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Citation for published version:
Kraaijeveld, O & De Smedt, J 2020, 'The predictive power of public Twitter sentiment for forecasting cryptocurrency prices', *Journal of International Financial Markets, Institutions and Money*. https://doi.org/10.1016/j.intfin.2020.101188

Digital Object Identifier (DOI):
10.1016/j.intfin.2020.101188

Link:
Link to publication record in Edinburgh Research Explorer

Document Version:
Peer reviewed version

Published In:
Journal of International Financial Markets, Institutions and Money

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Abstract

Cryptocurrencies have become a very popular topic recently, primarily due to their disruptive potential and reports of unprecedented returns. In addition, academics increasingly acknowledge the predictive power of Twitter for a wide variety of events and more specifically for financial markets. This paper studies to what extent public Twitter sentiment can be used to predict price returns for the nine largest cryptocurrencies: Bitcoin, Ethereum, XRP, Bitcoin Cash, EOS, Litecoin, Cardano, Stellar and TRON. By using a cryptocurrency-specific lexicon-based sentiment analysis approach, financial data and bilateral Granger-causality testing, it was found that Twitter sentiment has predictive power for the returns of Bitcoin, Bitcoin Cash and Litecoin. Using a bullishness ratio, predictive power is found for EOS and TRON. Finally, a heuristic approach is developed to discover that at least 1-14% of the obtained Tweets were posted by Twitter *"bot"* accounts. This paper is the first to cover the predictive power of Twitter sentiment in the setting of multiple cryptocurrencies and to explore the presence of cryptocurrency-related Twitter bots.

Keywords: cryptocurrencies, time series analysis, sentiment analysis, Natural Language Processing, Twitter, bots.

1. Introduction

Cryptocurrencies are digital currencies that make use of blockchain technology, a disruptive, decentralised and cryptographic technology that enables the digitalisation of trust. In the context of cryptocurrencies, blockchain technology (in theory) allows the role of governments as producers of currency and the role of intermediary (third-party) parties to verify a transaction to become obsolete. Although cryptocurrencies have been around since the launch of the cryptocurrency Bitcoin on 1 January 2009 (Nakamoto, 2008), their disruptive potential led to an explosive growth of the interest in, and development of, cryptocurrencies over the course of 2017 and early 2018. The growth and interest were primarily caused by news stories which reported the unprecedented returns of cryptocurrencies, that subsequently attracted a type of gold rush. Simultaneously, current global regulations on cryptocurrencies are very limited, as cryptocurrencies are not yet acknowledged as a mature asset class. This regulatory void, in combination with the high popularity and lack of an institutional guarantor, makes the cryptocurrency market so volatile that it has even been called a *"wild west"*.

The volatility of the cryptocurrency market is strongly fuelled by news messages and posts on social media. This effect is further reinforced, as investors struggle to discover whether the posted information is true or false. Due to the relatively young age of the cryptocurrency market, traditional news outlets do not always timely report events, what has led to social media being a primary source of information for cryptocurrency investors. Specifically, micro-blogging website Twitter[1] is a widely used source for cryptocurrency information. Not only does Twitter provide live updates on cryptocurrencies, it is also a rich source of emotional intelligence, as investors frequently express their sentiment. Behavioral economics tells us that sentiment and emotions can profoundly affect individual behavior and decision-making. With the vast amount of easily available data from Twitter containing the emotional intelligence of cryptocurrency users and investors, it is the main goal of this study to research to what extent public Twitter sentiment can be used to forecast the price fluctuations of cryptocurrencies. In addition, this research will also research both Tweet message volume and explore to what extent automated cryptocurrency-related Twitter *"bot"* accounts are present, as they are known to commonly spread misinformation and thus can potentially impact the findings of this study. It falls

[1] https://twitter.com/

outside of the scope of this work to research any effects such bot accounts might have on cryptocurrency prices. This study is unique in several ways. First, this work will provide a literature survey and provide an economic analysis of the cryptocurrency market and its predictability. Secondly, this work will construct a sentiment analysis tool specifically for cryptocurrency-related Tweets by accounting for jargon. Moreover, many previous academic works have only (or primarily) focused on Bitcoin. This study is one of the few works to research the cryptocurrency market in general and study beyond the scope of Bitcoin. The rationale for this study is further supported by well-known related works that obtained promising results for using Twitter sentiment to predict financial markets (Bollen et al., 2011; Li et al., 2017).

The rest of this study is structured as follows: Section 2 will provide an economic analysis of the cryptocurrency market and provide an extensive literature review of related studies. Section 3 will then discuss the methodology and subsequently, Section 4 and Section 5 will discuss the results and limitations of this work. The findings of this study are summarised in Section 6.

2. Literature review and related work

This section reviews the theoretical foundations and related works of several topics. First, cryptocurrencies are discussed, followed by Twitter sentiment analysis, its applications in financial markets, and its applications for cryptocurrencies. Then, works on bot identification are reviewed.

2.1. Cryptocurrencies

2.1.1. The cryptocurrency market

In late 2008, a new decentralised cryptographic cash system was anonymously published by pseudonym Satoshi Nakamoto, which formed the basis of blockchain technology. Simultaneously it launched blockchain technology's most commonly known application in the form of a cryptocurrency called Bitcoin (Nakamoto, 2008). Nakamoto's whitepaper is seen as a revolutionary work that solved the previous challenges in establishing a secure and robust digital currency such as the double-spending problem, hack attacks due to network centrality and the relative high costs and long periods associated with cross-border and/or interbank transactions. In the years after Bitcoin's inception, many other cryptocurrencies (referred to as *altcoins*) such as Ethereum[2] and Litecoin[3] were developed. Often, these altcoins were developed for a different purpose or tried to improve the limitations of Bitcoin, such as Bitcoin's limited supply, the network's high energy consumption or the Proof-of-Work user-consensus mechanism. Initially, cryptocurrencies had a questionable reputation by often being labelled as shady or *"currencies for criminals"* (Mihm, 2013), yet this changed when the interest in the cryptocurrency market exploded over the course of 2017 and early 2018, leading to a hype and an extreme bull market fuelled by *the fear of missing out*. As a result, the number of listed cryptocurrencies more than tripled to 1,865 and the total cryptocurrency market capitalisation grew from $17 billion on 1 January 2017 to $813 billion almost one year later (CoinMarketCap, 2018). A good example of this hype is illustrated in Corbet et al. (2019), who describe how announcing the development of a company-based cryptocurrency fueled the company's stock price.

It is often argued what type of asset class cryptocurrencies are. Although they are deemed currencies in the sense that they are digital mediums of exchange, there are also several limitations to that idea. The primary reason for individuals to use an established currency like the US Dollar (USD) or Euro (EUR) is that its value remains relatively consistent over time and that a government acts as a guarantor. Cryptocurrencies lack both elements, what causes the market to be extremely volatile and currently make cryptocurrencies unsuitable as a reliable storage of value or a medium of exchange (Ciaian et al., 2016). Days where the entire market's value in- or decreases by 20-30% are not uncommon and numerous currencies have experienced enormous gains or losses

[2]See `https://www.ethereum.org/`
[3]See `https://litecoin.org/`

in very short periods of time. From the peak of the market in December 2017 to October 2018, the market has lost more than 75% of its value (CoinMarketCap, 2018). Yermack (2015) names Bitcoin's scarcity and its instability as reasons for it not be classified as a "*real*" currency, which also applies to many other cryptocurrencies. Furthermore, data from Chainanalysis[4] in 2018 indicates that most investors do not use Bitcoin as a medium of exchange but rather see it as an investment tool. It indicates that 6 million Bitcoins are held by long-term (> 1 year) investors as opposed to 5 million Bitcoins held by short-term (< 1 year) speculators. The remaining 10 million Bitcoins are either deemed lost or have not been mined yet. The data also indicates that the vast majority of transactions of Bitcoin are between exchanges and that Bitcoin is seldom used to pay for goods or services (Murphy, 2018). The U.S. Securities and Exchange Commission reported in June 2018 that Bitcoin and Ethereum cannot be classified as securities but might become more akin to a commodity (Hinman, 2018). In addition, a study by Dyhrberg (2016) analyses Bitcoin by using GARCH-time-series modelling and finds that Bitcoin shows several similarities to gold and the USD. A more recent study by Baur et al. (2018) finds that Bitcoin is a speculative asset and not an alternative currency. It is difficult to know whether the results of such Bitcoin-specific studies are generalisable to all cryptocurrencies, especially since every currency serves its own purpose and has distinct characteristics such as supply, demand and transaction volume. To which asset class cryptocurrencies belong is therefore hard to define, as they share characteristics from various existing asset classes. It could potentially even be argued that cryptocurrencies form an entirely new asset class.

Regulators have therefore taken various stances on cryptocurrencies, while they try to understand their potential benefit and how they should be treated from a legislative perspective. Many cryptocurrency exchanges have had to comply with Anti Money Laundering (AML) and Know Your Customer (KYC) regulations, yet in many countries the cryptocurrency market remains highly

[4]See https://www.chainalysis.com/

unregulated. This lack of adequate regulation, the speculative nature of cryptocurrencies and the lack of a governmental or institutional guarantor contribute to the market's extreme volatility and have left the market prone to manipulation. Price manipulation for Bitcoin was researched by Gandal et al. (2018), who focus on suspicious trading activities on the Mt. Gox exchange between 2010 and 2013 and found that within two months, a single actor drove up Bitcoin's price from $150 to $1000. Griffin and Shams (2018) proves that in 2017, cryptocurrency exchange Bitfinex used Tether[5] to manipulate Bitcoin's price on a very large scale. Moreover, it was found that a prolonged manipulation campaign accounted for 50% of Bitcoin's price increase and 64% of major altcoin price increases between March 2017 and March 2018. Contributing to price manipulation opportunities is the unequality in the wealth distribution for the vast majority of listed cryptocurrencies. According to data from *Bitinfocharts.com* in June 2018, the top 10,000 wealthiest addresses control between 50-95% of the entire market capitalisation for most major cryptocurrencies. More specifically, the top 100 richest addresses control up to 15-45% of the entire market capitalisation of most major cryptocurrencies (Bitinfocharts.com, 2018). By holding large stakes (commonly referred to in the cryptocurrency/finance space as being a *whale*), these investors can steer prices through e.g. pump-and-dump schemes. Such schemes are deemed illegal within current global financial legislations, but the lack of regulation on cryptocurrencies have made these cartel schemes a common occurrence within the cryptocurrency market.

Several researchers and prominent individuals in the financial industry have also argued that Bitcoin and the cryptocurrency market follow all classic patterns found in asset bubbles and compared it to historical asset bubbles such as the 1999 DotCom bubble and the 1637 Dutch Tulip Mania (Authers, 2017; Phillips and Gorse, 2017; Sovbetov, 2018; Blau, 2018). By looking at their

[5]Tether is a cryptocurrency that profiles itself as a stable cryptocurrency (*"stablecoin"*) within the unstable market, aiming to continuously trade around $1 through reportedly being backed 1:1 with the USD.

statements it could be argued that, during its existence, the market has already experienced 5-6 bubbles. The market's behaviour also aligns with several important investment mania and euphoria conditions outlined by Kindleberger and O'Keefe (2001), such as the "*widespread adoption of an invention that has pervasive effects*" and investors who "*buy goods and securities to profit from the capital gains associated with the anticipated increases in the prices of these goods and securities*". The latter has also been an important argument in the on-going debate about the intrinsic value of cryptocurrencies. Critics argue that cryptocurrencies return no discounted future cash flows (e.g. dividends) and hence have no intrinsic value, as their value is only determined by the expectations of a future resale value (Silverman et al., 2017; Mai et al., 2018).

The use of cryptocurrencies as a hedging tool against political and financial market uncertainty has also been a commonly researched topic. The works of Brière et al. (2015), Dyhrberg (2016), Li and Wang (2017) and Bouri et al. (2017) find that Bitcoin can be used as a hedging tool against global uncertainty and that it forms a good investment portfolio diversifier for a wide range of indices, currencies and commodities. Price clustering for Bitcoin is also found by Urquhart (2017) and in addition, predictability and volatility of cryptocurrencies using GARCH-modelling is further studied in the works of Chu et al. (2017) and Katsiampa (2017).

2.1.2. Predictability and price discovery

The predictability of the cryptocurrency market is remarkable because according to the Efficient Market Hypothesis (EMH), a predictable market is informationally inefficient as the available information is not fully reflected in market prices. The market's inefficiency is further supported by various market anomalies. One example is the work of Ciaian et al. (2018), who find that Bitcoin's market and altcoin markets are very interdependent and that the correlation is stronger during the short-term than the long-term. This goes against the assumption of the EMH, which states that in an efficient market, successive price changes are independent (Fama, 1970). Another important assumption of the EMH states that investors are assumed to be rational and value an asset based on its fundamental value. In an article by Silverman et al. (2017), William Goetzmann - an economist at Yale University - states that due to the lack of intrinsic value and the prices of cryptocurrencies being driven by speculation, there is no way for cryptocurrencies to be valued fundamentally, making the market irrational. The cryptocurrency market also offers limited instruments and opportunities for investors to communicate a downward price potential, contributing to an inefficient market. Before the introduction of futures contracts for Bitcoin by the Chicago Mercantile Exchange (CME) and Chicago Board Options Exchange (CBOE) in December 2017, investors were limited to using margin trading tools available only on a limited number of cryptocurrency exchanges.

Some parties now also offer cryptocurrency option contracts, still for many cryptocurrencies there are currently limited methods - other than selling - to communicate a downward price potential, which fuels the possibility for a market to form a bubble. This is also why various institutional parties are looking to establish a cryptocurrency-based Exchange-Traded Fund (ETF) that will contribute to the maturation of the market. Furthermore, the prices of cryptocurrencies can vary substantially across various markets and exchanges, allowing for arbitrage - a characteristic of inefficient markets - to be a profitable trading strategy (Baker and Wurgler, 2006). The informational inefficiency also suggests why the market reacts so heavily to news messages. This is observed by Ciaian et al. (2016) and Sovbetov (2018), with investors gaining an informational advantage in predicting returns.

From a research perspective, the cryptocurrency's market efficiency is researched by Urquhart (2016), who observed Bitcoin prices between 2010 and 2016, and discovers that the Bitcoin market is inefficient but might be moving towards a more efficient market. Bariviera (2017) and Tiwari et al. (2018) find that Bitcoin's market is efficient, but it is unlikely that these results can be applied to the entire cryptocurrency market. A different study by Mensi et al. (2019) researches the efficiency of Bitcoin and Ethereum and finds a price dynamics pattern, suggesting that Bitcoin and Ethereum markets are inefficient. Sensoy (2019) compared weak form efficiency for the BTC/USD versus the BTC/EUR market and finds that the BTC/USD market is slightly more efficient and that both markets have become more efficient over time. Lastly, Aslan and Sensoy (2019) use several differing methods to estimate the Hurst exponent and find that the efficiency in the cryptocurrency market varies per cryptocurrency and per intrahourly sampling frequency. More specifically, market efficiency is found to follow a U-shaped pattern with weak form efficiency only occuring around the 5-min and 10-min intervals, supporting that hourly predictability for certain cryptocurrencies is possible. Mensi et al. (2019) and Sensoy (2019) also find that efficiency levels vary over different sampling frequencies. Note that again, there exists little research into other cryptocurrencies than Bitcoin.

The EMH is the neoclassical standard theory of financial markets but focuses less on the behavioural and emotional effects that market actors have on prices. Given the more behavioural nature of this work and strong presence of emotionally driven investment decisions, best observed through the strong volatility in the cryptocurrency market, the Adaptive Markets Hypothesis (AMH) proposed by Lo (2004) is deemed a more appropriate framework for this study. Lo (2004) argues that the EMH is not wrong but merely incomplete because it does not fully explain market behaviour as irrationality and rationality coexist in financial markets. To reconcile the omnipresent EMH and evolutionary behavioural aspects, the AMH states that "*markets are not always efficient, but are usually competitive and adaptive, varying in their degree of efficiency as the environment and investor population change over time*" (Lo, 2012). Where the EMH relies on the assumption of the homo economicus as a consistent rational actor, the AMH states that this only occurs at times of certainty. The actor's behaviour at times of uncertainty is difficult to explain, as this is driven by emotion and instinct. This is best demonstrated by *the flight-of-safety* principle, which is one of the key implications of the AMH and can also be observed in the cryptocurrency market. During volatile periods, where the market is dislocated and (extreme) greed and/or fear dominate through the so-called *madness of the mobs*, investors will divest their risky assets into defensive assets. As mentioned before and by Bolton (2018), many cryptocurrency investors will use stablecoins such as Tether, Paxos or USD Coin as a safe-haven when the market is more volatile. Once the volatility decreases, the market returns to the *wisdom of the crowds* and prices return to being a better reflection of the available information. In addition, Lo argues that "*a relatively new market is likely to be less efficient than a market that has been in existence for decades*" (Lo, 2012). This further supports the proposed argument that the cryptocurrency market is inefficient and thus can be predicted to a certain extent.

To find whether Twitter sentiment is a cryptocurrency price driving factor, it is important to explore other driving factors of cryptocurrency prices. Researchers have extensively studied these factors for a wide range of variables. The most credible academic works the price driving factors of cryptocurrencies are by Sovbetov (2018) and Ciaian et al. (2018). For Bitcoin specifically, the work of Kristoufek (2015) is comprehensive. This study distinguishes two types of factors that can affect cryptocurrency prices: internal factors (e.g. supply, demand and mining difficulty) and external (e.g. market trends and macro-economic factors). Other factors that affect cryptocurrency prices include, but are not limited to, the S&P 500 (Sovbetov, 2018), gold prices (Poyser, 2017), the USD/EUR exchange rate (Georgoula et al., 2015), mining difficulty (Li and Wang, 2017), the political situation of a country (e.g. Venezuela) (Poyser, 2017), Twitter mentions (Li and Wang, 2017), news sentiment and volume (Polasik et al., 2015), speculation (Sovbetov, 2018), regulation announcements, Initial Coin Offerings (ICO)[6], hard forks[7], airdrops [8], cryptocurrency exchange hacks

[6]An ICO or Initial Coin Offering is an unregulated fund-raising event for a new cryptocurrency project.

[7]A dispute between developers and/or miners, where a blockchain is cloned by a new team of developers who slightly alter the blockchain's protocol.

[8]An airdrop is an event where a blockchain project distributes a new currency for free amongst investors who own the currency in question.

and cryptocurrency exchange (de)listings. Furthermore, a survey by CoinDesk amongst 3,000 cryptocurrency investors indicates that a cryptocurrency's market capitalisation is the most important investment criterion, followed by exchange volume, number of exchanges that list that currency and a cryptocurrency's transaction volume (CoinDesk, 2018).

2.2. Twitter sentiment analysis and financial markets

2.2.1. Sentiment and predictability

Within the context of economics, Kaplanski and Levy (2010) define sentiment as any misperception that can lead to mispricing the fundamental value of an asset. Sentiment can therefore make assets speculative, as according to Baker and Wurgler (2007), the crucial characteristic defining what makes some assets more speculative than others is "*the difficulty and subjectivity of determining their true value*". This is related to a fundamental psychological concept of (financial) markets which states that decision-making is driven by psychological factors and/or emotions and that therefore market behaviour is not always synonymous with the fundamental value of an asset (Peterson, 2016). Investors can use this fundamental concept in a quest to profit from assets which, based on their sentiment, are either over- or undervalued.

As news is unpredictable, stock prices are also unpredictable (Fama et al., 1969). However, some researchers demonstrate that stock prices do not follow a random walk and are therefore predictable (Bollen et al., 2011). From previous works it is known that financial markets are significantly impacted by news and that news affects sentiment (Peterson, 2016). In more recent studies, researchers and investors have increasingly acknowledged the power of Natural Language Processing (NLP) and text mining approaches to extract sentiment from news, as shown with the Thomson Reuters MarketPsych Indices (TRMI) or in the works of Mao et al. (2011) and Li et al. (2014). Stock micro-blogs such as StockTwits[9], message boards and social media have also demonstrated to give

[9]See https://stocktwits.com/

useful results for predicting stock prices (Antweiler and Frank, 2004; Nguyen et al., 2015; Li et al., 2017). Traditionally, investors use various indicators to measure sentiment. Investor surveys such as the American Association of Individual Investors (AAII) or Investor Intelligence (II) are widely used but are limited by their need for recipients to obtain representative results (Baker and Wurgler, 2007). In addition, various technical sentiment indicators such as the CBOE Volatility Index (VIX) and crossovers in the Moving Average Convergence Divergence (MACD), 50-day and 200-day Moving Averages are used.

2.2.2. Twitter sentiment analysis

The use of separate sentiment indicators such as surveys, technical tools or news limits researchers and investors. Twitter for sentiment analysis has been an increasingly used source of data which can be attributed to the idea that Twitter offers a combination of both news and investor sentiment. Sentiment analysis or opinion mining is "*the computational study of people's opinions, appraisals, attitudes, and emotions toward entities, individuals, issues, events, topics and their attributes*" (Liu and Zhang, 2012) where the main goal is to assign a positive, negative or neutral sentiment polarity score to unstructured text. The 280-character length limitation of Tweets make them extremely noisy data and lead to sentence- or phrase level analysis to be the most suitable level of granularity (Giachanou and Crestani, 2016).

Within the Twitter sentiment analysis literature, Giachanou and Crestani (2016) distinguish four types of approaches: (1) a supervised machine learning-based, (2) a lexicon-based, (3) a hybrid (ML & LB) or (4) a graph-based approach. Tafti et al. (2016); Peterson (2016) and Li et al. (2017) state that micro-blogs such as Twitter are better able to adequately provide a broad and global live-stream of market information. In addition, micro-blogs spread generated content virally before news outlets report it and have an immediate market-moving impact on financial markets. Twitter data provides a rich source of information that can affect markets, which can be used to extract emotional intelligence through sentiment analysis. In related works, the use and effectiveness of Twitter sentiment analysis to predict financial markets is best demonstrated in the well-known study by Bollen et al. (2011) and more recently in the work of Li et al. (2017). Although the work of Bollen et al. (2011) is remarkable with an accuracy of 86.7%, the study has also been heavily criticised for making incorrect statistical assumptions (Lachanski and Pav, 2017). Li et al. (2017) use a Naive Bayes sentiment classifier, in combination with regression models, to find that stock-related Tweets have predictive power for daily stock returns. It is also shown that previous day volatility leads to increases in Twitter volume, suggesting that Twitter sentiment acts as both a *"cause"* and *"effect"* of financial markets. Other works that report the added benefit of including Twitter sentiment for predicting financial markets include Zhang et al. (2011) and Sprenger et al. (2014b). More specifically, Mao et al. (2011) show that although traditional investor sentiment does not have predictive power for financial markets, Twitter sentiment is able to have strong predictive power for the next 1-2 day(s) returns.

Most of the related works follow a sentiment analysis approach, in combination with regression models or a (Granger-)causality test, to examine the predictive power of Twitter sentiment in financial markets (Bollen et al., 2011; Mao et al., 2011; Porshnev et al., 2013; Sprenger et al., 2014a; Li et al., 2017). Some works also apply Neural Networks as an auxiliary test to explore the predictive factor of Twitter sentiment (Bollen et al., 2011; Porshnev et al., 2013). The studies vary in their sentiment analysis approach, where most authors either use a supervised machine learning approach with manually annotated data or follow a hybrid approach. Studies that use a hybrid or lexicon-based approach often use the Loughran & McDonald financial corpus and/or the Harvard IV-4 psychological corpus (Mao et al., 2011; Li et al., 2014). Loughran and McDonald (2011) demonstrate that the performance of a sentiment analysis classifier substantially improves when a context-specific dictionary is used. The predictive power of Twitter sentiment for financial markets is generally observed to be the strongest between 1-4 days (Bollen et al., 2011; Zhang et al., 2011;

Sprenger et al., 2014a; Li et al., 2017). There are several limitations of the Granger-causality test with regard to bias and assumptions. One of the main limitations of the original Granger-causality test is that it requires stationary data and assumes linear relations between the researched variables. Many of the related studies mentioned in this Section, use Granger-causality to find predictor variables for price (returns), yet only a number of works acknowledge that the relations between a variable and stock or cryptocurrency prices are almost certainly non-linear, especially since there are many different factors that affect prices (Bollen et al., 2011; Balcilar et al., 2017).

2.3. Twitter sentiment analysis and cryptocurrencies

Social media has become the primary source of information on cryptocurrencies and can be divided into Twitter, cryptocurrency-related forums and cryptocurrency news sites. Researchers have used messages from forums such as Reddit and Bitcointalk.org (Mai et al., 2015; Kim et al., 2016, 2017; Xie, 2017) in addition to various news sources (Karalevicius et al., 2018) to perform sentiment analysis and predict fluctuations in Bitcoin's price. Most researchers acknowledge the predictive power of social media and news sentiment for Bitcoin prices and/or trading volume on the short-term (1-7 days) and long-term (30-90 days). The volume of posts or messages also correlates with Bitcoin's trading volume (Mai et al., 2015). In addition, Karalevicius et al. (2018) confirm what was suggested earlier; cryptocurrency investors appear to overreact to news leading to a price pattern where the price initially moves with the sentiment and is then slightly corrected. Moreover, Phillip et al. (2018) use epidemic modeling and Reddit topic pages to accurately predict price bubbles and movements for Bitcoin, Ethereum, Litecoin and Monero.

Twitter sentiment analysis has been used in various studies to predict Bitcoin's price fluctuations. In a study by Georgoula et al. (2015), a Support Vector Machine (SVM) and various regression models were used to predict Bitcoin's price fluctuations using Twitter sentiment analysis. The authors obtained an accuracy of 89.6% and only found a short-term correlation between positive Twitter sentiment and Bitcoin's price. Garcia and Schweitzer (2015) use a lexicon-based approach with a Vector Autoregressive (VAR) model and Granger-causality testing, to find that increases in Twitter sentiment polarity precede Bitcoin price fluctuations. In addition, Mai et al. (2015) incorporate intraday analysis and show that Twitter posts are useful for predicting Bitcoin returns at an hourly interval. However, this study was limited by Bitcoin's price being sourced from only one exchange. Prices in the cryptocurrency market can vary substantially across exchanges, thereby making such a result questionable.

The mentioned related works have taken similar approaches as studies that predicted financial markets using Twitter sentiment, where a sentiment analysis approach is often combined with a (Granger-)causality test and/or (a) regression model(s). Researchers apply extensive pre-processing techniques such as tokenisation, stemming, stop-word removal and filtering out non-English Tweets, to clean their Twitter data. Of the various works that follow a lexicon-based approach, many use the Loughran & McDonald financial corpus (Mai et al., 2015; Xie, 2017; Karalevicius et al., 2018). The most effective number of lags is observed from 1-5 lags for interday analysis, and 2-4 lags for intraday analysis.

2.4. Limitations of current literature

It is found that the current literature on Twitter sentiment analysis to predict cryptocurrency prices is severely limited in multiple ways. Firstly, there are no known works that have attempted to predict altcoin price returns using Twitter sentiment analysis, other than the works of Xie (2017). Nearly all of the aforementioned studies have only, or primarily focused, on the properties and/or predictions of Bitcoin. For the academic works that have studied Bitcoin, the main issues are their scarcity - potentially due to the complex and relative young nature of cryptocurrencies - in addition to the rapid development of the market, making the results of some articles already outdated. Furthermore, the majority of the works is limited in their data collection by a small set of Twitter search query terms, the data collection limitations of the Twitter Search API and/or observing only short periods of time. Many works have searched for only one or two search terms and did not include any of the currencies' abbreviations and/or tickers. The Twitter Search API is limited, since it only allows a maximum number of 180 queries per 15 minutes. The combination of the above means that all of the aforementioned works have only captured a fraction of the full scope of Tweets available, thereby limiting the generalisability of their results. There also are various works that sourced their cryptocurrency prices from a single exchange. Another unexplored area within previous literature is that no previous papers have incorporated cryptocurrency specific slang or language into their sentiment classifier. This work offers a contribution to the field by incorporating and improving on the missing elements of previous works. Specifically, it focuses on a robust approach in collecting and processing data and researches various altcoins. Subsequently, a tailored approach for conducting Twitter sentiment analysis for cryptocurrencies is presented.

2.5. Identifying (cryptocurrency-related) Twitter bot accounts

Reutzel (2018) outlines four common cryptocurrency-related Twitter scam techniques used by bots and troll accounts: (1) The Tweet states to give away free cryptocurrency or give away free cryptocurrency after a small amount is transferred. (2) The Tweet posts links to other bot accounts which users are asked to follow. (3) The bot account usernames often impersonate other established names and/or accounts. (4) The Tweet calls another user or post a scam. More recently, an insightful report by Wright and Anise (2018) provides evidence for a cryptocurrency Twitter bot network, consisting of 15,000 accounts. Features that could be considered as relevant include a high ratio of following/followers, a high number of hashtags in a Tweet, whether the account is verified and the number of Tweets posted with identical content.

3. Methodology

3.1. Data collection

This study focuses on the prediction of price returns of the nine largest cryptocurrencies, where their size is based on their market capitalisation in May

2018. Specifically, in descending order of market capitalisation Bitcoin (*BTC*), Ethereum (*ETH*), XRP (*XRP*), Bitcoin Cash (*BCH*), EOS (*EOS*), Litecoin (*LTC*), Cardano (*ADA*), Stellar (*XLM*) and TRON (*TRX*) are researched. The data collection is divided into two sections. The first section focuses on the collection of Tweets from Twitter and the second section focuses on collecting financial data from CoinMarketCap[10]. An overview of the data collection can be found in Figure 1.

3.1.1. *Twitter data*

Tweets were obtained separately for each cryptocurrency between the period of 4 June 2018 and 4 August 2018, resulting in nine datasets with a total of 24,035,075 public Tweets. A live stream crawler was implemented using the Twitter API, that continuously stored Tweets as they were posted in real-time. This approach is advantageous compared to previous studies, it ensures that a wider spectrum of Tweets is collected[11]. It is common for the Twitter community to use hashtags (#) as a prefix to indicate topics and to use the dollar symbol ($) as a prefix to communicate about financial products such as cryptocurrencies or stocks. The used Twitter search terms were obtained by implementing various combinations of the cryptocurrency's name and its ticker. Non-English Tweets were filtered out and numerous (user) variables were collected to be used in the Twitter bot identification section of this study. More details of the Twitter datasets can be found in Table 1.

3.1.2. *Financial data*

Financial data for the nine researched cryptocurrencies was sourced from CoinMarketCap between 4 June 2018 and 4 August 2018. The rationale is that the prices of cryptocurrencies can vary substantially across various exchanges. CoinMarketCap is a widely used proxy for cryptocurrency prices as it combines prices from a large number of exchanges, thereby offering a more accurate and

[10] See https://coinmarketcap.com/

[11] See: https://github.com/twitterforcrypto/twitter-crawler for the full script.

general value representation that is independent of any exchange price bias. The CoinMarketCap API was used to collect financial data on a daily and hourly interval. Specifically, financial variables such as price in USD and BTC, daily trading volume, market capitalisation in USD and supply were obtained. Because this work will research the predictive power of Twitter sentiment and message volume on both intraday and interday levels, the financial data is converted into a time series. We use daily *"closing"* (e.g. 28 July 2018 0.00AM) and hourly (e.g. 28 July 2018 11.00AM) prices.

3.2. Data pre-processing and feature selection

Twitter data is known for its lack of structure and its high levels of noise. As a result, the collected Twitter data requires extensive pre-processing to make it useful in sentiment analysis. An array of 18 sentiment pre-processing techniques is applied, in combination with specifically designed techniques to filter out noise elements from Tweet texts. First, tokenisation and normalisation are applied by removing URLs, excess (white) spaces, and user mentions (e.g. *@account*) from the Tweets. Whether a Tweet was posted as a Retweet the *"RT"* at the start of the Tweet text is removed. Tweets with less than four tokens are omitted from the dataset as they are not suitable for sentence-level sentiment analysis. In addition, a new approach to extract the potential added linguistic value from hashtags is proposed. The hashtag prefix from the token is deleted if that token is present in the NLTK Reuters English dictionary[12]. If the token is not present in the dictionary, the entire hashtag is removed from the text. To illustrate, take the following Tweet as an example: *"This cryptocurrency is a #really #good #buy #buynow #btc #cryptocurrency"*. Omitting all hashtags in this Tweet would result in deleting a large part of its sentimental value. Following the above example, the sentence would then be processed to *"This cryptocurrency is a really good buy"*.

Following this, the contractions of tokens are expanded (e.g. *"we're"* into

[12] See: http://nltk.org

"we are'"), both ticker symbols (e.g. *"\$BTC"*) and tokens containing numerical characters (e.g. *"2nd"* or *"123"*) are removed and negations are handled (e.g. *"haven't"* into *"have not"*). Note that ticker symbols were used to obtain Tweets but are removed as they are noise in the context of sentiment analysis. (Cryptocurrency) (slang) abbreviations and acronyms (e.g. *"LOL"* or *"BTW"*) are handled using a manually compiled list and case-folding (e.g. *"BUY"* to *"buy"*) is also applied. The cryptocurrency word-list is created by using various online cryptocurrency-related articles and posts, as well as the findings from Section 2.1 and additional terms which are known to be frequent in the cryptocurrency space. The use of cryptocurrency specific jargon will be explained in more detail in the sentiment analysis section of this work. Tokens with character sequences longer than three characters are reduced to character sequences of three (e.g. *"heeeellllloo"* to *"heeellloo"*) and punctuation is removed to further reduce noise. Subsequently, irrelevant stop words (e.g. *"me"* or *"who"*) are removed by using a customised version of NLTK's English stop word list. Lemmatisation is applied using the WordNet Lemmatizer and stemming was explored by using both a Porter Stemmer and a Snowball Stemmer, but stemming is not applied to the data as the effects of both stemmers are found to be too aggressive. The handling of emoticons and spam will be discussed later in this study. Lastly, any possible time differences in the Twitter and financial datasets are mitigated by using UTC-1 timestamps for all data. An example of how the above techniques are applied is shown in Table 2 and more information about the datasets after pre-processing can be found in Table 3. The total number of Tweets after pre-processing was 22,912,039.

3.3. Methods

3.3.1. Testing for the presence of (cryptocurrency-related) Twitter bots

In Section 2.5, multiple studies and articles mentioned the large presence of bot accounts within the context of Twitter and cryptocurrencies, where it was found that none of the described works have quantified the presence of Twitter bots in their analysis. Therefore, this work will also explore the presence of

Twitter bots within the obtained datasets, by using a simple heuristic approach. Due to the scope and limitations of this study, the possible effects of Twitter bots on sentiment and/or prices are not researched.

To test for the presence of bot accounts in the collected Twitter data, six simple heuristics are proposed and implemented. These heuristics are based on the findings of Section 2.5 and patterns found through manual inspection of the datasets. To ensure a slightly better guarantee for identifying bots, a Tweet is considered to be posted by a cryptocurrency bot if it meets two (rather than one) or more of the following criteria: (1) The Tweet text contains *"give away"* or *"giving away"* (Reutzel, 2018). (2) The Tweet contains *"pump"* and either *"register"* or *"join"* (referring bots asking to join and/or register for fraudulent pump-and-dump schemes). (3) The Tweet contains more than 14 hashtags. (4) The Tweet contains more than 14 ticker symbols. (5) The platform source of the Tweet contains *"bot"*. (6) The user follows less than 1000 accounts and the ratio between the number of followed accounts and accounts that follow that user is larger than ten. The platform source refers to the Twitter client that was used to post the Tweet. Note that the values for (3), (4) and (6) were not chosen arbitrarily but were selected by taking a number which was two standard deviations from the observed mean number of hashtags, ticker symbols and follower/following ratio per Tweet for all nine datasets.

3.3.2. Sentiment analysis

Sentiment polarity scores are obtained using the Valence Aware Dictionary and Sentiment Reasoner (VADER) algorithm (Gilbert and Hutto, 2014), the Loughran & McDonald financial corpus (Loughran and McDonald, 2011) and a manually compiled cryptocurrency lexicon of 63 words and abbreviations. Tweets will either be classified as positive, neutral or negative to correspond with the financial recommendations of buy, hold or sell. The neutral class is included to reduce the likelihood that the sentiment analysis model will overfit.

3.3.2.1 Lexicon-based approach

A robust lexicon-based approach, tailored for cryptocurrency-related Tweets is used, where several lexicons are combined. The VADER algorithm (Gilbert and Hutto, 2014) is implemented as a baseline tool for the sentiment analysis. VADER is a lexicon and a rule-based sentiment analysis model that is specifically trained, and suitable for, sentiments expressed in social media. Moreover, in a similar study by Kim et al. (2016), the VADER algorithm was also used to obtain accurate polarity scores from social media texts to predict cryptocurrency price fluctuations. Gilbert and Hutto (2014) show that VADER can outperform both human annotators and most classifier benchmarks.

In addition to the pre-processing steps already performed in Section 3.2, VADER extracts additional sentimental value from negations, emoticons, punctuation, degree modifiers, slang and acronyms. The VADER lexicon is complemented by adding the tokens from the 2016 Loughran & McDonald financial corpus[13] that are not already present in the VADER lexicon. In addition, the manually compiled cryptocurrency lexicon of 63 relevant words, abbreviations, slang and acronyms is added to the initial lexicon. Using the valence scores, VADER computes a normalised weighted composite compound score between -1 and 1. This compound or polarity score indicates whether a Tweet is positive (≥ 0.05), neutral ($>$ -0.05 and $<$ 0.05) or negative ($\leq$ -0.05) (Gilbert and Hutto, 2014). Subsequently, these scores are used to classify trade recommendations accordingly. The polarity scores are then converted into time series and aggregated into daily and hourly intervals, which is performed by taking the mean score per interval. It falls outside of the scope of this work to research any effects of user influence. Tweets and users are therefore treated equally, regardless of Retweets, favourites or user characteristics.

[13] See `https://sraf.nd.edu/textual-analysis/resources/`

3.3.3. Granger-causality testing

To explore whether certain factors are driving prices, this work looks at the bivariate Granger-causality test. It is important to note that Granger-causality does not establish *actual* causality but rather finds a statistically significant pattern in lagged values of X and Y. This can be interpreted as *"X has predictive power for Y"* (Mao et al., 2011) and relates back to the key concept of statistics where correlation is not causation. In addition to the limitations of the original Granger-causality test mentioned in Section 2.2, testing for Granger-causality by using the F-test statistic when one or both time series are non-stationary, can lead to spurious relations. More specifically, Engle and Granger (1987) point out that when one or both series are non-stationary and co-integrated, the original Granger-causality test is invalid. To mitigate the above problems, this study applies the augmented Todo & Yamamoto ("T&Y") Granger-causality test proposed by Toda and Yamamoto (1995). The steps outlined by Toda and Yamamoto (1995) are particularly suitable for series that have different orders of integration and the approach does not require differencing and co-integration testing. This is beneficial as it circumvents the potential bias present in differencing techniques and co-integration tests. It can also be applied to any type of variable; regardless of the variables being in state I(0), I(1) or I(2), co-integrated or non co-integrated. An Augmented Dickey-Fuller (ADF) test is used to test for stationarity and determine the maximum order of integration D_{max}, where we allow for a drift in each of the series. To account for the autocorrelation in the residuals of the specified T&Y Vector Autoregressive (VAR) models, the commonly used Breusch-Godfrey LM test is used to evaluate. The procedure of T&Y is based on the following augmented VAR(l'+D_{max}) models:

$$X_t = \mu + \sum_{i=1}^{l'+D_{max}} \alpha_t Y_{t-i} + \sum_{i=1}^{l'+D_{max}} \beta_i X_{t-i} + \mu_{1t} \tag{1}$$

$$Y_t = \mu + \sum_{i=1}^{l'+D_{max}} \gamma_t X_{t-i} + \sum_{i=1}^{l'+D_{max}} \delta_i Y_{t-i} + \mu_{2t} \tag{2}$$

Here, l' represents the respective lag orders and μ represents the error terms. The approach ensures the error terms are not autocorrelated by increasing the appropriated number of lags l to the selected number of lags l'. This work also applies Johansen's Trace and Maximum Eigenvalue tests to test the validity of the T&Y results for series that involve at least one I(1) series. By cross-referencing the T&Y results with the results of Johansen's tests, a robust approach is ensured as co-integration between two time series implies Granger-causality, either one-way or in both directions (Engle and Granger, 1987). Furthermore, the original Granger-causality test is applied to all stationary I(0) series, again to be used as a cross-reference and to explore various lags. The number of lags for the original Granger-causality tests are chosen in line with results of the aforementioned studies from Section 2.3: up to five lags for interday analysis and up to six lags for intraday analysis. Similar works have also used Vector Error Correction Models (VECM) in the context of causality testing, yet VECM models are only used when the series are co-integrated and the estimated VAR model is used for other purposes than Granger-causality testing.

3.3.4. Metrics and variables

Daily and hourly Twitter sentiment S_T, bullishness B and message volume V_{mes} are individually used as independent variables X, to explore whether they exhibit predictive power for each of the dependent variables Y: price returns P_R and daily trading volume V^D_{trad}. The relations are bilaterally tested to explore whether causality exists in any direction. To avoid autocorrelation issues between prices and thus avoid spurious relations, this work uses price returns P_R instead of regular price time series, similar to the vast majority of aforementioned related studies. For the calculation of bullishness for a cryptocurrency c, let M_{buy} be the number of Tweets with a *"BUY"* recommendation and M_{sell} be the number of Tweets with a "*SELL*" recommendation at interval *t*. Based on the definition by Antweiler and Frank (2004) and Li et al. (2017), bullishness is calculated as:

$$B_t^c = \ln(1 + \frac{M_c^{buy}}{M_c^{sell}}) \quad (3)$$

Note that the function does not contain *"HOLD"* recommendations, because they provide neutral information. Message volume V_{mes} for a cryptocurrency c is calculated by taking the total number of Tweets M at interval t:

$$V_{mes}^c = \ln(1 + \sum_t^c M) \quad (4)$$

Trading volume V_{trad} data for a cryptocurrency c is only available on a daily interval and is defined as:

$$V_{trad}^c = \ln(1 + V_{trad}^c) \quad (5)$$

Lastly, the price returns P_R for a cryptocurrency c at interval t are calculated as follows:

$$P_{Rc}^t = \ln(1 + \frac{P_t^c}{P_{t-1}^c}) \quad (6)$$

Natural log transformations are applied to all time series for normalisation purposes and to enable the comparisons of time series, aligning with Sprenger et al. (2014b) and Li et al. (2017). Similar works such as have also studied the predictive power of sentiment in traditional financial markets. These works include abnormal returns to benchmark price returns with market returns and account for any date specific characteristics. This work does not include abnormal returns because only nine out of the more than 1,500 cryptocurrencies are studied and there exists no recognised cryptocurrency market price index that can be used as a benchmark. Date specific characteristics are also not accounted for, as the market is continuously trading and does not close like traditional financial markets do. Therefore, it is assumed that the cryptocurrency market behaves relatively similar over time, regardless of the time of day, day of the week or any holiday periods.

4. Results and analysis

4.1. The presence of (cryptocurrency-related) Twitter bots

Figure 2 and Table 4 summarise the findings for cryptocurrency-related Twitter bots within the obtained datasets. It can be observed that Twitter bots are commonly present, as they account for an estimated 1% - 14% of the Tweets posted. The presence of bot accounts is relevant because they can potentially be used to steer the sentiment of investors on Twitter and spread false information, thereby impacting the findings of this study. Interestingly, the lowest percentage of bots is found for Bitcoin, while this is the dominant and most popular cryptocurrency. The largest relative presence of bot accounts is observed for Tweets related to Cardano. Figure 2 also shows the percentual distribution of the number of bot characteristics per cryptocurrency. The results in Table 4 are close to the aforementioned estimations of Twitter, which reported that an estimated 8.5% of all Twitter accounts are bot accounts (Subrahmanian et al., 2016). However, it is likely that the actual number of Twitter bots within the cryptocurrency space is higher than the observed percentages. To illustrate, when for example a Tweet mentions a give away, it is extremely likely to be a bot account. Yet such a Tweet is only classified as a bot account if it meets an extra criterion. It is therefore more likely that the true number of bot accounts lies between the percentages observed for threshold one and two.

4.2. Sentiment analysis

The results from the sentiment analysis in Table 3 indicate that the polarity scores for all nine cryptocurrencies are relatively and similarly constant over time. The scores are also consistently positively skewed with a mean polarity of 0.33. This is consistent with the results of Kennedy and Inkpen (2006), who observe that lexicon-based approaches generally have a positive bias, which can be attributed to a human tendency to prefer positive language. Furthermore, the results suggest a seasonal pattern in the hourly sentiment for all nine cryptocurrencies, where the first 12 hours of day exhibit a bullish trend and the next

12 hours exhibit a bearish trend. Outliers in the sentiment polarity time series occur sporadically and usually quickly recover. A suggested explanation for this could be the observed bot accounts that post large volumes of nearly identical messages that obtain similar polarity scores. However, the findings of this study do not provide evidence to support this statement yet it could provide a simple explanation for the observed outliers.

4.3. Granger-causality testing

The central research question of this work is whether Twitter (sentiment) has predictive power for several important cryptocurrency-related variables. More specifically, this paper aims to find whether Twitter (sentiment) "*causes*" or reflects the cryptocurrency market. The results for the causality tests are shown in Appendix, Table 5 - 22, indicating the maximum order of integration D_{max}, the appropriate (l) and selected (l') number of lags and the p-values for the two types of causality tests (if both were applied). The results in Table 5 - 22 also demonstrate that the T&Y and original Granger-causality (OGC) approaches obtain very similar results when the same number of lags are selected, indicating the congruence in their methodologies. The various cryptocurrency price time series indicate excessive price volatility, what allows this study to perform the analysis under various market conditions. Due to the high number of tests, we mainly focus on the relations that are statistically significant ($p < 0.05$).

4.3.1. Results per cryptocurrency

For the daily intervals of Bitcoin, Twitter sentiment ($p < 0.01$) and bullishness ($p < 0.05$) strongly affect the trading volume for various lags. Although no causal relation is found under the T&Y approach, the OGC approach indicates significant predictive power ($p < 0.05$) of Twitter sentiment on price returns for the past three days. As the data is stationary and the OGC approach is more suitable for stationary data, the results from the OGC approach are assumed to be more representative. The relation between sentiment and price returns for Bitcoin also aligns with the findings of Garcia and Schweitzer (2015). Bullishness is observed to be a strong effect of price returns, indicating that Twitter users Tweet more positively or negatively depending on Bitcoin's price returns. On the hourly intervals, no predictive power in either direction was observed and in contrast to Mai et al. (2015), no causal relation between message volume and trading volume was found.

For the daily intervals of Ethereum, no predictive power for Twitter sentiment on price returns is found. In the opposite direction, it is observed that price returns Granger-cause the volume of messages for all the selected lags in the intraday analysis and in a number of cases on the interday interval (lags 2 and 4). This again indicates that Twitter merely responds to the price returns of Ethereum and does not Granger-cause its price returns.

No predictive power for Twitter sentiment on price returns is observed for XRP on the daily interval but Twitter sentiment is found to be an effect of price returns on the hourly interval. The results in Table 9 indicate that the effects of message volume on both price returns (lags 4 and 5) and trading volume (lag 5) are statistically significant ($p < 0.05$) and contrarily message volume is found to be a strong effect of price returns on the hourly interval. It was previously explained that Johansen's tests are used to cross-reference the results in the case of non-stationary datasets. The results from Johansen's tests for XRP contradict the findings of the T&Y approach, but it is likely that some causal relation exists beyond the selected lag. It is beyond the scope of this work to explore any such potential relations in the case of non-stationary data as the T&Y approach fits the optimal model with the optimal single lag.

Twitter sentiment can help predict the price returns of Bitcoin Cash, which is observed for various hourly lags (1 and 3) but not in the interday analysis. The other results in Appendix, Table 11 show that on the daily level Twitter rather responds to the market, as Twitter sentiment is a statistically significant response to daily trading volume. Furthermore, bullishness is caused by price returns on a daily level. Evidence for a causal relation between price returns and message volume was found for the first lag of the intraday analysis, indicating investors responding to price returns.

For EOS, no causal relationships were found other than a statistical significant effect of daily message volume on daily trading volume. In the hourly analysis, the results in Appendix, Table 14 indicate that Twitter sentiment can help predict price returns to a certain extent, but this effect is only statistically significant ($p < 0.05$) for bullishness on price returns.

Compared to the other researched cryptocurrencies, the results for Litecoin are the most interesting. A strong effect ($p < 0.05$) of daily Twitter sentiment on daily price returns is found for the first three lags, but the effect becomes insignificant thereafter. This can also clearly be observed in Figure 3. Furthermore, daily message volume is statistically significantly affecting both daily price returns and daily trading volume, what also corresponds with the findings of the applied Johansen's tests. On the hourly interval, the message volume and price returns for Litecoin are strongly correlated for various lags, occurring at various lags in both directions.

For Cardano, the predictive effect of Twitter sentiment on daily trading volume is observed to be present short term (lag 1). It can be observed that the results from Johansen's test again correspond with the findings of the causality tests and that the results of the T&Y approach are similar to the results from the OGC approach. On the intraday level, no causal relations are found. No causal relations are observed for Stellar in any of the directions. Lastly, the results for TRON were observed to only have predictive power on a daily interval. It was found that daily trading volume is strongly affected ($p < 0.05$) by both daily Twitter sentiment and daily bullishness. Daily bullishness is also a predictive indicator for the daily price returns of TRON.

4.3.2. General analysis

Overall it is found that Twitter has considerable predictive power for several cryptocurrency-related variables. More specifically, Twitter sentiment has significant predictive power for the price returns of Bitcoin, Bitcoin Cash and Litecoin. The results vary largely across different echelons, such as the cryptocurrency itself or the level of analysis (inter- or intraday). Using a bullishness ratio, predictive power for price returns is observed for EOS and TRON.

Twitter sentiment S_T and message volume V_{mes} are the overall strongest predictors on the interday level, followed by bullishness B and price returns P_R. Within the 17 observed Granger-causing relationships, the independent variables (Twitter sentiment, bullishness and message volume) occur more frequently as the "*causing*" variable than the dependent variables (price returns and trading volume) do. From the findings of this study, it could therefore be suggested that Twitter is slightly more of a "*cause*" than an "*effect*" of the cryptocurrency market on the daily level. In the case of hourly analysis, it is observed that in most cases Twitter merely responds to market activities rather than it having predictive power.

In addition, daily message volume is observed to Granger-cause daily trading volume but only for XRP, EOS and Litecoin. Figure 4 interestingly suggests that particularly for Bitcoin and Ethereum, their daily message and trading volume respectively follow very correlated patterns. Although no immediate cause for this is known, it would align with the findings of the study by Ciaian et al. (2018), who observe that Bitcoin and altcoin markets are strongly correlated. Another possible explanation could be some of the discussed price driving factors and/or the aforementioned price manipulation (schemes) that can affect the entire cryptocurrency market. The reason that the causality test results for Twitter sentiment and bullishness are not always parallel can be explained by the difference in the calculation of these variables through the exclusion of including *"HOLD"* recommendations.

5. Discussion

In this study, we have made assumptions have been made that may separate theory from practice. The daily datasets contained 61 instances, what is found to be close to suboptimal for the selected number of lags in the T&Y approach. Furthermore, the two levels of analysis, daily and hourly, might be too generic, as Twitter's nature warrants a short-term intraday analysis. Further limitations regarding the data include the general issue of contextual relevance due to the used search terms and use of hashtags by Twitter users. To illustrate, cryptocurrency-related Tweets often use many hashtags to attract attention in search queries. This results in Tweets that might reference a cryptocurrency, while the information presented in the Tweet does not concern the queried currency. A side-effect of the above is also that that the collected datasets likely contain overlapping Tweets. Lastly, no weighting was given to specific Tweets or user characteristics. Any effects of user or social influence were not researched.

With regard to the applied techniques, the primary limitation comes from using a lexicon-based approach for the sentiment analysis. Lexicon-based approaches are unsupervised and obtain lower accuracies compared to supervised techniques, due to their static rule-based nature. As a result, their generalisation is often very poor and the approach works less well on unstructured texts such as Tweets. In addition, some of the valence scores that were used for the cryptocurrency lexicon are subjective and have not been formally verified. Another point of discussion is that Section 2.1 mentioned that there are many price driving factors. If in a Granger-causality test, a factor Z influences both time series X and Y, the model will likely overfit due to spurious relationships. Moreover, this work has used a heuristic approach to explore the presence of bots, leading to only approximations of what are thought to be bot accounts. Lastly, both sentiment analysis and causality testing are subjective techniques that require a high level of detail in the analysis to be able to make the right inferences. It should also be mentioned that Tweets are very noisy data and one should be careful with drawing conclusions from such data. The results of this study should therefore be handled with care when applied in a real-life scenario.

6. Conclusion

Over the course of 2017 and early 2018, the cryptocurrency market received large-scale attention due to its extreme value gains and losses. While the potential of cryptocurrencies reaches far beyond prices, this study has researched to what extent public Twitter sentiment can be used to forecast the prices of the nine largest cryptocurrencies by market capitalisation.

By implementing a robust cryptocurrency-specific lexicon-based sentiment analysis approach in combination with bivariate Granger-causality tests, it was found that Twitter sentiment can be used to predict the price returns of Bitcoin, Bitcoin Cash and Litecoin. Using a bullishness ratio, predictive power for price returns was found for EOS and TRON. Message volume is a predictor of price returns of Litecoin and XRP, but for most other cryptocurrencies, price returns helps predict message volume, indicating that investors simply respond to the market. The strongest predictors on the daily level are Twitter sentiment and message volume, while price returns is the strongest predictor variable on the intraday level. It can thus be suggested that Twitter *causes*, rather than *follows*, the cryptocurrency market. However, this difference is marginal, as there are several cases where price returns cause sentiment, occurring mostly on the intraday level. By applying a set of heuristics to estimate the presence of cryptocurrency-related Twitter bots, it was found that 1-14% of the Tweets in the obtained datasets were posted by bots. This number is an estimate and it was found that the actual number is likely to be higher.

Cryptocurrencies form a young and uncharted research topic, where there are many topics available for future research. This work has offered a contribution to the limited amount of cryptocurrency research, by providing a literature survey on the topic, a cryptocurrency-specific Twitter sentiment analysis tool and researching beyond the scope of Bitcoin. As suggestions for future research, one could apply this research to a larger set of cryptocurrencies, extend the period of observation, experiment with various levels of granularity and/or research the effects of user/social influence. Another topic for future research would be to apply a supervised machine learning-based or hybrid approach. Also, this study has researched the presence, yet not the effects of cryptocurrency-related Twitter bots on prices and/or trading volumes. One could consider researching how to identify these bots more accurately and subsequently test their effects on Twitter sentiment and/or cryptocurrency prices. Lastly, one could test the reproducibility of this research by trying to replicate the results or use the findings to predict e.g. price returns. In a more advanced setting, these findings can be used to develop a trading strategy. However, it is important to state that the statistical significance observed in this study does not equate to practical significance, due to the inclusion of transaction costs in a real-life trading environment.

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7. Figures and tables

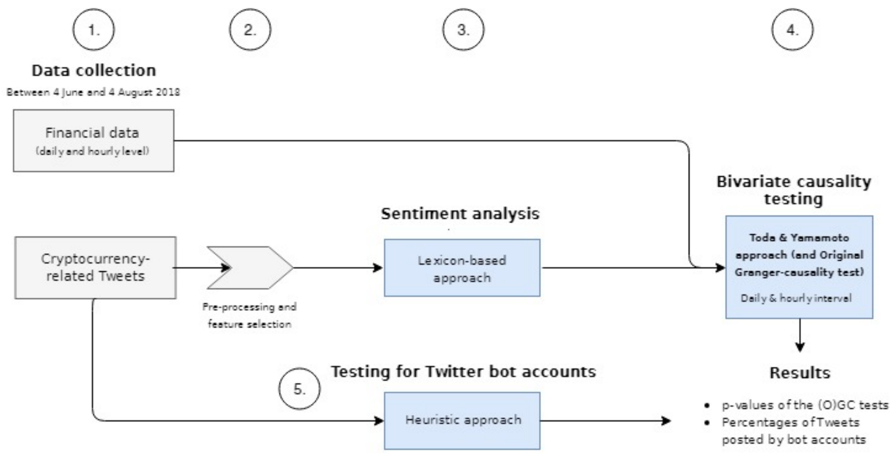


Figure 1: A general overview of the various phases of the methodology.

	Cryptocurrency	**Total number of collected Tweets**
1.	Bitcoin (BTC)	9,768,425
2.	Ethereum (ETH)	6,286,602
3.	XRP (XRP)	1,635,570
4.	Bitcoin Cash (BCH)	816,634
5.	EOS (EOS)	619,899
6.	Litecoin (LTC)	1,212,446
7.	Cardano (ADA)	489,321
8.	Stellar (XLM)	1,310,418
9.	TRON (TRX)	1,895,760
	Total	**24,035,075**

Table 1: Number of Tweets before pre-processing

	Processing technique	Result
0.	Original Tweet	RT @bitcoin https://twitter.com/FT/status/1022605086172872704 Bitcoin ETF rejected but buuuuuy!!! Ask yourself why you aren't buying lol, tomorrow it will reach 8000 #BUY #NOW #BITCOIN #BTC $BTC $ETH
1.	Remove *"RT"* if present	@bitcoin https://twitter.com/FT/status/1022605086172872704 Bitcoin ETF rejected but buuuuuy!!! Ask yourself why you aren't buying lol, tomorrow it will reach 8000 #BUY #NOW #BITCOIN #BTC $BTC $ETH
2.	Remove URLs, excess (white) space and mentions	Bitcoin ETF rejected but buuuuuy!!! Ask yourself why you aren't buying lol, tomorrow it will reach 8000 #BUY #NOW #BITCOIN #BTC $BTC $ETH
3.	Reduce character sequences >3 to 3	Bitcoin ETF rejected but buuuy!!! Ask yourself why you aren't buying lol, tomorrow it will reach 8000 #BUY #NOW #BITCOIN #BTC $BTC $ETH
4.	Apply case-folding	bitcoin etf rejected but buuuy!!! ask yourself why you aren't buying lol, tomorrow it will reach 8000 #buy #now #bitcoin #btc $btc $eth
5.	Remove Tweet if number of tokens <4	bitcoin etf rejected but buuuy!!! ask yourself why you aren't buying lol, tomorrow it will reach 8000 #buy #now #bitcoin #btc $btc $eth
6.	Remove hashtags if not in Reuters corpus	bitcoin etf rejected but buuuy!!! ask yourself why you aren't buying lol, tomorrow it will reach 8000 buy now $btc $eth
7.	Expand contractions	bitcoin etf rejected but buuuy!!! ask yourself why you are not buying lol, tomorrow it will reach 8000 buy now $btc $eth
8.	Handle slang and/or acronyms	bitcoin etf rejected but buuuy!!! ask yourself why you are not buying laughing out loud, tomorrow it will reach 8000 buy now $btc $eth
9.	Remove ticker symbols	bitcoin etf rejected but buuuy!!! ask yourself why you are not buying laughing out loud, tomorrow it will reach 8000 buy now
10.	Remove tokens with numerical characters	bitcoin etf rejected but buuuy!!! ask yourself why you are not buying laughing out loud, tomorrow it will reach buy now
11.	Apply WordNet lemmatisation	bitcoin etf rejected but buuuy!!! ask yourself why you are not buying laughing out loud, tomorrow it will reach buy now
12.	Remove stop words using custom list	bitcoin etf rejected but buuuy ask not buying laughing out loud tomorrow reach buy

Table 2: Example of the application of the applied pre-processing techniques

	Crypto-currency	Total number of Tweets	Number of unique users	Number of unique Tweets	Mean daily volume	SD daily volume	Mean polarity
1.	Bitcoin (BTC)	9,568,223	978,066	3,332,389	156,856.1	18,166.7	0.315
2.	Ethereum (ETH)	6,129,414	707,180	1,550,239	100,482.2	12,778.0	0.481
3.	XRP (XRP)	1,534,870	300,320	622,703	23,613.4	8,023.5	0.2882
4.	Bitcoin Cash (BCH)	733,504	123,818	366,982	11,461.0	3,260.7	0.23
5.	EOS (EOS)	516,431	99,226	189,517	7.945.1	2,726.9	0.35
6.	Litecoin (LTC)	1,128,391	197,770	442,052	17,631.1	6,169.3	0.328
7.	Cardano (ADA)	418,380	77,290	210,839	6,436.6	2,094.1	0.297
8.	Stellar (XLM)	1,082,282	428,779	368,036	16,153.5	9,835.5	0.314
9.	TRON (TRX)	1,800,544	546,635	309,023	28,133.5	23,437.1	0.367
	Total	**22,912,039**					**0.33**

Table 3: Details and statistics of the Twitter datasets after pre-processing.

	BTC	ETH	XRP	BCH	EOS	LTC	ADA	XLM	TRX
Percentage with 1 char.	16.63%	23.1%	27.0%	28.43%	42.83%	27.94%	48.1%	19.99%	39.21%
Percentage with 2 char.	1.50%	2.70%	5.58%	7.20%	6.41%	5.97%	14.39%	5.11%	3.37%

Table 4: Percentage per cryptocurrency of Tweets posted by cryptocurrency-related Twitter bot accounts.

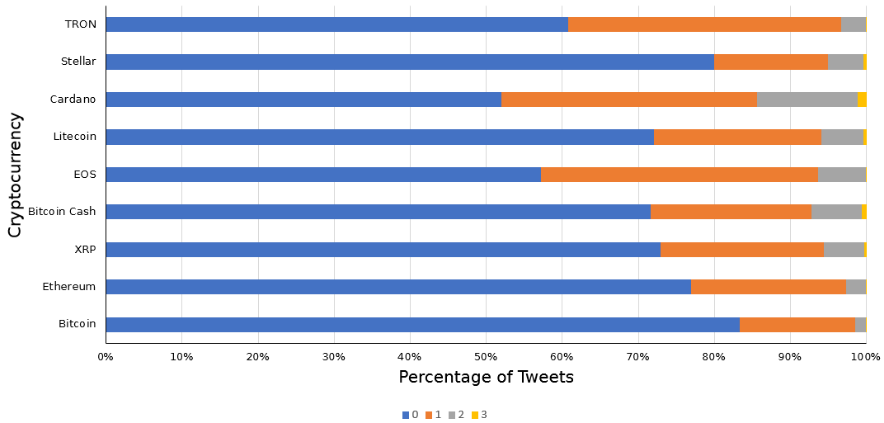
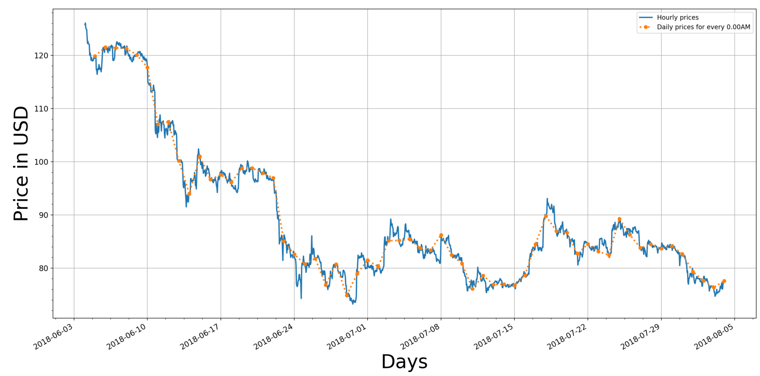
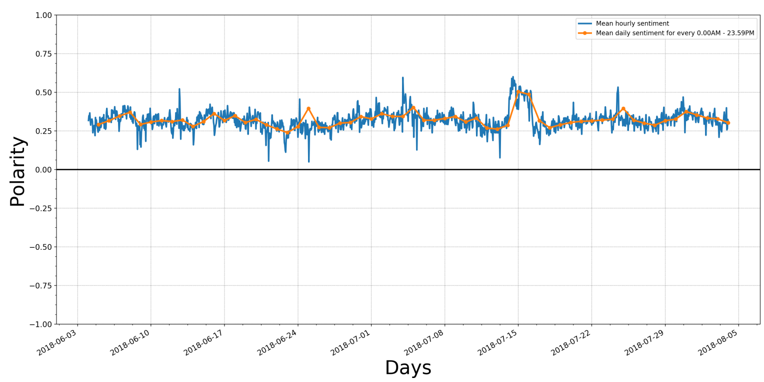


Figure 2: The percentual distribution of the number of bot characteristics per cryptocurrency Twitter dataset.

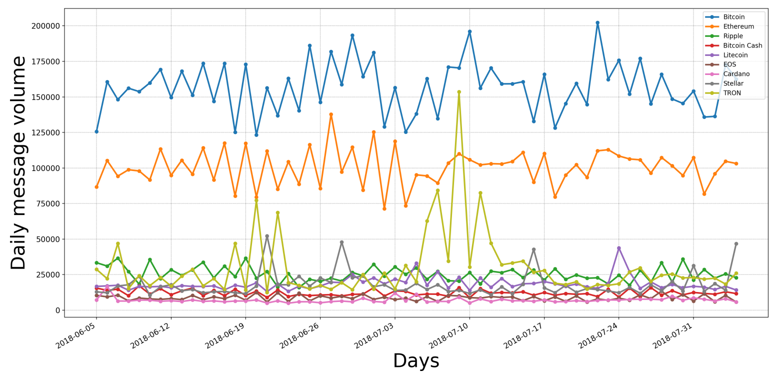


(a) The daily and hourly price (USD) for Litecoin (LTC) between 4 June 2018 and 4 August 2018

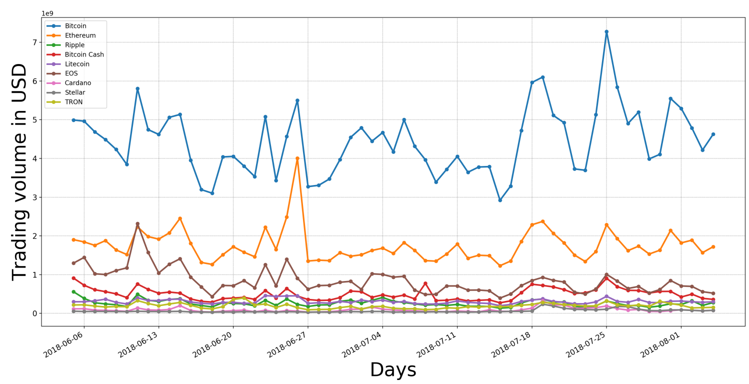


(b) The daily and hourly mean sentiment for Litecoin-related Tweets between 4 June 2018 and 4 August 2018

Figure 3: The results for Litecoin



(a) The daily message volume for each cryptocurrency



(b) The daily trading volume in billions of USD for each cryptocurrency

Figure 4: The daily message and trading volumes of all nine cryptocurrencies between 4 June 2018 and 4 August 2018

8. Appendix

8.1. Appendix: Granger-causality test results

CE = Number of co-integrating equations according to Johansen's Trace and Maximum Eigenvalue tests
OGC = Original Granger-causality test

7.1.1 Bitcoin (BTC)

							Statistics
Relation		D_{max}	l	l'	p	*CE*	*Lags & p-values OGC test*
S_T	$\longrightarrow P_R$	0	5	1	0.6283	N/A	1 (0.63), 2 (0.7692), 3 **(0.0475**)**, 4 (0.1452), 5 (0.076*)
P_R	$\longrightarrow S_T$	0	5	1	0.1472	N/A	1 (0.1526), 2 (0.3682), 3 (0.3718), 4 (0.4434), 5 (0.2879)
S_T	$\longrightarrow V_{trad}$	0	5	1	**0.0083*****	N/A	1 (**0.0107****), 2 (**0.0233****), 3 (**0.0325****), 4 (**0.0198****), 5 (**0.0367****)
V_{trad}	$\longrightarrow S_T$	0	5	1	0.50	N/A	1 (0.5027), 2 (0.0905*), 3 (0.1885), 4 (0.2954), 5 (0.221)
B	$\longrightarrow P_R$	0	5	1	0.4759	N/A	1 (0.4788), 2(0.5118), 3 (0.0566*), 4 (0.1791), 5 (0.2483)
P_R	$\longrightarrow B$	0	5	1	**0.0104****	N/A	1 (**0.0130****), 2 (**0.0473****), 3 (0.0752*), 4 (0.1297), 5 (0.0585*)
B	$\longrightarrow V_{trad}$	0	5	1	**0.0123****	N/A	1 (**0.0151****), 2 (**0.0294****), 3 (0.0582*), 4 (**0.0301****), 5 (**0.0379****)
V_{trad}	$\longrightarrow B$	0	5	1	0.3238	N/A	1 (0.3279), 2 (0.291), 3 (0.5488), 4 (0.6395), 5 (0.3387)
V_{mes}	$\longrightarrow P_R$	0	5	2	0.8185	N/A	1 (0.5835), 2 (0.8191), 3 (0.3429), 4 (0.5179), 5 (0.6387)
P_R	$\longrightarrow V_{mes}$	0	5	2	0.1811	N/A	1 (0.4509), 2 (0.1907), 3 (0.3709), 4 (0.6698), 5 (0.8137)
V_{mes}	$\longrightarrow V_{trad}$	0	5	2	0.8139	N/A	1 (0.6140), 2 (0.8145), 3 (0.9171), 4 (0.9429), 5 (0.9531)
V_{trad}	$\longrightarrow V_{mes}$	0	5	2	0.1231	N/A	1 (0.1475), 2 (0.133), 3 (0.1353), 4 (0.2319), 5 (0.1231)

*p < 0.1; **p <0.05; ***p<0.01

Table 5: Statistics for bivariate Granger causality tests on a daily interval between 4 June 2018 and 4 August 2018 for Bitcoin (BTC).

				Statistics			
Relation		D_{max}	l	l'	p	*CE*	*Lags & p-values OGC test*
S_T	$\longrightarrow P_R$	0	8	2	0.7251	N/A	1 (0.4775), 2 (0.7252), 3 (0.6103), 4 (0.7647), 5 (0.8645), 6 (0.8779)
P_R	$\longrightarrow S_T$	0	8	2	0.3607	N/A	1 (0.3439), 2 (0.3609), 3 (0.3831), 4 (0.3467), 5 (0.4806), 6 (0.5183)
B	$\longrightarrow P_R$	0	8	3	0.3992	N/A	1 (0.9188), 2 (0.9166), 3 (0.3995), 4 (0.5674), 5 (0.6598), 6 (0.7318)
P_R	$\longrightarrow B$	0	8	3	0.7972	N/A	1 (0.39), 2 (0.6008), 3 (0.7972), 4 (0.7427), 5 (0.7781), 6 (0.8611)
V_{mes}	$\longrightarrow P_R$	0	8	8	0.9409	N/A	1 (0.2667), 2 (0.5388), 3 (0.7615), 4 (0.8271), 5 (0.7358), 6 (0.8182)
P_R	$\longrightarrow V_{mes}$	0	8	8	0.3002	N/A	1 (0.1284), 2 (0.0803*), 3 (0.0743*), 4 (0.1261), 5 (0.1412), 6 (0.1484)

*p < 0.1; **p <0.05; ***p<0.01

Table 6: Statistics for bivariate Granger causality tests on an hourly interval between 4 June 2018 and 4 August 2018 for Bitcoin (BTC).

7.1.2 Ethereum (ETH)

		Statistics					
Relation		D_{max}	*l*	*l'*	*p*	*CE*	*Lags & p-values OGC test*
S_T	$\longrightarrow P_R$	0	5	1	0.7306	N/A	1 (0.7319), 2 (0.6844), 3 (0.8591), 4 (0.9554), 5 (0.6438)
P_R	$\longrightarrow S_T$	0	5	1	0.113	N/A	1 (0.1186), 2 (0.3014), 3 (0.352), 4 (0.4126), 5 (0.4771)
S_T	$\longrightarrow V_{trad}$	0	5	1	0.1721	N/A	1 (0.1775), 2 (0.2695), 3 (0.4610), 4 (0.2907), 5 (0.2787)
V_{trad}	$\longrightarrow S_T$	0	5	1	0.7995	N/A	1 (0.8004), 2 (0.923), 3 (0.95), 4 (0.8917), 5 (0.7659)
B	$\longrightarrow P_R$	0	5	1	0.2140	N/A	1 (0.2191), 2(0.3298), 3 (0.3170), 4 (0.5346), 5 (0.2012)
P_R	$\longrightarrow B$	0	5	1	0.1237	N/A	1 (0.1292), 2 (0.2922), 3 (0.2315), 4 (0.2946), 5 (0.3819)
B	$\longrightarrow V_{trad}$	0	5	1	0.0614*	N/A	1 (0.0666*), 2 (0.087*), 3 (0.1957), 4 (0.1831), 5 (0.2991)
V_{trad}	$\longrightarrow B$	0	5	1	0.9524	N/A	1 (0.9526), 2 (0.9956), 3 (0.8688), 4 (0.779), 5 (0.4953)
V_{mes}	$\longrightarrow P_R$	0	5	2	0.8185	N/A	1 (0.8324), 2 (0.9204), 3 (0.4495), 4 (0.5675), 5 (0.7383)
P_R	$\longrightarrow V_{mes}$	0	5	2	**0.0256****	N/A	1 (0.5457), 2 (**0.0322****), 3 (0.0841*), 4 (**0.0187****), 5 (0.0822*)
V_{mes}	$\longrightarrow V_{trad}$	0	5	2	0.7766	N/A	1 (0.8616), 2 (0.7775), 3 (0.9101), 4 (0.9895), 5 (0.9911)
V_{trad}	$\longrightarrow V_{mes}$	0	5	2	0.1198	N/A	1 (0.8282), 2 (0.1297), 3 (0.0808*), 4 (0.179), 5 (0.2229)

*p < 0.1; **p <0.05; ***p<0.01

Table 7: Statistics for bivariate Granger causality tests on a daily interval between 4 June 2018 and 4 August 2018 for Ethereum (ETH).

					Statistics		
Relation		D_{max}	l	l'	p	*CE*	*Lags & p-values OGC test*
S_T	$\longrightarrow P_R$	0	8	2	0.9739	N/A	1 (0.9710), 2 (0.9739), 3 (0.9922), 4 (0.9976), 5 (0.9979), 6 (0.9972)
P_R	$\longrightarrow S_T$	0	8	2	0.5038	N/A	1 (0.3877), 2 (0.5039), 3 (0.5997), 4 (0.4952), 5 (0.6435), 6 (0.6297)
B	$\longrightarrow P_R$	0	8	3	0.4676	N/A	1 (0.3002), 2 (0.3958), 3 (0.4678), 4 (0.48), 5 (0.6055), 6 (0.7287)
P_R	$\longrightarrow B$	0	8	3	0.9407	N/A	1 (0.949), 2 (0.9528), 3 (0.9407), 4 (0.9358), 5 (0.6537), 6 (0.572)
V_{mes}	$\longrightarrow P_R$	0	8	7	0.3350	N/A	1 (0.3606), 2 (0.17), 3 (0.2627), 4 (0.2862), 5 (0.2053), 6 (0.2542)
P_R	$\longrightarrow V_{mes}$	0	8	7	**0.0134****	N/A	1 (**0.0232****), 2 (**0.0224****), 3 (**0.0072*****), 4 (**0.0275****), 5 (**0.0085*****), 6 (**0.0113****)

*p < 0.1; **p <0.05; ***p<0.01

Table 8: Statistics for bivariate Granger causality tests on an hourly interval between 4 June 2018 and 4 August 2018 for Ethereum (ETH).

7.1.3 XRP (XRP)

							Statistics
Relation		D_{max}	l	l'	p	CE	*Lags & p-values OGC test*
S_T	$\longrightarrow P_R$	1	5	1	0.2483	2	N.A.: Non-stationary series involved
P_R	$\longrightarrow S_T$	1	5	1	0.4497	2	N.A.: Non-stationary series involved
S_T	$\longrightarrow V_{trad}$	1	5	1	0.7018	2	N.A.: Non-stationary series involved
V_{trad}	$\longrightarrow S_T$	1	5	1	0.598	2	N.A.: Non-stationary series involved
B	$\longrightarrow P_R$	1	5	1	0.3898	2	N.A.: Non-stationary series involved
P_R	$\longrightarrow B$	1	5	1	0.7219	2	N.A.: Non-stationary series involved
B	$\longrightarrow V_{trad}$	1	5	1	0.9559	0	N.A.: Non-stationary series involved
V_{trad}	$\longrightarrow B$	1	5	1	0.7985	0	N.A.: Non-stationary series involved
V_{mes}	$\longrightarrow P_R$	0	5	2	0.6637	N/A	1 (0.5187), 2 (0.6058), 3 (0.7927), 4 (**0.0278****), 5 (**0.0219****)
P_R	$\longrightarrow V_{mes}$	0	5	2	0.9930	N/A	1 (0.7414), 2 (0.9946), 3 (0.8599), 4 (0.9232), 5 (0.9268)
V_{mes}	$\longrightarrow V_{trad}$	0	5	5	**0.0343****	N/A	1 (0.5798), 2 (0.8864), 3 (0.9072), 4 (0.1494), 5 (0.0512*)
V_{trad}	$\longrightarrow V_{mes}$	0	5	5	0.7398	N/A	1 (0.1499), 2 (0.991), 3 (0.9569), 4 (0.9833), 5 (0.7388)

*p < 0.1; **p <0.05; ***p<0.01

Table 9: Statistics for bivariate Granger causality tests on a daily interval between 4 June 2018 and 4 August 2018 for XRP (XRP).

						Statistics		
Relation		D_{max}	l	l'	p	*CE*	*Lags & p-values OGC test*	
S_T	$\longrightarrow P_R$	0	8	8	8	0.8490	N/A	1 (0.4024), 2 (0.6619), 3 (0.6999), 4 (0.8202), 5 (0.8060), 6 (0.7850)
P_R	$\longrightarrow S_T$	0	8	8	8	0.074*	N/A	1 (0.183), 2 (0.0606*), 3 (0.0925*), 4 (0.1555), 5 (0.188), 6 (0.0751*)
B	$\longrightarrow P_R$	0	8	8	8	0.3563	N/A	1 (0.1704), 2 (0.3350), 3 (0.2323), 4 (0.2513), 5 (0.3482), 6 (0.2253)
P_R	$\longrightarrow B$	0	8	8	8	0.2337	N/A	1 (0.5657), 2 (0.3923), 3 (0.512), 4 (0.665), 5 (0.5564), 6 (0.3287)
V_{mes}	$\longrightarrow P_R$	0	8	7	7	0.3699	N/A	1 (0.4620), 2 (0.1769), 3 (0.3128), 4 (0.3002), 5 (0.3973), 6 (0.0084)
P_R	$\longrightarrow V_{mes}$	0	8	7	7	**0.0189****	N/A	1 (0.2924), 2 (0.4615), 3 (0.6373), 4 (**0.0056*****), 5 (**0.0072*****), 6 (0.4948)

*p < 0.1; **p <0.05; ***p<0.01

Table 10: Statistics for bivariate Granger causality tests on an hourly interval between 4 June 2018 and 4 August 2018 for XRP (XRP).

7.1.4 Bitcoin Cash (BCH)

					Statistics		
Relation		D_{max}	l	l'	p	*CE*	*Lags & p-values OGC test*
S_T	$\longrightarrow P_R$	0	5	1	0.2084	N/A	1 (0.2136), 2 (0.1146), 3 (0.1712), 4 (0.1952), 5 (0.3352)
P_R	$\longrightarrow S_T$	0	5	1	0.4424	N/A	1 (0.4455), 2 (0.8015), 3 (0.9663), 4 (0.9185), 5 (0.9149)
S_T	$\longrightarrow V_{trad}$	0	5	1	0.5797	N/A	1 (0.5819), 2 (0.3801), 3 (0.4071), 4 (0.5966), 5 (0.1562)
V_{trad}	$\longrightarrow S_T$	0	5	1	**0.0133****	N/A	1 (**0.0163****), 2 (**0.0058*****), 3 (**0.0148****), 4 (**0.0319****), 5 (0.0767*)
B	$\longrightarrow P_R$	0	5	7	0.3755	N/A	1 (0.1745), 2 (0.2081), 3 (0.3751), 4 (0.4756), 5 (0.641))
P_R	$\longrightarrow B$	0	5	7	**0.0404****	N/A	1 (0.5546), 2 (0.7991), 3 (0.4885), 4 (0.665), 5 (0.7373))
B	$\longrightarrow V_{trad}$	0	5	1	0.5569	N/A	1 (0.5592), 2 (0.446), 3 (0.5305), 4 (0.331), 5 (0.3454)
V_{trad}	$\longrightarrow B$	0	5	1	0.0923*	N/A	1 (0.0978), 2 (0.066*), 3 (0.0866*), 4 (0.1868), 5 (0.2473)
V_{mes}	$\longrightarrow P_R$	1	5	2	0.952	1	N.A.: Non-stationary series involved
P_R	$\longrightarrow V_{mes}$	1	5	2	0.388	1	N.A.: Non-stationary series involved
V_{mes}	$\longrightarrow V_{trad}$	1	5	2	0.8704	1	N.A.: Non-stationary series involved
V_{trad}	$\longrightarrow V_{mes}$	1	5	2	0.7639	1	N.A.: Non-stationary series involved

*p < 0.1; **p <0.05; ***p<0.01

Table 11: Statistics for bivariate Granger causality tests on a daily interval between 4 June 2018 and 4 August 2018 for Bitcoin Cash (BCH).

							Statistics
Relation		D_{max}	l	l'	p	*CE*	*Lags & p-values OGC test*
S_T	$\longrightarrow P_R$	0	8	6	0.2002	N/A	1 (0.016**), 2 (0.0534*), 3 (0.0348**), 4 (0.0677*), 5 (0.1189), 6 (0.2011)
P_R	$\longrightarrow S_T$	0	8	6	0.4833	N/A	1 (0.4296), 2 (0.1522), 3 (0.3618), 4 (0.6040), 5 (0.4361), 6 (0.4837)
B	$\longrightarrow P_R$	0	8	10	0.9228	N/A	1 (0.1002), 2 (0.2665), 3 (0.3938), 4 (0.5223), 5 (0.6323), 6 (0.7295)
P_R	$\longrightarrow B$	0	8	10	0.4635	N/A	1 (0.4518), 2 (0.2304), 3 (0.4598), 4 (0.5723), 5 (0.6182), 6 (0.6845)
V_{mes}	$\longrightarrow P_R$	0	8	5	0.3458	N/A	1 (0.0865*), 2 (0.0618*), 3 (0.1447), 4 (0.2638), 5 (0.3464), 6 (0.2719)
P_R	$\longrightarrow V_{mes}$	0	8	5	0.3548	N/A	1 (0.0359**), 2 (0.22), 3 (0.498), 4 (0.6263), 5 (0.3553), 6 (0.4794)

*p < 0.1; **p <0.05; ***p<0.01

Table 12: Statistics for bivariate Granger causality tests on an hourly interval between 4 June 2018 and 4 August 2018 for Bitcoin Cash (BCH).

7.1.5 EOS (EOS)

		Statistics					
Relation		D_{max}	l	l'	p	*CE*	*Lags & p-values OGC test*
S_T	$\longrightarrow P_R$	0	5	1	0.2215	N/A	1 (0.2265), 2 (0.3152), 3 (0.5015), 4 (0.4566), 5 (0.6786)
P_R	$\longrightarrow S_T$	0	5	1	0.1496	N/A	1 (0.155), 2 (0.394), 3 (0.4838), 4 (0.5856), 5 (0.6587)
S_T	$\longrightarrow V_{trad}$	0	5	1	0.0707*	N/A	1 (0.076*), 2 (0.2223), 3 (0.1843), 4 (0.3792), 5 (0.1822)
V_{trad}	$\longrightarrow S_T$	0	5	1	0.2563	N/A	1 (0.261), 2 (0.32), 3 (0.3314), 4 (0.2434), 5 (0.1069)
B	$\longrightarrow P_R$	0	5	1	0.5994	N/A	1 (0.6015), 2 (0.5601), 3 (0.7324), 4 (0.4244), 5 (0.5637)
P_R	$\longrightarrow B$	0	5	1	0.8507	N/A	1 (0.8514), 2 (0.9262), 3 (0.8028), 4 (0.7774), 5 (0.7651)
B	$\longrightarrow V_{trad}$	0	5	1	0.8887	N/A	1 (0.8892), 2 (0.8975), 3 (0.6088), 4 (0.7396), 5 (0.5773)
V_{trad}	$\longrightarrow B$	0	5	1	0.7192	N/A	1 (0.7206), 2 (0.8548), 3 (0.9512), 4 (0.8037), 5 (0.898)
V_{mes}	$\longrightarrow P_R$	0	5	2	0.67	N/A	1 (0.3057), 2 (0.672), 3 (0.8635), 4 (0.8523), 5 (0.8743)
P_R	$\longrightarrow V_{mes}$	0	5	2	0.7835	N/A	1 (0.3187), 2 (0.7844), 3 (0.9094), 4 (0.7495), 5 (0.7345)
V_{mes}	$\longrightarrow V_{trad}$	0	5	2	0.0955*	N/A	1 (**0.0439****), 2 (0.1051), 3 (0.2298), 4 (0.3814), 5 (0.0813*)
V_{trad}	$\longrightarrow V_{mes}$	0	5	2	0.6878	N/A	1 (0.7509), 2 (0.6895), 3 (0.6067), 4 (0.6615), 5 (0.7325)

*p < 0.1; **p <0.05; ***p<0.01

Table 13: Statistics for bivariate Granger causality tests on a daily interval between 4 June 2018 and 4 August 2018 for EOS (EOS).

		Statistics					
Relation		D_{max}	l	l'	p	*CE*	*Lags & p-values OGC test*
S_T	$\longrightarrow P_R$	0	8	6	0.0881*	N/A	1 (0.7569), 2 (0.9468), 3 (0.6289), 4 (0.6171), 5 (0.7517), 6 (0.089*)
P_R	$\longrightarrow S_T$	0	8	6	0.8235	N/A	1 (0.2389), 2 (0.331), 3 (0.5861), 4 (0.6667), 5 (0.6906), 6 (0.8234)
B	$\longrightarrow P_R$	0	8	7	**0.0142****	N/A	1 (0.3008), 2 (0.5853), 3 (0.1531), 4 (0.1955), 5 (0.2995), 6 (**0.0097*****)
P_R	$\longrightarrow B$	0	8	7	0.9298	N/A	1 (0.7521), 2 (0.9582), 3 (0.9974), 4 (0.9925), 5 (0.978), 6 (0.9002)
V_{mes}	$\longrightarrow P_R$	0	8	11	0.7206	N/A	1 (0.863), 2 (0.9669), 3 (0.967), 4 (0.9321), 5 (0.7585), 6 (0.8557)
P_R	$\longrightarrow V_{mes}$	0	8	11	0.234	N/A	1 (0.5099), 2 (0.6208), 3 (0.6807), 4 (0.7355), 5 (0.3959), 6 (0.4994)

*p $<$ 0.1; **p $<$0.05; ***p$<$0.01

Table 14: Statistics for bivariate Granger causality tests on an hourly interval between 4 June 2018 and 4 August 2018 for EOS (EOS).

7.1.6 Litecoin (LTC)

							Statistics
Relation		D_{max}	l	l'	p	*CE*	*Lags & p-values OGC test*
S_T	$\longrightarrow P_R$	0	5	2	**0.027****	N/A	1 (**0.0144****), 2 (**0.0337***), 3 (**0.0447****), 4 (0.0547*), 5 (0.0977*)
P_R	$\longrightarrow S_T$	0	5	2	0.451	N/A	1 (0.5957), 2 (0.4562), 3 (0.2417), 4 (0.2968), 5 (0.3093)
S_T	$\longrightarrow V_{trad}$	0	5	2	0.7543	N/A	1 (0.8571), 2 (0.7554), 3 (0.6419), 4 (0.5228), 5 (0.5224)
V_{trad}	$\longrightarrow S_T$	0	5	2	0.3832	N/A	1 (0.2329), 2 (0.3896), 3 (0.2409), 4 (0.2374), 5 (0.371)
B	$\longrightarrow P_R$	0	5	1	0.4092	N/A	1 (0.4126), 2 (0.7195), 3 (0.6374), 4 (0.3697), 5 (0.4632)
P_R	$\longrightarrow B$	0	5	1	0.2763	N/A	1 (0.2809), 2 (0.2096), 3 (0.311), 4 (0.3642), 5 (0.5914)
B	$\longrightarrow V_{trad}$	0	5	2	0.3482	N/A	1 (0.8487), 2 (0.3553), 3 (0.5252), 4 (0.5684), 5 (0.6196)
V_{trad}	$\longrightarrow B$	0	5	2	0.6847	N/A	1 (0.8334), 2 (0.6865), 3 (0.2931), 4 (0.2909), 5 (0.2156)
V_{mes}	$\longrightarrow P_R$	1	5	2	**0.0191****	2	N.A.: Non-stationary series involved
P_R	$\longrightarrow V_{mes}$	1	5	2	0.8313	2	N.A.: Non-stationary series involved
V_{mes}	$\longrightarrow V_{trad}$	1	5	2	**0.0139****	2	N.A.: Non-stationary series involved
V_{trad}	$\longrightarrow V_{mes}$	1	5	2	0.1559	2	N.A.: Non-stationary series involved

*p < 0.1; **p <0.05; ***p<0.01

Table 15: Statistics for bivariate Granger causality tests on a daily interval between 4 June 2018 and 4 August 2018 for Litecoin (LTC).

					Statistics		
Relation		D_{max}	l	l'	p	CE	*Lags & p-values OGC test*
S_T	$\longrightarrow P_R$	0	8	11	0.3428	N/A	1 (0.4089), 2 (0.4524), 3 (0.5744), 4 (0.3021), 5 (0.3202), 6 (0.2819)
P_R	$\longrightarrow S_T$	0	8	11	0.5332	N/A	1 (0.4502), 2 (0.5891), 3 (0.7884), 4 (0.7908), 5 (0.5679), 6 (0.6631)
B	$\longrightarrow P_R$	0	8	4	0.3823	N/A	1 (0.0554*), 2 (0.1447), 3 (0.2719), 4 (0.3827), 5 (0.4883), 6 (0.4612)
P_R	$\longrightarrow B$	0	8	4	0.4741	N/A	1 (0.3307), 2 (0.3034), 3 (0.4050), 4 (0.4744), 5 (0.2940), 6 (0.2794)
V_{mes}	$\longrightarrow P_R$	0	8	5	**0.0155****	N/A	1 (0.3715), 2 (0.0764*), 3 (0.1446), 4 (**0.0082*****), 5 (**0.0159****), 6 (0.2006)
P_R	$\longrightarrow V_{mes}$	0	8	5	0.2344	N/A	1 (0.1549), 2 (**0.0041*****), 3 (**0.0042*****), 4 (0.2194), 5 (0.2352), 6 (**0.0259****)

*p < 0.1; **p <0.05; ***p<0.01

Table 16: Statistics for bivariate Granger causality tests on an hourly interval between 4 June 2018 and 4 August 2018 for Litecoin (LTC).

7.1.7 Cardano (ADA)

							Statistics
Relation		D_{max}	l	l'	p	*CE*	*Lags & p-values OGC test*
S_T	$\longrightarrow P_R$	0	5	1	0.0747*	N/A	1 (0.08*), 2 (0.3518), 3 (0.5258), 4 (0.5392), 5 (0.3896)
P_R	$\longrightarrow S_T$	0	5	1	0.1314	N/A	1 (0.137), 2 (0.305), 3 (0.129), 4 (0.1795), 5 (0.2721)
S_T	$\longrightarrow V_{trad}$	0	5	1	**0.0425****	N/A	1 (**0.0472****), 2 (**0.0482****), 3 (0.0721*), 4 (0.1272), 5 (0.2314)
V_{trad}	$\longrightarrow S_T$	0	5	1	0.5872	N/A	1 (0.5893), 2 (0.7922), 3 (0.8892), 4 (0.9405), 5 (0.9815)
B	$\longrightarrow P_R$	0	5	5	0.1132	N/A	1 (0.5012), 2 (0.9163), 3 (0.8466), 4 (0.1603), 5 (0.1364)
P_R	$\longrightarrow B$	0	5	5	0.5818	N/A	1 (0.0772*), 2 (0.2057), 3 (0.1884), 4 (0.3318), 5 (0.5865)
B	$\longrightarrow V_{trad}$	0	5	1	0.3168	N/A	1 (0.3211), 2 (0.2587), 3 (0.225), 4 (0.2342), 5 (0.1736)
V_{trad}	$\longrightarrow B$	0	5	1	0.5894	N/A	1 (0.5915), 2 (0.7129), 3 (0.8639), 4 (0.8792), 5 (0.976)
V_{mes}	$\longrightarrow P_R$	1	5	8	0.4969	0	N.A.: Non-stationary series involved
P_R	$\longrightarrow V_{mes}$	1	5	8	0.9562	0	N.A.: Non-stationary series involved
V_{mes}	$\longrightarrow V_{trad}$	1	5	8	0.4905	0	N.A.: Non-stationary series involved
V_{trad}	$\longrightarrow V_{mes}$	1	5	2	0.9372	0	N.A.: Non-stationary series involved

*p < 0.1; **p <0.05; ***p<0.01

Table 17: Statistics for bivariate Granger causality tests on a daily interval between 4 June 2018 and 4 August 2018 for Cardano (ADA).

		Statistics					
Relation		D_{max}	l	l'	p	*CE*	*Lags & p-values OGC test*
S_T	$\longrightarrow P_R$	0	8	8	0.3086	N/A	1 (0.8964), 2 (0.9371), 3 (0.884), 4 (0.827), 5 (0.783), 6 (0.5579)
P_R	$\longrightarrow S_T$	0	8	8	0.7977	N/A	1 (0.9628), 2 (0.2576), 3 (0.4507), 4 (0.4713), 5 (0.5495), 6 (0.6341)
B	$\longrightarrow P_R$	0	8	9	0.8037	N/A	1 (0.6801), 2 (0.8724), 3 (0.9395), 4 (0.5135), 5 (0.6707), 6 (0.683)
P_R	$\longrightarrow B$	0	8	9	0.3681	N/A	1 (0.8784), 2 (0.1013), 3 (0.093*), 4 (0.1105), 5 (0.1745), 6 (0.2401)
V_{mes}	$\longrightarrow P_R$	0	8	2	0.1432	N/A	1 (0.1195), 2 (0.1436), 3 (0.2911), 4 (0.4058), 5 (0.3716), 6 (0.4120)
P_R	$\longrightarrow V_{mes}$	0	8	2	0.54	N/A	1 (0.6748), 2 (0.5402), 3 (0.7009), 4 (0.2699), 5 (0.3534), 6 (0.4444)

*p $<$ 0.1; **p $<$0.05; ***p$<$0.01

Table 18: Statistics for bivariate Granger causality tests on an hourly interval between 4 June 2018 and 4 August 2018 for Cardano (ADA).

7.1.8 Stellar (XLM)

		Statistics					
Relation		D_{max}	l	l'	p	*CE*	*Lags & p-values OGC test*
S_T	$\longrightarrow P_R$	0	5	1	0.5969	N/A	1 (0.5989), 2 (0.9065), 3 (0.7669), 4 (0.6966), 5 (0.7859)
P_R	$\longrightarrow S_T$	0	5	1	0.3904	N/A	1 (0.394), 2 (0.6989), 3 (0.3955), 4 (0.606), 5 (0.7536)
S_T	$\longrightarrow V_{trad}$	1	5	1	0.6885	1	N.A.: Non-stationary series involved
V_{trad}	$\longrightarrow S_T$	1	5	1	0.5085	1	N.A.: Non-stationary series involved
B	$\longrightarrow P_R$	0	5	7	0.8009	N/A	1 (0.8018), 2 (0.5114), 3 (0.6509), 4 (0.5828), 5 (0.6183)
P_R	$\longrightarrow B$	0	5	7	0.8117	N/A	1 (0.8125), 2 (0.9089), 3 (0.4881), 4 (0.6971), 5 (0.7536)
B	$\longrightarrow V_{trad}$	1	5	1	0.4872	1	N.A.: Non-stationary series involved
V_{trad}	$\longrightarrow B$	1	5	1	0.4462	1	N.A.: Non-stationary series involved
V_{mes}	$\longrightarrow P_R$	0	5	1	0.9838	N/A	1 (0.9838), 2 (0.4538), 3 (0.1596), 4 (0.3237), 5 (0.1818)
P_R	$\longrightarrow V_{mes}$	0	5	1	0.2057	N/A	1 (0.2109), 2 (0.3171), 3 (0.4062), 4 (0.1508), 5 (0.1754)
V_{mes}	$\longrightarrow V_{trad}$	1	5	1	0.3672	0	N.A.: Non-stationary series involved
V_{trad}	$\longrightarrow V_{mes}$	1	5	1	0.3048	0	N.A.: Non-stationary series involved

*p $<$ 0.1; **p $<$0.05; ***p$<$0.01

Table 19: Statistics for bivariate Granger causality tests on a daily interval between 4 June 2018 and 4 August 2018 for Stellar (XLM).

							Statistics
Relation		D_{max}	l	l'	p	CE	*Lags & p-values OGC test*
S_T	$\longrightarrow P_R$	0	8	10	0.5693	N/A	1 (0.2612), 2 (0.2947), 3 (0.4322), 4 (0.5025), 5 (0.5338), 6 (0.6714)
P_R	$\longrightarrow S_T$	0	8	10	0.5663	N/A	1 (0.7504), 2 (0.3162), 3 (0.36), 4 (0.4284), 5 (0.5096), 6 (0.4595)
B	$\longrightarrow P_R$	0	8	4	0.3202	N/A	1 (0.4289), 2 (0.2042), 3 (0.3508), 4 (0.3207), 5 (0.2319), 6 (0.3471)
P_R	$\longrightarrow B$	0	8	4	0.4848	N/A	1 (0.6924), 2 (0.7685), 3 (0.5024), 4 (0.485), 5 (0.426), 6 (0.5427)
V_{mes}	$\longrightarrow P_R$	0	8	4	0.5743	N/A	1 (0.3171), 2 (0.5265), 3 (0.6103), 4 (0.5745), 5 (0.4911), 6 (0.6601)
P_R	$\longrightarrow V_{mes}$	0	8	4	0.1823	N/A	1 (0.292), 2 (0.0691*), 3 (0.1242), 4 (0.183), 5 (0.1748), 6 (0.0887)

*p < 0.1; **p <0.05; ***p<0.01

Table 20: Statistics for bivariate Granger causality tests on an hourly interval between 4 June 2018 and 4 August 2018 for Stellar (XLM).

6.6.9 TRON (TRX)

		Statistics					
Relation		D_{max}	l	l'	p	*CE*	*Lags & p-values OGC test*
S_T	$\longrightarrow P_R$	0	5	1	0.2242	N/A	1 (0.2292), 2 (0.5015), 3 (0.6575), 4 (0.8945), 5 (0.9449)
P_R	$\longrightarrow S_T$	0	5	1	0.4984	N/A	1 (0.5011), 2 (0.8629), 3 (0.1674), 4 (0.103), 5 (0.1806)
S_T	$\longrightarrow V_{trad}$	0	5	1	**0.0154****	N/A	1 (**0.0186****), 2 (0.0558*), 3 (0.0766*), 4 (**0.0178****), 5 (**0.0497****)
V_{trad}	$\longrightarrow S_T$	0	5	1	0.7634	N/A	1 (0.7645), 2 (0.168), 3 (0.2668), 4 (0.1992), 5 (0.4913)
B	$\longrightarrow P_R$	0	5	1	**0.0178****	N/A	1 (**0.0212****), 2 (**0.0479****), 3 (0.1052), 4 (0.3005), 5 (0.4227)
P_R	$\longrightarrow B$	0	5	1	0.3715	N/A	1 (0.3752), 2 (0.7019), 3 (0.2729), 4 (0.3843), 5 (0.2608)
B	$\longrightarrow V_{trad}$	0	5	8	**0.0116****	N/A	1 (0.1041), 2 (**0.0246****), 3 (**0.0408****), 4 (**0.0035*****), 5 (**0.009*****)
V_{trad}	$\longrightarrow B$	0	5	8	0.1636	N/A	1 (0.8496), 2 (0.3268), 3 (0.4985), 4 (0.2106), 5 (0.3398)
V_{mes}	$\longrightarrow P_R$	1	5	5	0.1887	0	N.A.: Non-stationary series involved
P_R	$\longrightarrow V_{mes}$	1	5	5	0.9124	0	N.A.: Non-stationary series involved
V_{mes}	$\longrightarrow V_{trad}$	1	5	2	0.3925	0	N.A.: Non-stationary series involved
V_{trad}	$\longrightarrow V_{mes}$	1	5	2	0.2256	0	N.A.: Non-stationary series involved

*p < 0.1; **p <0.05; ***p<0.01

Table 21: Statistics for bivariate Granger causality tests on a daily interval between 4 June 2018 and 4 August 2018 for TRON (TRX).

							Statistics
Relation		D_{max}	l	l'	p	*CE*	*Lags & p-values OGC test*
S_T	$\longrightarrow P_R$	0	8	7	0.8713	N/A	1 (0.9697), 2 (0.9955), 3 (0.9975), 4 (0.6884), 5 (0.7967), 6 (0.8257)
P_R	$\longrightarrow S_T$	0	8	7	0.2787	N/A	1 (0.462), 2 (0.7766), 3 (0.8364), 4 (0.9139), 5 (0.9722), 6 (0.2070)
B	$\longrightarrow P_R$	0	8	4	0.7411	N/A	1 (0.5302), 2 (0.7293), 3 (0.8994), 4 (0.7411), 5 (0.8458), 6 (0.8774)
P_R	$\longrightarrow B$	0	8	4	0.4105	N/A	1 (0.3089), 2 (0.2539), 3 (0.313), 4 (0.4109), 5 (0.5582), 6 (0.3367)
V_{mes}	$\longrightarrow P_R$	0	8	7	0.6736	N/A	1 (0.1432), 2 (0.2437), 3 (0.4573), 4 (0.6589), 5 (0.7671), 6 (0.8404)
P_R	$\longrightarrow V_{mes}$	0	8	7	0.2674	N/A	1 (0.0845*), 2 (0.1542), 3 (0.1964), 4 (0.2726), 5 (0.189), 6 (0.2413)

*p < 0.1; **p <0.05; ***p<0.01

Table 22: Statistics for bivariate Granger causality tests on an hourly interval between 4 June 2018 and 4 August 2018 for TRON (TRX).