UNIVERSIDADE CATÓLICA PORTUGUESA

Explosive behaviour in Cryptocurrency Prices

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"Success consists of going from failure to failure without loss of enthusiasm" – Winston Churchill.

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RESUMO

A Bitcoin e outras criptomoedas passaram por vários episódios bem documentados de exuberância de preços desde que surgiram. No entanto, em Maio de 2022, uma tempestade quase perfeita abalou o mundo das criptomoedas, fazendo com que os respetivos preços caíssem para mínimos inesperados. Este Trabalho Final de Mestrado pretende contribuir para a procura de episódios de exuberância, que sugiram bolhas, nos preços das criptomoedas, através da realização de uma análise empírica abrangente que recorre a testes de última geração para comportamento explosivo: o teste Generalized Supremum Augmented Dickey Fuller (GSADF) desenvolvido por Phillips, Shi e Yu (2015) e, como contributo original, a sua versão em painel proposta por Pavlidis et al. (2016). Estes testes são complementados por um conjunto de outras técnicas econométricas, tais como testes de raiz unitária e cointegração e testes de causalidade de Granger, com vista a realizar uma investigação formal abrangente de períodos de explosão nos preços das criptomoedas. A análise formal é complementada e aperfeiçoada por uma análise narrativa com vista a esclarecer os fatores que desencadearam os episódios de explosão. Uma análise minuciosa das causas destes episódios é oportuna, pois a recente queda drástica nos preços das criptomoedas evoca episódios anteriores de bolhas. Para tal, utilizo dados para (pelo menos) os últimos 5 anos (2017-2022) para 7 principais criptomoedas, que figuram entre as 20 principais criptomoedas por capitalização de mercado (Coinmarketcap.com, 18 de julho de 2022). Além disso, após detetar os períodos de exuberância nos preços das criptomoedas e analisar as suas causas, estudo se ocorreram períodos sincronizados de explosão nas criptomoedas selecionadas. Analiso igualmente se a explosão numa ou mais criptomoedas individuais conduziu a episódios globais de explosão em todas as principais criptomoedas utilizando um modelo Logit. Além do mais, recorrendo a testes de causalidade de Granger, estabeleço a conectividade entre criptomoedas, revelando algumas ligações causais entre as mesmas. Para definir o cenário para a investigação empírica, apresento uma breve introdução sobre bolhas, tipos de bolhas e deteção de bolhas nos mercados de ativos. Posteriormente, apresento uma revisão completa da literatura relevante sobre criptomoedas como uma classe de ativos diferente e as evidências existentes de bolhas nos mercados de criptomoedas. Na análise empírica, recorrendo ao teste GSADF, detetei vários períodos de explosão (bolha) nas criptomoedas individuais e no painel composto pelas criptomoedas selecionadas. Os resultados revelam que a Bitcoin experienciou a maioria das bolhas de longa duração. A maioria dos períodos de explosão detetados coincidem com os documentados por estudos anteriores. No entanto, dado que o período de dados da minha análise inclui os dois anos mais recentes, presto especial atenção ao período 2020-2021. Revelo evidências de sincronicidade entre criptomoedas, especialmente durante períodos de turbulência financeira. Este Trabalho Final de Mestrado contribui para o debate em curso sobre bolhas especulativas nos mercados de criptomoedas, recorrendo a um conjunto de dados alargado e realizando não apenas testes GSADF para criptomoedas individuais, mas também o GSADF Painel para detetar possíveis múltiplas bolhas nos mercados de criptomoedas, assim como demonstrando a existência de períodos sincronizados de explosão das criptomoedas que, em última análise, podem ajudar os investidores em termos de gestão de portfolios.

Palavras-chave*:* Bolhas do Mercado de Ativos; Bolhas Especulativas Racionais; Comportamento explosivo; Exuberância; Mercado de criptomoedas; Teste SADF; Teste GSADF; Teste GSADF Painel; Períodos sincronizados de explosão; Regressão Logit; Causalidade de Granger.

Número de Palavras: 10 557

ABSTRACT

Bitcoin and other cryptocurrencies have enjoyed several well-documented episodes of price exuberance since they emerged on the scene. However, in May 2022, an almost perfect storm shook their world, causing their prices to plummet to unexpected lows. This dissertation aims to contribute to the quest for episodes of exuberance, suggestive of bubbles, in cryptocurrency prices by conducting a comprehensive empirical analysis, which employs state-of-the-art tests for explosive behaviour: the Generalized Supremum Augmented Dickey Fuller (GSADF) test developed by Phillips, Shi and Yu (2015) and, as an original contribution, its panel version proposed by Pavlidis et al (2016). These tests are complemented by an array of other econometric techniques, such as unit root and cointegration tests, and Granger causality tests, to conduct a comprehensive formal investigation of periods of explosiveness in cryptocurrency prices. The formal analysis is complemented and enhanced by a narrative analysis, which aims to shed light on the factors that triggered the episodes of explosiveness. A thorough examinations of the causes of these episodes is timely, as the recent dramatic crash in the prices of cryptocurrencies is evocative of past bubble episodes. To this end, I use data for (at least) the last 5 years (2017-2022) for 7 major cryptocurrencies, which feature in the top 20 cryptocurrencies by market capitalization (Coinmarketcap.com, 18 July 2022). Moreover, after detecting the periods of exuberance in cryptocurrency prices and analysing their causes, I examine whether there have been synchronized periods of explosiveness across the selected cryptocurrencies. Furthermore, I analyse if explosiveness in one or more individual cryptocurrencies led to global explosiveness episodes across all major cryptocurrencies by using a Logit model. Additionally, using Granger causality tests, I establish connectedness across cryptocurrencies, by unveiling some causal links between them. To set the scene for the empirical investigation, I provide a brief introduction about bubbles, types of bubbles, and detection of bubbles in asset markets. Subsequently, I provide a thorough review of the relevant literature on cryptocurrencies as a different asset class, and the existing evidence of bubbles in the cryptocurrency markets. In the empirical analysis, using the GSADF test I detected several explosiveness (bubble) periods in the individual cryptocurrencies and in the panel made of selected currencies. The results reveal that Bitcoin experienced most of the long-lived bubbles. Most of the detected explosivity periods coincide with the ones documented by previous studies. However, given that the data span of my analysis includes the more recent two years, I pay special attention to the period 2020-2021. I unveil evidence of synchronicity among cryptocurrencies, especially during periods of financial turbulence. This dissertation contributes to the ongoing debate about speculative bubbles in cryptocurrency markets, by using an extended the dataset and by conducting not only GSADF tests for individual cryptocurrencies, but also the Panel GSADF in order to detect possible multiple bubbles in the cryptocurrency markets, as well as by demonstrating the existence of synchronised periods of explosivity among cryptocurrencies, that ultimately can help investors in terms of portfolio management.

Keywords: Asset Market Bubbles; Rational Speculative Bubbles; Explosive behaviour; Exuberance; Cryptocurrency market; SADF Test; GSADF Test; Panel GSADF Test; Synchronized periods of price explosiveness; Logit regression; Granger causality.

Number of words: 10 557

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CHAPTER 1 – INTRODUCTION

During the last decade, the cryptocurrency world started to capture public interest, raising several questions, and socio-economic issues. At the same time, several organizations have increasingly begun to accept cryptocurrencies as a means of payment. However, according to recent events, "The Crypto crash" (Bloomberg.com, 2022), the prices of numerous cryptocurrencies such as Bitcoin, Ethereum, Binance Coin, Solana, and Cardano have fallen dramatically in the last few months. Bitcoin's price today (10^{th} of August 2022) is 23 105.20 US dollars, 33.46% lower than the price reached on the 10^{th} of November 2021 (Coinmarketcap.com).

Therefore, I think it is interesting and timely to analyse the movements in the prices of cryptocurrencies over the past years' events, paying special attention to the years 2017-2018 and 2021-2022, with the aim of documenting (by means of formal testing) the occurrence of periods of explosiveness (exuberance), potentially bubble episodes, in the prices of cryptocurrencies, as well as attempting to understand, using the extant literature financial newspaper commentaries and personal analysis, what were the main causes that led to such episodes in the cryptocurrency markets. In addition, I believe it is noteworthy to investigate whether synchronized periods of explosivity can be detected across cryptocurrencies, that is, to examine whether episodes of explosive behaviour occurred at the same time in several cryptocurrencies. I will employ an array of different econometric methods to answer the following research questions: (i) "What caused price explosiveness periods in the cryptocurrency markets?"; (ii) "Are there synchronized periods of price explosiveness among the cryptocurrency markets?".

First, cryptocurrencies are digital currencies that can be used for direct purchases. Nevertheless, they are different from other assets, as they are not subject to any centralized institutional authority, they do not have any physical representation, they have a decentralized nature, and are seen as a speculative asset class. Cryptocurrencies can be defined as peer-to-peer electronic cash systems, which allow online payments directly from one party to another, without passing through a financial institution. The transactions and circulation of cryptocurrencies are anonymous. The value of cryptocurrencies is yielded by the combination of demand for that currency and limited supply. Today, there are more than 9 900 cryptocurrencies in circulation, however, I will focus my research on the daily prices of 7 of them (Bitcoin, Ethereum, Litecoin, Binance Coin, Ripple, Cardano, and Dogecoin) according with the information provided by Yahoo Finance; the choice is based on market capitalization (Coinmarketcap.com, 18 July 2022). Moreover, one of the intended contributions of this study is to consider, for the empirical analysis, a period that considers more recent developments in comparison to that used by extant studies, by using at least 5 years of (daily) data until the 26th of June 2022.

Several authors stated that a bubble can be defined as the "systematic deviation of the market value from the fundamental value of the asset" (Diba and Grossman, 1988, and West, 1987). There are three main types of bubbles: rational, irrational, and experimental. However, in my research I will focus on rational bubbles, more specifically, rational speculative bubbles.

Nonetheless, the fundamental value of cryptocurrencies has been documented by some authors as being zero (Cheah et al., 2015) or as having an unclear value (Waters et al., 2021). Thus, I will apply the Generalized Supremum Augmented Dickey-Fuller test (GSADF, Phillips et al., 2015), to test for the presence of multiple bubbles during the sample interval.

The methodology proposed by Phillips et al. (op. cit.) is state-of-the-art and effective as a real time bubble detection algorithm. The GSADF null hypothesis of unit root and auxiliary regression are based on the ADF test (Phillips et al., 2015). According to that, if an explosive root (characteristic of a bubble) occurs in a time series, then the Alternative hypothesis of explosive behaviour cannot be rejected, thus, providing the tools for recognition of an episode of explosiveness (potentially a bubble). A testing procedure put forward in the same paper by Phillips et al. (2015), the recursive Backwards Supremum ADF (BSADF) enables date-stamping of the origination and termination (burst) of the period of explosiveness (bubble). According to the Null hypothesis of the GSADF test, there is no explosive price behaviour. On the other hand, the Alternative hypothesis supports the existence of mildly explosive price behaviour.

Additionally, I will apply the panel version of the GSADF test of Pavlidis et al. (2016), to identify possible synchronization explosive periods among the studied cryptocurrencies. Finally, to corroborate the existence of overall synchronization explosive periods in the cryptocurrency markets, I will estimate a Logistic regression model. Lastly, based on the Granger causality tests, I will establish some short-term relationship between the studied cryptocurrencies.

The remainder of this dissertation is structured as follows: Chapter 2 provides a review of the relevant literature. Chapter 3 discusses the theoretical model and the methodology. Chapter 4 introduces the methodology and data used and Chapter 5 reports and discusses the results of the empirical analysis. The last chapter concludes and proposes ideas for future research.

CHAPTER 2 - LITERATURE REVIEW

In this chapter, thanks to the previous empirical and theoretical studies, I will review two main categories: bubble definition, types of bubbles, existence, and detection in asset markets; and bubbles in the cryptocurrency markets.

2.1 BUBBLE DEFINITION AND TYPES OF BUBBLES

According to several authors, a bubble can be defined as a "systematic deviation of the market value from the fundamental value of the asset" (Diba and Grossman, 1988, and West, 1987). Minford and Peel (2019), state that bubbles are related to the future market expectations, this means, expectations about the fundamentals. At the same time, a bubble is different from a fad. According to Shiller (1984, 1989, 1997), a fad can be described as a deviation of the price from the fundamental values, due to the psychological changes induced by market sentiment. Minford et al. (2019), related the presence of bubbles and fads to the existence of market inefficiency. Consequently, an efficient market requires the complete elimination of fads and noise traders.

There are various types of bubbles, however, as I mentioned previously, I will focus my research on rational speculative bubbles. Speculative bubbles can be categorized into rational or irrational (Dale et al., 2005).

2.2.1 RATIONAL BUBBLES

The meaning of "rationality" and "irrationality" from an economic perspective seems to be evolving over time. Rationality can be described by a conceptual tool used in economic models (LeRoy, 2004). The simple idea of rationality provides the foundations for a model describing human behaviour that assumes coherent choices. Thus, the price deviation from the fundamental value does not necessarily reflect irrational behaviour (Koustas et al., 2005). According to Koustas et al. (op. cit.), in cases where there is an expectation of a discounted capital gain from holding the stock in the future, asset price bubbles are consistent with rational behaviour. This means that rational bubbles occur when investors predict that they can profit from selling overvalued assets at a higher price. LeRoy (op. cit.) claimed that rational bubble models are defined by the existence of agents that are aware that the security they hold is traded at a higher price than the price justified by their dividends. Thus, they hold these securities because they rationally believe that these price differences will increase over time. However, along these lines there is room for irrational behaviour. According to Zeira (1999), even rational speculation may be accompanied by periods of mass hysteria or herding investing behaviour.

2.2.2 *Irrational bubbles*

Irrationality plays a great role in financial markets. LeRoy (op. cit.) stated that irrationality can be identified by the existence of investors who trade by reasons that are no modeled, the so called "noise traders". According with this perspective, bubbles can be defined as the difference between assets prices with noise traders and asset prices without noise traders. Thus, irrational bubbles can reflect the herding behaviour of traders, these traders who bid prices is at higher levels than the ones justified by rational calculations. On the other hand, rational traders perceive this mispricing, and they bet against it. However, because they are risk averse, the rational agents' trades are not sufficient to eliminate the mispricing, which ultimately leads to the formation of price bubbles. Additionally, irrational bubbles can be formed when investors are driven by psychological factors unconnected to the asset's fundamental value. This means that, when investors are influenced by simple heuristic driven bias (Dwyer, 2014; Shiller, 2005; Weber, 2014). Dale (2005) states that according with these circumstances the relationship between fundamental value and price breaks down and a bubble can occur.

2.2 HISTORICAL BUBBLES, EXISTENCE AND DETECTION IN ASSET MARKETS

Speculation and bubbles have been endemic throughout human history. One of the first documented bubbles in asset prices was the Dutch Tulip Mania (1634-1637), characterize by the prices of rare tulip bulbs rising steeply. These higher prices came to an abrupt freeze when bulb prices plummeted in February 1637. Another important bubble, during the 18th century, was the Mississippi Bubble (1719-1720), characterized by the huge inflation of the share prices of the Mississippi Company[1]. Moreover, the South Sea Bubble (1720) happened in parallel with the Mississippi bubble. This bubble experienced a similar trajectory, the rapid rise in the market price of the South Sea Company[2]. Other bubble episodes happened in the United States, such as the Roaring Twenties (1920), followed by the stock market crash, the Black Tuesday (1929) when stock prices on the New York Stock Exchange plummeted. More recently, the economic history experienced two main bubbles. The Dot-Com bubble (1994-2000), characterized by the inflationary prices of the internet stocks (Malkiel, 2019). Lastly, the U.S. Housing Price Bubble (2001-2006), that was considered as one of the triggers of the global financial crisis of 2007/2008. These episodes highlighted the importance of being able to detect and monitor the occurrence of bubbles in the financial markets[3].

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[1] This company held a monopoly on the expansion of France's vast territory in Mississippi (North America).

[2] The South Sea Company a British trading company that held a trading monopoly with the Spanish colonies (West Indies and South America).

[3] Interestingly, the author Wöckl (2019) provided a review of the relevant methodologies used to detect multiple and periodical bubbles. Wöckl (2019) pointed out that one of the main methodologies is the GSADF

Interestingly, there are several reported episodes across the history of bubbles (exuberance) in the cryptocurrency markets, I will address some of these episodes in the next section.

2.3 BUBBLES IN THE CRYPTOCURRENCY MARKETS

There is a growing number of academic papers that focus on cryptocurrencies, some are based around asset pricing bubbles, others on market efficiency, contagion and co-explosivity effects, volatility clustering, to name but a few aspects covered by this strand of the literature.

2.3.1 CRYPTOCURRENCIES AS A NEW ASSET CLASS

Several authors compared the characteristics of cryptocurrencies with those present in the traditional asset classes. Authors such as Krueckeberg et al. (2018), believed that cryptocurrencies showed different characteristics from the traditional asset class, due to several factors such as the absence of correlation with any traditional asset, high volatility, low market stability, and strong correlation among cryptocurrencies. By using a comparison analysis in terms of investability, correlation, liquidity, stability, and portfolio optimization, the results suggested a sharp distinction between the 10 largest cryptocurrencies by market capitalization (December 2017) and traditional assets, demonstrating to be a supplement to the traditional portfolios. At the same time, cryptocurrencies showed significantly higher liquidity. Similarly, Ram (2019), analysed Bitcoin as a new asset class, discussing and comparing investability, politico-economic relationships, correlation of returns and risk-reward profiles. Ram (op.cit.) concluded the same result as Scholz (2018): Bitcoin represents an alternative and unique asset class and investment opportunity, presenting a political-economic

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test proposed by Phillips et al. (2015), followed by the regime-switching tests, and the fractional integration tests.

decentralized profile, sharing no or low correlation with other asset classes. Therefore, according to both authors it is important to understand that Bitcoin represents a new asset class and an alternative investment, affecting the investors' decisions.

2.3.2 *COMPARISON BETWEEN BUBBLES IN CRYPTOCURRENCY MARKETS WITH BUBBLES IN ASSET MARKETS*

The study by Taskinsoy (2019) asserts that the high volatility of the Bitcoin market is very resemblant to the phenomenon of the Dutch Tulip mania (1634-37), and the U.S. and the Dot-Com bubble (2000). According to Taskinsoy (op. cit.), neither Bitcoin nor Tulip mania was a real mania, but the similarity between the two is very noticeable. Another important similarity between the two is their inconsequential impact on the broad economy. However, the levels of speculation were more severe in Bitcoin than in Tulip mania, but the collapse of prices and duration were almost identical. The main conclusion is that both Bitcoin and Tulip mania exerted an indirect impact on spending and investing habits, since investors are tempted to take more risks and spend more during periods of bubbles (the "wealth effect"). This conclusion is consistent with Garber (1989), who suggests that we do not have sufficient information to conclude that Tulip mania is in fact a mania.

Demmler and Domínguez (2021) compared the speculative bubble tendencies in the Bitcoin market to a well-known historical asset price bubble, the South Sea Bubble (1720), using three statistical tests methodologies based on Baur et al. (2018) and Phillips et al. (2015). They concluded that according to the results of the SADF and GSADF tests, there was evidence that both Bitcoin and South Sea Company experienced multiple bubble periods, confirming important similarities between the two assets. Lastly, the authors provided evidence that Bitcoin price movements, from 2017 until 2018, showed two phases of an asset price bubble and crash like the South Sea Company. In conclusion, the paper by Demler and Fernández Domínguez (2021) characterized Bitcoin as a speculative asset that is constantly susceptible to financial bubbles, a conclusion also drawn by Taskinsoy (2019).

2.3.3 *HERDING BEHAVIOUR IN THE CRYPTOCURRENCY MARKETS*

Some papers studied the presence of herding behaviour[4] in the cryptocurrency markets, such as the paper by Bouri et al. (2019). Herding behaviour can explain the appearance of bubbles and crashes, two characteristic features of the cryptocurrency markets. The herding behaviour in the cryptocurrency markets is easily observed due to the internet and social media, that allows investors to share information. They capture the herding behaviour using a benchmark model developed by Chang et al. (2000), and some testing hypothesis[5]. According with the methodology proposed by Chang et al. (op. cit.), they used a cross-sectional absolute standard deviation (CSAD) among the cryptocurrencies studied with the objective of defining a non-linear relation between the overall cryptocurrency markets return and the level of cryptocurrency return dispersion. Chang et al. (op. cit.) state that during periods of market stress herding behaviour is more likely to occur in the market. Using the Bai and Perron test (2003), they concluded that between 28/04/2013 and 02/05/2018, they captured five major breaks on the studied cryptocurrencies. The authors detected several herding behaviours, specially from April 2016 to September 2017. These evidence of herding, suggest that the trading decisions of the investors in the cryptocurrency markets are not made in isolation, and at the same time crypto investors seems to present the believe that the prices of the cryptocurrencies will not fall in the

[4] Bouri et al. (2019) described herding behaviour as the imitation by other investors of the investment decisions, without reference to the fundamentals.

[5] According with the Null hypothesis there is no herding effect; thus, according with the Alternative hypothesis herding or anti-herding exists.

near future (overestimation). The paper by Huber and Sornette (2022) addresses the role of speculative bubbles in the Bitcoin market, by analyzing social-economic dynamics; their results support the hypothesis that bubbles can have a net positive benefit, such as social and technological changes[6]. They used the "Social Bubble Hypothesis", that states that bubbles are intrinsic components of technological innovations. According to Huber and Sornette (op. cit.) Bitcoin can help to anticipate and understand future technological innovations[7]. The hype cycles pattern of Bitcoin seems to be the consequence of herding and imitation behaviour by the investors, which can give rise to speculative bubbles.

2.3.4 *Empirical bubble detection strategies*

Most of the literature about bubbles in the cryptocurrency markets used the methodology proposed by Phillips et al. (2015) to capture multiple bubbles. Cheung et al. (2015), stated that the collapse of the biggest bitcoin exchange (Mt. Gox Exchange[8]), contributed to the presence of multiple bubbles in the Bitcoin market, being the cause of the bursting of the bubble. 33 episodes of bubbles in the Bitcoin market were identified, with most being short-lived bubbles. They captured 3 long-lived bubbles during 2011-2013, lasting from 66-106 days. In this paper Cheung et al. (2015) cited the author Grinberg (2012), describing that Bitcoin is susceptible to speculative bubbles: Bitcoin does not have any fundamental value, and its value is derived from being a "speculative

[6] Huber and Sornette (2022) conduct an analysis based on technological-economic feedback loops that influence network effects and Bitcoin prices.

[7] Bitcoin prices can be characterized by a hierarchy of exponential and repeating rising bubbles, and bubbles of this type can be understood as a source of technological innovations.

[8] Mt. Gox emerged as a Bitcoin exchange on 18th July 2010. The hacker attack to Mt. Gox[8] started in 2011 and ended in February 2014, following the declaration of bankruptcy.

commodity". Therefore, he believed that Bitcoin and cryptocurrencies are prone to speculative bubbles.

The study by Cheah and Fry (2015), combined both Google trend search Index with the methodology proposed by Phillips et al. (2015). This study argued that Bitcoin prices are highly speculative, the markets are subject to bubbles, and at the same time the fundamental value of Bitcoin is zero. The main results reported in this study showed that Bitcoin prices exhibit high and volatile market dynamics especially during the period of 2013; at the same time, the Google trends search index showed a prominent peak, underlining the social prominence of the speculative bubble. By using three different methodologies[9] they reached the same results, the presence of a Bitcoin bubble in the time interval.

A broad number of studies have explored more meticulously the economic aspects of cryptocurrencies and speculative bubbles. The paper by Ricci and Scaringi (2017), applied quantitative models[10] for the study of Bitcoin and Ethereum. They stated that, in the cryptocurrency markets, like in the financial market, after negative shocks, volatility increases more than after positive ones, thus, incorporating the "leverage effect". They concluded that both methodologies used showed evidence in favour of the presence of long-lived bubble periods in Bitcoin during May and September of 2017. Using the same methodology proposed by Phillips et al. (2015), Li et al. (2018), analyzed when multiple Bitcoin bubbles occurred and collapsed, both in Chinese and U.S. Bitcoin markets. During the period of 2017, the authors concluded that Bitcoin prices contain explosive sub-periods, according to the SADF and GSADF test

[9] The authors used the Johansen et al. (2000) test, Andersen and Sornette (2004) model, and Philips et al. (2015) testing methodology.

[10] They combined two important methodologies, namely the Log Periodic Power Law (LPPL), and the Phillips et al. (2015) methodology.

results. In conclusion, there were six and five Bitcoin bubbles during the sample period in China and U.S. markets respectively. Additionally, the authors established that during periods of financial crisis investors seeks for an alternative to the traditional currencies, leading to an increase in the demand for Bitcoins; this leads to an explosion of the value of Bitcoins, thus, can be one of the causes of bubbles in the Bitcoin market. Another paper that used this methodology is Corbet et al. (2018). They examined the presence of bubbles both in Bitcoin and Ethereum. The main results stated that there are two distinctive periods when bubbles occurred. Bitcoin shows bubble behaviour between the end of 2013 and the beginning of 2014. Additionally, using the methodology proposed by Phillips et al. (2015), Bouri et al. (2019) argued that Bitcoin can be the biggest bubble in history. These authors studied the possibility of co-explosivity in the cryptocurrency markets. Concluding that during the studied period, August 7, 2015, to December 31, 2017, cryptocurrencies experienced several explosivity episodes, mostly in 2017, and more in Bitcoin and Litecoin[11]. In terms of evidence of co-explosivity, the main result is that Bitcoin price explosivity causes the presence of explosivity in other cryptocurrencies. The overall result stated that the likelihood of occurrence of explosivity periods in one cryptocurrency increases with the rise of the probability of another cryptocurrency experiencing as well.

Geuder et al. (2019) examined bubble-type behaviour in Bitcoin prices during 2016-2018. The two methodologies used[12] identified the existence of bubbles in the Bitcoin prices: the PSY technique identified several sub-periods of bubble

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[11] Bitcoin and Dash experienced long-lived explosive episodes. Conversely, Ripple, Ethereum, Litecoin, Dash, and Stellar exhibited explosiveness for periods lasting mostly less than 10 days (short-lived explosiveness episodes).

[12] They use two different methodologies, namely the Phillips et al. (PSY, 2015) testing methodology, and the Log-periodic Power Law (LPPL) approach proposed by Filimonov and Sornette (2013), to test for the presence of bubbles.

behaviour, especially during 2017, mostly in line with the findings from the LPPL approach. The paper by Enoksena et al. (2020), detects the presence of bubbles using the methodology proposed by Phillips et al. (2015), which defines a bubble as an explosive episode in the price behaviour and studies the variables that can predict bubbles in the price of eight important cryptocurrencies, with focus on uncertainty measures (VIX Index[13], EPU Index[14]). At the same time, Enoksena et al. (2020) consider Google trends, volatility, transactions, and volume into the analysis to measure the public interest in cryptocurrencies. They observed several cryptocurrencies bubbles during the sample interval, especially during 2017 and 2018. Caferra et al. (2021), analyzed the 2017 Bitcoin bubble to understand the reasons behind the price hike. Using a dynamic time warping (DTW) algorithm and the methodology proposed by Phillips et al. (2015), they identified a group of assets that had similar characteristics with cryptocurrency bubble and verified that the Bitcoin bubble had strong similarity with the NASDAQ[15] Dotcom Index. The main results stated that by using data at a low frequency, the securities seem to be more synchronized with Bitcoin than by using high frequency, reinforcing the overall idea of poor relation between the cryptocurrencies and the real economy, thus, revealing portfolio hedging. Lastly, they observed that investor switching behaviour is more common in presence of positive news about cryptocurrencies, especially when investors' moved capital from gold (represented in this study by the XAU Index[16]) and NASDAQ index to Bitcoin. Additionally, using the LPPLS[17] methodology, and the modified

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[13] The VIX index corresponds to the CBOE Volatility Index, this means is a real time index. Represents the markets expectations for the relative strength of near-term price changes of the S&P 500 Index.

[14] EPU-Index measures daily uncertainty about legislation and regulation.

[15] NASDAQ index is a market capitalization-weighted index, associated to important technology sectors.

[16] XAU Index or Philadelphia Gold and Silver Index is a market capitalization index of precious metal mining company stocks, it includes both gold and silver mining companies.

[17] Log-Periodic Power Law Singularity.

Lagrange regularization method, Shu et al. (2021) aimed to identify and monitor the Bitcoin bubbles and crashes, using different data frequencies. During this period one cluster of negative bubbles and two clusters of positive bubbles can be clearly observed. Another important conclusion is the existence of an endogenous bubble between November 2020 and mid-January 2021, characteristic of herding and imitative behaviour in the market. While from mid-January 2021 to mid-April 2021, the bubble seems to be an exogenous bubble driven by extrinsic events, such as the Tesla announcement that it has purchased $1.5 billion of Bitcoin on 8 February 2021.

The paper by Chowdhury et al. (2021) has as main objective to measure the spillovers effects, and make a distinction between contagion, asset rotation and independence effects on cryptocurrencies, using the Phillips et al. (2015) methodology to predict bubbles and crashes. The authors detected multiple periods of crashes and bubbles. The global financial crisis that occurred in 2007/2008 affected all cryptocurrencies besides Ripple. Overall, there is compelling evidence of interdependence and contagion during bubbles, especially during market downturns. The evidence related to market rotation[18] involves mostly Ripple. Bubbles in Ripple coincide with crashes in Bitcoin, Ethereum and Litecoin. However, bubbles in other cryptocurrencies do not cause crashes in Ripple, thus, Ripple presents some unique features. This suggests that Ripple is against the trend. Another paper that provided insights about the contagion effects between Bitcoin and other cryptocurrencies is the study by Ferreira and Pereira (2019), which uses the Detrended Cross-Correlation Analysis correlation coefficient[19], comparing the period before and after the crash

[18] Market rotation is related to the act of moving money, this means, moving money from one area of the market to another one that is performing better, with the main objective of achieving greater profit.

[19] The Detrended Cross-Correlation Analysis correlation coefficient ($\Delta\rho DCCA$) is a tool to measure the contagion effect, in time series of size (N), at a different time scale (n), Guedes et al. (2018). This coefficient considers the temporal order of the data, this means the temporal dependence between different variables. The DCCA cross-correlation coefficient ranges is from $-1 \leq \rho DCCA \leq 1$.

in the cryptocurrency markets, as measure of contagion (Da Silva et al., 2016). The main results showed that, except for Tether, Waves and Dogecoin, all other cryptocurrencies (Ethereum, Ripple, Litecoin, Stellar, Monero, Dash, NEM), demonstrated an increased correlation with Bitcoin, implying that the cryptocurrency markets are integrated and most of the cryptocurrencies are more sensitive to fluctuations in the price of Bitcoin, that can cause some instability in the financial market.

By addressing the relationship between the explosive behaviour of cryptocurrencies (co-explosivity), using the testing methodology proposed by Phillips et al. (2015), Agosto and Cafferata (2020) documented multiple bubbles in all five cryptocurrencies used in their study[20] in the mid/end of 2017 and the beginning of 2018. They noticed that among the cryptocurrencies considered, Bitcoin is the one that experienced the highest number of explosive episodes. Moreover, Ethereum presented a positive explosive impact on both Ripple and Litecoin, which represents evidence of co-explosivity. Also, Ripple had a positive impact on Stellar, and Stellar a positive impact on Ripple. However, Ripple presented a negative impact on Bitcoin this can be related with the different nature of the analysed cryptocurrencies. According to Agosto and Cafferata (op. cit.), these findings suggest that while Bitcoin and Litecoin are objects of speculative activity, Ethereum is related with technology for the creation of smart contracts, and both Ripple and Stellar, are services platforms. Overall, Bitcoin is largely influenced by the other cryptocurrencies explosivity. Nevertheless, not all the estimated effects increase in magnitude in the presence of a bubble.

Thus, a $\rho DCCA = 1,$ means a perfect cross correlation; $\rho DCCA = 0$ means no cross $-$ correlation; $\rho DCCA = -1$means perfectly anti cross-correlation. If we have two different moments separated by some phenomenon (for example a bubble), then $\Delta\rho DCCA = {\rho_{DCCA}}^{after}(n) - {\rho_{DCCA}}^{before}(n)$. Where, ${\rho_{DCCA}}^{after}(n)$ and ${\rho_{DCCA}}^{before}(n)$ correspond to the coefficients before and after that phenomenon. The statistical test proposed by Guedes et al. (2018), is based on the Null hypothesis for $\Delta\rho DCCA$. The Null hypothesis states that $\Delta\rho DCCA = 0$, thus, there are no significant differences, the Alternative hypothesis states that $\Delta\rho DCCA \neq 0$, the differences are significant.

[20] Bitcoin, Ethereum, Ripple, Litecoin and Stellar.

Another important problem addressed in this research is the lack of fundamental values to evaluate cryptocurrencies. The existence of an unclear fundamental value leads to an increase in herding behaviour among investors' (Devenow and Welch, 1996).

Lastly, an interesting paper by Kumar et al. (2021), implements at the same time the GSADF test (Phillips et al., 2015) and the recursive panel GSADF test (Pavlidis et al., 2016) to analyse individual and synchronized explosive behaviour in six major cryptocurrencies. They captured evidence in favour of price explosivity in the individual cryptocurrencies; especially during the periods of 2015-2016, which they argue that can be attributed to endogenous and exogenous factors, such as the creation of a new Bitcoin in August 2015[21]. Additionally, Bitcoin, Ethereum and Dash showed the highest number of explosiveness periods. Ethereum and Dash presented one of the most prolonged explosive periods. Furthermore, Bitcoin and Ethereum are the only cryptocurrencies that presented explosive periods before 2017. In terms of the panel results, four common explosive periods are identified during 2016-2018, presenting evidence of synchronization in the cryptocurrency markets, mostly during periods of turbulence. Kuman and Anandarao (op. cit.) captured a large synchronization period, across most of the cryptocurrencies, during 2017-2018. They attributed this phenomenon to the Chinese government crackdown on cryptocurrencies activities in January 2017. Another period captured by the panel GSADF test was from November 19, 2018, to December 19, 2018. Therefore, the study by Kuman and Anandarao (2021) presented strong evidence of synchronized explosive periods in the overall cryptocurrency markets, thus, suggestive of strong comovement between the cryptocurrencies.

[21] A new fork in Bitcoin was created in August 2015, yielding a new cryptocurrency called Bitcoin Cash.

2.3.5 *EMPIRICAL GRANGER CAUSALITY RELATIONSHIPS*

The paper by Bouoiyour et al. (2014) explored the Granger Causality relationship between Bitcoin price and investors' attractiveness, and between Bitcoin price and business transactions, measured by the Exchange-trade ratio. To measure the investors' attractiveness interest in Bitcoin, Bouoiyour et al. (op. cit.), used the daily Bitcoin views from Google search queries. Using a frequency domain-based methodology[22] they established two types of causal relationships between the variables: one is unconditional, while the other is conditional on the Chinese stock market, and on the processing power of Bitcoin network, the hash rate[23]. The main conclusion from this research is that Bitcoin prices Granger-cause business transactions, both in short and medium-run. However, the reverse link is not supported by the results. Lastly, both the Chinese market index and the hash rate led to ambiguous results established between Bitcoin prices and speculation. Milunovich (2018) uses a Granger causality test to examine the degree of connectedness within a group of five popular cryptocurrencies, six major asset classes, plus two risk factors (TED spread and Geopolitical risk index[24]), using, at the same time, a forecast error variance decomposition connectedness table proposed by Diebold and Ylmaz (2014). The results captured Granger causality relationships between Bitcoin and Ripple, Bitcoin and Ethereum, Ethereum and Monero, Litecoin and Ripple, and Ripple and Moreno. Overall, the main conclusions reported that there are six Granger causality relationships from non-digital assets to cryptocurrencies, and two casual

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[22] This frequency domain-based methodology enables testing for short-run and long-run causality developed by Breitung and Candelon's (2006),

[23] The hash rate is a measure of the total computational power. It is used by a proof-of-work cryptocurrency in order to process transactions in a blockchain.

[24] The Geopolitical risk index is a measure of adverse geopolitical events, with focus on newspaper articles covering geopolitical tensions, examine its economic effects and evolution since 1900.

relationships from digital assets to non-digital assets. In general, this analysis illustrated relative weakness of the uncovered connection between digital and non-digital assets. This means the risk of price distress in the cryptocurrency markets is not likely to be transmitted to non-digital assets. Along the same lines, Huynh (2019) aimed to analyse the spillover risks among five major cryptocurrencies by using Granger causality within a VAR-SVAR modelling framework and Student's-t Copula's methodologies. He found evidence of some contagion effects among cryptocurrencies.

2.4 CONCLUDING REMARKS

The studies reviewed in this chapter can be considered as a starting point in my research because they draw attention to the existence of episodes of price explosiveness in the cryptocurrency markets. There is now a vast literature on cryptocurrencies, covering aspects related to portfolio risk management, market efficiency, trading strategies, and the ongoing discussion about the presence of bubbles in the cryptocurrency markets. One of the main common characteristics across the papers included in this literature survey is related to the methodology used. A good number of them used the methodology proposed by Phillips et al. (2015) to identify the presence of episodes of explosiveness in the cryptocurrency markets. The GSADF is the preferred test, and most studies employ daily data. The highly volatile, speculative characteristics of cryptocurrencies are clearly highlighted and supported by the empirical evidence in a growing number of studies.

CHAPTER 3- METHODOLOGY

This chapter describes the methodology employed in this dissertation to test for the presence of multiple episodes of explosiveness in both individual cryptocurrency price series and in a panel of cryptocurrencies. In an attempt to shed lighter on the relationship between the prices of the seven selected cryptocurrencies, the Logit model and the Granger causality tests will also be employed.

3.1 DETECTION OF PRICE EXPLOSIVENESS: SADF AND GSADF TESTS

Minford and Peel (op. cit.) provided the asset price equation to analyse speculative bubbles. Assuming that investors are risk neutral, so that the expected returns are equal to the risk-free asset with rate of return $\bar{R}$, and assuming that this rate is constant so that, $E_t R_{t+1} = \bar{R}$, then:

$$P_t = \frac{1}{(1+\bar{R})} E_t P_{t+1} + \frac{1}{(1+\bar{R})} E_t D_{t+1} \qquad (1)$$

Where P_t is the ex-dividend price of the asset; P_{t+1} is the ex-dividend price of the asset at $t+1$; D_{t+1} is the payoff received by the asset holder at $t+1$ (i.e., dividend); and $\bar{R}$ is the risk-free interest rate.

Second, assuming rational expectations and solving this model N periods forward, we obtain:

$$P_t = E_t \left[\sum_{i=1}^{N} \frac{D_{t+i}}{(1+\bar{R})^i}\right] + \frac{E_t P_{t+N}}{(1+\bar{R})^i} \qquad (2)$$

Where the second term ($\frac{E_t P_{t+N}}{(1+\bar{R})^i}$) corresponds to the discounted value of the stock price N periods into the future. When N tends to infinity, in the absence of speculative bubbles the second term tends to zero. Thus, in the absence of bubbles:

$$P_t = E_t \left[\sum_{i=1}^{N} \frac{D_{t+i}}{(1+\bar{R})^i}\right] = F_t \qquad (3)$$

Which suggests that the current price P_t equals the expected value of the stream of dividends in the indefinite future (as we allow N to tend to infinity). This means that the expression on the right-side of equation (3) is equal to the fundamental of the process (F_t) in the absence of speculative bubbles. Therefore, this is consistent with the rational expectation solutions. In the presence of bubbles, the current price as an asset can be written as the sum of two components:

$$P_t = F_t + B_t \qquad (4)$$

Where the B_t represents the bubble component, which is added to the fundamental component (F_t). The quantity $P_f^t = P_t - B_t$, is often called the market fundamental; typically, it is assumed that B_t follows a submartingale process:

$$E_t(B_{t+1}) = (1 + \bar{R})\, B_t \qquad (5)$$

This equation makes clear that the deterministic solution for B_t represents an asymptotic explosive process. By substituting equation (4) in (1) we get:

$$P_t = F_t + B_t = \frac{1}{(1+\bar{R})} E_t B_{t+1} + \frac{1}{(1+\bar{R})} E_t F_{t+1} + \frac{1}{(1+\bar{R})} E_t D_{t+1} \qquad (6)$$

According with this equation, if investors believe that the bubble process B_t is the driver of the asset prices then this will be a "rational" solution.

Thus, I can state that in the absence of bubbles, equivalent to B_t= 0, the degree of non-stationarity of the asset price is controlled by the unobserved fundamentals and dividend series. However, this pricing equation cannot be applied in the case of cryptocurrencies as they do not offer a stream of payments similar to the dividends provided by stocks. Moreover, establishing the fundamental value of the price of a cryptocurrency is not an easy task, and has been a matter of debate. Waters and Bui (2021) asked and attempted to answer the question "What are the fundamentals?". They stated that none of the cryptocurrencies pays dividends or earnings or rent. According with Robert Shiller, a 2013 Nobel prize laureate, stated that "any attempt to start estimating the fundamental value of Bitcoin will seem silly". The empirical analysis conducted by Cheah et al. (2015) lends support to the view that the fundamental value of Bitcoin is zero. John Cochrane (2018) argued that it is time to think about the convenience yield of holding Bitcoin as a medium of exchange, however, the volatility displayed by the Bitcoin's value makes it minimally useful for purchases. Moreover, the purpose cryptocurrencies serve continue to remain an open question.

In a seminal study, which proposes what has become a state-of-the-art testing methodology, Phillips et al. (2015) show that in some dynamic structures, a time-varying discount rate can lead to temporary explosive behaviour in the asset price. Thus, this is a key sign of market exuberance[25] during bubble periods, that can be tested using the GSADF test they develop.

The main aim of this dissertation is to examine the presence of periods of explosiveness, which may correspond to bubbles, in the prices of a group of selected cryptocurrencies. If the argument put forward by Cheah and Fry (2015) that the fundamental value of Bitcoin is zero is adopted and extended to the other cryptocurrencies included in this study, then according to equation (4) above, the price of a cryptocurrency will not have a fundamental component, but only a bubble one, so a test for explosive behaviour can be regarded as a test for bubble(s). Therefore, the tests originally developed by Phillips et al. (2011) and

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[25] Exuberance is just another term for explosiveness in prices. The term "exuberance" was first used in connection with developments in asset markets by the former chairman of the Federal Reserve Board, Alan Greenspan, in a speech given at the American Enterprise Institute during the dotcom bubble episode at the end of the 1990's. In this speech, Greenspan asked what has now become a famous question: "How do we know when irrational exuberance has unduly escalated asset values..."? The phrase "irrational exuberance" was then regarded as a warning that the U.S. stock market might be witnessing a period of overvaluation. While Alan Greenspan was the first to use it, the term was coined by Robert Shiller, who used it as the title for his famous book "Irrational Exuberance". In this dissertation, the term "exuberance" will be used to reflect the explosive features of cryptocurrency prices.

Phillips et al. (2015) to detect explosive behaviour can also be employed as tests for bubbles in the case of cryptocurrencies prices. According to Phillips et al. (2015), the GSADF offers an improvement in the discriminatory power when multiple bubbles occur compared to its predecessor the SADF test proposed in Phillips et al. (PWY, 2011). My analysis of the data, and the findings of existing studies on the topic suggest that multiple periods of explosive behaviour are more likely to have occurred in the prices of cryptocurrencies than a single period. According to the authors, if there is a single bubble in the time series examined, the PWY dating strategy is consistent. However, in the presence of multiple explosive episodes, the SADF testing method has lower power compared to GSADF and may fail to reveal the existence of some of these periods of explosiveness. Therefore, to overcome this issue, Phillips, Shi, and Yu (PSY, 2015) proposed a refined version of the SADF test, the Generalized Sup Augmented Dickey-Fuller (GSADF) methodology to test for the presence of multiple bubbles. This methodology not only tests for bubbles, but also implements a recursive backward regression technique (in the estimation of the BSADF testing sequence) to enable the date-stamping of the detected bubble episodes, by indicating the origination and the termination of the bubble. The test is estimated backward to minimize the impact of collapsing time periods. In addition, the GSADF testing procedure uses flexible windows[26]. Hence, the PSY procedure outperforms the PWY if one has to test for multiple episodes of explosive behaviour. This methodology will be the most well suited to perform my research.

[26] The use of flexible windows, which extends the sample coverage, by changing both the start and the end points, which means different re-initializations in the implementation of the recursive right tailed ADF test.

To perform the Supremum Augmented Dickey-Fuller (SADF) test, Phillips et al. (2015), firstly the following model, which is the model under the Null hypothesis of the test, is specified.

$$y_t = \mu_y + \theta y_{t-1} + \varepsilon_t \text{ , where } \varepsilon_t \sim \text{iid } (0, \sigma^2), where \ \theta = 1 \qquad (7)$$

In the framework of the SADF test, the Null hypothesis allows for a martingale process with an asymptotic drift to capture the mild drift in price processes.

In this regression, $\mu_y = \alpha T^{-\pi}$, where α is a constant, T is the sample size, and π is a localizing coefficient that controls the magnitude of the intercept and drift as T tend to infinitive. According to Phillips et al. (2015), the drift term is asymptotically negligible. For example, if $\pi > 0$, the drift will be smaller than the linear trend; if $\pi > 0.5$, the drift is smaller than the stochastic trend; if $\pi = 0.5$ and, at the same time, T tends to infinity than the series y_t will behave like a Brownian motion with a drift.

To test for the presence of explosive behaviour using the SADF test, under the Null hypothesis the process has a unit root, while according to the Alternative hypothesis, the process exhibits mildly explosive behaviour:

H0: $\theta = 1$ (Unit root, non-stationarity, no explosive behaviour).

H1: $\theta > 1$ (Explosive behaviour).

Thus, according to the specification in equation (7) and the hypotheses outlined above, the SADF shares some common features with the standard Augmented-Dickey Fuller (ADF) test, but it is a right-tailed version of it, rather than being left-tailed one. The auxiliary regression is the same for both SADF and standard ADF tests, but the two tests have different alternative hypotheses: in the standard ADF test, the alternative is that of stationarity (no unit root) while in SADF the alternative hypothesis captures mild explosive behaviour in the series.

The model specification in (7) is typically complemented with transient dynamics to conduct tests for exuberance. This recursive approach involves a rolling window ADF regression style implementation. Suppose that the rolling window sample starts at r_1 fraction of the total sample T and ends at the r_2 fraction of the sample. This means $r_2 = r_1 + r_w$, where $r_w > 0$ is the window size of the regression. This model, which is the auxiliary regression of the standard ADF test, can be written as:

$$\Delta y_t = \mu_y + (\theta - 1) y_{i,t-1} + \sum_{j=1}^{J} \Delta y_{t-j} + \varepsilon_t \text{ , where } \varepsilon_t \sim \text{iid } (0, \sigma^2) \quad (8)$$

In this model the J represents the (transient) lag order and Δ is the first difference operator. The number of observations in this regression is the $T_w = \lfloor T r_w \rfloor$, where $\lfloor . \rfloor$ corresponds to the floor function. Additionally, the ADF statistic based on this regression is defined by ADF_{r_1,r_2} .

Using an OLS estimation, estimates are calculated for rolling windows of width n, where $n \epsilon (r_0, T)$, r_0 is the starting window size, with r_1 and r_2 being the window start point and end point, respectively.

According to the standard ADF-test statistic for the window of size n:

$$ADF_{r_1,r_2} = \frac{\theta_{r_1,r_2}}{se(\theta_{r_1,r_2})} \quad (9)$$

Again, the Null Hypothesis is $\theta = 1$, meaning that y_{t-1} is a unit root process (Δy_t is stationary). According to the Alternative hypothesis, $\theta > 1$, this means that y_{t-1} is explosive (Δy_t is non-stationary).

However, according to Phillips et al. (2015), the standard ADF test has rather low discriminatory power in detecting bubbles, thus, they are sensitive to changes (Evans, 1991). This means when a process experiences changes from an explosive root to a unit root or vice versus. Therefore, when detecting periods of periodically collapsing bubbles, this test is prone to limited power.

Thus, Phillips et al. (op. cit.) propose the Supremum Augmented Dickey-Fuller test (known as the SADF test) for bubbles:

$$SADF(r_0) = \text{Sup}_{r_2 \in (r_0,1)} \left\{ADF_0^{r_2}\right\} \quad (10)$$

The ADF statistic for a sample that ranges from 0 to r_2 is defined by $ADF_0^{r_2}$. Nevertheless, this test is only effective for a single bubble episode.

Third, to overcome the above-mentioned weakness of SADFs, the GSADF test introduces flexible windows in this model, by allowing changes in both the starting and ending points. It allows the r_1 point to change from 0 to $r_2 - r_0$.

The GSADF test statistic is (known also as the PSY test for Bubbles):

$$GSADF(r_0) = \text{Sup}_{r_2 \in (r_0,1),\, r_1 \in (0, r_2 - r_0)} \left\{ADF_{r_1}^{r_2}\right\} \quad (11)$$

Note that the limit distribution of the GSADF test statistic depends on the starting window size (r_0)[27].

Additionally, after detecting the existence of a bubble/more than one bubble, the start and end points of a bubble can be analysed by using the backward SADF (BSADF) test of Phillips et al. (op. cit.):

[27] This means that I should choose an r_0 such that the starting window is large enough to estimate a regression on it, and at the same time, it should be smaller than the distance separating any two bubbles. According to Phillips et al. (op. cit.), the value of $r_0 = 0.01 + \frac{1.8}{\sqrt{T}}$.

$$BSADF_{r_2}(r_0) = \text{Sup}_{r_1 \epsilon (0, r_2 - r_0)} \left\{ADF_{r_1}^{r_2}\right\} \qquad (12)$$

According to this, the end of the rolling window is fixed at r_2, and the window expands from r_0 to r_2.

In addition, explosive periods are defined based on the GSADF test:

$$\hat{r}_e = inf_{r_2 \epsilon (r_0, 1)} \left\{r_2 : BSADF_{r_2} > cv_{r_2}^{\alpha_T}\right\} \qquad (13)$$

$$\hat{r}_f = inf_{r_2 \epsilon (\hat{r}_e, 1)} \left\{r_2 : BSADF_{r_2} < cv_{r_2}^{\alpha_T}\right\} \qquad (14)$$

Where $cv_{r_2}^{\alpha_T}$ corresponds to the 100 (1 - α_t)% critical value of the SADF statistics based on r_2 observations, and assuming a constant value for α_t equal to 5%.

Thus, to identify when a bubble occurs and collapses, I will use the date stamping strategy presented above. It is important to mention that a bubble start date is defined as the first observation for which the backward GSADF test statistic is bigger than the critical value of the backward GSADF statistic (obtained from Monte Carlo simulations). Hence, the end date of a bubble is defined as the first observation after that start date on which the GSADF test statistic value is lower than the critical value.

3.2 SYNCHRONIZED PERIODS OF PRICE EXPLOSIVENESS

3.2.1 THE PANEL GSADF

The SADF and GSADF tests described above can only be applied to individual time series, therefore, do not provide any insights about the panel nature of cryptocurrency price data. Building on the panel unit root test proposed by Im, Pesaran, and Shin (2003), Pavlidis et al. (2016) proposed an extension of the GSADF test to a panel setting, which works with heterogeneous panels, and which is suitable to apply to a panel of cryptocurrencies as an alternative to using individual cryptocurrency price series, as periods of exuberance may have occurred in more than one cryptocurrency. To explore this idea, consider the panel version of Equation (8):

$$\Delta y_{i,t} = \mu_{i,y} + (\theta - 1) y_{i,t-1} + \sum_{j=1}^{J} \Delta y_{i,t-j} + \varepsilon_{i,t} \text{ , where } \varepsilon_{i,t} \sim \text{iid}\ (0, \sigma^2) \quad (15)$$

Where i denotes the individual series and the other variables are explained in the previous sub-section. The panel GSADF test examines the Null hypothesis of a unit root, H0: $\theta = 1$, for all N panel members (cryptocurrency prices in our case), against the Alternative hypothesis of an explosive behaviour in a subset of cryptocurrencies, H1: $\theta > 1$ for some i. This test allows θ to differ across cross sectional units in the panel (in this case, individual cryptocurrencies), being more general than the tests that impose a homogenous alternative.

This test involves creating a measure of overall exuberance by averaging the individual BSADF statistics at each period:

$$Panel\ \ BSADF_{r_2}(r_0) = \frac{1}{N} \sum_{i=1}^{N} BSADF_{i,r_2}(r_0) \quad (16)$$

Following Equation (16), the panel definition of the GSADF is described by:

$$Panel\ GSADF\ \ (r_0) = \ \mathrm{Sup}_{r_2\,\epsilon\,(r_0,1)}\ Panel\ BSADF_{r_2}\,(r_0) \quad (17)$$

According to Maddala and Wu (1999) and Chang (2004), the limit distribution based on mean unit root statistics of panel unit root tests is not invariant to the cross-sectional dependence in the error terms. Therefore, a sieve bootstrap approach, designed to solve the problem of cross-correlated errors in the panel version, is employed to estimate the critical values of the test. The panel GSADF test has been successfully used to capture explosive price behaviour in equity markets (Liaqat et al., 2019), energy markets (Li et al., 2020), and house price markets (Pavlidis et al., 2016).

3.2.2 LOGIT REGRESSION

To uncover evidence of overall synchronized periods of price exuberance across cryptocurrencies, a Logistic regression, with a dependent variable constructed based on the date-stamping from the Panel GSADF is estimated. The results of the Logistic regression can show if an explosiveness in one cryptocurrency led to global explosiveness episodes across all cryptocurrencies.

In this case, the explained variable ($y_{i,t}$) is not a quantitative measure of some outcome, but rather an indicator variable. The explained variable can take only two values, 1 if a particular cryptocurrency exhibits explosive and 0 otherwise.

$$y_{i,t}=\begin{cases} 1, if\ there\ is\ an\ axplosive\ behaviour\ \ (BSADF_{r_2}\ \geq cv_{r_2}^{\alpha_T}\ ) \\ 0, if\ there\ is\ no\ explosive\ behaviour\ (BSADF_{r_2}\ < cv_{r_2}^{\alpha_T}). \end{cases}$$

Thus, the binary response (logistic) regression model can be written as follow:

$$y_{i,t}^{*} = \ \theta_0 \ + \ x_{i,t}{}'\theta_i + \varepsilon_{i,t} \quad (18)$$

$$Y_{i,t}=\begin{cases} 1, \ \ y_{i,t}^{*}\ \geq 0 \\ 0, \ y_{i,t}^{*} < 0. \end{cases}$$

Where $y^*_{i,t}$ corresponds to the so-called latent variable. θ_0 is a constant, $x_{i,t}$ represents a set of 7 cryptocurrencies using data on the logarithm of daily prices from 9 November 2017 to 26 June 2017. Lastly, the $\varepsilon_{i,t}$ represents the error term assumed to follow a logistic distribution.

Thus, if I assume that $\varepsilon_{i,t}$ follows a logistic distribution; a mathematical convenient distribution can be described by:

$$Prob\left(y_{i,t} = 1 \middle| x_{i,t}\right) = F(x_{i,t}{}'\theta_i) = \Lambda(x_{i,t}{}'\theta_i) = \frac{e^{x_{i,t}{}'\theta_i}}{1 + e^{x_{i,t}{}'\theta_i}} \quad (19)$$

$$\log\left(\frac{Prob(y_{i,t} = 1|\, x_{i,t})}{1 - Prob(y_{i,t} = 1|\, x_{i,t})}\right) = \theta_0 + x_{i,t}{}'\theta_i \quad (20)$$

Where $Prob\left(y_{i,t} = 1 \middle| x_{i,t}\right)$ corresponds to the probability that a bubble occurs in the logarithm of the price of the cryptocurrency. This analysis is similar to the ones performed by Bouri et al. (2019) and Agosto and Cafferata (2020).

3.3 Granger Causality

According to Hill et al. (2018), Granger causality refers to the ability of the lagged values of one variable to contribute to the forecast of another variable. This means that if x Granger causes y, then past values of x should contain information that helps to forecast y above and beyond the past information contained only in y. Therefore, the testing hypotheses can be described as follows:

H0: $x \text{ does not Granger causes } y \ (x \nrightarrow y);$

H1: $x \text{ does Granger causes } y \ (x \rightarrow y).$

It can be tested by using an F-test for testing joint linear hypotheses. The rejection of the Null hypothesis means that x Granger causes y. However, if x

Granger causes y, it does not necessarily imply a direct causal relationship between x and y. It only means that having information on past values of x will improve the y forecast. To check for bivariate Granger causality, I need to compute the reverse Granger causality test. In my analysis, x and y correspond to two different cryptocurrency prices. However, I acknowledge that Granger causality was not developed for series that are mildly explosive; Granger causality was developed for series that have a unit root (are integrated of order one) and are also co-integrated, or if not cointegrated, then the Granger causality test is conducted for the series taken in first differences, if they are integrated of order 1, or in levels if the series are stationary.

CHAPTER 4 - DATA

The data employed in the empirical analysis conducted in this dissertation consists of daily close prices, in U.S. dollars, of seven cryptocurrencies: Bitcoin, and Litecoin (from September 17, 2014, to June 26, 2022) and Ethereum, Binance Coin, Ripple, Cardano, and Dogecoin (from November 11, 2017, to June 26, 2022)[28].

Cryptocurrency	From	To	Number of observations
Bitcoin (BTC-USD)	17-09-2014	26-06-2022	2840
Ethereum (ETH-USD)	09-11-2017	26-06-2022	1691
Litecoin (LTC-USD)	17-09-2014	26-06-2022	2840
Binance Coin (BNB-USD)	09-11-2017	26-06-2022	1691
Ripple (XRP-USD)	09-11-2017	26-06-2022	1691
Cardano (ADA-USD)	09-11-2017	26-06-2022	1691
Dogecoin (DOGE-USD)	09-11-2017	26-06-2022	1691

TABLE 1: Time period employed for each cryptocurrency.

Table 1 presents the start and end dates of the price dataset for the seven cryptocurrencies selected in this study. Although it is possible to obtain earlier data from other sources, I chose to use these data sets due to their source's reliability compared with other sources.

Figure 1 shows the daily close prices in U.S. dollars for all cryptocurrencies. The prices experienced huge fluctuations specially during the period of 2018 and the beginning of 2021. To improve this dissertation readability, I report, in figure 13, the cryptocurrencies logarithms daily adjusted close price. During periods of financial turmoil, investors search for alternative investments; this can be one of

[28] The starting date for each cryptocurrency was selected based on data availability. The cryptocurrencies to be considered were chosen based on the length of their data sets, their popularity, and their total market capitalisation according to the information provided by Coinmarketcap.com and Yahoo Finance.

the explanations for the huge fluctuations that occurred in 2017/2018. After an unprecedented boom in the cryptocurrency markets in 2017, the 2018 "Great crypto crash" was the sell-off of most cryptocurrencies starting in January 2018. From January 6 to February 6 of 2018 the price of Bitcoin fell by 65% (Coinmarketcap.com). Furthermore, the notable peak in late 2020 (beginning of 2021) illustrates the hit of the Covid-19 pandemic. At the same time, during this period, cryptocurrencies started to gain more and more public attention from the social media platforms, and several CEOs, such as Elon Musk. Finally, the notable break in the prices of all cryptocurrencies is reported by the mid of 2022 ("The Crypto crash", Bloomberg.com, 2022).

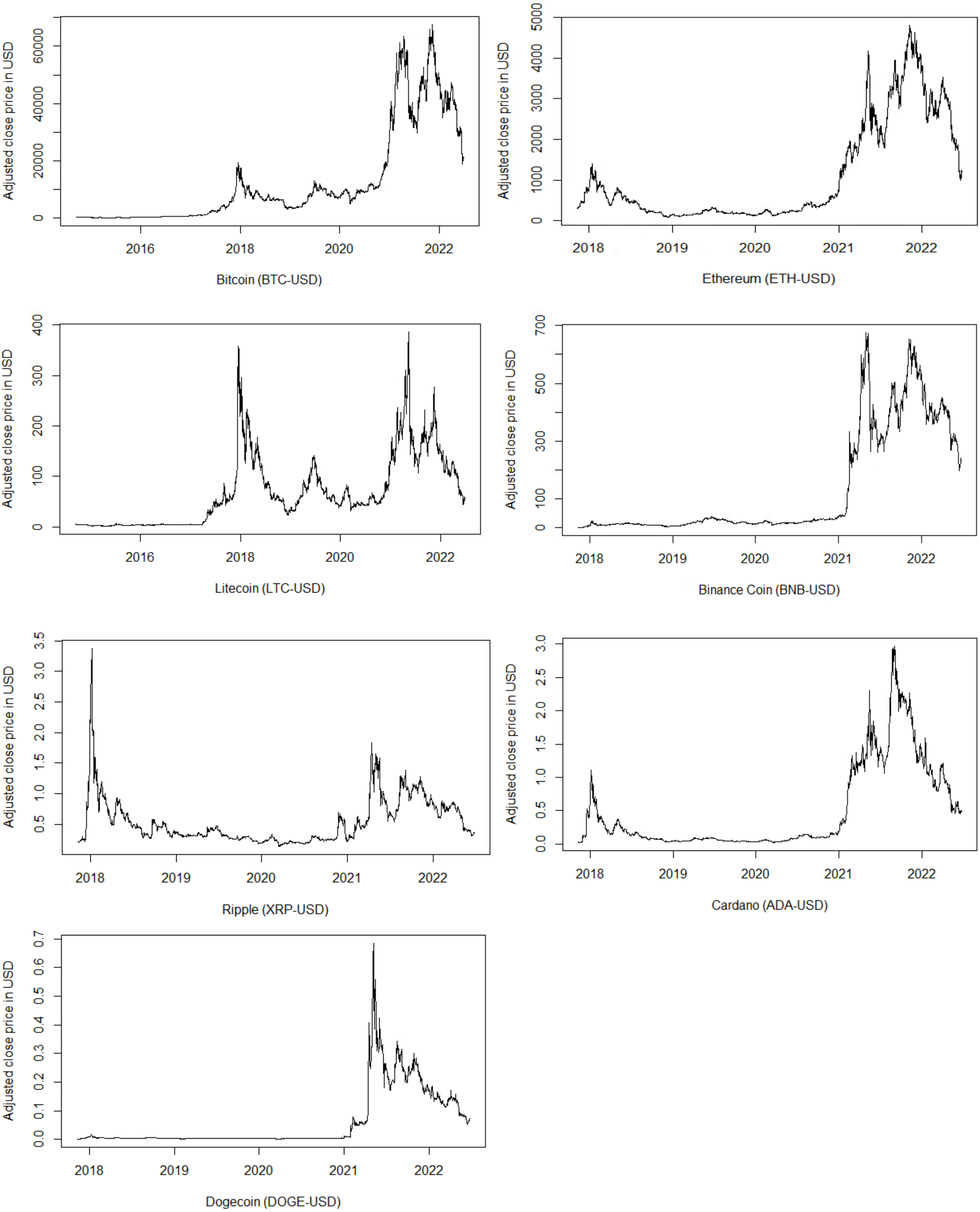

FIGURE 1: Cryptocurrencies daily adjusted close price over the sample period.

Variables	Daily Obs.	Mean	Standard Deviation	Min	Max	Skewness	Kurtosis
Bitcoin	2840	0.0013	0.0392	-0.4647	0.2251	-0.7781	13.785
Ethereum	1691	0.0008	0.0521	-0.5507	0.2347	-0.9534	9.7834
Litecoin	2840	0.0008	0.0566	-0.5146	0.5114	0.0930	12.631
Binance Coin	1691	0.0028	0.0608	-0.5431	0.5292	0.3803	13.980
Ripple	1691	0.0003	0.0656	-0.5505	0.6068	0.8276	15.862
Cardano	1691	0.0016	0.0698	-0.5036	0.8615	1.9184	23.059
Dogecoin	1691	0.0023	0.0804	-0.5151	1.5163	4.7980	83.288

TABLE 2: Summary Statistics.

Table 2 shows the overall summary statistics for the log-returns series and illustrates that cryptocurrencies prices exhibit volatile and rich market dynamics. For all the cryptocurrencies, the standard deviation is higher than the mean, suggesting that cryptocurrency prices are somewhat over-dispersed, indicating a huge volatility. Additionally, a significant departure from the normal distribution is found. The prices of both Bitcoin and Ethereum have negatively skewed distributions, while the distributions of prices of all other cryptocurrencies are positively skewed. Overall, cryptocurrencies present excess kurtosis. Noticeably, Dogecoin has the heaviest value on the fat tail. All cryptocurrencies exhibit characteristics of a non-normal distribution.

To corroborate the previous conclusion, I performed the Jarque-Bera test for normality in the data, for all selected cryptocurrencies (table 3). According with that, the results were statistically significant (p-value < $2.2e^{-16}$), suggesting once again the presence of non-normality in the data.

Table 4 shows the results of the standard ADF test. According to that, I can accept the Null hypothesis of a unit root (non-stationarity) for all cryptocurrencies except for Dogecoin, which is stationary at the 1% level of significance, but non-stationary (has a unit root) at the 5% level (p-value < 0.05).

Jarque-Bera test			
Variables	**Chi-Squared**	**Degrees of Freedom**	**P-Value**
Bitcoin	14047	2	$< 2.2e^{-16}$
Ethereum	7017.4	2	$< 2.2e^{-16}$
Litecoin	18910	2	$< 2.2e^{-16}$
Binance Coin	13842	2	$< 2.2e^{-16}$
Ripple	17961	2	$< 2.2e^{-16}$
Cardano	38582	2	$< 2.2e^{-16}$
Dogecoin	496166	2	$< 2.2e^{-16}$

TABLE 3: Jarque-Bera test for normality[29].

Standard ADF test		
Variables	**Augmented Dickey-Fuller Test Statistic**	**P-Value**
Bitcoin	-0.6461	0.8578
Ethereum	-0.9761	0.7632
Litecoin	-0.8867	0.7929
Binance Coin	-1.7512	0.4049
Ripple	-1.6744	0.4441
Cardano	--0.7762	0.8249
Dogecoin	-3.1770**	0.0218

TABLE 4: Standard ADF test[30].

As a pre-requisite to performing the Johansen multivariate cointegration test, based on the previous results of the standard ADF unit root test for all cryptocurrencies (table 4), I concluded that all cryptocurrencies have a unit root

[29] Note: The p-values are in displayed by RStudio software in scientific format.

[30] Note: The Null hypothesis is that there is a unit root, and the Alternative is that there is no unit root (stationarity). ***, **, and * indicate the rejection of Null at 1%, 5% and 10% significant levels, respectively.

in their levels (are non-stationary), apart from Dogecoin. However, Dogecoin, which just marginally has a unit root at the 5% level of significance, all other series are clearly integrated of order one (have a unit root, are non-stationary). Therefore, I decided to perform the Johansen multivariate cointegration test.

Johansen Test Results for Cointegration across Cryptocurrencies								
Rank of the error correction matrix	Test statistic (Eigen Value Approach)	10% Critical Value	5% Critical Value	1% Critical Value	Test Statistic (Trace-statistic Approach)	10% Critical Value	5% Critical Value	1% Critical Value
r = 0	96.28	43.25	46.45	51.91	212.08	126.58	131.70	143.09
r ≤ 1	40.72	37.45	40.30	46.82	115.80	97.18	102.14	111.01
r ≤ 2	30.45	31.66	34.40	39.79	75.07	71.86	76.07	84.45
r ≤ 3	23.59	25.56	28.14	33.24	44.62	49.65	53.12	60.16
r ≤ 4	10.99	19.77	22.00	26.81	21.02	32.00	34.91	41.07
r ≤ 5	7.87	13.75	15.67	20.20	10.03	17.85	19.96	24.60
r ≤ 6	2.16	7.52	9.24	12.97	2.16	7.52	9.24	12.97

TABLE 5: Johansen Test Results for Cointegration across Cryptocurrencies[31].

Based on the Johansen Cointegration test results displayed in table 5, I can reject the Null hypothesis for both r=0 and r ≤1. This means that the test statistics for both Eigenvalue approach and Trace-statistic approach are higher than the critical value, assuming a 5% significance level. However, the test statistic for r≤2 is lower than the critical value for both approaches, assuming a 5% significance level. Thus, I cannot reject the Null hypothesis, and hence conclude that there exists at most one cointegration vector among the cryptocurrencies. These results seem to indicate that there exists a long-run equilibrium

[31] Note: The Null hypothesis states that there is no cointegration vector between cryptocurrencies, and the Alternative hypothesis states that there is cointegration vector between cryptocurrencies.

relationship between cryptocurrencies, which suggests that the markets of the cryptocurrencies selected for this analysis are integrated. However, as argued in the seminal paper by Evans (1991), standard cointegration tests have low power in the presence of periodically collapsing bubbles.

CHAPTER 5 - EMPIRICAL RESULTS

This chapter presents and discusses the results of the empirical analysis conducted in this dissertation, focusing on whether episodes of explosiveness occurred in the prices of the seven selected as well trying to uncover the presence of synchronize periods of price explosiveness across cryptocurrencies.

5.1 SADF AND GSADF TESTS

The following table summarizes the results of the univariate ADF, SADF and GSADF results ([32]). The sample-based values of the test statistics and shown together with the corresponding 90%, 95% and 99% Monte Carlo-simulated critical values for each cryptocurrency.

Analysing the right-tailed ADF test, the module of the test statistics is higher than the critical value for all the cryptocurrencies at the 1% significance level, showing that the time series have explosive features in their dynamics. Overall, the univariate SADF and GSADF tests provide evidence of explosive price behaviour for all cryptocurrencies. The SADF test rejects the Null hypothesis of a unit root for Bitcoin and Litecoin at 1% significance level, whereas in the case of Dogecoin, the Null is rejected at 5% significance level. Additionally, looking at

[32] First, to compute the recursive unit root SADF and GSADF test statistics, I needed to compute the minimum window size (r_0) and the choose of the optimal autoregressive lag length (K). I selected the optimal lag according to the information selection criterion, namely the Akaike Information Criterion (AIC). I used the rule of thumb provided by Phillips et al., (2015): $r_0 = 0.01 + \frac{1.8}{\sqrt{T}}$.

Second, the implementation of the above-mentioned SADF, GSADF and BSADF tests also requires their limit distributions, depending on the minimum window size. Therefore, critical values must be obtained through Monte Carlo or bootstrapping simulations for the individual SADF and GSADF tests. In my dissertation, I used the Monte Carlo critical values, for 99%, 95% and 90%. I set the number of Monte Carlo repetitions to 2000.

Additionally, I specified that the "seed", that represents if and how the random number should be initialized, is equal to 145. However, for the panel version of the GSADF test I used the critical values provided by the panel sieve bootstrap methodology proposed by Pavlidis et al. (2016).

Finally, I choose to neglect very short periods of exuberance by setting a minimum duration period. Phillips et al. (2015) recommend a minimum duration of $\frac{Log(T)}{T}$. According to my sample interval, both Bitcoin and Litecoin (T=2840) have a minimum duration equal to 8 days. For all other cryptocurrencies (T=1691) the minimum duration is 7 days.

the GSADF test results, the Null of a unit root is rejected in favour of explosive price behaviour for all cryptocurrencies. For Bitcoin, Litecoin, Binance Coin and Dogecoin the Null is rejected at 1% significance level, whereas for all the others (Ethereum, Ripple and Cardano) is rejected at 5% significance level. I can state that I found evidence of explosive price behaviour (exuberance), especially, I can assert the presence of bubble periods in all cryptocurrencies. At the same time the GSADF tests point towards the possibility of multiple explosive price periods. As I expected, the GSADF outperforms the SADF test in detecting multiple episodes of explosive price behaviours, since GSADF test has greater window flexibility and covers more sub-samples of the data. However, the bubble periods captured by the SADF test are mostly long-lived bubbles.

Individual ADF, SADF and GSADF Test Results

Cryptocurrency	**Bitcoin**			**Ethereum**			**Litecoin**		
	ADF	SADF	GSADF	ADF	SADF	GSADF	ADF	SADF	GSADF
Test Statistic	-0.947***	3.780***	3.890***	-0.994***	0.450	2.750**	-1.240***	2.460***	4.600***
90% Critical Value	-0.436	1.390	2.230	-0.349	1.360	2.210	-0.436	1.390	2.230
95% Critical Value	-0.088	1.580	2.490	-0.093	1.580	2.450	-0.088	1.580	2.490
99% Critical Value	0.550	2.080	2.910	0.766	2.080	3.020	0.550	2.080	2.910
Cryptocurrency	**Binance Coin**			**Ripple**			**Cardano**		
	ADF	SADF	GSADF	ADF	SADF	GSADF	ADF	SADF	GSADF
Test Statistic	-1.760***	-0.211	4.110***	-2.710***	-1.610	2.570**	-1.610***	-0.505	2.680**
90% Critical Value	-0.349	1.360	2.210	-0.349	1.360	2.210	-0.3490	1.360	2.210
95% Critical Value	-0.093	1.580	2.450	-0.093	1.580	2.450	-0.093	1.580	2.450
99% Critical Value	0.766	2.080	3.020	0.766	2.080	3.020	0.766	2.080	3.020
Cryptocurrency	**Dogecoin**								
	ADF	SADF	GSADF						
Test Statistic	-1.070***	1.990**	3.800***						
90% Critical Value	-0.349	1.360	2.210						
95% Critical Value	-0.093	1.580	2.450						
99% Critical Value	0.766	2.080	3.020						

TABLE 6: Individual ADF, SADF and GSADF Test Results [33].

[33] Note: The Null hypothesis is that there is a unit root, and the Alternative is that there is explosive behaviour. ***, **, and * indicate the rejection of Null at 1%, 5% and 10% significant levels, respectively. Additionally, the ADF test presented in this table is the right-tailed ADF test.

Table 7 displays the date stamping periods of price explosivity behaviour, detected using the SADF and GSADF tests, for all cryptocurrencies. As I described earlier, I considered a minimum bubble duration of 8 days for both Bitcoin and Litecoin, and a minimum bubble duration of 7 days for all the other cryptocurrencies[34]. In general, most of the detected bubbles are short-lived, and only last for a few days. However, I captured seven long-lived bubbles among all cryptocurrencies.

The first bubble occurred in the Litecoin market on 29 June 2015 and lasted 12 days until 11 July 2015. During 2016, Bitcoin started to gain a lot of public attention, and its price was mainly driven by good news. At this time, the cryptocurrency markets were not very regulated in most countries. As a result, and based on noise, investors were over optimistic about the future of cryptocurrencies. Bitcoin experienced the second bubble that occurred in the cryptocurrency markets (over the period analysed in this dissertation), from 21 December 2016 to 11 January 2017. Thus, this bubble was possibly caused by noise traders and overoptimistic expectations. Furthermore, Bitcoin exhibited most of the long-lived bubbles and the most prolonged explosive period in its case lasted around 118 days, from 27 September 2017 to 23 January 2018, according to the GSADF test results; during this time, Bitcoin's price was very volatile. Another long-lived bubble, which lasted around 53 days, occurred in the Bitcoin price from 17 May 2017 to 9 July 2017. Similar to Bitcoin, Litecoin and Cardano also exhibited long bubbles, which lasted 96 and 46 days respectively. Bitcoin and Litecoin bubbles during 2017 can be associated with the large number of Initial Coin Offerings[35]. According to Kaal and Dell'Erba (2017), Initial Coin

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[34] Note that the start date of a bubble is denoted by the first observation where the BADF/BSADF test statistic exceeds the critical value. The end data of a bubble is defined as the first observation after the start data in which the BADF/BSADF test statistics goes below the critical value.

[35] Initial Coin Offering is related with the cryptocurrency market and equivalent of an initial public offer. For example, investors can buy an initial coin offering I order to receive a new cryptocurrency token.

Offerings facilitate faster capital formation for cryptocurrency start-ups. In addition, venture capital funds can capitalize on the opportunities presented by Initial Coin Offerings, which can result in the exponential growth of cryptocurrencies. This led to a sharp rise in the price of cryptocurrencies during 2017 (López-Cabarcos et al., 2019), and increased the need for more regulation in the cryptocurrency markets, especially in Japan, China, and South Korea, thus, leading to the crackdown of the cryptocurrency markets. However, Bitcoin prices continued to rise at the end of 2017 due to the increasing popularity of the Blockchain technology around the world (Baig et al., 2019). The cryptocurrency prices started to decrease in early 2018, due to the extensive global regulation, leading to the burst of the bubbles for both Bitcoin and Litecoin.

Ethereum presented two short-lived bubbles at the beginning of 2021. Similar, two short-lived explosive price periods have been experienced by Cardano and Dogecoin both during 2021. Beyond 2021, there is no explosive behaviour with a minimum duration higher than seven days for Ripple. In general, most of the bubbles occurred in the Bitcoin market, followed by Litecoin and Binance Coin.

The bubble in the Bitcoin market, which started on the 22 December 2016, and burst at beginning of January 2017, has also been captured by Li et al. (2018). According to them, this episode can be explained by the rapid development of the block chain technology at that time, leading to an appreciation of the Bitcoin price. Li et al. (op. cit.) stated that investors hedged Bitcoin due to inflationary expectations and lower exchange rate in China, leading to a short-lived bubble during this period. Moreover, the third bubble detected by the GSADF test in the Bitcoin market coincides with the fifth bubble captured by Li et al. (op. cit.), from May until the end of June of 2017. The surge in prices was the impact of the hacker attack named "WannaCry". This is especially related to the fact that, in order to make some short-term profits in the Bitcoin futures market, some investors choose to hit the spot market, with the main objective of affecting the trend in

Bitcoin prices. This can indicate the enormous influence of the Chinese market operations on Bitcoin market. Li et al. (op. cit.) captured the start of the last Bitcoin bubble around 27 of July 2017[36]; this coincides with the bubble that I captured at the beginning of August 2017 (more precisely, 4 August 2017). According to Li et al. (op. Cit.), Bitcoin has become a tool for short-term speculators in pursuit of their interests. Its price is easily manipulated by speculators; that leads to a high speculation risk.

The majority of the bubble episodes occurred during 2017-2018 and the end of 2020, beginning of 2021. Several papers[37] have supported the existence of bubbles in these periods, which supports the findings of my analysis. Most of afore-mentioned authors attributed this price behaviour to the "Crypto crash" at the end of 2017 beginning of 2018. One of the main causes was linked to the hacking of the biggest Japan cryptocurrency markets, Coincheck[38].

Furthermore, the bubbles that occurred at the beginning of 2021 were detected as well by several past studies (surveyed in the literature review chapter). This period was characterized by a sharp rise in cryptocurrencies prices, with Bitcoin's prices reaching a peak around 64 000 U.S. dollars in April 2021. Shu et al. (2021) confirmed the existence of cryptocurrency bubbles between November 2020 and mid-January 2021. The authors established a relationship between this explosivity episode and the hit of the Covid-19 pandemic, as well as the increase of the importance of cryptocurrencies on social media planforms. Unlike the previous cryptocurrency bubbles, the cryptocurrency bubbles that occurred

[36] The sample period that Li et al. (op. Cit.) used was between June 16th 2011, to September 18th 2017).

[37] For example, Ricci et al. (2017) captured bubble periods in the price of Bitcoin during May and September of 2017. Corbet et al. (2018), stated that cryptocurrencies experienced several explosivity episodes, mostly in 2017, and more in Bitcoin and Litecoin. Other authors, such as Geuder et al. (2019), Agosto et al. (2020), Chowdhury et al. (2021), and Kumar et al. (2021) reported empirical evidence supporting the fact that cryptocurrencies experienced most of the bubble periods during 2017 and 2018.

[38] Approximately 530 million U.S. dollars were stolen by the hacker of the New Economy Movement platform[38], which caused Coincheck to suspend trading indefinitely. The New Economy Movement is a technological platform intended to be used to manage data and assets in an easy way and cheaply.

during 2020/2021 were caused by a combination of factors, the most important being the Covid-19 pandemic, investors sentiment and irrational behaviour. The positive sentiment of individual investors towards cryptocurrencies was one of the drivers. At the same time, the loss of confidence in traditional assets led to an increase in the attention towards the cryptocurrency markets, stimulating the demand for cryptocurrencies, which resulted in a rise in their prices.

Moreover, I observed some similarities, especially between the bubble periods of Bitcoin and Litecoin. The results of the tests indicate that price explosiveness occurred more frequently during 2017 compared with other years, a result that is potentially related to the artificial manipulation on the cryptocurrency markets and the hacker attack at beginning of 2018, and more in Bitcoin and Litecoin, compared with the other cryptocurrencies.

Periods of Explosive Behaviour						
	SADF Test			GSADF Test		
Cryptocurrency	Start	End	Duration (Days)	Start	End	Duration (Days)
Bitcoin	21/12/2016	11/01/2017	21	12/06/2016	21/06/2016	9
	17/01/2017	24/03/2017	66	22/12/2016	08/01/2017	17
	27/03/2017	08/09/2018	530	17/05/2017	09/07/2017	53
	30/12/2020	19/05/2021	140	04/08/2017	14/09/2017	41
	06/10/2021	18/11/2021	43	27/09/2017	23/01/2018	118
				11/05/2019	03/06/2019	23
				22/06/2019	30/06/2019	8
				18/11/2020	26/11/2020	8
				16/12/2020	21/01/2021	36
				08/02/2021	25/02/2021	17
				09/03/2021	22/03/2021	13
Ethereum				02/01/2021	11/01/2021	9
				12/01/2021	20/01/2021	8
Litecoin	03/05/2017	13/06/2018	406	29/06/2015	11/07/2015	12
	14/06/2018	22/06/2018	8	11/06/2016	21/06/2016	10
				23/04/2017	28/07/2017	96
				05/08/2017	13/08/2017	8
				23/08/2017	14/09/2017	22
				08/12/2017	16/01/2018	39
				03/01/2021	11/01/2021	8
Binance Coin				04/03/2019	18/03/2019	14
				23/09/2019	06/10/2019	13
				04/02/2021	25/02/2021	21
				07/04/2021	12/05/2021	35
Cardano				05/02/2021	23/03/2021	46
				25/03/2021	02/04/2021	8
Dogecoin	12/04/2021	20/06/2021	69	27/01/2021	16/02/2021	20
	22/06/2021	11/07/2021	19	13/04/2021	18/05/2021	35
	06/08/2021	06/09/2021	31			

TABLE 7: Date stamping periods of price explosivity behaviour for all the individual cryptocurrencies.

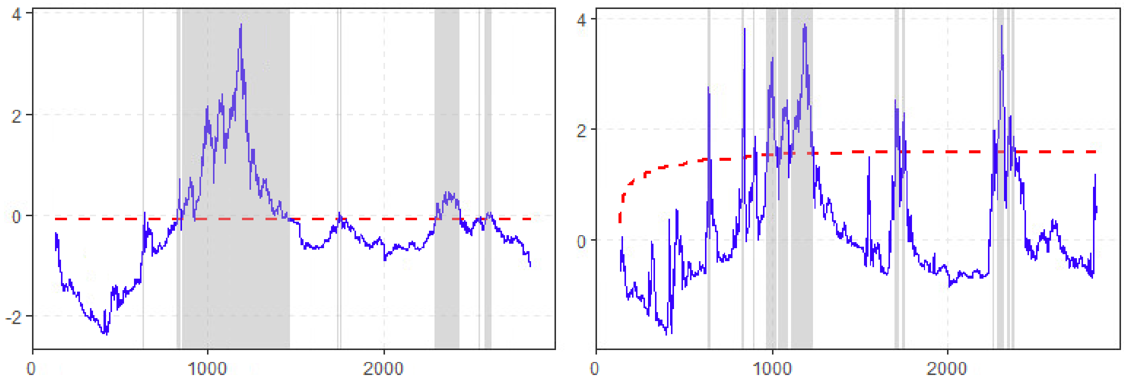

FIGURE 2: Date stamping with the **SADF test** (LEFT) and **GSADF test** (RIGHT) for **Bitcoin** log prices in US dollars from 17-09-2014 to 26-06-2022.

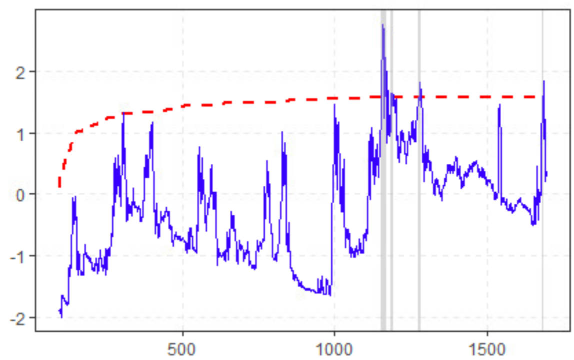

FIGURE 3: Date stamping with the **GSADF test** for **Ethereum** log prices in US dollars from 09-11-2017 to 26-06-2022.

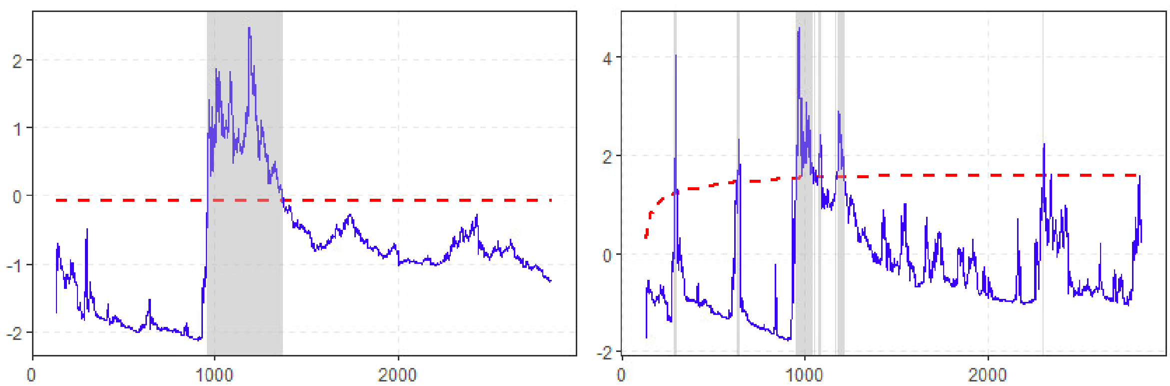

FIGURE 4: Date stamping with the **SADF test** (left) AND **GSADF test** (right) for **Litecoin** log prices in US dollars from 17-09-2014 to 26-06-2022.

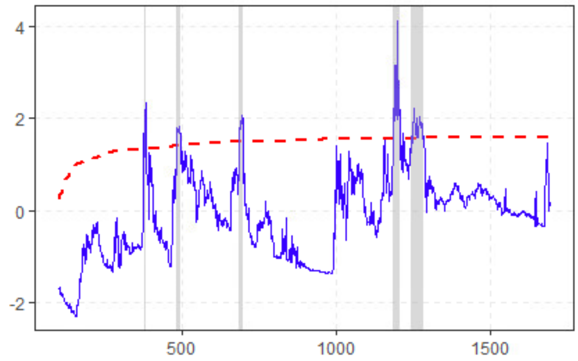

FIGURE 7: Date stamping with the **GSADF test** for **Binance coin** log prices in US dollars from 09-11-2017 to 26-06-2022.

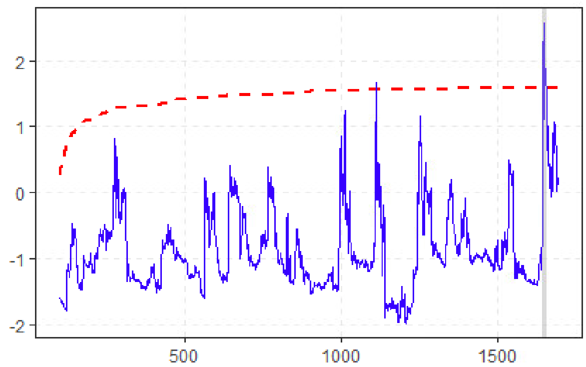

FIGURE 6: Date stamping with the **GSADF test** for **Ripple** log prices in US dollars from 09-11-2017 to 26-06-2022.

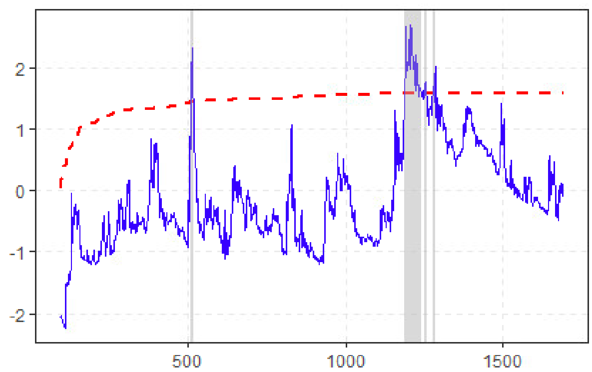

FIGURE 5: Date stamping with the **GSADF test** for **Cardano** log prices in US dollars from 09-11-2017 to 26-06-2022.

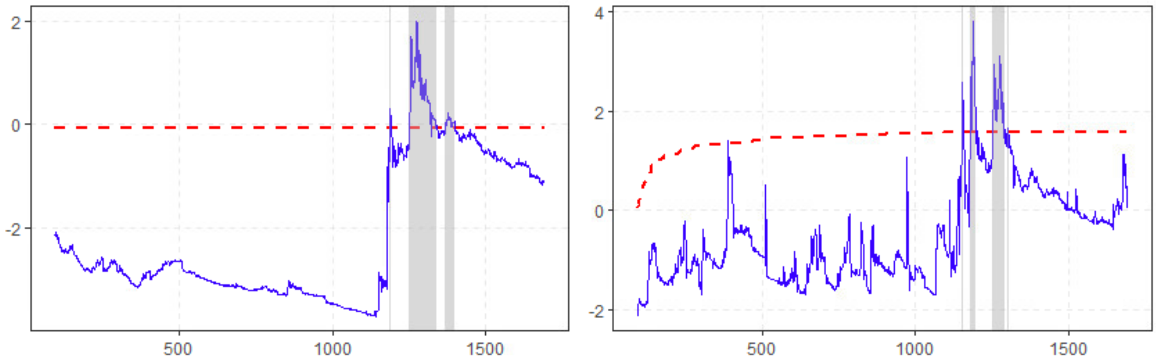

FIGURE 8: Date stamping with the **SADF test** (left) AND **GSADF test** (right) for **Dogecoin** log prices in US dollars from 09-11-2017 to 26-06-2022.

Figures 2 to 8 above show the periods during which the individual cryptocurrencies experienced price explosiveness episodes. According to the date stamping procedure proposed by Phillips et al. (2015), these episodes are detected on the graphs above as the periods in which the blue line[39] exceeds the red line[40]. When the bubble bursts, both statistics fall below the critical bound. Note that the *x*-axis corresponds to the observation number. These bubble periods are identified by the shaded areas for all individual cryptocurrencies. In the next section I will analyse the results from the panel version of the GSADF test.

[39] The blue line corresponding to the BADF and BSADF test statistics of the SADF and GSADF tests respectively.

[40] The red line corresponding to their sequence of critical value.

5.2 Detection of synchronized periods of price explosiveness across cryptocurrencies

5.2.1 The Panel GSADF test

Due to data availability, I conducted the Panel GSADF analysis for two different panels. The first one consists of Bitcoin and Litecoin, for which longer price time series are available, and covers the period 17 September 2014 to 26 June 2022 (table 8). The second panel comprises all seven selected cryptocurrencies, but spans a shorter time period, from 9 November 2017 until 26 June 2022 (table 10).

Panel GSADF Statistics	
	GSADF
Test Statistic	3.08***
90% Critical Value	1.34
95% Critical Value	1.45
99% Critical Value	1.74

TABLE 8: Panel GSADF Test for **Bitcoin** and **Litecoin** from 17-09-2014 to 26-06-2022 [41].

Based on the results shown in table 8, the Null hypothesis of unit root in the prices of the two panel members, Bitcoin and Litecoin, can be rejected at the 1% (and higher) level(s) of significance, which suggests that at least one of the prices exhibits explosive behaviour. Taken in conjunction with the results of the GSADF test for the individual Bitcoin and Litecoin price series, the results of the Panel GSADF test suggest that there have been some periods of common exuberance. To date-stamp these periods, I applied the panel BSADF procedure

[41] Note: ***, **, and * indicate the rejection of the Null at 1%, 5% and 10% significant levels, respectively.

developed by Pavlidis et al. (2016), which is particularly appealing because it measures the degree of overall exuberance in cryptocurrency markets. For the common explosiveness periods, I considered a minimum duration of 8 days. Table 9 displays the common periods of price explosiveness in Bitcoin and Litecoin.

	Panel GSADF Test		
	Start	**End**	**Duration (Days)**
Panel	28/05/2016	22/06/2016	25
(Bitcoin and Litecoin)	22/04/2017	29/03/2018	341
	14/04/2018	11/05/2018	27
	06/12/2018	17/12/2018	11
	10/05/2019	04/06/2019	25
	10/06/2019	01/07/2019	21
	03/07/2019	11/07/2019	8
	17/11/2020	26/11/2020	9
	29/11/2020	10/12/2020	11
	13/12/2020	27/01/2021	45
	01/02/2021	25/03/2021	52
	26/03/2021	24/04/2021	29
	26/04/2021	12/05/2021	16
	12/06/2022	21/06/2022	9

TABLE 9: Date stamping periods of price explosivity behaviour for the panel version of the GSADF test, including Bitcoin and Litecoin, from 17-09-2014 to 26-06-2022.

The first instance of common explosive behaviour in Bitcoin and Litecoin occurred during 2016. Bitcoin was affected by various exogenous shocks during that period, such as the hackers' episode that stole 120 000 Bitcoin from BitFinex[42] (Reuters, 2016), leading to a rise in security concerns in the cryptocurrency markets. A total of four common explosive periods were identified during 2016-

[42] BitFinex is one of the world largest dollar exchanges for Bitcoin.

2018. Furthermore, a large common explosivity period was detected for the two cryptocurrencies from 22 April 2017 to 29 March 2018 (around 341 days). This can be attributed to some of the exogenous and endogenous shocks that cryptocurrency faced at that time. For example, the Chinese government cracked down on cryptocurrency activities both in January and November 2017. At same time, in August 2017 a new Bitcoin was created (Bitcoin cash). In December of the same year (2017), the Chicago Board Options Exchange listed Bitcoin futures. Still, Bitcoin prices started to decrease after those episodes[43].

Bitcoin prices dropped drastically in February 2018. After that, another small overall explosive period was captured by the panel GSADF test from April to May 2018 (around 27 days), with another small period of explosiveness, lasting only 11 days detected during December 2018. This was followed by another period of 21 days in 2019. Others significant episodes of explosiveness with duration of 45 days, 52 days and 29 days respectively were captured at the end of 2020/beginning of 2021, possible related to the onset of the Covid-19 pandemic. During this period, to stimulate the economy several governments, such as that of the United States, adopted loose monetary policies thus, encouraging investors to move to more risky assets, such as cryptocurrencies. Additionally, mainstream companies such as PayPal, Tesla, JPMorgan, and many others, started to buy cryptocurrencies, especially Bitcoin, in large numbers. Another potential cause of explosive features in cryptocurrency prices during this period is associated with the sharp rise in inflation[44]. Most of the common explosive periods coincide with the explosive periods captured by the individual GSADF tests for Bitcoin and Litecoin.

[43] According to Kumar and Anandarao (2021), this can be related to exogenous impacts, such as the rumours of South Korea banning cryptocurrency operations, the hacking of the Japanese OTC market Coincheck and the announcement of the cryptocurrency exchange Bitconnet's of winding up some of their operations.

[44] Investors were attracted by assets offering higher returns than the rate of inflation (Chen, 2007). Due to their high volatility, cryptocurrencies were considered a good investment.

Figure 9 provides a timeline of significant explosive periods for Bitcoin (BTC-USD) and Litecoin (LTC-USD) prices as detected by the Panel GSADF procedure, suggesting that the two prices exhibited explosive behaviour over several common periods.

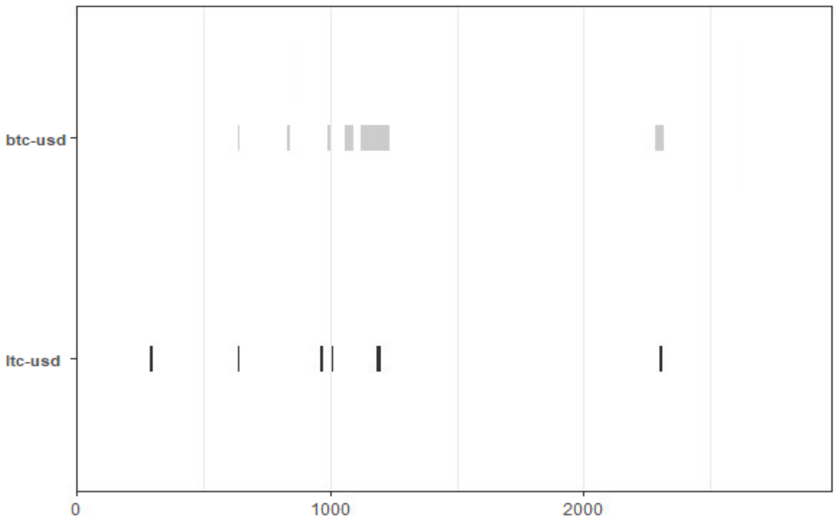

FIGURE 9: Explosive behaviour period comparison for **Bitcoin** (BTC-USD) and **Litecoin** (LTC-USD) from 17-09-2014 to 26-06-2022.

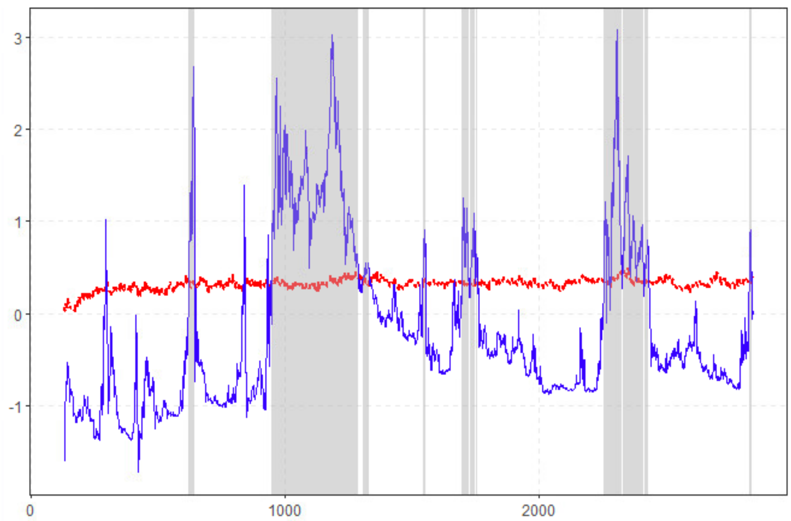

FIGURE 10: Common periods of explosive behaviour across the panel version, for **Bitcoin** (BTC-USD) and **Litecoin** (LTC-USD) from 17-09-2014 to 26-06-2022.

Table 10 provides the results of the Panel GSADF test for a panel made of all cryptocurrencies included in this study. According to these results, I can reject the Null hypothesis of unit root behaviour for the whole panel at the 1% significance level, which suggests that the prices of at least some (if not all) cryptocurrencies included in the panel displayed explosive behaviour.

Panel GSADF Statistics	
	GSADF
Test Statistic	1.96***
90% Critical Value	0.446
95% Critical Value	0.483
99% Critical Value	0.603

TABLE 10: Panel GSADF Test for all cryptocurrencies from 09-11-2017 to 26-06-2022 [45].

	Panel GSADF Test		
	Start	**End**	**Duration (Days)**
Panel	03/12/2018	17/12/2018	14
	02/04/2019	13/04/2019	11
	19/05/2019	04/06/2019	16
	19/06/2019	27/06/2019	8
	16/12/2020	23/12/2020	7
	24/12/2020	18/06/2021	176
	11/08/2021	07/09/2021	27
	08/11/2021	16/11/2021	8
	21/01/2022	01/02/2022	11
	11/06/2022	24/06/2022	13

TABLE 11: Date stamping of the Panel GSADF Test for all cryptocurrencies from 09-11-2017 to 26-06-2022.

[45] Note: ***, **, and * indicate the rejection of Null at 1%, 5% and 10% significant levels, respectively.

Table 11 provides the date stamping results for the panel version of the GSADF test for all cryptocurrencies. According to them, the most significant period of overall explosive behaviour occurred between 24 December 2020 and 18 June 2021, lasting 176 days. This period coincides with the episodes of exuberance captured by GSADF test in the individual cryptocurrencies. This period was characterized by a rapid rise in the prices of cryptocurrencies; for instance, Bitcoin's price increased by more than 55 000 US dollars in February 2021. Moreover, the panel GSADF test results provide evidence that the bubble periods in 2017/2018 and 2020/2021 were indeed the manifestation of global exuberance in the markets of the selected cryptocurrencies. As mentioned above, the panel results indicate that the Null hypothesis of a unit root can be rejected at all conventional levels, providing evidence in favor of global exuberance.

Figure 11 provides a comparison of significant explosive periods for all cryptocurrencies. It indicates that most of the overall explosive periods occurred around the beginning of 2019, and during 2020-2021, as stated earlier. Lastly, Figure 12 provides the common periods of price explosivity (bubble periods) for the panel version of the GSADF test for all cryptocurrencies. The larger shaded area corresponds to the most evident bubble period between 24 December 2020 and 18 June 2021. Once again this demonstrates the synchronization of explosiveness periods in the cryptocurrency markets during periods of turbulence.

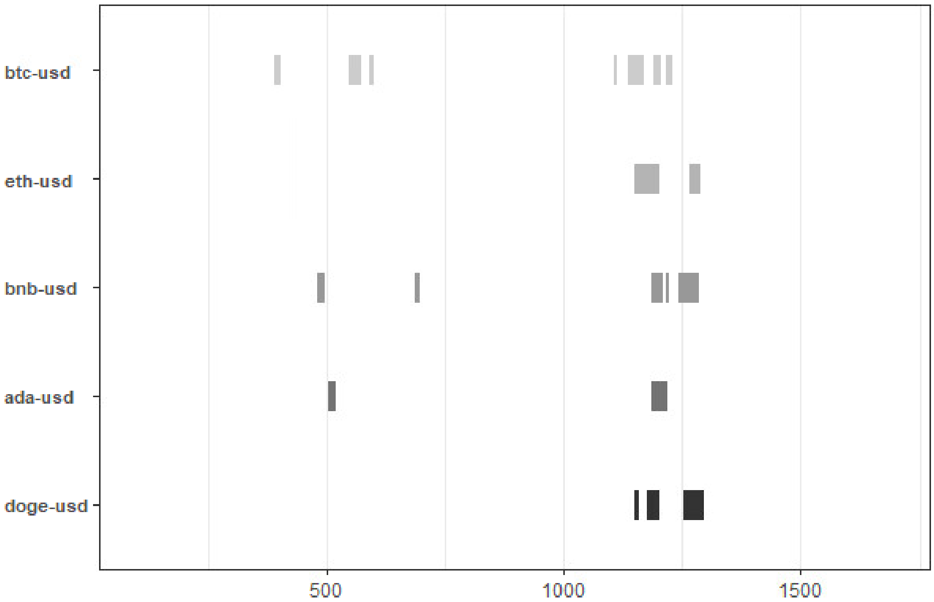

FIGURE 11: Explosive behaviour period comparison for Bitcoin (BTC-USD), Litecoin (LTC-USD), Ethereum (ETH-USD), Binance (BNB-USD), Cardano (ADA-USD), Dogecoin (DOGE-USD) from 09-11-2017 to 26-06-2022.

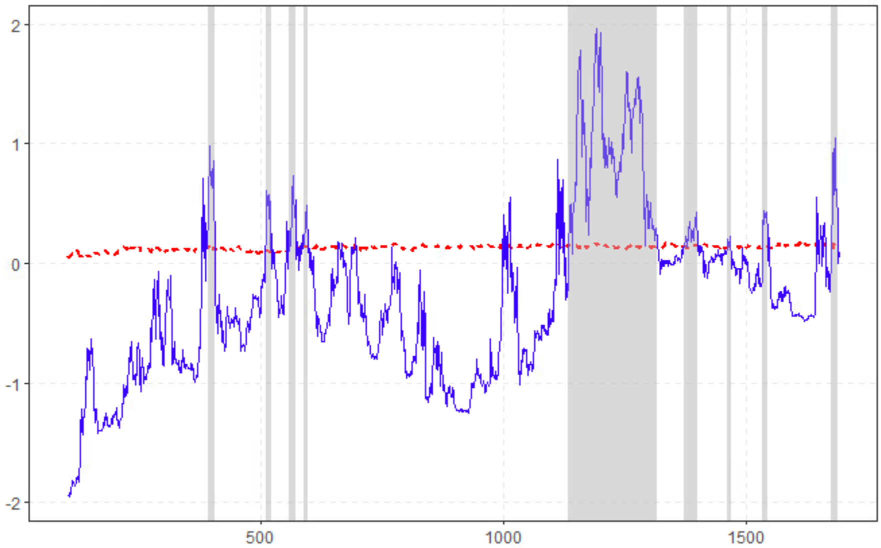

FIGURE 12: Common periods of explosive behaviour across the panel of all cryptocurrencies from 09-11-2017 to 26-06-2022.

5.2.2 LOGIT REGRESSION

Before conducting the Logistic regression, I investigated the correlation coefficients for pairs of prices of the seven cryptocurrencies (in logarithmic form). The results are described in table 12.

Correlation Matrix							
	Bitcoin	Ethereum	Litecoin	Binance Coin	Ripple	Cardano	Dogecoin
Bitcoin	1.00						
Ethereum	0.93***	1.00					
Litecoin	0.72***	0.79***	1.00				
Binance Coin	0.91***	0.86***	0.58***	1.00			
Ripple	0.60***	0.77***	0.82***	0.57***	1.00		
Cardano	0.89***	0.97***	0.81***	0.85***	0.82***	1.00	
Dogecoin	0.90***	0.93***	0.67***	0.93***	0.72***	0.93***	1.00

TABLE 12: Correlation Matrix [46].

According to table 12, there are evidence of strong correlations between all the seven cryptocurrencies at the 1% significance level. This means all the correlation coefficients are statistically significant, showing that cryptocurrencies prices can move together.

I used the information provided by the Panel version of the GSADF test to estimate a Logit model with the main objective of corroborating my previous conclusion of the presence of synchronization price explosiveness periods across the seven cryptocurrencies, from 9 November 2017 until 26 of June 2022. The Logit regression results are described in the table below.

[46] Note: ***, **, and * indicate statistical significance of correlation at 1%, 5% and 10%, respectively.

Dependent variable: $y_{i,t}$	
Constant	-19.377
	(2.8951)
	[$2.18e^{-11}$] ***
Bitcoin	3.9781
	(0.6190)
	[$1.30e^{-10}$] ***
Ethereum	-3.8380
	(0.4434)
	[$< 2e^{-16}$] ***
Litecoin	2.4041
	(0.4242)
	[$1.45e^{-8}$] ***
Binance Coin	-0.4423
	(0.2024)
	[0.0289] **
Ripple	-1.3962
	(0.4418)
	[0.0016] ***
Cardano	-0.2191
	(0.2642)
	[0.4069]
Dogecoin	1.5651
	(0.2140)
	[$2.58e^{-13}$]***
Observations	1691

TABLE 13: Logit Regression Results – Panel Regression [47].

[47] Note: The dependent variable $y_{i,t}$ only takes the value 1 (explosive dates) and 0 (non-explosive dates). The independent variables include all the (log) prices of all cryptocurrencies from 09-11-2017 to 26-06-2022. Standard errors in parentheses. P-values in square brackets. ***, **, and * indicate the rejection of Null at 1%, 5% and 10% significant levels, respectively.

Positive coefficients indicate a higher predicted probability[48]. Contrary, a negative coefficient indicates a lower probability of explosive price behaviour. Additionally, a higher absolute value of the coefficient indicates a possible higher significance.

Looking at the results described in table 13, Bitcoin, Litecoin and Dogecoin presented a positive coefficient. This means that the higher the logarithm of the prices of these cryptocurrencies the higher will the probability of existence of a bubble in the cryptocurrency markets. Besides Cardano, all other cryptocurrencies have a statistically significant coefficient. Bitcoin, Ethereum, Litecoin, Ripple and Dogecoin present statistically significant coefficients at the 1% significance level, and Binance coin at the 5% significance level. Overall, the presence of statistically significant coefficients in this Logit regression corroborates my previous observation that one explosiveness in one cryptocurrency can lead to global explosiveness episodes across all cryptocurrencies. Bitcoin is the one with higher impact on other cryptocurrencies. However, the explosivity in smaller cryptocurrencies, such as Dogecoin, seems to be important to the price behaviour of others, due to the statistically significant coefficients. Similar conclusions have been reported by several authors, such as Bouri et al. (2019) and Ferreira and Pereira (2019).

[48] This means that an increase in the independent variable is therefore associated with higher probability of explosive price behaviour.

5.3 GRANGER CAUSALITY ANALYSIS

Granger casualty test cannot detect co-explosivity among cryptocurrencies, but only predictive ability, in other words, whether past movements in the price of one cryptocurrency can help predict (current) movements in the price of another currency. However, there is a caveat: the Granger causality test was not aimed at series that are (mildly) explosive. But currently we don't really have a Granger causality test for explosive series. The results[49] are illustrated in the table below.

Granger Causality Test Results

Null Hypothesis	F-test	Degrees of freedom	P-Value	Decision
Bitcoin does not Granger cause Ethereum	4.0856	9	$3.3040e^{-5}$ ***	**Reject**
Bitcoin does not Granger cause Litecoin	2.8357	9	0.0026***	**Reject**
Bitcoin does not Granger cause Binance Coin	3.4619	9	0.0003***	**Reject**
Bitcoin does not Granger cause Ripple	4.0246	9	$4.1170e^{-5}$ ***	**Reject**
Bitcoin does not Granger cause Cardano	2.5116	9	0.0074***	**Reject**
Bitcoin does not Granger cause Dogecoin	0.8031	9	0.6135	Do not reject
Ethereum does not Granger cause Bitcoin	2.2373	9	0.0176**	**Reject**
Ethereum does not Granger cause Litecoin	0.7591	9	0.6546	Do not reject
Ethereum does not Granger cause Binance Coin	1.5596	9	0.1221	Do not reject
Ethereum does not Granger cause Ripple	2.3352	9	0.0130**	**Reject**
Ethereum does not Granger cause Cardano	1.3934	9	0.1856	Do not reject
Ethereum does not Granger cause Dogecoin	1.7002	9	0.0839	Do not reject
Litecoin does not Granger cause Bitcoin	3.2047	9	0.0007***	**Reject**
Litecoin does not Granger cause Ethereum	2.0906	9	0.0274**	**Reject**
Litecoin does not Granger cause Binance Coin	1.4120	9	0.1773	Do not reject
Litecoin does not Granger cause Ripple	2.0085	9	0.0350**	**Reject**
Litecoin does not Granger cause Cardano	1.4141	9	0.1764	Do not reject

[49] To perform the Granger causality analysis, I used the function provided by the RStudio package ("grangertest").

Granger Causality Test Results				
Litecoin does not Granger cause Dogecoin	1.1779	9	0.3049	Do not reject
Binance Coin does not Granger cause Bitcoin	3.0276	9	0.0014***	Reject
Binance Coin does not Granger cause Ethereum	3.4914	9	0.0003***	Reject
Binance Coin does not Granger cause Litecoin	5.3917	9	$2.6300e^{-7}$***	Reject
Binance Coin does not Granger cause Ripple	5.3868	9	$2.6790e^{-7}$***	Reject
Binance Coin does not Granger cause Cardano	4.0918	9	$3.2300e^{-5}$***	Reject
Binance Coin does not Granger cause Dogecoin	2.7867	9	0.0030***	Reject
Ripple does not Granger cause Bitcoin	1.9080	9	0.0468**	Reject
Ripple does not Granger cause Ethereum	3.2974	9	0.0005***	Reject
Ripple does not Granger cause Litecoin	5.3663	9	$2.8950e^{-7}$***	Reject
Ripple does not Granger cause Binance Coin	1.8108	9	0.0618*	Reject
Ripple does not Granger cause Cardano	4.3450	9	$1.2870e^{-5}$***	Reject
Ripple does not Granger cause Dogecoin	3.3733	9	0.0004***	Reject
Cardano does not Granger cause Bitcoin	1.6290	9	0.1017	Do not reject
Cardano does not Granger cause Ethereum	2.7317	9	0.0036***	Reject
Cardano does not Granger cause Litecoin	2.4586	9	0.0088***	Reject
Cardano does not Granger cause Binance Coin	2.3776	9	0.0114**	Reject
Cardano does not Granger cause Ripple	2.6426	9	0.0048***	Reject
Cardano does not Granger cause Dogecoin	1.3628	9	0.1998	Do not reject
Dogecoin does not Granger cause Bitcoin	4.9885	9	$1.1940e^{-6}$***	Reject
Dogecoin does not Granger cause Ethereum	6.1206	9	$1.6510e^{-8}$***	Reject
Dogecoin does not Granger cause Litecoin	3.6293	9	0.0002***	Reject
Dogecoin does not Granger cause Binance Coin	1.4234	9	0.1724	Do not reject
Dogecoin does not Granger cause Ripple	6.4756	9	$4.2310e^{-9}$***	Reject
Dogecoin does not Granger cause Cardano	4.7737	9	$2.6550e^{-6}$***	Reject

TABLE 14: Granger causality test results [50].

[50] Note: The Null hypothesis states that that one variable does not Granger causes the other. The Alternative hypothesis states that one variable does Granger causes the other. ***, **, and * indicate the rejection of Null at 1%, 5% and 10% significant levels, respectively.

As shown in table 14, Bitcoin does Granger cause all other cryptocurrencies besides Dogecoin, at the 1% significance level. Additionally, there is bidirectional causality running from Bitcoin to Ethereum, Bitcoin to Litecoin, Bitcoin to Binance Coin, and Bitcoin to Ripple. Moreover, there is a unidirectional causality between Dogecoin and Bitcoin, Dogecoin does Granger causes Bitcoin, at the 1% significance level. There is also one way-causality from Bitcoin to Cardano. Test results suggest that Ethereum does Granger causes Ripple, at the 5% significance level and Ripple does Granger causes Ethereum, at the 1% significance level. This means they have bidirectional causality. In addition, there is one-way causality between Litecoin and Ethereum, and bidirectional causality between Litecoin and Ripple. Binance Coin does Granger cause all other cryptocurrencies at the 1% significance level, and there is bidirectional causality between Ripple and Cardano. With special attention to Ripple, I can state that there is a Granger causality relationship between all other cryptocurrencies. Furthermore, a bidirectional causality between Cardano and Dogecoin, at the 1% significance level, is identified in the results. Cardano Granger causes all other cryptocurrencies, besides Bitcoin and Dogecoin; unidirectional causality with Ethereum and Litecoin, and bidirectional causality between Binance Coin and Ripple. Lastly, Dogecoin Granger causes Bitcoin, Ethereum, Litecoin, Ripple and Cardano. Besides that, there is a unidirectional causality with Ethereum, Litecoin and Cardano. Overall, there is an interaction between all cryptocurrencies in short-run dynamics.

CHAPTER 6 - CONCLUSION

The cryptocurrency markets have grown significantly in recent years. This sharp growth has been characterized by crashes and bubbles, along with high volatility in the cryptocurrency price dynamics. In this dissertation, I documented the occurrence of periods of explosiveness (exuberance) in the prices of seven cryptocurrencies with high market capitalisation, by using the recursive and rolling window testing methodology proposed by Phillips et al. (SADF, 2011) and Phillips et al. (GSADF, 2015). Furthermore, I employed a Panel GSADF test proposed by Pavlidis et al. (2016) to establish an overall picture of the explosives price behaviour in the cryptocurrency markets and identify possible synchronization explosive periods among the studied cryptocurrencies.

In chapter 5, I applied the BSADF date stamping procedure which complements the GSADF test, and identified significant explosive periods, especially during the end of 2016, 2017-2019, and 2020-2021. Both short- and long-lived bubbles have been revealed in the selected cryptocurrencies under scrutiny. Bitcoin, in particular, is more subject to long-lived bubbles. I identified both exogenous and endogenous impacts that could have been the cause or the trigger of most of the origination and bursting of these bubbles. Additionally, the Panel GSADF analysis identified several common periods of explosive price behaviour, suggesting, in conjunction with the results of the GSADF tests for individual cryptocurrencies, that the prices of (most likely) all cryptocurrencies included in the panel displayed explosive behaviour.

During 2017-2018 the cryptocurrency markets were characterized by a boom and subsequently a crash at beginning of 2018. Finally, the cryptocurrency bubbles reported between the end of 2020 and beginning of 2021 were caused by a combination of economic factors and investment sentiment. During the Covid-

19 pandemic, several governments adopted a loose monetary policy, and investors started to look for alternatives to the traditional assets. Also, the recent sharp decreases in the prices of cryptocurrencies ("The Crypto crash", Bloomberg.com 2022), suggest that we are not at the peak of cryptocurrency bubble, on the contrary, the "winter" of cryptos seems to be coming, the bubble has burst. This leads me to conclude, that during periods of financial turbulence, there is a synchronise behaviour in the cryptocurrency markets.

Moreover, in the last subsection of chapter 5, I used a Logit regression analysis and a Granger causality test; I can state that there exist synchronized periods of price explosiveness both in short and long-run between the studied cryptocurrencies. The analysis from the Logit regression shows that the likelihood of explosive periods in one cryptocurrency generally depends on the presence of explosive price behaviour in other cryptocurrencies. Furthermore, this study examined Granger causality and identified some short-term relationships between cryptocurrencies. However, Granger causality test was not aimed at series that are (mildly) explosive.

There is no shortage of events that created the conditions for the bubble to burst in the cryptocurrency markets. One of the main causes that contributed to one of the many bursting's of the cryptocurrency bubbles was the lack of regulation or the implementation of new regulation (such as regulatory actions in China, South Korea, and Japan). On the other hand, the Mt Gox Exchange collapse, the several hackers' episodes, and the noise trader's sentiment, can be identified as other causes of cryptocurrency's bubbles burst. Overall, these results provide important information for current or potential cryptocurrency investors when analysing financial risks.

In addition, one of the limitations of this dissertation is related to the unclear or, as some authors (Cheah and Fry, 2015, among others) argued, zero fundamental value of a cryptocurrency. Due to this, and following the established definition of bubbles as systematic departures of asset prices from their fundamental value, since I could not test both the cryptocurrency price and fundamental separately, or a price to fundamental ratio, the Phillips et al. (2015) methodology, strictly speaking, detect and date-stamp episodes of explosiveness in cryptocurrency prices. Whether I can label them as bubbles, as some extant papers do, is a matter open to debate. However, it can be argued that the high volatility and speculative nature of cryptocurrencies tilts the balance in favour of labelling the explosive episodes in their prices as (speculative) bubbles.

Another limitation, which opens an avenue for future research, is that the lead-lag relationship between cryptocurrencies could have been examined in more depth, based on the methodology used by Bouri et al. (2019), where individual Probit regressions are estimated for each cryptocurrency, with the dependent variable being a dummy whose values are based on the results of date-stamping of explosiveness episodes for an individual cryptocurrency rather than one based on the results provided by the Panel GSADF test. However, the Granger causality analysis conducted in this dissertation does shed some light on lead-lag relationships between the prices of the selected cryptocurrencies.

Potential ideas for future research on bubbles in the cryptocurrency markets include a more in-depth consideration of causal links between different cryptocurrencies by implementing the Time-Varying Granger Causality tests developed by Hurn, Phillips and Shi (2018, 2021), as alternative to the static Granger causality test used so far. Therefore, using the same methodology, one could see how the casual relationship between different cryptocurrencies changes over time. I intend to explore this in future research.

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APPENDIX A

TABLE 15: A synopsis of the literature on cryptocurrencies.

Paper Name	Authors	Year	Dep. Variable	Research question	Methodology	Frequency	Data	Main results and Conclusions
"Is Bitcoin business income or speculative bubble? Unconditional vs. conditional frequency domain analysis"	Bouoiyour, Jamal and Selmi, Refk and Tiwari, Aviral	2014	Price Index	Explored the Granger Causality relationship between: Bitcoin price and investors attractiveness; and Bitcoin price and transactions. Established two types of causality relationships between the variables.	Granger Causality. Breitung and Candelon's (2006) methodology.	Daily	https://blockchain.info/ http://www.quandl.com/	Bitcoin pries in fact Granger-causes exchange-trade ratio both in short and medium-run cyclical components. Presence of a speculative nature of Bitcoin. Both Chinese market index and hash rate leaded to ambiguous results.

"The digital traces of bubbles: feedback cycles between socio-economic signals in the Bitcoin economy"	David Garcia, Claudio J. Tessone, Pavlin Mavrodiev and Nicolas Perony	2014	Price, volume of word-of-mouth communication in online social media, user base growth and volume of information search.	Measured socio-economic signals using digital currencies, focusing on Bitcoin, with the objective to stablish some insights about the volume and volatility, and financial returns. Using Google search trends, Wikipedia search as well tweets search, and Facebook search.	Vector-autoregressive model (VAR).	Daily	http://blockexplorer.com http://www.google.com/trends/explore http://en.wikipedia.org/wiki/Bitcoin http://stats.grok.se. http://topsy.com http://www.face book.com/bitcoins http://bitcoincharts.com	Two main cycles: the "social" cycle and the "user adoption" cycle. Negative relation between search and price Defined two main bubbles on the Bitcoin market during the period of 18 October 2011, and 28 November 2012.
"Crypto-currency bubbles: an application of the Phillips-Shi-Yu (2013)	Adrian Cheung, Eduardo Roca and Jen-je Su	2015	Price	Detects the existence of bubbles (explosive behaviour) in the	Test of Phillips et al. (2013a).	Daily	https://bitcoincharts.com	Detected several short-lived bubbles (2010-2014). Detected three long-lived bubbles during the period of 2011-2014.

methodology on Mt. Gox bitcoin prices”				cryptocurrency market.				
“Speculative bubbles in the Bitcoin Market? An empirical investigation into the fundamental value of Bitcoin.”	Cheah, E. and Fry, J.	2015	Price	Show that Bitcoin displays speculative bubbles and proves that the fundamental price of the Bitcoin is zero.	Bubble model derived from the theory of complex systems in physics: MacDonell (2014) model; Johansen et al. (2000) model; Geraskin and Fantazzini (2013) and Philips et al. (2011) models.	Daily	https://www.coindesk.com	Bitcoin prices are subject to speculative bubbles. The bubble component in the Bitcoin prices is substantial. The fundamental price of the Bitcoin is zero.
“Are cryptocurrencies real financial bubbles? Evidence from quantitative analysis”	M., Ricci, C. and Scaringi, M.	2017	Price	Applied quantitative models for the study of the relation between two cryptocurrencies and financial risk of a speculative bubble.	Log Periodic Power Law (LPPL), and the Phillips et al. methodology, PSY statistical tests (BSADF and BSADF*). OLS, GLS, MLE estimations.	Daily	Bloomberg (XBTUSD Curncy) Etherscan	Concluded that both models coherently exhibited the presence of strong bubble periods on Bitcoin from May and September 2017.

"Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions"	Elie Bouri, Rangan Gupta, Aviral Kumar Tiwari, David Roubaud.	2017	Price	Analysed if Bitcoin can hedge uncertainty, by using the first principal component of the VIX Index of 14 developed or developing equity markets.	OLS regression; the wavelet approach methodology with QQ-regressions.	Daily	DataStream of Thomson Reuters. www.coindesk.com/price	Using OLS-regressions uncertainty negatively affects raw Bitcoin returns, during long investment horizons. Using a Quantile-regression indicates that Bitcoin act as hedge against uncertainty. Using a QQ-regression, hedging is observed both for upper and lower of Bitcoin returns and global uncertainty. Identified that Bitcoin can be used as a hedge against uncertainty during short-term horizons, helping the investors.
"The Market Efficiency of Bitcoin: A Weekly Anomaly Perspective"	Yutaka Kurihara, Akio Fukushima	2017	Price	Analysed if weekly price anomalies exist by examine the market efficiency of Bitcoin.	OLS Model estimation. RLS Model estimation. Ljung-Box test.	Daily	www.bitcoinaverage.com	Bitcoin market is not efficient. Therefore, subjected to market anomalies. Bitcoin market can be translated into a more efficient market
"A new look at Cryptocurrencies"	Andrew Phillip, Jennifer S.K. Chan, Shelton Peiris	2018	Price	Combined a model to measure the different natures of Cryptocurrencies, with the main	Stochastic volatility Model of Taylor (1986). Shephard Model (2005).	Daily	Brave New Coin (BNC) Digital Currency Indices.	Cryptocurrencies with lower market capitalizations exhibit higher variability. The 5 largest cryptocurrencies by market capitalization showed evidence of time dependent volatility and long memory.

				objective of evaluate their investability.	Generalized long memory (GLM). Stochastic volatility (SV). Leverage and heavy tails (LVG-HT).			Ripple showed intense volatility characteristics and the weakest leverage effect. Ripple is the only cryptocurrency with no counter party credit risk. Ethereum and Dash are user-friendly, and they have lower liquidity risk comparing with Bitcoin. Cryptocurrencies exhibit leverage, excess Kurtosis, long memory, heavy tails, and stochastic volatility.
"Cryptocurrencies, Mainstream Asset Classes and Risk Factors - A Study of Connectedness."	Milunovich, G.	2018	Price	Established relationships between five popular cryptocurrencies, six major asset classes, plus two risk factors	Granger causality test. Forecast error variance decomposition connectedness table proposed by Diebold and Ylmaz (2014).	Daily	CryptoCompare Datastream Federal Reserve Bank of St. Louis https://www2.bc.edu/matteo-iacoviello/gpr.htm	There are six Granger causal relationships from non-digital assets to cryptocurrencies, and two casual relationships from digital assets to non-digital assets. The error variance decomposition illustrated relative weakness of the uncovered connection between digital and non-digital assets. The risk of price distress in the cryptocurrency market is not very likely to be transmitted to non-digital assets.
"Cryptocurrencies as an Asset Class?"	Krueckeberg, S. and Scholz, P.	2018	Daily volume, weighted average, prices, and the total	Showed that cryptocurrencies presented different characteristics	Using a comparison analysis in terms of investability, correlation,		https://coinmarketcap.com Reuters Datastream	Sharp distinction between cryptocurrencies and traditional assets, demonstrating to be a supplement to the traditional portfolios.

			trading volume.	from the traditional asset class.	liquidity, stability, and portfolio optimization.		and Bloomberg Terminal.	Cryptocurrencies showed significantly higher liquidity. By adding cryptocurrencies to the traditional portfolios improved quarterly ex-post Sharpe ratios.
"Datestamping the Bitcoin and Ethereum bubbles"	Shaen Corbet, Brian Lucey, Larisa Yarovaya	2018	Price	Examined the presence of bubbles both in Bitcoin and Ethereum.	Methodology proposed Phillips et al. (2011).	Daily	-	There is no clear evidence of a persistence bubble both in Bitcoin and Ethereum market. There are distinct short-term periods in which the fundamental effects the price dynamic of the cryptocurrencies.
"Does Bitcoin bubble burst?"	Zheng-Zheng Li, Ran Tao, Chi-Wei Su, Oana-Ramona Lobonț	2018	Price	Estimate the existence of multiple Bitcoin bubbles, both in Chinese and U.S. bitcoin markets, and comparing both.	Generalised Supremum Augmented Dickey-Fuller Test of Phillips et al. (2015).	Weekly	https://www. wind.com	There are six and five Bitcoin bubbles during the sample period in China and U.S. markets respectively. Presence of multiple bubbles in the Bitcoin market.
"Herding behaviour in cryptocurrencies"	Elie Bouri, Rangan Gupta and David Roubaud	2018	Price	Examine the presence of herding behaviour in the cryptocurrency market.	Cross-sectional absolute standard deviation (CSAD) Model of Chang et al. (2000). Probit Model.	Daily	https://coinma rketcap. com	Cryptocurrency market present herding behaviour. Cryptocurrency investors mimics the investment decisions of others, reducing market efficiency.

"What causes the attention of Bitcoin?"	Andrew Urquhart	2018	Price	Studied the attention given to Bitcoin using Google trends data.	Granger causality. VAR Model. RV Model. Bai and Perron Test (2003).	Weekly Daily	www.google.com/trends/correlated/ www.bitcoincharts.com	Studied the attention given to Bitcoin using Google trends data. Examined the relationship between Bitcoin fundamentals and investors' attention. Past volatility significantly influences investors search queries. Past volume provides information about future search queries. When Bitcoin returns are high the number of search queries increased. Investors' attention does not provide any predictive power in forecasting volume, realized volatility, or returns.
"Bitcoin as a new asset class"	Ram, A.	2019	Price	Analysed the Bitcoin as a new asset class, discussing and comparing investability, politico-economic, correlation of returns and risk-reward profiles.	Sharpe Ratio analyses. Comparison analyses.	Daily	https://coinmarketcap.com www.bitcoincharts.com	Bitcoin represents and alternative and unique asset class and investment opportunity. Presenting a pollical-economic decentralized profile, sharing none or low correlation with other asset classes. Bitcoin provided risk-adjusted returns above and over most asset classes.

"Bitcoin: The Longest Running Mania -Tulips of the 21st Century?"	John Taskinsoy	2019	Price	Compare the Bitcoin manias with the Tulip mania investigating the nature of the markets.	-	Monthly	https://www.buybitcoinworldwide.com/price/	Bitcoin mania nor tulip mania was a real mania, but the similarity between the two are very prominent. Bitcoin and Tulip manias had indirect impact on spending and investing habits.
"Co-explosivity in the cryptocurrency market"	Elie Bouri, Syed Jawad Hussain Shahzad, David Roubaud	2019	Price	Investigated if the explosivity in one cryptocurrency can lead to explosivity in others.	Generalised Supremum Augmented Dickey-Fuller Test of Phillips et al. (2015). Backward Supremum Augmented Dickey-Fuller (BSADF) test.	Daily	https://coinmarketcap. com	Bitcoin is the cryptocurrency that present the longest-lived explosivity. Generally, the probability of explosive periods in one cryptocurrency depends on the existence of explosivity in other cryptocurrencies. Explosivity does not necessary depends on the size of the cryptocurrency.
"Contagion Effect in Cryptocurrency Market"	Paulo Ferreira and Éder Pereira	2019	Price	Evaluate the contagion effects between Bitcoin and other cryptocurrencies in the market.	Detrended Cross-Correlation Analysis correlation coefficient; Combining the DCCA with Detrended Fluctuation	Daily	https://coinmarketcap.com	Contagion effect between the Bitcoin returns and the returns of most of the other's cryptocurrencies. Increasing integration between the main cryptocurrencies after the 2017 bubble.

					Analysis (DFA), Zebende (2011).			
"Cryptocurrencies as financial bubbles: The case of Bitcoin"	Julian Geuder, Harald Kinateder, Niklas F. Wagner	2019	Price	Studies bubble behaviour in Bitcoin prices during 2016 to 2018.	Phillips et al. PSY test methodology (GSADF test). Filimonov and Sornette (2013) Log-periodic Power Law (LPPL) approach.	Daily	https://coinmarketcap. com	Both models identified the existence of bubbles in the Bitcoin prices during this period.
"Sentiment-Induced Bubbles in the Cryptocurrency Market"	Cathy Yi-Hsuan Chen, and Christian M. Hafner	2019	CRIX index	Predicted bubbles in the cryptocurrency market using "StockTwits" sentiment.	"StockTwits" sentiment, and a smooth transaction autoregressive model (STAR).	Daily Monthly Quarterly	thecrix.de	Detected asymmetry in the impact of positive or negative innovations on volatility is modelled by changes on the sentiment index, and the volatility is higher during bubble periods. Volatility increased when the sentiment index decreased. The sentiment index identified some explosive bubble periods and measured the impact on volatility.
"Spillover Risks on Cryptocurrency Markets: A Look from VAR-SVAR Granger Causality and Student's-t Copulas"	Luu Duc Huynh, T.	2019	Price	Analysing the spillover risks among five major cryptocurrencies.	VAR-SVAR Granger causality. Student's-t Copula's methodologies.	Daily	-	Ethereum is the most independent coin in the market. Ripple is likely to bear spillover risks from Bitcoin, Stellar and Litecoin. Stellar Granger causes Litecoin.

								Bitcoin tended to be the spillover effect recipient. All cryptocurrencies have linear correlations.
"Financial Bubbles: A study of Co-Explosivity in the Cryptocurrency Market"	Arianna Agosto and Alessia Cafferata	2020	Price	Detects the existence of bubbles (explosive behaviour) in the cryptocurrency market. Addresses the relationship between the explosive behaviour (co-explosivity) of cryptocurrencies.	Supremum Augmented Dickey-Fuller Test of Phillips et al. (2015). Backward Supremum Augmented Dickey-Fuller (BSADF) test.	Daily	https://coinmarketcap. com	Observed multiple bubbles in all five cryptocurrencies. Overall, a bubble burst in one cryptocurrency increases the probability of a bubble burst in the other. Bitcoin is the one that experience the highest number of explosive behaviours. Price dynamics of the cryptocurrencies are very interdependent.
"Understanding risk of bubbles in cryptocurrencies"	F.A. Enoksena, Ch.J. Landsnesa, K. Lucˇivjanskáb,1 , P. Molnár	2020	Price and Trading Volume.	Detects the presence of bubbles and studies the variables that can predict bubbles in the cryptocurrency market.	Generalised Supremum Augmented Dickey-Fuller Test of Phillips et al. (2015), PSY test.	Daily	https://coinmarketcap.com https://coinmetrics.io/ https://www. policyuncertainty.com/	Observed several cryptocurrencies bubbles during the sample interval. Several variables can predict bubbles in the cryptocurrency market.

							https://fred.stlouisfed.org/	
"Bubbles and crashes in cryptocurrencies: Interdependence contagion, or asset rotation?"	M Chowdhury, D Damianov, A Elsayed	2021	Price	Measure the spillovers effects, and make a distinction between contagion, asset rotation and independence effects on cryptocurrencies.	Phillips et al. (2015) methodology to predict bubbles. Forecast-error variance decompositions of a VAR model. Quantile connectedness measure for the upper and lower quantile of returns.	Daily	https://coinmarketcap.com	Detected multiple periods of crashes and bubble. The financial crashed occurred in 2018 affected all cryptocurrencies besides Ripple. Evidence of interdependence and contagion during bubbles, especially during market downturns.
"Bitcoin and the South Sea Company: A comparative analysis."	Demmler, M. and Fernández Domínguez, A.O.	2021	Price	Compared the speculative bubble tendencies in the Bitcoin market to the South Sea Bubble (1720), with the aim of identifying possible similarities.	Tests methodologies based on Baur et al. (2018) and Phillips et al. (2015), SADF and GSADF tests.	Daily	European State Finance Database CoinDesk (2020a). https://coinmarketcap.com/	There was evidence that both Bitcoin and South Sea Company experienced multiple bubble periods. Confirmed important similarities between the two assets, such as descriptive statistics Bitcoin price movements, from 2017 until 2018, showed two phases of an asset price bubble and crash like the South Sea Company.

"Bitcoin: Bubble that burst or Gold that glitters?"	Rocco Caferra, Gabriele Tedeschi and Andrea Morone	2021	Daily closing values of nine currency exchange rates against US dollars. Daily closing value of seven index.	Analysed the 2017 Bitcoin bubble and understand the reasons behind this price hike. Studied the synchronization among these assets and Bitcoin. Studied the switching behaviour between the securities and the Bitcoin.	Dynamic time warping algorithm (DTW). Phillips et al. (SADF test). ARFIMA model.	Daily	Yahoo Finance. Investing.com	Identified a group of assets that had similar characteristics with cryptocurrency bubble. Verified that the Bitcoin bubble had strong similarity with 2000 NASDAQ Dotcom Index. The overall idea of poor relation between the cryptocurrencies and the real economy. Observed that the investor switching behaviour is more common in presence of positive news about cryptocurrencies.
"Crypto: a new asset class?"	Nathan, A., Galbraith, G.	2021	-	Report provided by Goldman Sachs with the objective of	Interview analyses.	-	-	Cryptocurrencies are now an official asset class (Michael Novogratz).

	and Grimberg, J.			asking to some financial experts whether cryptocurrencies should be considered as a new asset class.				Bitcoin can be seen to hedge against inflation, and to diversify investors' portfolios to achieve higher risk-adjusted returns (Michael Sonnenshein). Cryptos can act as stores of value, (Mikhail Sprogis and Jeff Curri). Cryptocurrencies cannot be considered as a store of value, a new asset class, or a currency (Nouriel Roubini).
"Explosivity in Cryptocurrency Market: A Panel GSADF Approach"	Kumar, A. S., K, H., & Anandarao, S.	2021	Price	Analysed individual and synchronize explosive behaviour in six major cryptocurrencies.	GSADF test (Phillips et al., 2015) and the recursive panel GSADF test (Pavlidis et al., 2016).	Daily	https://coinmarketcap. com	They captured evidence in favour of individual price explosivity, especially during 2015-2016. Bitcoin, Ethereum and Dash showed the highest number of explosivity periods. Ethereum and Dash presented one of the most prolonged explosive periods. Bitcoin and Ethereum are the only cryptocurrencies that presented explosive periods before 2017. Four common explosive period are identified during 2016-2018, presenting evidence of synchronization in the cryptocurrency market.

								They captured a large synchronization period, across most of the cryptocurrencies, during 2017-2018 and from November 19, 2018, to December 19, 2018.
"The 2021 Bitcoin Bubbles and Crashes – Detection and Classification"	Min Shu 1, Ruiqiang Song, and Wei Zhu	2021	Price	Tried to identify and monitoring the Bitcoin Bubbles and crashed, using different time scales.	Log-Periodic Power Law Singularity (LPPLS) methodology, and the Modified Lagrange regularization method.	Daily	https://www.coinbase.com	During this period one cluster of negative bubbles and two clusters of positive bubbles can be observed. Existence of an endogenous bubble between November 2020 to mid-January 2021, while from mid-January 2021 to mid-April 2021 the bubble seems to be an exogenous bubble.
"Boom, Busy, and Bitcoin: Bitcoin-Bubbles as Innovation Accelerators"	Tobias A., Huber and Didier Sornette	2022	-	Addresses the role of speculative bubbles in the Bitcoins market, by analysing social-economic dynamics.	"Social Bubble Hypothesis".	-	-	Bitcoin present technological adoption cycles. The hype cycles pattern of Bitcoin seems to be consequence of herding and imitation behaviour by the investors, which can give rise to speculative bubbles.

APPENDIX B

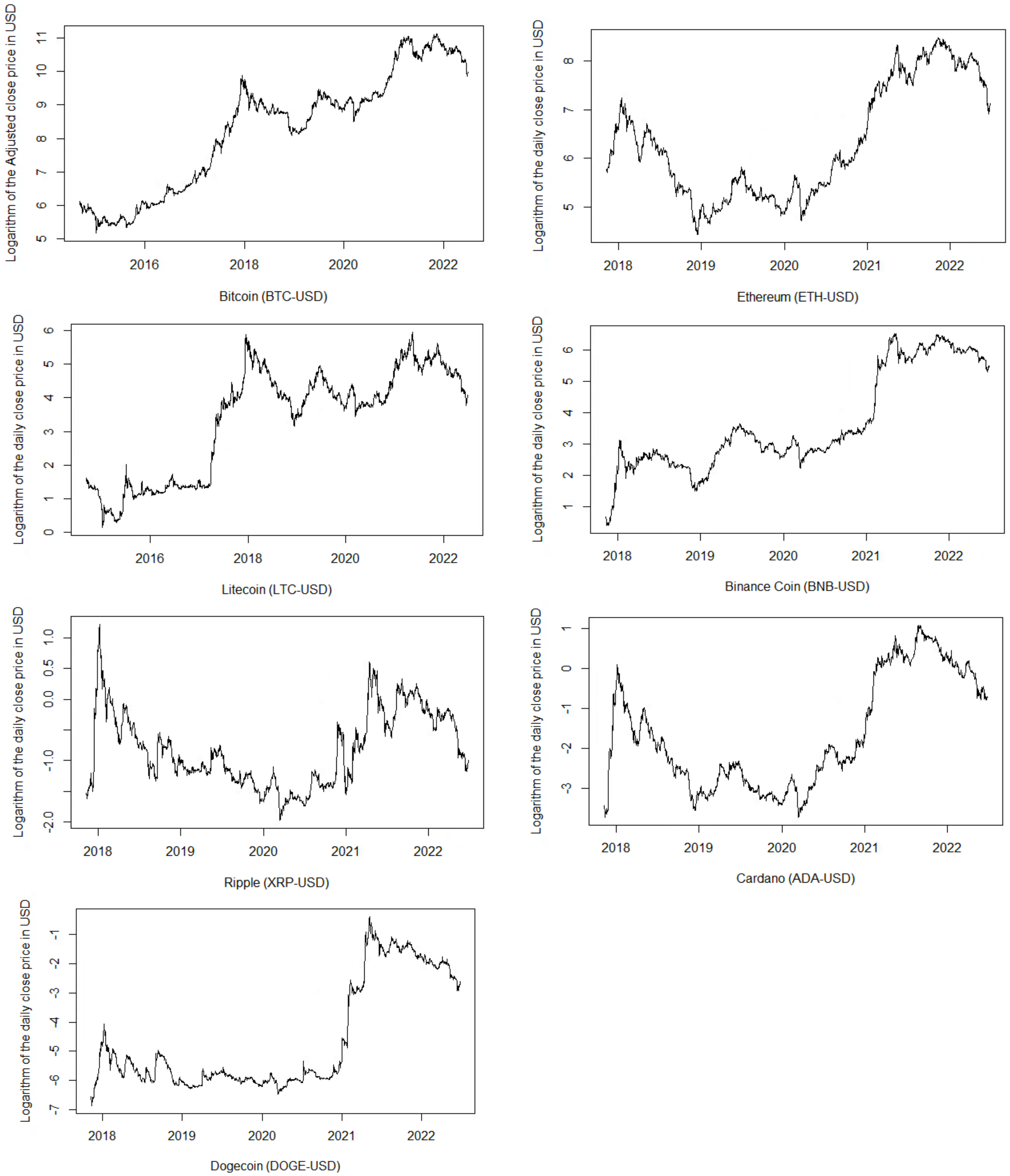

FIGURE 13: Cryptocurrencies logarithms daily adjusted close price over the sample period.