Table 15: Performance ratios over 2010 to 2020 (weekly data)

Table 15: Full Sample (weekly data)	Post-transaction costs Performance Measures							
Strategy	Sharpe Ratio		Sortino ratio		Treynor Ratio (CCi30)		Treynor Ratio (Artificial market index)	
	BUY	SELL	BUY	SELL	BUY	SELL	BUY	SELL
MA 1-50	2.2903	3.9283	0.9360	0.9865	-0.5988	1.8168	-2.8148	10.5600
MA 1-200	2.1320	3.4297	0.9253	0.9774	-0.2013	-0.3069	-1.6695	-9.9393
MA 1-150	2.1636	3.6591	0.9276	0.9820	-0.1840	-0.2512	-2.9306	4.6574
MA 2-200	2.1245	3.4143	0.9247	0.9771	-0.1973	-0.2990	-1.4859	-5.0686
MA 5-150	2.1654	3.6862	0.9277	0.9825	-0.1776	-0.2337	-2.7374	5.4907
MACD	2.2343	3.8661	0.9325	0.9859	-0.7414	0.6068	-1.9151	-6.5231
MACD SIGNAL	2.0382	3.9210	0.9181	0.9864	-1.1074	0.6855	-1.6322	14.8729
MACD HISTOGRAM	2.3187	3.9428	0.9377	0.9867	-0.4390	0.5432	-2.3744	16.3286
ROC	2.3061	3.4328	0.9370	0.9781	-0.7435	0.5089	-3.8296	1.8832
RSI	1.2212	1.6969	0.8027	0.8620	-0.1452	0.2149	-0.7794	-1.3868
BOLLINGER BANDS	0.4944	1.5467	0.9765	0.8653	0.0084	-0.5648	-0.4325	1.9670
Artificial Index	0.1004		0.2235					

Table 15 displays the BUY and SELL averages of the Sharpe, Treynor and Sortino ratios for the buy and sell days for each technical trading rule over the period 2015 to 2020. Both the CCi30 and the artificial market indices are analysed in this time period. This is due to the CCi30's available data corresponding to this sub-period. Therefore, this sub-period allows the performance comparison of the technical trading rules against two benchmarks.

4.6 Summary of results

The results support the use of the Kalman filter in the cryptocurrency market. We can conclude that the Kalman filter was effectively able to generate the efficient price of the cryptocurrency in question. This was seen in Table 2 where the Kalman filter's efficient price across the 30 cryptocurrencies was statistically indistinguishable from the actual cryptocurrency price 100% of the time. This satisfied Hypothesis 1 in that the Kalman filter is able to identify the permanent price (the efficient price) and the transitory price (pricing error) with a significant amount of accuracy. Additionally, when the Kalman filter is used as a strategy to generate buy and sell opportunities the results indicate that the ability of the Kalman filter is competitive against the technical trading rules used in the present study. Moreover, the Kalman filter is able to outperform the technical trading rules.

In an additional analysis, the above results provide significant evidence in support of technical analysis' ability to generate returns greater than the passive buy and hold benchmark net of transaction costs. The results from this analysis clearly indicate the value in using technical analysis in trading. There has been much scepticism about technical analysis amongst the academic world due to its conflict with the efficient market hypothesis. However, the above results clearly indicate value in technical analysis, especially in the cryptocurrency market. The results satisfied the objective of the study in that the price discovery process was explored and the results support an element of predictability in the cryptocurrency market.

5. Conclusion

The present study explored the price discovery process through the Kalman filter and technical analysis in the cryptocurrency market. The Kalman filter was first used to generate the efficient price (permanent price) and the transitory price (pricing error). This was achieved by applying the Kalman filter to 30 cryptocurrencies over the period 2010 to 2020. The “efficient” price level of the Kalman filter was then used as a reference point to determine whether a specific cryptocurrency was overbought or oversold, resulting in buy and sell opportunities.

Importantly to note is that the efficient price generated by the Kalman filter was taken as being the true and current efficient price of the cryptocurrency in question, allowing the determination of whether the cryptocurrency in question was overvalued or undervalued. The outcome was a buy and sell opportunity generated by the Kalman filter at each point in time. This simple trading strategy was then compared to the technical trading rules which included a family of five different trading rules that where examined using different parameters. The performance of the Kalman filter against these trading rules was then examined.

In an additional analysis, the performance of the family of technical trading rules was examined. More specifically, the weak form market efficiency of the cryptocurrency market is explored by analysing whether the buy and sell signals of the technical trading rules are able to generate returns in excess of the passive buy and hold benchmarks. The sample period included daily data from 2010 to 2020. However, many of the cryptocurrencies, as well as the CCI30 market index, did have data that went as far back as 2010. It would be more favourable to have examined the price discovery process and technical analysis on a larger sample period. However, the sample period in this study is strictly limited to the availability of data. This is a result of many of the cryptocurrencies being launched fairly recently as well as the limited available data one is able to obtain from cryptocurrencies. Overall, the lack of data is one of the biggest limitations of the study.

In order to account for data snooping the technical trading rules are examined in the full sample as well as in two sub-periods, 2010 to 2015 and 2015 to 2020. The present study also looks at the performance of the technical trading rules once transaction costs have been considered. There is a possibility that not all trading costs have been considered, which mainly include the market impact cost of trading. However, the trading costs included should give a fair and adequate indication of the impact of trading costs on the significance and profitability of the trading rules generated portfolios when compared to the passive buy and hold benchmarks.

Lastly, the technical strategies were examined by analysing the average buy and sell returns as well as through the use of three performance measures, the Sharpe, Treynor and Sortino ratios.

Although the employed methodology includes improvements in comparison to the existing literature, it is still not flawless. Firstly, the study is based solely on five technical trading indicators. Nowadays, market participants have a large universe of indicators to choose from. For example, one could combine numerous indicators in order to generate a more complete trading system. Secondly, the considered technical trading indicators are old and have been used in practice since the 1970's. However, this is not yet proven within the cryptocurrency market, which this study attempts to address.

The results from the first part of the analysis indicate the superior ability of the Kalman filter to identify overbought and oversold levels of the cryptocurrency in question, and to then generate buy and sell opportunities. When comparing the buy and sell opportunities of the Kalman filter to those of the technical trading rules, the results indicate that the Kalman filter is able to generate superior returns to that of the technical trading rules. This surprising result proves that a simple strategy involving the Kalman filter is able to outperform the more "sophisticated" strategies of the technical trading rules. The results further indicate that the Kalman filter is able to accurately identify overbought and oversold levels of the cryptocurrency in question.

Overall, the Kalman filter is able to accurately identify the determinants of what drives the price discovery process in the cryptocurrency market. This speaks to the capability of the filter in identifying when buyers or sellers are more active in the cryptocurrency market at any given time. These were seen in the buy and sell opportunities generated from the Kalman filter and their ability to outperform the technical trading rules. This indicates that the efficient price generated by the Kalman filter is one that traders can rely on when determining the "balanced" price between supply and demand. Additionally, the Kalman filter's buy and sell recommendations were able outperform the passive buy and hold benchmark. Overall, these results provide convincing evidence of the Kalman filter's ability as a model in the cryptocurrency market.

The results from the second part of the analysis, that looked at determining whether the technical trading rules can perform better than the passive buy and hold benchmark, provide strong evidence in favour of technical trading rules. The technical trading rules, the Moving

Average (MA), Moving Average Convergence Divergence (MACD), Rate of Change (ROC), Relative Strength Index (RSI) and Bollinger Bands (BB) are all found to generate returns in excess of the passive buy and hold benchmark. This is seen in the full sample period (2010 to 2020), as well as in the sub-periods (2010 to 2015 and 2015 to 2020). When transaction costs are included the results still hold, with the technical trading rules still able to generate returns in excess of the passive buy and hold benchmark. Additionally, when compared on a risk adjusted basis, a large majority (number/percentage) of the trading rules are able to yield greater Sharpe and Sortino ratios than that of the passive buy and hold benchmark.

This dominant performance of the technical trading rules certainly questions the weak form efficiency of the cryptocurrency market. However, refuting the efficiency of the cryptocurrency market should be done with caution. Rather than using the results to refute the weak form EMH, the results from this Chapter are used to highlight the value in technical analysis and its relevance within the financial sphere. The results from this analysis indicate the value in using technical analysis in trading. There has been much scepticism about technical analysis amongst the academic world due to its conflict with the weak form EMH. However, the above results clearly indicate that despite technical analysis being somewhat of a "black sheep", this by no means discredits the actual ability and value of technical analysis, especially in the cryptocurrency market.

Future studies should aim to use Kalman filter on different types of asset classes and in different time periods. More specifically, the present study focused on cryptocurrencies. Future research could use the Kalman filter or state space modelling for difficult to value asset classes. The lack of available data was a limitation in the present study. Future work should aim to utilise more data and over longer holding periods to determine if the results still hold. Additionally, more technical trading rules can be used on different sample periods so as to determine whether other trading rules are as successful as the ones used in the present study. Lastly, a greater percentage of transaction costs can be considered in future studies. Preferably a percentage that is more accurately described by those used in practice. This should improve the present study in determining whether the technical trading rules still outperform the passive buy and hold benchmark when higher transaction costs are used. Future studies can also explore the statistical significance of the difference in profitability in the various trading rules during 'normal times' versus economic/financial crises periods- such as the 1997-8 emerging markets crisis, 2007-9 global financial crisis, 2010-12 European debt crisis, and global economic/financial crisis emanating from the 2020 Covid-19 pandemic, but also during the different phases of the business cycle, and bubbles and anti-bubbles periods.

Overall, the results of the present study provide useful insight into the identification of the price discovery process in the cryptocurrency market. The Kalman filter provides a useful tool into this identification process and when used as a simple trading strategy, proves to be a favourable one. Additionally, the value of technical analysis is confirmed and proven to be useful in the cryptocurrency market.

References

Alhashel, B. S., Almudhaf, F. W., & Hansz, J. A. (2018). Can technical analysis generate superior returns in securitized property markets? Evidence from East Asia markets. *Pacific-Basin Finance Journal*, *47*, 92-108. doi: https://doi.org/10.1016/j.pacfin.2017.12.005

Anghel, D. G. (2020). A reality check on trading rule performance in the cryptocurrency market: Machine learning vs. technical analysis. *Finance Research Letters*, 101655.doi: https://doi.org/10.1016/j.frl.2020.101655

Athey, S., Parashkevov, I., Sarukkai, V., & Xia, J. (2016). Bitcoin pricing, adoption, and usage: Theory and evidence. Retrieved from https://ssrn.com/abstract=2826674

Auret, C., & Sayed, A. (2020). The effects of uncertainty on investor expectations and volatility in the South African white maize futures market. *Investment Analysts Journal, 1-15.* doi: https://doi.org/10.1080/10293523.2020.1776503

Baillie, R. T., Booth, G. G., Tse, Y., & Zabotina, T. (2002). Price discovery and common factor models. Journal of financial markets, 5(3), 309-321. 321 doi: 10.1016/s1386-4181(02)00027-7

Bajgrowicz, P., & Scaillet, O. (2012). Technical trading revisited: False discoveries, persistence tests, and transaction costs. *Journal of Financial Economics, 106(3), 473-491*. doi: https://doi.org/10.1016/j.jfineco.2012.06.001

Bessembinder, H., & Chan, K. (1998). Market efficiency and the returns to technical analysis. Financial management, 5-17. doi: 10.2307/3666289

Bolt, W., & Oordt, M. (2016). On the Value of Virtual Currencies. Bank of Canada. Retrieved from https://www.bankofcanada.ca/wp-content/uploads/2016/08/swp2016-42.pdf

Bouri, E., Shahzad, S. J. H., & Roubaud, D. (2019). Co-explosivity in the cryptocurrency market. *Finance Research Letters*, *29*, 178-183. doi: https://doi.org/10.1016/j.frl.2018.07.005

Brandvold, M., Molnár, P., Vagstad, K., & Valstad, O. C. A. (2015). Price discovery on Bitcoin exchanges. *Journal of International Financial Markets, Institutions and Money, 36, 18-35.* doi: https://doi.org/10.1016/j.intfin.2015.02.010

Brock, W., Lakonishok, J., & LeBaron, B. (1992). Simple technical trading rules and the stochastic properties of stock returns. *The Journal of finance, 47(5), 1731-1764.* doi: https://doi.org/10.1111/j.1540-6261.1992.tb04681.x

Brogaard, J., Hendershott, T., & Riordan, R. (2014). High-frequency trading and price discovery. *The Review of Financial Studies, 27(8), 2267-2306.* doi: https://doi.org/10.1093/rfs/hhu032

Caginalp, G., & Laurent, H. (1998). The predictive power of price patterns. *Applied Mathematical Finance*, *5*(3-4), 181-205. doi: https://doi.org/10.1080/135048698334637

Chang, E. J., Lima, E. J. A., & Tabak, B. M. (2004). Testing for predictability in emerging equity markets. *Emerging Markets Review*, *5*(3), 295-316. doi: https://doi.org/10.1016/j.jbankfin.2005.08.001

Chen, C. P., & Metghalchi, M. (2012). Weak-form market efficiency: Evidence from the Brazilian stock market. *International journal of economics and finance, 4(7), 22-32*. doi: 10.5539/ijef.v4n7p22

Chen, C. W., Huang, C. S., & Lai, H. W. (2009). The impact of data snooping on the testing of technical analysis: An empirical study of Asian stock markets. *Journal of Asian Economics*, *20*(5), 580-591. doi: https://doi.org/10.1016/j.asieco.2009.07.008

Chen, Y., & Lai, K. K. (2013). Examination on the relationship between VHSI, HSI and future realized volatility with Kalman filter. *Eurasian Business Review, 3(2), 200-216*. doi: https://doi.org/10.14208/ebr.2013.03.02.005

Chong, T. T. L., & Ng, W. K. (2008). Technical analysis and the London stock exchange: testing the MACD and RSI rules using the FT30. *Applied Economics Letters, 15(14), 1111-1114*. doi: https://doi.org/10.1080/13504850600993598

Chong, T. T. L., Ng, W. K., & Liew, V. K. S. (2014). Revisiting the Performance of MACD and RSI Oscillators. *Journal of risk and financial management, 7(1), 1-12*. doi https://doi.org/10.3390/jrfm7010001

Chow, K. V., & Denning, K. C. (1993). A simple multiple variance ratio test. *Journal of Econometrics*, *58*(3), 385-401. doi: https://doi.org/10.1016/0304-4076(93)90051-6

Cooper, M., & Gulen, H. (2006). Is time-series-based predictability evident in real time? *The Journal of Business, 79(3), 1263-1292.* doi: 10.1086/500676

Corbet, S., Eraslan, V., Lucey, B., & Sensoy, A. (2019). The effectiveness of technical trading rules in cryptocurrency markets. *Finance Research Letters*, *31*, 32-37. doi: https://doi.org/10.1016/j.frl.2019.04.027

Corrado, C. J., & Lee, S. H. (1992). Filter rule tests of the economic significance of serial dependencies in daily stock returns. *Journal of Financial Research*, *15*(4), 369-387. doi: https://doi.org/10.1111/j.1475-6803.1992.tb00119.x

Cowles III, A. (1933). Can stock market forecasters forecast? *Econometrica*, 1(3), 309-324. doi: https://doi.org/10.2307/1907042

Cryptocurrencies Index 30. (2020). Retrieved from Cryptocurrencies Index 30 https://cci30.com/

Darolles, S., Gourieroux, C., & Le Fol, G. (2000). Intraday transaction price dynamics. Annales d'Economie et de Statistique, 207-238. doi: 10.2307/20076261

Detzel, A., Liu, H., Strauss, J., Zhou, G., & Zhu, Y. (2018). Bitcoin: Predictability and profitability via technical analysis. *SSRN Electron. J. Retrieved from* https://www.paris-december.eu/sites/default/files/pdf/parismeeting/2018/STRAUSS_2018.pdf

Detzel, A., Liu, H., Strauss, J., Zhou, G., & Zhu, Y. (2018). Bitcoin: Predictability and profitability via technical analysis. *SSRN Electron. J. Retrieved from* https://www.paris-december.eu/sites/default/files/pdf/parismeeting/2018/STRAUSS_2018.pdf

Dimson, E., & Mussavian, M. (1998). A brief history of market efficiency. *European financial management*, *4*(1), 91-103. doi: https://doi.org/10.1111/1468-036X.00056

Drake, J., & Downs, E. (2003). Profiting with indicators. Omnitrader's Technical Analysis Training Series. Retrieved from https://www.omnitrader.com/PDFs/indicators.pdf

Durbin, J. and S. J. Koopman (2001). Time-series Analysis by State Space Methods. *New York, Oxford University press.* Retrieved from https://www.researchgate.net/publication/227468262_Time_Series_Analysis_by_State_Space_Methods

Fama, E. F. (1965). The behavior of stock-market prices. The journal of Business, 38(1), 34-105. doi: https://doi.org/10.1086/294743

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance, 25(2), 383-417*. doi: 10.2307/2325486

Fama, E. F., & Blume, M. E. (1966). Filter rules and stock-market trading. *The Journal of Business, 39(1), 226-241.* Retrieved from http://momentum.technicalanalysis.org.uk/FaBl66.pdf

Fifield, S. G., Power, D. M., & Donald Sinclair, C. (2005). An analysis of trading strategies in eleven European stock markets. The European Journal of Finance, 11(6), 531-548. doi: https://doi.org/10.1080/1351847042000304099

Fisal, S. (2017). Predicting Stock Price Movements Using Technical Analysis. *Proceeding of the 4th International Conference on Management and Muamalah 2017, e-ISBN, 978-967.* Retrieved from http://conference.kuis.edu.my/icomm/4th/eproceedings/IC%20018.pdf

Foster, A. J. (1996). Price discovery in oil markets: a time varying analysis of the 1990–1991 Gulf conflict. *Energy Economics*, *18*(3), 231-246. doi: https://doi.org/10.1016/0140-9883(96)00020-5

Fritz, F., & Weinhardt, C. (2016). Technical Analysis, Liquidity, and Price Discovery. *In Paris December 2016 Finance Meeting EUROFIDAI-AFFI.* doi: https://dx.doi.org/10.2139/ssrn.2788997

Gerritsen, D. F. (2016). Are chartists artists? The determinants and profitability of recommendations based on technical analysis. International *Review of Financial Analysis, 47, 179-196.* doi: https://doi.org/10.1016/j.irfa.2016.06.008

Gerritsen, D. F., Bouri, E., Ramezanifar, E., & Roubaud, D. (2020). The profitability of technical trading rules in the Bitcoin market. *Finance Research Letters, 34, 101263.* doi: https://doi.org/10.1016/j.frl.2019.08.011

Giudici, P., & Polinesi, G. (2019). Crypto price discovery through correlation networks. *Annals of Operations Research*, 1-15. Doi: https://doi.org/10.1007/s10479-019-03282-3

Gonzalo, J., & Granger, C. (1995). Estimation of common long-memory components in cointegrated systems. *Journal of Business & Economic Statistics*, *13*(1), 27-35. doi: 10.1080/07350015.1995.10524576

Grobys, K., Ahmed, S., & Sapkota, N. (2020). Technical trading rules in the cryptocurrency market. *Finance Research Letters*, *32*, 101396. doi: https://doi.org/10.1016/j.frl.2019.101396

Gupta, E., Bedi, P., & Lakra, P. (2014). Efficient Market Hypothesis V/S Behavioural Finance. *IOSR Journal of Business and Management*, *16*(4), 56-60. Retrieved from http://iosrjournals.org/iosr-jbm/papers/Vol16-issue4/Version-4/H016445660.pdf

Gusev, M., Kroujiline, D., Govorkov, B., Sharov, S. V., Ushanov, D., & Zhilyaev, M. (2015). Predictable markets? A news-driven model of the stock market. Algorithmic Finance, 4(1-2), 5-51. doi:10.3233/AF-150042

Hanousek, J., & Kočenda, E. (2009). Intraday price discovery in emerging European stock markets. CERGE-EI working paper, (382). doi: https://dx.doi.org/10.2139/ssrn.1448618

Harlow, W. V. (1991). Asset allocation in a downside-risk framework. Financial analysts' journal, 47(5), 28-40. doi: https://doi.org/10.2469/faj.v47.n5.28

Hasbrouck, J. (1995). One security, many markets: Determining the contributions to price discovery. *The journal of Finance*, *50*(4), 1175-1199. doi: https://doi.org/10.1111/j.1540-6261.1995.tb04054.x

Hendershott, T., & Menkveld, A. J. (2014). Price pressures. *Journal of Financial Economics, 114(3), 405-423.* doi: https://doi.org/10.1016/j.jfineco.2014.08.001

Hsu, P. H., Taylor, M. P., & Wang, Z. (2016). Technical trading: Is it still beating the foreign exchange market? *Journal of International Economics*, *102*, 188-208. doi: https://doi.org/10.1016/j.jinteco.2016.03.012

Hudson, R., & Urquhart, A. (2019). Technical trading and cryptocurrencies. Annals of Operations Research, 1-30. Retrieved from file:///C:/Users/User/Downloads/Hudson-Urquhart2019_Article_TechnicalTradingAndCryptocurre%20(2).pdf

Hudson, R., & Urquhart, A. (2019). Technical trading and cryptocurrencies. *Annals of Operations Research*, 1-30. Retrieved from file:///C:/Users/User/Downloads/Hudson-Urquhart2019_Article_TechnicalTradingAndCryptocurre%20(3).pdf

Hudson, R., Dempsey, M., & Keasey, K. (1996). A note on the weak form efficiency of capital markets: The application of simple technical trading rules to UK stock prices-1935 to 1994. Journal of Banking & Finance, 20(6), 1121-1132. doi: https://doi.org/10.1016/0378-4266(95)00043-7

James, F. E. (1968). Monthly moving averages—an effective investment tool? *Journal of financial and quantitative analysis*, *3*(3), 315-326. doi: 10.2307/2329816

Jensen, M. C., & Benington, G. A. (1970). Random walks and technical theories: Some additional evidence. *The Journal of Finance, 25(2), 469-482.* doi: 10.2307/2325495

Jiang, F., Tong, G., & Song, G. (2019). Technical analysis profitability without data snooping bias: evidence from Chinese stock market. *International Review of Finance, 19(1), 191-206.* doi: https://doi.org/10.1111/irfi.12161

Kalman, R. E. (1960). A new approach to linear filtering and prediction problems. Retrieved from http://www.unitedthc.com/DSP/Kalman1960.pdf

Kambeu, E., Mpofu, O., & Muchochoma, D. (2017). Price Discovery and Volatility: A theoretical Approach. *International Journal of Finance & Banking Studies (2147-4486), 6(2), 37-43.* Retrieved from http://www.ssbfnet.com/ojs/index.php/ijfbs/article/view/30/31

Kendall, M. G., & Hill, A. B. (1953). The analysis of economic time-series-part i: Prices. *Journal of the Royal Statistical Society. Series A (General)*, *116*(1), 11-34. doi: 10.2307/2980947

Keynes, J. M. (1937). The general theory of employment. *The quarterly journal of economics, 51(2), 209-223*. doi: https://doi.org/10.2307/1882087

Kuang, P., Schröder, M., & Wang, Q. (2014). Illusory profitability of technical analysis in emerging foreign exchange markets. *International Journal of Forecasting, 30(2), 192-205.* doi: https://doi.org/10.1016/j.ijforecast.2013.07.01

Kwon, K. Y., & Kish, R. J. (2002). Technical trading strategies and return predictability: NYSE. *Applied Financial Economics, 12(9), 639-653.* doi: https://doi.org/10.1080/09603100010016139

Lento, C., Gradojevic, N., & Wright, C. S. (2007). Investment information content in Bollinger Bands? *Applied Financial Economics Letters, 3(4), 263-267.* doi: https://doi.org/10.1080/17446540701206576

Levy, R. A. (1967a). Random walks: Reality or myth. *Financial Analysts Journal*, *23*(6), 69-77.

Levy, R. A. (1967b). Relative strength as a criterion for investment selection. *The Journal of Finance*, *22*(4), 595-610. doi: 10.2307/2326004

Levy, R. A. (1967c). The Principle of Portfolio Upgrading. *IMR; Industrial Management Review (pre-1986)*, *9*(1), 82

Lo, A. W., Mamaysky, H., & Wang, J. (2000). Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation. *The journal of finance*, *55*(4), 1705-1765. doi: https://doi.org/10.1111/0022-1082.00265

Lukac, L. P., Brorsen, B. W., & Irwin, S. H. (1988). A test of futures market disequilibrium using twelve different technical trading systems. Applied Economics, 20(5), 623-639. doi: https://doi.org/10.1080/00036848800000113

Malkiel, B. G. (2005). Reflections on the efficient market hypothesis: 30 years later. *Financial Review*, *40*(1), 1-9. doi: https://doi.org/10.1111/j.0732-8516.2005.00090.x

Marney, J. P., Tarbert, H., & Fyfe, C. (2000). *Technical Trading Versus Market Efficiency-A Genetic Programming Approach* (No. 169). Society for Computational Economics. Retrieved from https://ideas.repec.org/p/sce/scecf0/169.html

Menkhoff, L. (2010). The use of technical analysis by fund managers: International evidence. *Journal of Banking & Finance*, *34*(11), 2573-2586. doi: https://doi.org/10.1016/j.jbankfin.2010.04.014

Menkveld, A. J., Koopman, S. J., & Lucas, A. (2007). Modeling around-the-clock price discovery for cross-listed stocks using state space methods. *Journal of Business & Economic Statistics, 25(2), 213-225*. doi: https://doi.org/10.1198/073500106000000594

Metghalchi, M., Chang, Y. H., & Marcucci, J. (2008). Is the Swedish stock market efficient? Evidence from some simple trading rules. *International Review of Financial Analysis, 17(3), 475-490.* doi: https://doi.org/10.1016/j.irfa.2007.05.001

Moss, D. A., & Kintgen, E. (2009). The Dojima Rice Market and the Origins of Futures Trading. Retrieved from https://edisciplinas.usp.br/pluginfile.php/151297/mod_resource/content/2/Dojima_Rice_Market_Case.pdf

Murphy, J. J. (1999). Technical Analysis of the Financial Markets: A Comprehensive Guide to Trading Methods and Applications. New York Institute of Finance

Nadarajah, S., & Chu, J. (2017). On the inefficiency of Bitcoin. Economics Letters, 150, 6-9. doi: https://doi.org/10.1016/j.econlet.2016.10.033

Nadarajah, S., & Chu, J. (2017). On the inefficiency of Bitcoin. *Economics Letters*, *150*, 6-9. doi: https://doi.org/10.1016/j.econlet.2016.10.033

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. Bitcoin.–URL: https://bitcoin. org/bitcoin. Pdf.

Neely, C. J. (1997). Technical analysis in the foreign exchange market: a layman's guide. Review-Federal Reserve Bank of St. Louis, 79(5), 23. Retrieved from https://www.questia.com/library/journal/1P3-24000769/technical-analysis-in-the-foreign-exchange-market

Neely, C. J., & Weller, P. A. (2003). Intraday technical trading in the foreign exchange market. *Journal of International Money and Finance, 22(2), 223-237*. doi: https://doi.org/10.1016/s0261-5606(02)00101-8

Neely, C. J., Rapach, D. E., Tu, J., & Zhou, G. (2014). Forecasting the equity risk premium: the role of technical indicators. Management science, 60(7), 1772-1791. doi: https://doi.org/10.1287/mnsc.2013.1838

Pagnotta, E., & Buraschi, A. (2018). An equilibrium valuation of bitcoin and decentralized network assets. doi: https://dx.doi.org/10.2139/ssrn.3142022

Park, C. H., & Irwin, S. H. (2007). What do we know about the profitability of technical analysis? *Journal of Economic surveys, 21(4), 786-826.* doi: https://doi.org/10.1111/j.1467-6419.2007.00519.x

Peeperkorn, J., & Seetharam, Y. (2016). A learning-augmented approach to pricing risk in South Africa. *Eurasian Business Review, 6(1), 117-139*. Retrieved from file:///C:/Users/User/Downloads/Peeperkorn-Seetharam2016_Article_ALearning-augmentedApproachToP%20(1).pdf.

Ratner, M., & Leal, R. P. (1999). Tests of technical trading strategies in the emerging equity markets of Latin America and Asia. *Journal of Banking & Finance, 23(12), 1887-1905.* doi: https://doi.org/10.1016/S0378-4266(99)00042-4

Rivin, I., & Scevola, C. (2018). An investable crypto-currency index. *Available at SSRN 3154706*. doi: https://dx.doi.org/10.2139/ssrn.3154706

Roberts, H. V. (1959). Stock-market" patterns" and financial analysis: Methodological suggestions. *The Journal of Finance*, *14*(1), 1-10. doi: https://doi.org/10.2307/2976094

Samuelson, P. A. (1965). Proof that properly anticipated prices fluctuate randomly. In The world scientific handbook of futures markets (pp. 25-38). doi: https://doi.org/10.1142/9789814566926_0002

Schreiber, P.S & Schwartz, R.A. (1986). Price discovery in securities markets. *The Journal of Portfolio Management, Vol 12(4) pp43-48*. doi: 10.3905/jpm.1986.409071

Senanedsch, J. (2012). A General Methodology for Testing the Performance of Technical Analysis on Financial Markets. *Journal of Computations & Modelling, 2(2), 79-94.* doi: http://www.scienpress.com/Upload/JCM/Vol%202_2_4.pdf

Sharpe, W. F. (1966). Mutual fund performance. *The Journal of business*, *39*(1), 119-138. Retrieved from https://www.jstor.org/stable/2351741

Shynkevich, A. (2020). Bitcoin Futures, Technical Analysis and Return Predictability in Bitcoin Prices. *Journal of Forecasting*. doi: https://doi.org/10.1002/for.2656

Shynkevich, A. (2012). Performance of technical analysis in growth and small cap segments of the US equity market. *Journal of Banking & Finance, 36(1), 193-208*. doi: https://doi.org/10.1016/j.jbankfin.2011.07.001

Smidt, S. (1965). Amateur Speculators: A Survey of Trading Styles, Information Sources and Patterns of Entry Into and Exit from Commodity-futures Markets by Non-professional Speculators. *Graduate School of Business and Public Administration, Cornell University*.

Sortino, F. A., & Price, L. N. (1994). Performance measurement in a downside risk framework. *The Journal of Investing, 3(3), 59-64.* doi: https://doi.org/10.3905/joi.3.3.59

Sullivan, R., Timmermann, A., & White, H. (1999). Data-snooping, technical trading rule performance, and the bootstrap. *The journal of Finance, 54(5), 1647-1691*. doi: https://doi.org/10.1111/0022-1082.00163

Sweeney, R. J. (1988). Some new filter rule tests: Methods and results. *Journal of Financial and Quantitative Analysis, 23(3), 285-300.* doi: 10.2307/2331068

Timmermann, A., & Granger, C. W. (2004). Efficient market hypothesis and forecasting. *International Journal of forecasting, 20(1), 15-27*. doi: https://doi.org/10.1016/s0169-2070(03)00012-8

Treynor, J. L. (1965). How to rate mutual fund performance. Harvard Business Review, 43, 63-75. Retrieved from https://www.jstor.org/stable/2351741

Urquhart, A. (2016). The inefficiency of Bitcoin. *Economics Letters*, *148*, 80-82. doi: https://doi.org/10.1016/j.econlet.2016.09.019

Van Horne, J. C., & Parker, G. G. (1967). The random-walk theory: an empirical test. *Financial Analysts Journal, 23(6), 87-92.* doi: https://doi.org/10.2469/faj.v23.n6.87

Van Horne, J. C., & Parker, G. G. (1968). Technical trading rules: A comment. *Financial Analysts Journal*, *24*(4), 128-132. doi: https://doi.org/10.2469/faj.v24.n4.128

Wang, L., An, H., Liu, X., & Huang, X. (2016). Selecting dynamic moving average trading rules in the crude oil futures market using a genetic approach. Applied energy, 162, 1608-1618. doi: https://doi.org/10.1016/j.apenergy.2015.08.132

Wang, T., & Sun, Q. (2015). Why investors use technical analysis? Information discovery versus herding behavior. *China Finance Review International*. doi: https://doi.org/10.1108/cfri-08-2014-0033

Welch, G., & Bishop, G. (1995). An introduction to the Kalman filter. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.336.5576&rep=rep1&type=pdf

Wong, W. K., Manzur, M., & Chew, B. K. (2003). How rewarding is technical analysis? Evidence from Singapore stock market. *Applied Financial Economics, 13(7), 543-551.* doi: https://doi.org/10.1080/09603100220000020906

Yen, S. M. F., & Hsu, Y. L. (2010). Profitability of technical analysis in financial and commodity futures markets—A reality check. *Decision Support Systems*, *50*(1), 128-139. doi: https://doi.org/10.1016/j.dss.2010.07.008

Yoon, H. (2013). A Change of Order Balance Implies Intraday Price Trend in Japanese Stock Market. In Proceedings of the International Conference on Parallel and Distributed Processing Techniques and Applications (PDPTA) (p. 191). The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp).

Zhang, Q., & Jaffy, S. (2015). High frequency volatility spillover effect based on the Shanghai-Hong Kong Stock Connect Program. *Investment management and financial innovations, 8-15.*

Zhu, H., Jiang, Z. Q., Li, S. P., & Zhou, W. X. (2015). Profitability of simple technical trading rules of Chinese stock exchange indexes. Physica A: Statistical Mechanics and its Applications, 439, 75-84. doi: https://doi.org/10.1016/j.physa.2015.07.032

Appendix A: Pre-transaction costs

The below tables consist of the results before transaction costs are considered across the full sample period (2010 to 2020) and across the two sub-periods (201 to 2015 and 2015 to 2020). Table A1 examines the performance of the technical trading rules over the full sample period (2010 to 2020) before transaction costs are considered. Overall, the results in Table A1 indicate strong support of the technical trading rules ability to generate returns greater than that of the passive buy and hold benchmark. It can be seen that all the trading rules are able to generate returns in excess of the passive buy and hold benchmark. Furthermore, all the t- statistics are significant indicating that the technical trading rules are all able to generate returns that are significantly different from the passive buy and hold benchmark.

Table A1: Performance of the technical trading rules (2010 to 2020)

Table A1: Full Sample			**Pre- Transaction costs**				
Strategy	**X(B)-X(H)**	**X(S)-X(H)**	**X(B)-X(S)**	**SD(B)**	**SD(S)**	**N(B)**	**N(S)**
MA 1-50	0.048312 (19.7599)	0.0524 (17.69263)	-0.00408 (1.97352)	0.06103	0.07216	623	594
MA 1-200	0.05197 (17.31902)	0.04979 (17.66576)	0.00218 (0.90802)	0.07413	0.06940	610	606
MA 1-150	0.04910 (18.04339)	0.05173 (17.75662)	-0.00263 (2.37405)	0.06748	0.07147	615	602
MA 2-200	0.05454 (17.37165)	0.04765 (17.53561)	0.00689 (1.86878)	0.07772	0.06678	613	604
MA 5-150	0.05462 (17.39627)	0.04752 (17.52829)	0.00711 (2.40359)	0.07792	0.06645	616	601
MACD	0.05469 (17.66672)	0.04705 (17.20400)	0.00764 (4.62319)	0.07799	0.06596	635	582
MACD SIGNAL	0.05523 (17.81678)	0.04676 (17.14250)	0.00846 (4.57283)	0.07818	0.06572	636	581
MACD HISTOGRAM	0.05059 (17.82456)	0.0500 (17.98496)	0.00059 (0.31076)	0.07002	0.06855	609	608
ROC	0.04889 (20.13343)	0.05129 (17.68768)	-0.00239 (2.23819)	0.06137	0.06970	639	578
RSI	0.04402 (5.36682)	0.123712 (7.94593)	-0.0796942 -	0.06032	0.17686	54	129
BOLLINGER BANDS	0.05667 (3.95497)	0.14053 (9.47601)	-0.08385466 -	0.08522	0.16933	35	130

Table A1 displays X(B) and X(S) which are the mean returns of the buys and sells. X(H) is the mean return for the buy and hold strategy, which in this period is the artificial market index based on the cryptocurrencies that make up 80% or more of the market. N(B) and N(S) are the number of buy and sell days. SD(B) and SD(S) are the standard deviation of the buy and sell days. The values in parentheses are the t-statistics testing the difference of the mean buy and mean sell from the mean buy and hold, and buy-sell from zero. '-' indicates the square root of a negative number which is not a real number.

Table A2 presents the results of the technical trading indicators in the sub-sample 2015 to 2020, pre-transaction costs. Similar to the results in the full (Table A1) the ability of the technical trading rules to generate returns in excess of both passive buy and hold benchmarks is highlighted. Despite the artificial market index having a higher return than the CCi30 index, 0.009 as opposed to 0.0002 respectively, all the technical trading rules are able to yield positive mean returns in excess of both market indices. This is seen for both the buy and sell days. This is evident by the statistically significant t-statistics for all the technical trading rules, across both the buy and sell signals. The Bollinger Bands and RSI indicators show superior performance in comparison to the other technical trading rules. The Bollinger Bands yield the highest mean returns for buy and sell days and across both passive benchmarks. Overall, the results in Table 5A are in strong support of the technical trading rules, as all the trading rules are able to generate returns greater than that of the passive buy and hold benchmark. Importantly to note are the extreme t-statistics for the sell signals for the Rate of Change (ROC) trading rule. These results are outliers driven by a higher than usual average mean return which drastically increases the final t-statistic when compared to the other technical trading strategies,

Table A2: Performance of the technical trading rules (2015 to 2020)

Table A2: 2015 to 2020			**Pre- Transaction costs**						
Strategy	**X(B)-X(H)**	**X(S)-X(H)**	**X(B)-X(H*)**	**X(S)-X(H*)**	**X(B)-X(S)**	**SD(B)**	**SD(S)**	**N(B)**	**N(S)**
MA 1-50	0.04739 (19.38964)	0.05215 (17.18464)	0.04804 (19.65713)	0.05280 (17.40007)	-0.00476 (1.39678)	0.05871	0.07194	577	562
MA 1-200	0.05123 (16.97314)	0.04932 (17.08124)	0.05189 (17.18973)	0.04997 (17.30766)	0.00191 (0.98987)	0.07213	0.06882	571	568
MA 1-150	0.04833 (17.87848)	0.05128 (17.04401)	0.04899 (18.12030)	0.05194 (17.26127)	-0.00295 (1.77806)	0.06494	0.07134	577	562
MA 2-200	0.05378 (17.01602)	0.04721 (16.95442)	0.05444 (17.22285)	0.04787 (17.18916)	0.00657 (1.94708)	0.07569	0.06623	574	566
MA 5-150	0.05386 (17.13309)	0.04707 (16.85929)	0.05451 (17.34104)	0.04772 (17.09344)	0.00679 (2.80979)	0.07551	0.06620	577	562
MACD	0.05438 (17.33217)	0.04609 (16.68937)	0.05504 (17.54052)	0.04674 (16.92611)	0.0083 (5.02975)	0.07677	0.06420	599	541
MACD SIGNAL	0.05489 (17.37427)	0.04587 (16.74416)	0.05555 (17.58118)	0.04652 (16.98279)	0.00902 (4.88644)	0.07707	0.06391	595	544
MACD HISTOGRAM	0.04888 (17.25051)	0.05044 (17.62859)	0.04954 (17.48122)	0.05110 (17.85704)	-0.0016 -	0.06685	0.06907	557	583
ROC	0.0482 (20.06837)	0.5088952 (170.82270)	0.04907 (20.33934)	0.509548932 (171.04214)	-0.46048 -	0.06011	0.06782	621	518
RSI	0.04676 (5.18727)	0.11645 (7.32600)	0.04742 (5.25979)	0.11710 (7.36713)	-0.06969 -	0.06604	0.16784	54	112
BOLLINGER BANDS	0.06036 (4.96448)	0.15000 (8.60061)	0.06101 (5.01825)	0.15065 (8.63809)	-0.08964 -	0.09006	0.17527	55	101

Table A2 displays X(B) and X(S) which are the mean returns of the buys and sells. X(H) is the mean return for the buy and hold strategy, which in this period is the artificial market index based on the cryptocurrencies that make up 80% or more of the market. X(H) is the mean return for an additional benchmark, the CCi30 index which contains the top 30 cryptocurrencies. The reason for the inclusion of the CCi30 in this sub- period and not the* *other sub periods is due to the CCi30 index only having data available from 2015 onwards. N(B) and N(S) are the number of buy and sell days. SD(B) and SD(S) are the standard deviation of the buy and sell days.*

Table A3 presents the average results of the technical trading rules for the sub-period 2010 to 2015 across all 30 cryptocurrencies. Importantly to note in this sub-period is that it only consisted of approximately 6 cryptocurrencies. This is because many of the cryptocurrencies in the full sample period launched fairly recently, for example some cryptocurrencies launched in 2017 while others even launched in 2020. This resulted in a lack of data across this sub-sample (2010 to 2015). Consequently, this sub-sample only had data for 6 cryptocurrencies. The average return of the artificial market index is higher than in the previous samples, being 0.001. Despite the higher average return for the market index, the technical trading rules still stand out. Similar to the results in the previous tables, the findings displayed in Table A3 clearly indicate the superior performance of the 5 technical trading rules. Each trading rule is able to produce positive returns in excess of the passive buy and hold benchmark. These returns in excess of the passive buy and hold benchmark all have statistically significant t-statistics for all the trading rules.

Table A3: Performance of the technical trading rules (2010 to 2014)

Table A3: 2010 to 2014			Pre- Transaction costs				
Strategy	X(B)-X(H)	X(S)-X(H)	X(B)-X(S)	SD(B)	SD(S)	N(B)	N(S)
MA 1-50	0.05446 (10.98217)	0.04835 (9.97717)	0.00611 (5.22529)	0.07066	0.06511	208	181
MA 1-200	0.05296 (10.25515)	0.04871 (10.64891)	0.00425 (1.46055)	0.07270	0.06227	198	185
MA 1-150	0.053834 (9.80669)	0.04785 (11.18657)	0.00598 -	0.07554	0.05961	189	194
MA 2-200	0.05267 (10.22992)	0.04885 (10.65941)	0.00382 (1.38337)	0.07257	0.06231	199	185
MA 5-150	0.05432 (9.84312)	0.04757 (11.17382)	0.00674 -	0.07573	0.05948	188	195
MACD	0.05596 (11.00218)	0.04634 (10.01989)	0.00963 (4.53768)	0.07412	0.06051	212	171
MACD SIGNAL	0.05571 (11.20829)	0.04669 (9.64015)	0.00902 (6.37806)	0.07246	0.06336	213	171
MACD HISTOGRAM	0.05410 (10.82235)	0.04872 (10.13062)	0.00539 -	0.06912	0.06669	191	192
ROC	0.05718 (11.58869)	0.04453 (9.41570)	0.01265 (7.28758)	0.07363	0.05998	223	161
RSI	0.05854 (4.62496)	0.13251 (6.12251)	-0.07397 -	0.06971	0.16340	30	57
BOLLINGER BANDS	0.07850 (4.45986)	0.25306 (4.50902)	-0.17456 (1.69556)	0.09174	0.27494	27	24

Table A3 displays X(B) and X(S) which are the mean returns of the buys and sells. X(H) is the mean return for the buy and hold strategy, which in this period is the artificial market index based on the cryptocurrencies that make up 80% or more of the market. N(B) and N(S) are the number of buy and sell days. SD(B) and SD(S) are the standard deviation of the buy and sell days. The values in parentheses are the t-statistics testing the difference of *the mean buy and mean sell from the mean buy and hold, and buy-sell from zero. '-' indicates the square root of a negative number which is not a real number.*

The Bollinger Bands still generate the greatest returns in both the buy and sell signals, thus outperforming the other technical trading rules as well as the passive market index. The RSI also shows great outperformance, but only for the sell signals. The Bollinger Bands have the highest standard deviation for both the buy and sell signals (0.0917 and 0.2749 respectively). Finally, in contrast to the large difference in the number of buys and sells for the RSI and BB's strategies in the previous sample periods, the difference in this sub-period is greatly reduced. Overall, similar to the other two sample periods, Table A3 provides strong support in favour of the technical trading rules.