INVESTIGATION OF THE DETERMINANTS OF THE MARKET VALUE OF A PORTFOLIO CONSISTING OF CRYPTOCURRENCIES

by

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To my loving parents and Sevi

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Preface

This post-doctoral dissertation investigates matters connected with digital forms of liquidity and investment (cryptocurrencies) and focuses on which influential factors can prove to be of major importance for determining the optimal synthesis of a portfolio consisting of such innovative investment assets.

Chapter 1 of this thesis, based on empirical findings from pertinent academic literature, offers a thorough survey of the return and volatility spillovers of cryptocurrencies. According to evidence, Bitcoin is the most influential digital coin, both as a transmitter of spillovers to other digital coins and as a recipient of those from virtual currencies and other alternative assets. The most significant connections between Ethereum, Litecoin, and Ripple are with Bitcoin. Although volatility spillovers frequently have a bi-directional character, return spillovers are more evident. Bitcoin and national currencies are both experiencing volatility shock transmission, but economic policy uncertainty is not a factor. This chapter offers helpful advice on the contentious subject of reforming and decentralizing financial institutions.

Chapter 2 conducts a systematic survey on whether the pricing behavior of cryptocurrencies is predictable thus the Efficient Market Hypothesis (Fama, 1970) is rejected and speculation is feasible via trading. We center interest on the R/S and DFA as well as other relevant methodologies of testing long memory in returns and volatility. It is found that the majority of academic papers provides evidence for inefficiency of Bitcoin and other digital currencies of primary importance. Nevertheless, large steps towards efficiency in cryptocurrencies have been traced during the last years. This can lead to less profitable trading strategies for speculators.

Chapter 3 constitutes a review of the academic literature on the development of price bubbles in markets for digital currencies. Studies show that the price of bitcoin has gone through multiple bubble stages, primarily between 2013 and 2017. Other significant digital currencies, like Ethereum and Litecoin, also experience many bubble stages. The most often used methods for bubble detection and measurement are Augmented Dickey Fuller (ADF) and Log-Periodic Power Law (LPPL). According to extensive academic studying, Ethereum, NEM, Stellar, Ripple, Litecoin, and Dash have been identified as having bubble-like features since September 2015, while Bitcoin looks to have been in a bubble phase since June 2015. Since early 2018, this latter group has provided scant academic proof of bubbles. A comprehensive bibliography that focuses on significant market quote deviations from fundamental values is used to present a broad viewpoint that can serve as a reference for investors, researchers, and legislators.

Chapter 4 investigates the connections between the three digital currencies with the biggest market capitalization and cryptocurrencies related to the cannabis industry. Daily data from 26 October 2017 through 3 January 2020 are used. To examine volatility characteristics, generalized autoregressive schemes such as GARCH, EGARCH, TGARCH, and GJR-GARCH are used. The results show that in most circumstances, GARCH and GJR-GARCH specifications are the most suitable. Overall, the data shows that Ripple has the weakest connections to cannabis cryptocurrency, whereas Bitcoin exhibits medium to significant positive links. As a result, none of the prominent digital currencies under consideration can act as a reliable hedge against cannabis cryptocurrency.

In Chapter 5, examination is made on the existence of herding phenomena in the markets for digital currencies under volatile market conditions. Daily data are used in two different sub-periods, encompassing a wide range of cryptocurrencies. The novel approach of Phillips and Sul (2007, 2009) enables empirical estimations for detecting club convergence and clustering. Econometric results show that herding behavior is intense and that a very big convergence club forms, while also forming a smaller one during moments of prosperity. While segmentation occurs, the herding phenomenon persists and nine clubs are formed during bear markets. Principal cryptocurrencies continue to play a significant role, but not all of them belong to the same club. When clubs are paired together, secondary herding occurs. Investors give up the idea that "the major cryptocurrencies lead the market" out of fear of losses. Findings help investors diversify their portfolios more effectively and reduce the risk-return trade-off they experience during extreme events.

In Chapter 6, analysis takes place of the policy implications generated by each chapter. Overall, outcomes reveal that spillover impacts and the low levels of efficiency in cryptocurrency markets are important determinants of their risk-adjusted performance and also contribute to the appearance of bubble phenomena in market values. Furthermore, major cryptocurrencies are found to be useful for hedges against innovative cryptocurrencies. Moreover, it is documented that herding phenomena exist in markets of digital currencies during extreme conditions and that the formation of clubs is based on major cryptocurrencies. Larger segmentation occurs during bear markets and secondary herding among clubs is also detected.

Chapter 1

A Survey on Empirical Findings about Spillovers in Cryptocurrency Markets

1. Introduction

Since the bull market of 2017, a great number of cryptocurrencies have emerged, sparking a contentious discussion on whether Bitcoin can continue to hold the top spot in the markets for digital coins. Studying transactions involving virtual currencies significantly enhances monetary economics research and offers insightful input to investors, policymakers, researchers, and the financial press. More particularly, the analysis of connections and spillovers among these cutting-edge forms of liquidity encapsulates an important aspect of global finance and has important implications for trade.

Regarding cryptocurrencies, a number of significant academic research contributions have been made. Earlier papers have been focusing on characteristics (Selgin, 2015; Böhme et al., 2015; Ammous, 2018), volatility measurement (Katsiampa, 2017, 2018; Chaim and Laurini, 2018; Beneki et al., 2019; Kyriazis et al., 2019) and inefficiency in the markets of digital coins (Urquhart, 2016; Nadarajah and Zhu, 2017; Bariviera, 2017). Another line of research has focused on the features of hedging and speculating in markets for virtual currencies (Dyhrberg, 2016; Bouri et al., 2017; Fang et al., 2019). Current empirical research typically focuses on high-capitalization cryptocurrencies to determine whether coins like Ethereum, Ripple, Litecoin, or Stellar could significantly displace Bitcoin in terms of investor preferences. Additionally, two integrated surveys that offer broad perspectives on the characteristics of digital currencies have been done (Corbet et al., 2019; Kyriazis, 2019).

A discussion about the creation of stablecoins, or coins linked to well-known assets like the US dollar, and whether they could replace Bitcoin in cross-border transactions, has been sparked by the extraordinarily high levels of volatility inherent in cryptocurrencies. The Facebook-planned stablecoin "Libra" has drawn significant interest from financial institutions, academia, and governmental bodies as it is viewed as the main driver of a fully decentralized digital payment system. Despite assertions to the contrary, the news of the launch of Libra has sparked even more intense interest in cryptocurrencies.

Looking at the existing literature, it is clear that there haven't been many scholarly articles written about the spillover effects across digital currencies. Existing empirical research mostly examines the relationships between virtual currencies of key importance, but it also makes econometric projections regarding the effects on smaller-cap currencies. Spillovers among digital currencies are thought to be one of the most important axes for shedding light on cryptocurrency marketplaces and gaining insight into the usage of cutting-edge forms of money for consumption and investments, in sharp contrast to the majority of pertinent research.

This survey research focuses on the dominant issue of spillover affects in their returns and volatilities rather than mixing up with co-movements amongst virtual coins. We focus on all eleven of the empirical studies that essentially serve as the foundation for this systematic survey in order to further discuss the conclusions that this body of literature has brought to light. The purpose of this work is to investigate spillover interconnections and to provide a path for future pertinent research on digital currency.

The rest of this study is organized as follows. The literature on return and volatility spillovers among cryptocurrencies is presented in Section 2. In Section 3, the economic ramifications of spillovers between digital currencies and other assets are also explored. Section 4 finishes with summarizing the results. Figures 1 through 9 in the Appendix present a comprehensive overview of unique characteristics pertaining to the research under consideration.

2. Studies about spillovers among cryptocurrency markets

Academics, policymakers, investors, and the financial press have been interested in the spillover effects of digital currencies, which has led to a nascent but growing and fascinating array of studies in reputable journals. As a result, the research on cryptocurrency spillovers has gained momentum, and estimation approaches have become more sophisticated.

To be more specific, Katsiampa et al. (2018) use three pairwise bivariate models to examine the conditional volatility dynamics as well as the connectivity and conditional correlations between the prices of Bitcoin-Ethereum, Bitcoin-Litecoin, and Ethereum-Litecoin. Based on the Baba-Engle-Kraft-Kroner (BEKK) technique, these requirements. There is proof that each digital currency's historical shocks and volatility have a significant impact on its conditional covariance. Additionally, they offer proof that shock transmission is reciprocal for the pairs Bitcoin-Ethereum and Bitcoin-Litecoin. However, the results show that there is just one-way shock spillover from Ethereum to Litecoin. Bi-directional impacts are found between each of the three pairs under consideration when it comes to volatility spillovers. Overall, empirical findings are in favor of the bitcoin markets moving toward more integration.

Koutmos (2018) also looks into the relationships between 18 significant digital currencies. The methodology used is based on variance decomposition, Vector Autoregressive (VAR) methods, and the creation of a spillover index. Additionally, robustness tests are performed using Generalized Autoregressive Conditional Heteroskedasticity (GARCH) techniques. Bitcoin is the most significant cryptocurrency in terms of generating return and volatility spillovers towards other high-capitalization virtual currencies, according to the decomposition of return and volatility shocks. Results show that the severity of these spillovers has been steadily increasing over time. Furthermore, it is discovered that significant news causes greater spillovers. Due to the increasing interconnectedness of digital currencies, emphasis is placed on the rising level of contagion risk among cryptocurrency markets. Due to changes in spillovers over time, this is accompanied with a higher level of uncertainty in such markets.

Similar to this, Kumar and Amandarao (2019) investigate volatility spillover dynamics in relation to the returns of Bitcoin, Ethereum, Ripple, and Litecoin. They use the IGARCH(1,1)-DCC(1,1) specification, which stands for Integrated Generalized Autoregressive Conditional Heteroskedasticity-Dynamic Conditional Correlations. The results of GARCH calculations show that there are sizable volatility spillovers from Bitcoin to Ethereum and Litecoin. Additionally, estimates based on conditional correlations show a slight co-movement pattern in the returns of digital currencies. They also demonstrate that since the optimistic trend in the markets for virtual currencies, volatility co-movement has become stronger after being weaker in earlier years. It should be highlighted that the wavelet cross-spectra used for analysis support the DCC methods' conclusions. Overall, there is evidence to suggest that among cryptocurrencies, Bitcoin is the most well-known and significant. Additionally, Huynh (2019) uses a variety of approaches to analyze the risks of spillover among markets for digital currencies. To find interdependency between Bitcoin, Ethereum, Ripple, Litecoin, and Stellar, Pearson correlations, Vector Autoregressive (VAR) and Structural Vector Autoregressive (SVAR) causation, as well as Student's -t copulas, are used. The results show that Bitcoin does not receive or have any spillover effects on the other currency under investigation.

By using a different approach, Omane-Adjepong and Alagidede (2019) look at market coherences and the relationship between volatility in Bitcoin, BitShares, Litecoin, Stellar, Ripple, Monero, and Dash. They do this by using wavelet-based methodologies and parametric and non-parametric tests. The wavelet coefficients are obtained using the Maximum Overlap Discrete Wavelet Transform (MODWT), and the wavelet multiple correlation (WMC) is computed. Additionally, two specifications are used to measure conditional volatility: the Glosten-Jagannathan-Runkle Generalized Autoregressive Conditional Heteroskedasticity (GJR-GARCH(1,1)) and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH(1,1)). Further, Vector Autoregressive (VAR) frameworks use traditional Granger causality checks. Econometric estimates show that all of the currencies under consideration are only weakly to moderately interconnected. The two most influential ones are discovered to be Bitcoin and Ripple. There is proof that Dash-Ripple, Monero-Ripple, and Dash-Stellar are the most closely linked couples. The findings demonstrate the non-homogeneous directions of connectivity as a considerable proportion of couples show only one-way shock transmissions or (non-)linear feedback nexi. Greater links between pairings are seen with longer-term investments. It is underlined that trading scales and the proxies for market volatility play a significant role in the links and causality regarding volatility.

Zieba et al. (2019) use the Minimum Spanning Tree (MST) approach and Vector Autoregressive (VAR) models that are based on clusters produced by the MST results to evaluate the interdependencies between log-returns of digital currencies. Despite Bitcoin's dominance in the cryptocurrency markets, evidence suggests that changes in Bitcoin's market value do not affect other digital currencies in the same way. Additionally, the reverse transmission method is invalid. Surprisingly, Litecoin and Dogecoin are found to have a greater impact on spillovers to other virtual currencies. Furthermore, the grouping of the currencies Bitcoin, Monero, and Dash shows strong connections. The same is true for the grouping of BitShares, Ripple, Stellar, and Dogecoin.

3. Studies about spillovers between cryptocurrency markets and markets of other assets or economic conditions

Investigation into digital currency spillovers has beyond the boundaries of cryptocurrency markets. Because of this, a decent number of eminent academic studies have clarified the connections between virtual currency and conventional assets like stocks or currencies. It should be emphasized that research has also been done on how uncertainty in economic policy affects the use of digital currencies.

More precisely, in both bullish and bearish market conditions, Bouri et al. (2018) look into the return and volatility spillovers between Bitcoin and equities, commodities, currencies, and bonds. They use a smooth transition vector autoregressive (STVAR) method to capture changes in market circumstances and a bivariate generalized autoregressive conditional correlation (DCC) specification to represent volatility (STVAR-BTGARCH-M). Additionally, estimates are made using the Glosten-Jagannathan-Runkle Generalized Autoregressive Conditional Heteroskedasticity (GJR-GARCH) approach. Results show that there are time- and market-dependent spillover effects between Bitcoin and other assets, and that there is a stronger correlation between returns than volatility. There is evidence that spillovers are asymmetric and that Bitcoin is typically the recipient rather than the source of volatility impacts. The extent of the spillover effect is said to vary depending on the state of the market. Additionally, in order to examine the effects of spillover between Bitcoin and energy and technology companies, Symitsi and Chalvatzis (2018) adopt an asymmetric multivariate Vector Autoregressive- Generalized Autoregressive Conditional Heteroskedasticity based on the Baba-Engle-Kraft-Kroner (VAR-BEKK-AGARCH) specification. Evidence from empirical findings shows that stocks in the energy and technology sectors produce large return spillovers to bitcoin. The results show that when it comes to volatility, short-run volatility spillovers towards Bitcoin are caused by technological companies, whereas long-run volatility spillovers towards this dominant currency are caused by energy industries. It is discovered that while there is little dynamic correlation between Bitcoin and equities indexes, there are bi-directional asymmetric shock spillovers between them.

According to Trabelsi (2018), there may be connections between the markets for virtual currencies, the Bitcoin index (BPI), and well-known assets like currencies, equity market indexes, gold, and Brent oil. The spectral representation of variance decomposition in networks is used in conjunction with the spillover index developed by Diebold and Yilmaz (2012) and Barunik and Kfehlik (2017) to measure the links. Findings show that there are no significant spillover effects between the markets for traditional assets and digital currency. Regarding Gillaizeau et al. (2019), they use frequency domain analysis and the generalized variance decomposition technique developed by Diebold and Yilmaz (2012) to evaluate the outward and inward volatility spillovers in cross-market Bitcoin prices. Examined are the exchange rates for bitcoin in respect to the USD, AUD, CAD, EUR, and GBP. Volatility is measured using the Garman-Glass and Parkinson's High-Low Historical Volatility (HL-HV) measures. The volatility shocks to the BTC/EUR and BTC/USD exchange rates are also shown to have an impact, according to the evidence. Additionally, it has been discovered that the BTC/EUR market of currency values is the most susceptible to uncertainty regarding other exchange rates, with the BTC/USD following closely behind. In contrast, the BTC/GBP market is both very weakly influenced and influential. According to the argument, BTC/CAD and BTC/EUR markets are net consumers of volatility, whereas BTC/USD acts as a net supplier of negative net volatility. Overall, the other rates can account for 15% to 20% of the forecast error variance in volatility of each rate. The findings on return spillovers are consistent with those regarding volatility spillovers. It is said that uncertainty and investor emotions increase volatility.

Wang et al. (2019) use a different perspective and use a multivariate quantile model, the Granger causality risk test, and a conditional autoregressive value-at-risk framework (MVQM-CAViaR(1,1)) to investigate the risk spillover consequences from Economic Policy Uncertainty (EPU) to Bitcoin. EPU is represented by the US EPU index, the stock market uncertainty index, and the VIX index. The risk spillover impact from EPU to Bitcoin is not considerable, according to econometric estimates, and the value-at-risk of Bitcoin is influenced by the values of this measure and volatility in the past. The findings are unaffected by estimations at various quantiles and time lags, data frequency, the 2013 Bitcoin price fall event, or contemporaneous or instantaneous relationships.

Evidence from primary studies shows that Bitcoin not only receives spillover effects from high-capitalization digital coins and more conventional assets, such as prestigious equities, currencies, and commodities, but also exerts them on cryptocurrency markets. This supports claims that Bitcoin continues to dominate the market for digital currencies, but that it is primarily unaffected by global economic factors like traditional assets, significant news, and uncertain economic policies. These results show that digital currencies, particularly Bitcoin, should be integrated into international financial markets, but they also show that significant steps must be made toward digitalizing payment networks before Bitcoin can be considered the mainstay of the global financial system.

Table 1.1. gives a summary of the factors considered, data frequency, and time period analyzed in the original papers of this survey. Additionally, the data source, the methodology used, and the findings on spillover effects are described.

Table 1.1. Overview of studies investigating spillovers related with cryptocurrencies

Autho rs	Variables examined	Freque ncy of data	Time period exami ned	Data Source	Methodol ogy	Conclusions about spillovers
Bouri et al. (2018)	Bitcoin MSCI World	Daily	19 July 2010- 31 Octobe r 2017	Coindesk Datastream	STVAR-BTGARC H-M as in Kundu and	Asymmetric spillovers. Bitcoin is usually the receiver.

	MSCI Emerging Markets MASCI China SP SGCI Commodity SP SGCI energy Gold US dollar index US 10-year Treasury yields				Sarkar (2016) GJR-GARCH by Glosten et al. (1993) DCC-GARCH by Engle (2002)	Return spillovers higher than volatility spillovers.
Gillaizeau et al. (2019)	BTC/USD BTC/AUD BTC/CAD BTC/EUR BTC/GBP EPU	Daily	12 March 2013-31 January 2018	www.bitcoincharts.com Mt.Gox Bitstamp LocalBitcoins	Generalized Variance Decomposition (GVD) approach by Diebold and Yilmaz (2012) in VAR models Parkinson's High-Low historical volatility (HL-HV) model by Parkinson (1980) Garman-Klass measure for volatility by Garman and Klass (1980)	BTC/USD has high predictive power BTC/EUR is net receiver of volatility spillovers
Katsiampa et al. (2019)	Bitcoin Ethereum Litecoin	Daily	7 August 2015 to 10 July 2018	Coinmarketcap.com	BEKK-MGARCH model by Engle and	Bi-directional spillover effects between Bitcoin-

					Kroner (1995)	Ethereum and between Bitcoin-Litecoin Uni-directional shock spillover from Ethereum to Litecoin Bi-directional volatility spillover between all three pairs
Koutmos (2018)	Bitcoin Ethereum Ripple Litecoin Dash Stellar NEM Monero Tether Bytecoin BitShares Verge Dogecoin DigiByte MaidSafe Coin MonaCoin ReddCoin Emercoin	Daily	7 August 2015-17 July 2018	Coinmarketcap.com	GARCH methodologies by Engle (1982) and Bollerslev (1986) Random rotations by Diebold and Yilmaz (2009) Generalized decomposition in VAR models by Pesaran and Shin (1998)	Bitcoin is the dominant contributor of return and volatility spillovers Steady increase of spillovers over time Spikes in spillovers during major events
Kumar and Anandarao (2019)	Bitcoin Ethereum Ripple Litecoin	Daily	15 August 2015-18 January 2018	Coinmarketcap.com	IGARCH(1,1) – DCC GARCH(1,1) by Engle and Bollerslev (1986) and Engle (2002) Wavelet cross spectra	Significant volatility spillover from Bitcoin to Ethereum and Litecoin

Luu Duc Huynh (2019)	Bitcoin Ethereum Ripple Litecoin Stellar	Daily	8 September 2015-4 January 2019	-	Pearson correlation VAR-SVAR causality t-Student's copulas (Gaussian, Student's-t)	Bitcoin is receiver of spillovers Ethereum is not affected
Omane-Adjepong and Alagidede (2019)	Bitcoin BitShares Litecoin Stellar Ripple Monero Dash	Daily	8 May 2014-12 February 2018	Coinmarketcap.com	Maximum Overlap Discrete Wavelet Transform (MODWT) Granger causality (Granger, 1969) in a VAR system GARCH GJR-GARCH by Glosten et al. (1993)	(Non)linear feedback linkages or unidirectional transmission of shocks Bitcoin and Ethereum most influential
Symitsi and Chalvatzis (2018)	Bitcoin SP Global Clean Energy Index (SPGCE) MSCI World Energy Index (MSCIWE) MSCI World Information Technology Index (MSCIWIT)	Daily	22 August 2011-15 February 2018	Datastream	VAR(1)-BEKK-AGARCH model by McAleer et al. (2009)	Significant return spillovers from energy and technology stocks to Bitcoin Short-run volatility spillovers from technology companies and long-run towards energy companies. Bi-directional asymmetric character

Trabelsi (2018)	Bitcoin Ethereum Ripple Litecoin Bitcoin Price Index SP500 NASDAQ FTSE100 HangSeng Nikkei225 EUR/USD GBP/USD USD/JPY USD/CHF USD/CAD Gold Brent futures contracts	Daily	7 October 2010-8 February 2018	Coindesk -	Spillover index approach by Diebold and Yilmaz (2009) FEVD by Diebold and Yilmaz (2012) and Barunik and Kfehlik (2017)	No significant spillover effects
Wang et al. (2018)	Bitcoin US EPU index Equity market uncertainty index VIX index	Daily	18 July 2010-31 May 2018	www.policyuncertainty.com by Baker et al. (2016) Coindesk	MVQM-CAViaR model based on White et al. (2015) and Engle and Manganelli (2004)	Negligible risk spillover impact from EPU to Bitcoin
Zięba et al. (2019)	Pura Emercoin Verge LEOcoin Nexus NewYork Coin Monetary Union Dimecoin I.O.Coin Groestlcoin Energycoin NeosCoin Cloakcoin Ubiq BitBay ECC Mooncoin Monacoin FedoraCoin	Daily	01 September 2015-19 December 2016 20 December 2016-02 May 2018	Coinmarketcap.com	Minimum-Spanning Tree (MST) by Mantegna (1999) and Mantegna and Stanley (1999) VAR models and causality by Granger (1969)	No significant spillover effects towards or from Bitcoin. Linkages among Bitcoin, Monero and Dash. Also interconnectedness among Dogecoin, Ripple, Stellar and BitShares

	BitSend Crown CasinoCoin Tether BitCNY Mintcoin Siacoin Boolberry Monero Aeon PotCoin Viacoin FlorinCoin Burst MaidSafe Coin Ethereum Clams DigitalNote NavCoin ByteCoin Omni ReddCoin Stealthcoin Blocknet Bean.Cash Dash FoldingCoin GridCoin Myriad Einstenium OKCash FairCoin WhiteCoin SolarCoin RubyCoin Gulden Feathercoin Diamond Unobtanium DNotes NEM GameCredits DigiByte Counterparty Syscoin					

	VeriCoin BitcoinDa rk Primecoin Dogecoin BlackCoin Vertcoin Nxt Stellar Ripple BitShares Namecoin Peercoin Litecoin Bitcoin					

4. **Conclusions**

An integrated review of empirical studies on return and volatility spillovers across cryptocurrency marketplaces is presented in this publication. Results about the connections between digital currencies are based on a variety of approaches. Econometric findings shed insight on whether herding behavior occurs in the markets for virtual currencies and whether the popularity of new coins introduced through Initial Coin Offerings (ICOs) could lessen Bitcoin's hegemonic impact. This methodical study aims to shed light on hitherto unrecognized aspects of spillovers among novel forms of liquidity and assist investors in determining if trading with virtual currencies is a concept worth considering in the broader context of financial digitalization.

This study expands on a growing body of research on the interactions between popular digital currencies and less liquid ones, as well as the literature on spillovers among cryptocurrencies with high market capitalization. In primary investigations, influences with conventional assets like currencies, equities, gold, and oil are also explored. Additionally, evaluations of links with uncertainty indexes are made. A comprehensive description of the methodology used, the caliber of the data used, and the economic foundations of the results is given.

More particular, it is shown that Bitcoin continues to be the most popular cryptocurrency, the most significant giver in terms of virtual currency, and the biggest recipient of spillover effects in terms of high-capitalization cryptocurrencies and other assets. As recipients of Bitcoin's spillovers, currencies like Ethereum, Litecoin, and Ripple are discovered to have close ties to the digital currency. There is evidence that volatility spillovers occur more frequently but that return spillovers are more pronounced.

Overall, the findings point to the possibility of a herding behavior that is sustainable in the markets for digital currencies, with Bitcoin continuing to be the main driver of this phenomena. Because virtual coins and traditional assets are interconnected, portfolio managers may be able to reduce risk by creating diversified portfolios with the right mix of assets. Spillover effects are a sign that the cryptocurrency markets are moving in the direction of greater integration with the international financial markets.

This study can be used as a road map for academic scholars, regulatory agencies, investors, and the financial press to better understand how these highly speculative kinds of trading are interconnected. Future study in the area of virtual currencies should look closely at how returns and volatility of cryptocurrencies move together and how it influences herding behavior in the markets for stablecoins and digital currencies.

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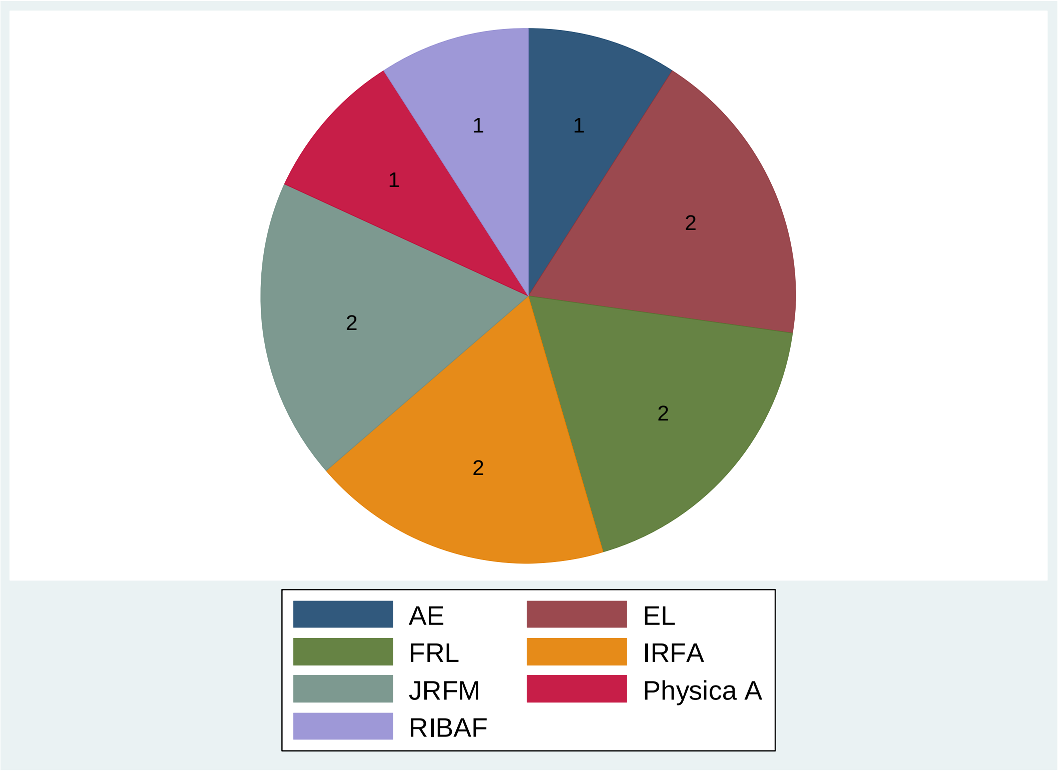
APPENDIX

Figure 1.A1. Google trends for ‘’Bitcoin’’ in a global level *(source: https://trends.google.com)*

Figure 1.A2. Frequency of articles published in journals *(extracted on: 30 August 2019)*



<u>*Notes*</u>: AE, EL, FRL, IRFA, JRFM, Physica A and RIBAF stand for Applied Economics, Economics Letters, Finance Research Letters, International Review of Financial Analysis, Journal of Risk and Financial Management, Physica A: *Statistical Mechanics and its Applications, and Research in International Business and Finance, respectively.*

Figure 1.A3. H-index scores for each journal *(extracted on: 30 August 2019)*

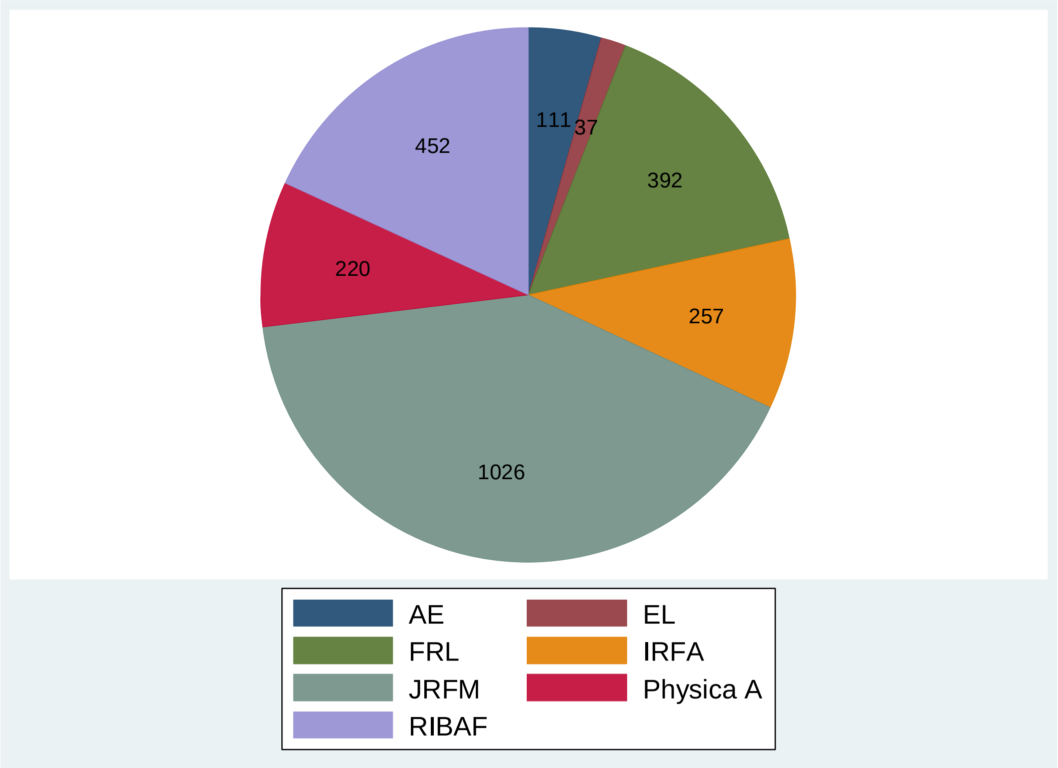


Figure 1.A4. Average abstract views concerning each journal *(extracted on: 30 August 2019)*

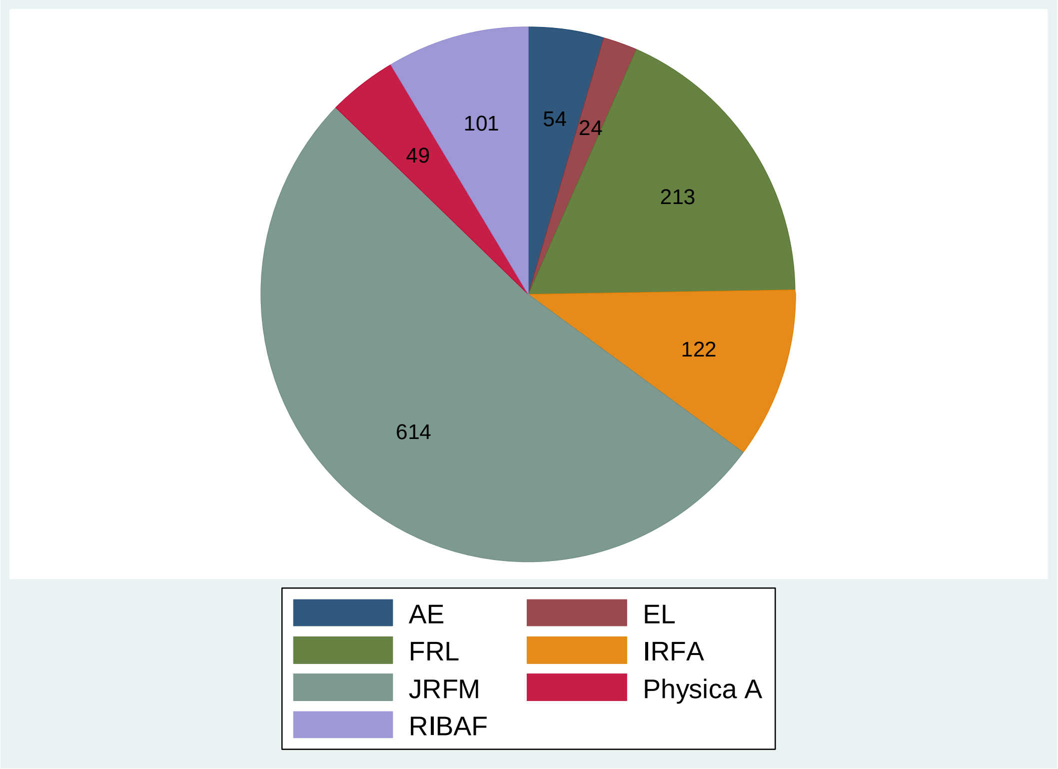


Figure 1.A5. Average downloads concerning each journal *(extracted on: 30 August 2019)*

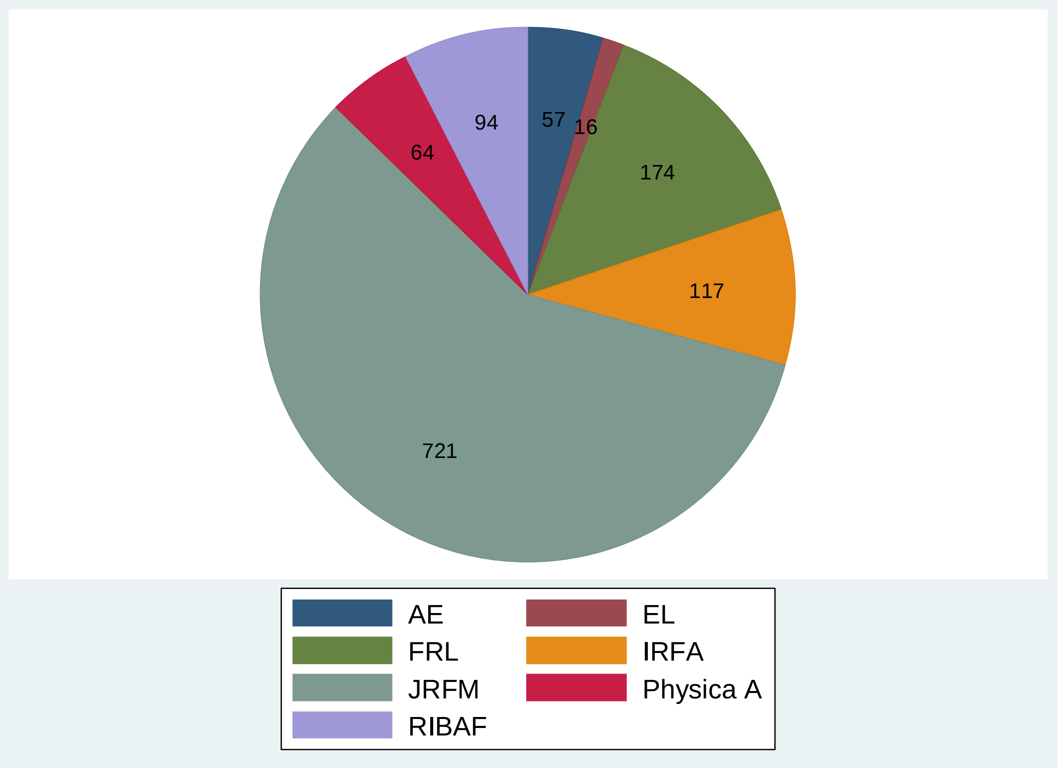


Figure 1.A6. Citations per academic paper *(extracted on: 30 August 2019)*

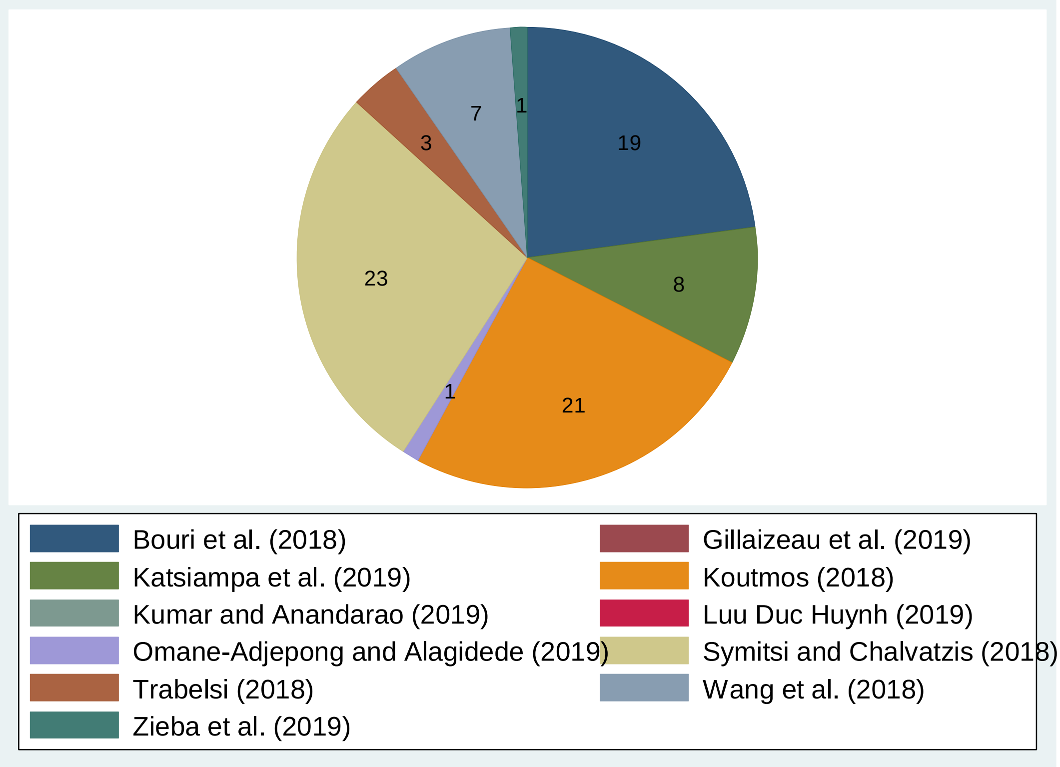


Figure 1.A7. Number of references used by academic papers *(extracted on: 30 August 2019)*

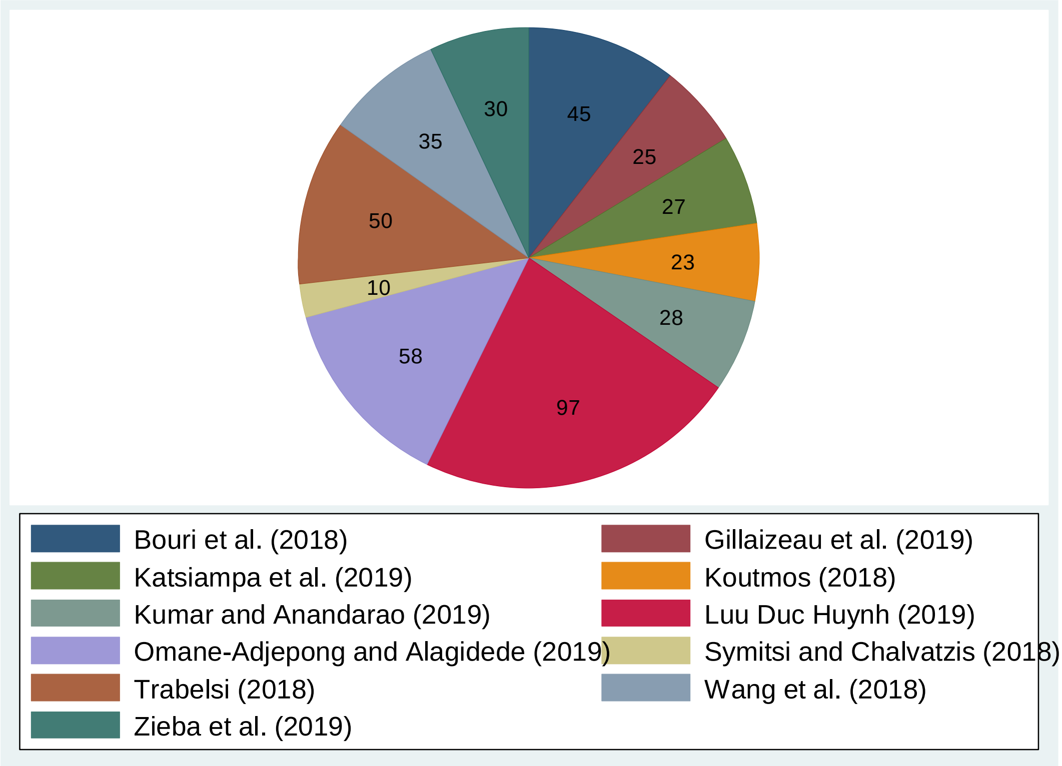


Figure 1.A8. Country location of universities where authors about cryptocurrency spillovers are employed *(information extracted on: 30 August 2019)*

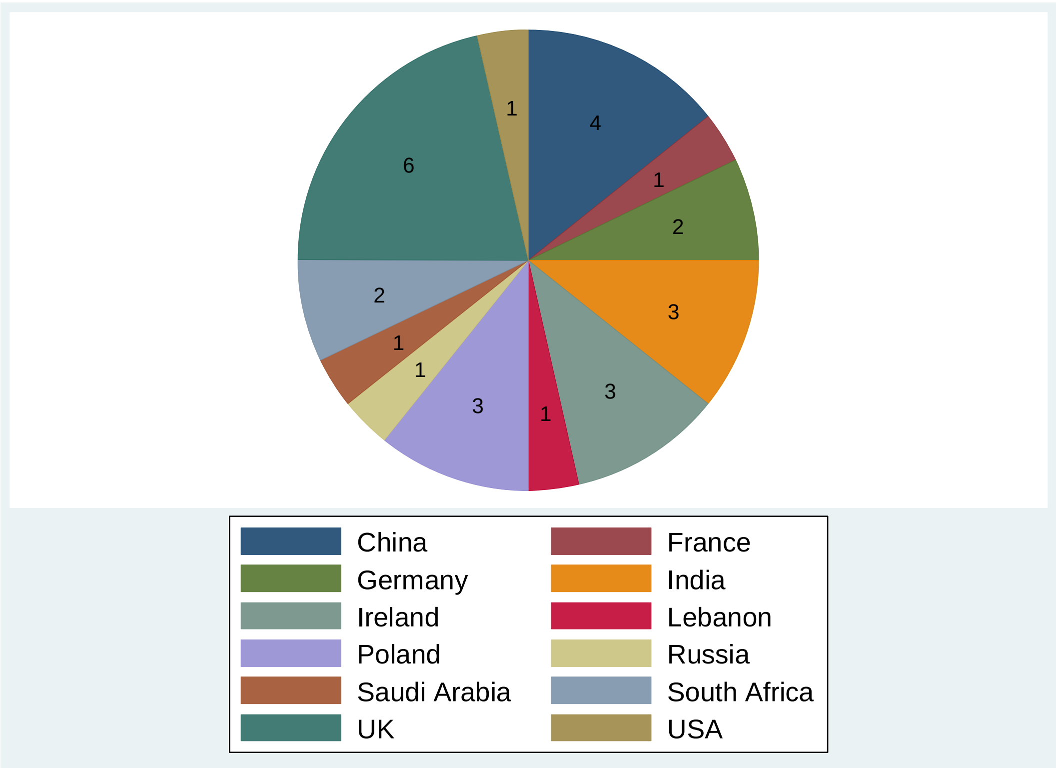
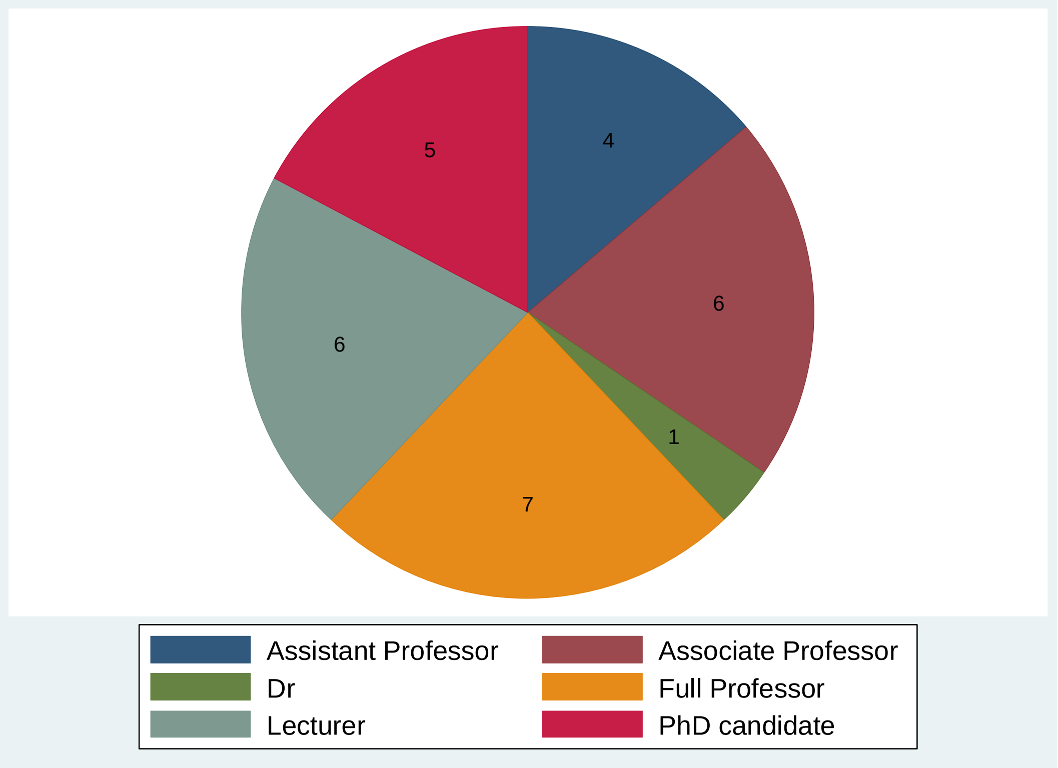


Figure 1.A9. Academic ranks of researchers about spillover effects in cryptocurrency markets *(information extracted on: 30 August 2019)*



Chapter 2

A Survey on Efficiency and Profitable Trading Opportunities in Cryptocurrency Markets

1. Introduction

The exponential expansion of Bitcoin and other digital currencies since its introduction by Nakamoto (2008) has sparked a flurry of interest from governments, academics, investors, traders, and portfolio managers. The term "cryptocurrency" is used to describe this brand-new kind of money, which possesses traits of both a commodity and money (Selgin 2015; Ammous 2018). The most well-known cryptocurrency, Bitcoin, has sparked a growing body of academic research on its returns and volatility characteristics, including Dyhrberg (2016a, 2016b), Fry and Cheah (2016), Katsiampa (2017), Urquhart (2016, 2017), Corbet et al. (2018, 2019), Bouri et al. (2017a, 2017b), Baur et al. (2018a, 2018b), and Beneki et al. (2019). Whether such markets are consistent with the Efficient Markets Hypothesis (EMH) is one of the fundamental elements of digital currencies that has drawn increasing attention.

The three variants of the Efficient Markets Hypothesis, as stated by Fama (1970), are one of the most radical approaches to modeling financial data in order to find any predicted patterns that could serve as the foundation for successful trading techniques. The cornerstone of financial economics, the Efficient Market Hypothesis, was developed by Bachelier in the early 20th century and Fama in 1970. According to Fama, a market is said to be informationally adequate when "prices reflect full information" in it.

These are the main types of informational competence that are most frequently used. First off, quotes for assets show all the information that has been suppressed in past prices for these assets. Second, semi-strong efficiency refers to current prices that reflect all readily available information. Thirdly, quotes today reflect all information, both public and private, as is represented by strong-form efficiency.

The weak-form EMH, one of the three types of the EMH, is the one that is most frequently used to describe how interested investors struggle to predict the future values of investible assets by using knowledge about past quotes for such assets. Financial asset time series cannot have a long memory if the Efficient Markets Hypothesis is true. Therefore, investors who attempt to adhere to a profitable investing plan with minimal risk will not be able to earn abnormal returns. In other words, when the EMH holds, speculation based on long-term reliance on returns is irrelevant.

To the best of our knowledge, no study has yet delved into the entire body of academic literature on successful cryptocurrency trading. According to Differently, the current study is the first to conduct an extensive and comprehensive analysis of the available empirical studies on whether cryptocurrency markets can outperform the market, resulting in anomalous profit-making by investors. A few, yet significant, recent publications, including Urquhart (2016), Nadarajah and Chu (2017), and Bariviera (2017), have opened the road for a more developed perspective on the effectiveness of virtual currency exchanges.

The rest of this essay is organized as follows. The research on the effectiveness of the Bitcoin markets are presented in Section 2. A summary of Efficient Market Hypothesis testing in a wider range of cryptocurrencies is given in Section 3, which is still in its infancy but is already quite useful. The conclusions are analyzed in Section 4.

2. Studies about Efficiency in Bitcoin markets

Numerous academic studies have looked into long-range reliance and how it might interact with the Efficient Market Hypothesis. The validity of weak-form efficiency in the Bitcoin market has been evaluated using a series of tests. The vast majority of Bitcoin-related articles' empirical findings show inefficiency, which creates profitable trading possibilities. However, it should be noted that as the Bitcoin market becomes more established, it becomes harder to outperform the market by investing in it.

Urquhart (2016, 2017), Nadarajah and Zhu (2017), and Bariviera (2017) are a few of the first significant research examining the effectiveness of the Bitcoin market. In order to assess the informative effectiveness of Bitcoin between August 1, 2010, and July 31, 2016, Urquhart (2016) uses daily data. He looks at two 9-year subperiods, with 2013's Fourth of July acting as the break between them. The Ljung-Box (1978) test, the runs test (Wald and Wolowitz, 1940), the Bartels (1982) test, the variance ratio of Lo and MacKinlay (1988), the wild-bootstrapped test of Kim (2009), the BDS test of Brock et al. (1996), and the Hurst (1951) exponent are just a few of the tests that the author uses to evaluate long memory. The Hurst exponent supports the existence of strong anti-persistence, and these tests deny randomness. In light of these facts, it may be said that there is no efficiency in the Bitcoin market, despite a trend towards one since August 2013. In order to look into price clustering in Bitcoin markets, Urquhart (2017) also uses data from multiple Bitcoin exchanges from May 1, 2012, to April 30, 2017. Given that more than ten percent of prices terminate in 00 digits, there is evidence that clustering occurs at round values. Additionally, there is less proof that there is clustering around the 50 and 99 digits. It has been discovered that returns from increasing prices show a positive trend 1, 2, 3, 5 and 10 days prior to a round number, however returns from increasing prices after that point are unfavorable and statistically insignificant. Overall, the results support Harris' (1991) bargaining hypothesis because price clustering is correlated with Bitcoin trade volume and quotes.

In a similar vein, Nadarajah and Zhu (2017) analyze Bitcoin market efficiency using data from August 1, 2010, to July 31, 2016. Additionally, they split the sample into two sub-periods, the first one covering the period from August 1, 2010, to July 31, 2013, and the second one covering the period from August 1, 2013, to July 31, 2016. They add on Urquhart's (2016) research by using eight tests to look into the EMH. In more detail, the runs test (Wald and Walowitz, 1940), the Bartel's test (Bartel, 1982), and the wild bootstrapped automatic variance ratio test (Kim, 2009) are employed. In addition, the generalized spectrum test (Escanciano and Libato, 2006), the portmanteau test (Escanciano and Libato, 2009), the BDS test (Brock et al., 1996), and the spectral shape tests (Durlauf, 1991) are carried out. Most of them offer proof of the independence of returns. As a result, the Bitcoin market could not see unusual earnings.

Using daily data from August 18, 2011, through February 15, 2017, Bariviera (2017) examines the long-term dependency of Bitcoin returns and volatility. Utilizing Detrended Fluctuation Analysis (DFA) and overlapping sliding windows, the Hurst exponent methodology is used. Results show that Bitcoin's returns show durability from 2011 to 2014, but that there is a tendency towards efficiency beyond that year. Results about Bitcoin's volatility, however, suggest that this hasn't changed during the course of the investigation. Additionally, Bariviera et al. (2017) employ intraday data from 2013 to 2016 and daily data from 2011 to 2017 regarding Bitcoin prices as well as the USD-expressed values of the EUR and GBP currencies. To calculate long-range dependence, the Hurst exponent via Detrended Fluctuation Analysis (DFA) in a sliding window is used. The findings show that the Hurst exponent values fluctuate significantly in the early years of Bitcoin, from 2009 to 2014, but that they gradually begin to stabilize as time goes on as their value hovers around 0.5. Alternative time scales are proven not to have a major impact on long-term memory. Furthermore, there is proof that long-term dependency is unaffected by market liquidity.

To shed more light on whether or not there is efficiency with regard to Bitcoin, Jiang et al. (2017) analyze if there is long-term dependency in the Bitcoin market. The adopted statistics are collected on a daily basis and cover the time period from December 1, 2010, to November 30, 2017. A rolling-window strategy with a 14-day shift is used, along with the Hurst exponent. Additionally, the Ljung-Box test and AVR test are used to gauge market efficiency for bitcoin. Empirical findings show that this market is not efficient since long-memory is found and the inefficiency ratio has a high value. But as time goes on, an inclination towards efficiency has been discovered. Detrended fluctuation analysis (DFA) is used by Alvarez-Ramirez et al. (2017) to analyze the period from June 2013 to June 2017 and find long-range correlations for Bitcoin returns. The Hurst component is found to exhibit cycles, and Bitcoin exhibits periods of efficiency as well as periods of inefficiency. There are asymmetric correlations that are dependent on whether price trends are upward or downward, which results in anti-persistence's inefficiency. Additionally, Kurihara and Fukushima (2017) examine the effectiveness of the Bitcoin market to determine whether or not there are weekly price anomalies. They use standardized Ordinary Least Squares (OLS) and Robust Least Squares (RLS) approaches to extract data over the time range of July 17, 2010, to December 29, 2016. Findings suggest that weak-form efficiency is not a feature of the Bitcoin market. However, as time goes on, the Bitcoin market reveals increased degrees of efficiency.

The extremely optimistic market of 2017 led to an increase in the amount of scholarly research into the Bitcoin markets. This indicates the growing interest among researchers, investors, speculators, and portfolio managers in the cryptocurrency market's leading coin. Such a bibliography sheds light on the factors that influence investors' decision-making because it is widely held that investor sentiment toward Bitcoin substantially influences cryptocurrency markets in general.

The daily data from July 18, 2010, to June 16, 2017, is used by Tiwari et al. (2018) to run a series of tests on Bitcoin's long-term dependency and informational efficiency. They especially use the Centered Moving Average-squared Absolute Fluctuation (CMA-1), Centered Moving Average-mean Absolute Fluctuation (CMA-2), and Detrended Fluctuation Analysis (DFA). Additionally, they employ the Periodogram-LS (Least Squares) and Periodogram-LAD (Least Absolute Deviation) tools. Additionally, the Geweke-Porter-Hudak (GPH) and maximum-likelihood estimator (MLE) approaches are used. Overall results show that the Bitcoin market is productive. However, results that support inefficiency are discovered during the subperiods of April to August 2013 and August to November 2016. Cheah et al. (2018) use daily closing Bitcoin prices for the markets in Europe, the United States, Australia, Canada, and the United Kingdom from November 27, 2011, to March 17, 2017, in their article to examine cross-national interdependence. Evidence of informational inefficiency between markets is produced by treating cross-market Bitcoin quotes as long-memory operations using a fractionally cointegrated VAR (FCVAR) specification. As a result, both the five-market structure and individual Bitcoin markets have long memories. Along with medium to high levels of market inefficiency across the board and long-memory traits that allow for trading profits, it is discovered that uncertainty has a detrimental effect on Bitcoin markets. Since disequilibrium errors correct slowly, stochastic shocks may have a significant impact on independent Bitcoin markets.

In order to determine the effects of the introduction of Bitcoin futures on Bitcoin's efficiency, Köchling et al. (2018) conducted a number of efficiency tests using data from before the launch of Bitcoin futures (August 10, 2017–December 10, 2017) and immediately after the launch (December 10, 2017–April 10, 2018). The inefficiency of these futures before they were started is demonstrated by seven of the nine tests that were used. However, since the Bitcoin futures contracts began trading, no inefficiency has been found, indicating that weak-form efficiency has existed. Furthermore, BitcoinCash, a hard fork of Bitcoin, does not appear to be inefficient in any way. Sensoy (2018) uses data on tick-by-tick trades in 15, 20, 30, 40, and 45-minute intervals regarding trading volumes and prices of Bitcoin in respect to USD and EUR from January 1, 2013, to March 5, 2015. Efficiency is estimated using a time-varying approach with rolling samples called permutation entropy, which is based on Shannon's entropy. Results show that since the start of 2016, informational efficiency levels for BTC to USD and EUR exchange rates have increased. It should be observed that this improvement in efficiency displays a cyclical pattern when the cryptocurrency's value is compared to the US dollar, but a gradual increase is seen when the cryptocurrency is compared to the euro. Additionally, it is discovered that the earlier exchange rate is more effective than the later. Evidence suggests that greater frequencies result in less efficient pricing. Additionally, while higher volatility has a detrimental effect on efficiency in Bitcoin markets, higher liquidity has a favorable relationship with informational efficiency.

Kristoufek (2018) is one pertinent study that looks into whether there is efficiency in two Bitcoin marketplaces relative to the US dollar and the Chinese yuan. He makes use of information that began on February 1, 2014, and ended in July 2017. Efficiency is measured using the Efficiency Index (EI), which was created by Kristoufek and Vosvrda (2014). In addition, measurements for the Hurst exponent, fractal dimension, and entropy are used. Results show that from the middle of 2011 to the middle of 2012, the USD market is efficient. The same is true for the time frame of March through November 2014. However, empirical results support the finding that across the seven-year study period, both the USD and CNY Bitcoin markets were largely inefficient. Efficiency only becomes obvious when Bitcoin price renders too high and stabilizing intervention becomes necessary. Additionally, until the date of July 31, 2017, Phillip et al. (2018a) adopted daily data regarding Bitcoin, Ethereum, Ripple, NEM, and Dash from alternative trading platforms. They use the GLM-SV-LGV-HT model to measure Generalized Long Memory (GLM), Stochastic Volatility (SV), Leverage (LVG), and Heavy Tails (HT). As their markets develop, it is shown that these most capitalized currencies have a tendency to perform similarly in terms of their long-memory traits. There is proof that the markets for digital currencies are inefficient. It should be noted that all of the cryptocurrencies under consideration exhibit long memory, leverage, stochastic volatility, and heavy tailedness features. Almudhaf (2018) uses daily data on the closing price and the Net Asset Value (NAV) from May 4, 2015 to November 18, 2016, to examine the pricing effectiveness of the Bitcoin Investment Trust (BIT). The Newey West's (HAC) estimators are combined with the Ordinary Least Squares (OLS) approach. Evidence points to a significant and advantageous relationship between prices and NAV. There is a strong and positive correlation between Bitcoin Investment Trust returns and premiums, as measured by current percentage deviations. It is determined that the premium is about equal to 44% of the NAV. Results show that inefficiency exists. As a result, effective trading techniques could be used.

Khuntia and Pattanayak (2018) examine the Adaptive Market Hypothesis (AMH) and changes in return predictability in the Bitcoin market using daily Bitcoin data from July 18, 2010 to December 21, 2017. In a rolling window framework, the Martingale Difference Hypothesis (MDH) is tested, and linear and non-linear dependence in quotes are found using the Dominguez- Lobato (DL) consistent test and generalized spectral (GS) test. Results show that high levels of efficiency were present from the middle of 2012 to November 2013, as well as since 2015. However, it is discovered that inefficiency existed between August 2011 and August 2012 and between December 2013 and December 2014. Periods of efficiency are followed by periods of inefficiency, proving that efficiency is evolving and that the AMH is reliable.

Using daily Bitcoin prices covering the period from July 19, 2010, to March 20, 2018, Aggarwal (2018) investigates the effectiveness of Bitcoin marketplaces. He uses the ARCH test, unit root tests, and serial correlation coefficient tests to do this. The estimation findings show that Bitcoin returns do not behave randomly. Thus, proof that the Bitcoin market is highly inefficient is offered. The hypothesis that excessive volatility persistence in returns is accountable for such inefficiencies is further supported by tests for non-linear dependence.

Vidal-Tomás and Ibañez (2018) use daily data for the Bitstamp and Mt.Gox markets, respectively, from September 13, 2011, to December 17, 2017, and from September 13, 2011, to February 25, in their research. They concentrate on determining if Bitcoin markets exhibit semi-strong efficiency and how changes in monetary policy and news about this currency effect Bitcoin returns. They demonstrate that while negative events are significant for both models by adopting the AR-CGARCH and AR-CGARCH-M specifications, positive news only significantly influences Bitstamp and the Bitstamp market is more effective than Mt.Gox. Additionally, as time goes on, the Bitcoin market becomes more effective. It should be highlighted that while this digital currency is influenced by local events, news about central bank policymaking on a global scale has a significant impact. As a result, greater degrees of inefficiency are noticeable in reaction to changes in monetary policy. Al-Yahyaee et al. (2018) also compare the effectiveness of the Bitcoin market to the markets for other important alternative assets, such as the gold, equities, and foreign currency markets. Daily statistics are extracted for the period under consideration, which runs from July 18, 2010, to October 31, 2017. They use the multifractal detrected fluctuation analysis (MF-DFA) method, which was created by Kantdhardt et al. (2002) and is thought to be more flexible than the MF and DFA methodologies, to assess efficiency. Long-memory traits are represented by the slopes of generalized Hurst exponents. The equities market is the most efficient market, according to empirical findings, whereas Bitcoin is the least efficient and has the most time-varying efficiency asset among the markets examined. Notably, it has been discovered that Bitcoin has the highest level of long-range persistence. Small fluctuations are better for detecting multifractality and long memory, and such results may be a result of Bitcoin investors' loss of faith. In accordance with the research of Urquhart (2017), the academic work of Mbanga (2018) examines the day-of-week pattern of price clustering in Bitcoin using daily volume and closing prices of Bitstamp for the time period from February 20, 2011, to May 15, 2018. Results show that Bitcoin prices tend to cluster around whole numbers. Furthermore, it is discovered that price clustering is not a phenomenon that only occurs on Mondays or Fridays, despite the fact that data suggests that it is more pronounced on Fridays than on other days of the week. The figures that end in decimal places most frequently on Fridays are 0.00, 0.99, and 0.50. Overall, there is no proof that the clustering of Bitcoin prices has a weekend effect.

Lahmiri and Bekiros (2018) present a perspective on cryptocurrencies based on econophysics. To analyze the chaos, randomness, and multi-scale correlation structure of prices and returns in a low- and a high-regime period, they use daily Bitcoin data spanning the period from July 18, 2010, to October 23, 2017. Estimates are made using the highest Lyapunov exponent, Shannon entropy, multi-fractal detrended fluctuation analysis (MF-DFA), and generalized Hurst exponent. Evidence supports the idea that there was greater return uncertainty during the high-price regime period. Prices and returns during both periods exhibit multifractality, which is caused by fat-tailed distributions. Additionally, under the low regime, short returns changes predominate, while long returns changes predominate during the high regime period. Overall, the high-price level regime reveals non-linear tendencies in the Bitcoin market. In a slightly related line, Lahmiri et al. (2018) explore long-term memory of Bitcoin volatility by using data from seven Bitcoin markets at a daily frequency. The Shannon entropy measure and the fractionally integrated GARCH (FIGARCH) approach are used. The study is conducted using four different distributions: Normal, Student's t, Generalized Error (GED), and t-skewed. No matter what distribution assumption is used, empirical results show that long-term memory exists. It has been discovered that forecasts of volatility can be made using historical volatility data. The level of inefficiency is lowest for BITX and highest for COINBASE. Overall, the Efficient Market Hypothesis is strongly refuted, and it is determined that the Bitcoin markets are too hazardous to be used for hedging.

Numerous Japanese writers have likewise looked into virtual money. Takaishi (2018) uses 1-minute data from January 2014 to December 2016 to investigate the statistical characteristics of Bitcoin using the GARCH, GJR-GARCH, and RGARCH models as well as the multifractal detrended fluctuation analysis (MF-DFA) and MF-DFA. The findings show that Bitcoin prices display multifractality, which is caused by temporal correlation and the fat-tailed distribution, allowing for the identification of market inefficiencies. Furthermore, it is determined that Bitcoin was unaffected by the Brexit outcome. Takaishi and Adachi (2018) extract information from a 1-minute Bitcoin price index (BPI), as well as 1-minute data on the EUR-GBP, USD-CHF, and USD-JPY exchange rates, over the time period January 1, 2014 to December 31, 2017. There is research being done on Taylor effects in Bitcoin time series. Results from empirical studies support the presence of a Taylor effect. Furthermore, it is discovered that a temporal lag in the autocorrelation function affects the power value that maximizes the autocorrelation of the power of absolute returns. Additionally, there was no evidence of daily seasonality in the Bitcoin Taylor effect. As they show daily seasonality, this is in contrast to the Taylor influence regarding currency values in reference to foreign currencies. Hattori and Ishida (2019) use intraday data from the CBOE futures price on open contracts and the Gemini price from Bloomberg to examine how investors engage in arbitrage between Bitcoin spot and futures markets. The used data span the months of December 2017 and December 2018. They conclude that arbitrage is adequate in normal circumstances, but that market crashes offer opportunity to engage in arbitrage.

Additionally, there are a number of recent scholarly articles on cryptocurrency efficiency, including Zargar and Kumar (2019b) and Bouri et al. (2019).By also investigating for structural break effects, Bouri et al. (2019) analyze the consistency of the level and volatility of the Bitcoin price. Bitstamp has extracted data that span the time frame of August 19, 2011, to April 29, 2016. Additionally, information spanning the years July 18, 2010, and December 15, 2015 is derived from the Coindesk price index. The use of semi-parametric and parametric approaches provides proof that shocks have a permanent nature and that level mean reversion does not exist. The dynamics of Bitcoin show structural changes, and at least four structural fractures are identified for each period. Both the absolute and squared return measures of volatility show long memory, while the latter case also reveals certain instances of short memory. Overall, there is room for benefit-trading given the evidence of inefficiency.

Data about Bitstamp exchange transactions from January 21, 2013, to January 8, 2018, are used by Zargar and Kumar (2019a). More specifically, daily, 15-, 30-, 60-, and 120-minute data are used. They use the Kuan and Lee (KL) test, the Joint Variance Ratio (JVR) test, the Automatic Variance Ratio (AVR) test, and the Multiple Variance Ratio (MVR) test to determine whether the martingale hypothesis holds true in the Bitcoin market. Findings show that using higher frequencies causes informational inefficiency in the Bitcoin market. Full sample, non-overlapping window, and overlapping moving window estimations all support this. In order to determine whether there is long memory in the Bitcoin market, Zargar and Kumar (2019b) use data from the same time period and frequency as Zargar and Kumar (2019a). The ARMA-FIAPARCH model, the exact Local Whittle estimator (ELW), and the Local Whittle estimator (LW) are used. The results show that there are statistically significant long-memory factors that are stable for both unconditional and conditional volatility measures over different time periods. The analysis of "realized" volatilities calculated using the LW, ELW, and ARFIMA techniques also reveals inefficiency. Estimates from quarterly non-overlapping rolling windows also demonstrate significant persistence. As a result, the market for bitcoins is determined to be inefficient.

3. Studies about Efficiency in Cryptocurrency markets in general

Despite the earliest academic articles only looking at Bitcoin, the bullish market of 2017 has given rise to a number of important studies looking at other high-capitalization digital currencies. This is due to the fact that investment in other digital coins, which offered a solution to lower-budget investors, caused Bitcoin to lose a sizable amount of its market share during this boom time.

From April 28, 2013, through April 30, 2018, Zhang et al. (2018) used daily data on Bitcoin, Ethereum, Ripple, Litecoin, Stellar, Dash, Monero, and Nem. To find stylized facts about digital currencies, they use skewness, kurtosis, and Jarque-Bera tests, autocorrelations, GARCH, and GJR specifications, as well as Detrended Moving Average cross-correlation analysis. These approaches are used to examine these cryptocurrencies' heavy tails, autocorrelations, volatility clustering, impacts of leverage, long-range dependence, and power-law correlation. The Hurst exponent, which has a value of about 0.5, along with rolling windows show that the Bitcoin market is becoming more efficient. Bitcoin, Ethereum, and Nem all exhibit long-range dependency of volatility during each time period under consideration. Furthermore, Philip et al.'s (2018b) analysis uses data from 149 digital currencies with various commencement dates, all of which extend through December 31, 2017. Due to cryptocurrencies' extreme volatility, researchers examine whether long-run autocorrelation is present in daily-based volatility measurements. They look into volatility's jump habit. More specifically, the Jump BAR SV Gegenbauer Log Range (JBAR-SV-GLR) model is used to analyze Bitcoin, Ethereum, Ripple, Litecoin, Dash, and Monero. The use of volatility oscillation memory ratios (VOMRs) allows analysts to determine whether a currency has oscillatory characteristics. Results show that cryptocurrencies with slower transaction times, like Bitcoin, have less oscillatory behavior than cryptocurrencies with quick transaction times, such Ripple (VOMR>1). It is determined that volatility dynamics, not returns, should be used to study long-run atocorrelations in digital currency.

Brauneis and Mestel (2018) examine the effectiveness of 73 digital currencies using daily data encompassing quotations, dollar volume, and market capitalization for the time period from August 31, 2015, to November 30, 2017. They use the runs test (Wald and Wolfowitz, 1940), the variance ratio test (Lo and MacKinlay, 1988), the Kim wild bootstrapped VR test (Chow and Denning, 1993), and the Ljung and Box (1978) test for autocorrelation. Additionally, the Hurst exponent, the Bartels (1982), the Brock et al. (1996) non-parametric BDS tests, and the Kim (2009) automatic version of the latter (Choi, 1999) are used. In addition, the non-parametric market efficiency measure (Godfrey, 2017) is used. The Amihud's (2002) ratio is used to determine liquidity. According to the findings, Bitcoin is the most effective cryptocurrency. It should be emphasized that a digital currency becomes less effective the higher its level of liquidity. Therefore, greater liquidity increases one's ability to make abnormal profits. Charfeddine and Maouchi (2018) used daily closing prices for Bitcoin, Ethereum, Ripple, and Litecoin for periods spanning their launches through February 2018 for their research. They look at the returns and volatility of these cryptocurrencies' long-range dependence (LRD). The LRD behavior (if it exists) in the returns series for Bitcoin, Litecoin, and Ripple, as well as in the volatility series for Ethereum, is a true behavior, not a statistical artifact, according to empirical results. Due to the fact that Ethereum is the only digital coin with an efficient market, evidence suggests that the other three analyzed digital coins have inefficient markets.

Wei (2018) gathers data on 458 cryptocurrencies' prices and overall volume for the year 2017. Liquidity is assessed using the Amihud's (2002) illiquidity ratio, and indications of autocorrelation and non-independence are looked for using a set of efficiency tests. Since the Hurst exponent test only accepts values lower than 0.5, data suggests that anti-persistence exists in illiquid markets. Additionally, it has been shown that smaller currencies experience brief boom-bust cycles that are influenced by speculators' moods. It is clear that in more liquid cryptocurrencies, where the digital currencies under investigation are divided into five categories based on their level of liquidity, the Hurst exponent assumes values close to 0.5. Because markets are more efficient and prices follow a random walk with larger levels of liquidity, it is impossible to generate anomalous returns through speculating. Additionally, Caporale et al. (2018) use daily data for the longest time period up to 2017 for the four cryptocurrencies with the highest market capitalization: Bitcoin, Litecoin, Ripple, and Dash. They use fractional integration and R/S Hurst analysis as their techniques. Results show that there are numerous fluctuations because the amount of persistence is not steady over time. In the case of Litecoin, this is more obvious. Results show that a higher degree of efficiency develops with time, supporting Lo's (1991) Adaptive Market Hypothesis. At first, Litecoin was far more inefficient. Bitcoin, Litecoin, and Dash are shown to be more efficient than Ripple based on values of the Hurst exponent. Overall, it is discovered that the cryptocurrency market is still inefficient, but progress has been made since the Hurst exponent is declining. Overall, there are still prospects for profitable cryptocurrency trading.

The SP500 index, the USD to EUR exchange rate, and a sample of Bitcoin and gold returns for the period between April 2013 and May 2018 are all used by Chaim and Laurini (2018). They start with a conventional log-normal volatility model and add the possibility of discontinuous jumps in volatility and returns. For estimations, Markov Chain Monte Carlo (MCMC) techniques are used. It is suggested that although leaps to mean returns merely have contemporaneous effects, jumps to volatility have a permanent aspect. It is clear that the Mt.Gox catastrophe is associated with the first volatility phase, which runs from late 2013 to early 2014. The second period covers 2017, with December exhibiting the biggest volatility as a result of rising public interest. Jumps to mean returns have been observed to be associated with significant, downward price swings brought on by unsuccessful hacking and forking attempts. Similar to this, Chaim and Laurini (2019) make use of data pertaining to nine significant cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin, Stellar, Dash, Monero, Nem, and Verge) from August 16, 2015 to October 31, 2018. To take into account frequent jumps to the mean and return volatility, they use the multivariate non-linear stochastic volatility model developed by Laurini et al. (2016). This is based on a hybrid MCMC approach that uses a Bayesian mechanism. Findings show that since early 2017, transitory mean jumps have grown greater and are more frequent. Simulations show that stationary models with jump components accurately capture the properties of long-memory reliance.

In order to investigate seasonality trends in the returns, volatility, trading volume, and a spread estimator of Bitcoin, BitcoinCash, Cardano, Dash, Ethereum, IOTA, Litecoin, NEO, Ripple, and Monero, Kaiser (2018) uses daily data for each of these cryptocurrencies. To be more specific, he examines the impact of the following events: (i) Monday effect, (ii) weekend effect, (iii) January effect, (iv) turn of the month effect, and (v) Halloween effect. Overall, it is impossible to reject the EMH in its current state. No consistent or significant calendar effect was found. On the Bitcoin market, however, Monday and backward January effects are visible. Additionally, some relevance is discovered in relation to trade volume, volatility, and spreads. In a recent study, Köchling et al. (2019) used information on 75 cryptocurrencies that covered the time from August 31, 2015, to August 31, 2018, in their analysis. We only take into account currencies with a capitalisation of at least $1,000,000 USD. In order to analyze the temporal delay of digital currency markets to price information, they apply the three delay measurements suggested by Hou and Moscowitz (2005). Results show that price delay decreases dramatically during the course of the study period. It is clear that as time goes on, bitcoin marketplaces become more effective. Results also strongly suggest that market capitalisation and liquidity have a considerable relationship with price delay. Table 2.1 displays the studies investigating the existence or not of efficiency in this survey.

Table 2.1. Studies examining efficiency in cryptocurrencies

Study	Data source	Methodology	Efficiency or not
Aggarwal (2019)	www.coindesk.com	Augmented Dickey-Fuller (1979) test Phillips-Perron (1987) test KPSS (1992) test Zivot and Andrews (1992) structural breakpoint test Lo and Mackinlay (1988) multiple variance ratio (MVR) test BDS test by Broock et al. (1996) ARCH by Engle (1982) GARCH by Bollerslev et al. (1992) E-GARCH by Nelson (1991) TARCH by Zakoian (1994)	Inefficiency
Almudhaf (2018)	http://grayscale.co/bitcoin-investment-trust	OLS with Newey-West's covariance estimator	Inefficiency
Alvarez-Ramirez et al. (2018)	www.coindesk.com	Detrended Fluctuation Analysis (DFA) Scaling Exponent over Sliding Window Asymmetric Scaling Exponent	Inefficiency
Al- Yahyaee et al. (2018)	Datastream Coindesk Price Index website	Multifractal Detrended	Inefficiency

		Fluctuation Analysis (MF-DFA)	
Bariviera (2017)	Datastream	Hurst (1951) exponent Detrended Fluctuation Analysis (DFA)	Inefficiency but decreasing
Bariviera et al. (2017)	Datastream	Hurst (1951) exponent Detrended Fluctuation Analysis (DFA)	Inefficiency/ Efficiency
Bouri et al. (2019)	Bitstamp Coindesk Price Index website	ARIMA (parametric, semiparametric d estimations) Bai and Perron's (2003) structural break tests	Inefficiency
Brauneis and Mestel (2018)	Coinmarketcap.com	Ljung and Box (1978) test Wald and Wolfowitz (1940) runs-test Variance ratio test by Lo and MacKinlay (1998) Kim (2009) wild bootstrap automatic variance ratio test based on Chow and Denning (1993) Bartels (1982) test Hurst (1951) exponent	Higher efficiency in Bitcoin
Caporale et al. (2018)	Coinmarketcap.com	R/S analysis Fractional integration	Inefficiency
Chaim and Laurini (2018)	Coinmetrics.io FRED database	Laurini et al. (2016) model	Inefficiency
Chaim and Laurini (2019)	Coinmetrics.io	Laurini et al. (2016) model	Inefficiency
Charfeddine and Maouchi (2018)	Coinmarketcap.com	Geweke and Porter-Hudak (1983) (GHP) test Gaussian semi parametric (GSP) test of Robinson (1995a) Local Whittle (LW) of Robinson (1995b)	Inefficiency, Efficiency (ETH)

		Exact Local Whittle (ELW) of Shimotsu and Phillips (2005) R/S test of Lo (1991) Rescaled Variance (V/S) test of Giraitis et al. (2003)	
Cheah et al. (2018)	www.bitcoincharts.com	FCVAR by Johansen and Nielsen (2012)	Inefficiency
Hattori and Ishida (2019)	Bloomberg	Regression	Inefficiency
Jiang et al. (2018)	www.bitcoinaverage.com	Hurst (1951) exponent and rolling windows Ljung -Box test AVR test	Inefficiency
Kaiser (2018)	Coinmarketcap.com	Bid-ask spread estimation as by Abdi and Ranaldo (2017) Volatility estimation as by Roger and Satchell (1991) GARCH by Bollerlev (1986)	Efficiency
Khuntia and Pattanayak (2018)	www.coindesk.com	Dominguez-Lobato (DL) test Generalized Spectral (GS) test	Efficiency evolving-(Adaptive Market)
Köchling et al. (2018)	www.bitcoinaverage.com	Ljung and Box (1978) test Escanciano and Lobato (2009) automatic portmanteau test Wald and Wolfowitz (1940) runs-test Bartels (1982) Durlauf (1991) spectral shape test Escanciano and Velasco (2006) generalized spectral test Kim (2009) wild bootstrap automatic variance ratio test	Inefficiency but decreasing

		Brock et al. (1996) BDS test Hurst (1951) exponent	
Köchling et al. (2019)	Coimarketcap.com	3 delay measures by Hou and Moskowitz (2005)	Inefficiency but decreasing
Kristoufek (2018)	www.coindesk.com	Efficiency Index of Kristoufek and Vosvrda (2013)	Inefficiency Efficiency only after cooling down of bubbles
Kurihara and Fukushima (2017)	www.bitcoinaverage.com	Ordinary Least Squares (OLS) Robust Least Squares (RLS)	Inefficiency
Lahmiri and Bekiros (2018)	www.coindesk.com	Largest Lyapunov Exponent (LLE) Shannon entropy (SE) Multi-fractal Detrended Fluctuation Analysis (MF-DFA)	Inefficiency
Lahmiri et al. (2018)	data.Bitcoinity.org	Fractionally integrated GARCH (FIGARCH) by Baillie et al. (1996) Shannon entropy by Shannon (1948)	Inefficiency
Mbanga (2018)	www.bitcoincharts.com	Huber (1964) M estimations	Inefficiency
Nadarajah and Chu (2017)	www.bitcoinaverage.com	Ljung and Box (1986) test Runs test by Wald and Wolowitz (1940) Bartels (1982) test Wild-bootstrapped AVR test by Kim (2009) Spectral shape tests by Durlauf (1991) and Choi (1999) BDS test by Brock et al. (1996) Portmanteau test by Escanciano and Lobato (2009) Generalized spectral test by Escanciano and Lobato (2006)	Inefficiency

Phillip et al. (2018a)	Brave New Coin (BNC) Digital Currency indices	Ljung and Box (1986) test Kolmogorov-Smirnov (1951) test Generalized long-term memory by Gray et al. (1989) Generalized long memory (GLM)-stochastic volatility (SV)-leverage (LVG) and heavy tails (HT) model	Inefficiency
Phillip et al. (2018b)	Brave New Coin (BNC) Digital Currency indices	Jump BAR SV Gegenbauer Log Range (JBAR-SV-GLR) model, as combination of Zhu et al. (2014) and Taylor (2007)	Inefficiency
Sensoy (2018)	64 Bitcoin exchanges	Matilla-Garcia and Marin (2008) Lopez et al. (2010)	Inefficiency More efficient since 2016
Takaishi and Adachi (2019)	www.coindesk.com Histdata.com	Autocorrelation tests	Inefficiency
Tiwari et al. (2018)	www.coindesk.com	Hurst (1951) exponent DFA CMA-1 and CMA-2 by Bashan et al. (2008) Periodogram-LAD and Periodogram-LS by Taqqu et al. (1995) GPH by Geweke et al. (1983) MLE estimators by Haslett and Raftery (1989)	Inefficiency
Urquhart (2016)	www.bitcoinaverage.com	Ljung and Box (1986) test Runs test by Wald and Wolowitz (1940) Automatic variance test (AVR) Wild-bootstrapped AVR test by Kim (2009)	Inefficiency

		BDS test by Brock et al. (1996) Hurst (1951) exponent	
Urquhart (2017)	www.bitcoincharts.com	Clustering test Probit model	Inefficiency
Vidal-Tomás and Ibañez (2018)	Bitstamp and Mt.Gox	CGARCH, AR-CGARCH-M	Inefficiency but decreasing
Wei (2018)	www.coinmarketcap.com	Ljung and Box (1986) test Runs test by Wald and Wolowitz (1940) Bartels test Automatic variance test (AVR) Wild-bootstrapped AVR test by Kim (2009) BDS test by Brock et al. (1996) Hurst (1951) exponent Amihud's (2002) illiquidity ratio	Inefficiency
Zargar and Kumar (2019a)	Bloomberg	Variance ratio (VR) test by Lo and MacKinlay (1988) Multiple Variance Ratio (MVR) test by Chow and Denning (1993) Automatic Variance Ratio (AVR) test by Choi (1999) Joint Variance Ratio (JVR) test by Chen and Deo (2006) Kuan and Lee (KL) (2004) test	Inefficiency at higher data frequencies
Zargar and Kumar (2019b)	Bloomberg	Local Whittle (LW) estimator Exact Local Whittle (ELW) estimator ARFIMA	Inefficiency
Zhang et al. (2018)	Coinmarketcap.com	Autocorrelation tests, GARCH by Bollerslev (1986), GJR model by	Inefficiency

		Glosten et al. (1993), Detrended Fluctuation Analysis (DFA by Peng et al. (1994), Detrended Moving Average Correlation Analysis (DMCA) by He and Chen (2011) Hurst (1951) exponent	

4. Conclusions

The body of research attempting to gauge the effects of the Efficient Market Hypothesis (EMH) on cryptocurrencies has been accumulating data at an ever-increasing rate. There is already a sizable body of academic research that supports the inefficiencies of digital currency markets, particularly the Bitcoin market.

The vast majority of the thirty-eight studies under review examined weak-form efficiency, which determines whether prices represent the information contained in the previous series of prices. The majority of the scholarly studies that were analyzed argue against the validity of the EMH. As dependence on previous returns becomes apparent, long memory in bitcoin time series is detected. There is a wide range of tests used, including the Hurst exponent, the Bartels test, the Variance Ratio test, and its parameters. Investors can thus forecast future returns using information from the past. This makes it possible for traders to employ winning techniques with very little risk.

It should be mentioned that in the markets for Bitcoin as well as in the cryptocurrency market generally, long-range dependence that results in inefficiency is shown to diminish over time. This offers helpful insight and sparks a more lively discussion regarding the future of digital currency. These coins are incredibly complex investment instruments that have drawn a sizable number of new investors and are anticipated to play a key role in the future of finance.

By offering a holistic perspective on the efficiency characteristics and profit prospects in digital currency exchanges, the present study fills a vacuum in the pertinent literature. To inform policymakers, academics, investors, and the economic press about the profitability dynamics restrained in the markets of these novel liquidity forms, a systematic survey was conducted.

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Chapter 3

A Systematic Review on Bubble Dynamics of Cryptocurrency Prices

1. Introduction

The existence of bubbles has been studied across a variety of relevant fields, including information source, contagion effects, the rate of development, signal processing, the impact of algorithmic trading, and the distribution of news via social media. The reasons for this interest are far from complicated to comprehend, as investors, governments, and regulators have long been interested in significant price changes in investment forms. In addition, unexpected changes in asset prices, such as the creation and exacerbation of social and economic inequities, have been of primary interest due to their societal influences.

Unsurprisingly, this has led to a great deal of interest in the development of price bubbles (Frehen et al., 2013; Corsi and Sornetter, 2014; Vogel and Werner, 2015), particularly when the asset under consideration is a brand-new, promising tool that can be used for reserve and liquidity management and has a fascinating level of appeal to speculative investors looking for untapped profit margins. Notably, a wide range of opposing viewpoints regarding the definition of bubbles have emerged. The method that views assets as investing tools capable of significantly separating their nominal value from their intrinsic value is the asset-pricing approach, which is the most well-known of these (West, 1987; Diba and Grossman, 1988). It should be emphasized that an asset's nominal value is defined as the price at which it may be purchased or sold, whereas its fundamental value is lower and typically determined by its manufacturing costs. The 'average distance' between bubble and fundamental prices is how Cheah and Fry (2015) define the bubble component. When investors are influenced by psychological variables unrelated to the inherent worth of the asset, irrational bubbles develop. They concur that Bitcoin's intrinsic value is zero. Contrarily, the market value of cryptocurrencies exhibits bubble-like behavior. The multiplicity by which nominal prices surpass fundamental ones keeps growing, which causes explosive behavior and the bursting of bubbles. Such discrepancies from underlying prices are mostly caused by excessively upbeat market sentiment, which raises the amount of overall asset demand. When supply is steady or declining, as it is for the majority of digital currencies, this phenomena of abrupt demand elevation is amplified.

Regarding their unique qualities, such as their nature and purposes and whether they are considered commodities or fiat money, digital currencies have been a topic of attention. According to Baur et al. (2018), Bitcoin is a cross between fiat money and commodity money. While digital coins avoid the requirement for commercial banks' intermediary services by using peer-to-peer (P2P) networks and open-source software to prevent double spending (Dwyer, 2015). The majority of cryptocurrencies are rather decentralized. The limited supply and high demand for this digital currency are the two factors that determine its value. According to Ammous (2018), only Bitcoin can act as a store of value since it is viewed as more reliable than other virtual currencies, its supply can be forecast, and it can withstand manipulation owing to its dominance in the cryptocurrency industry. But according to Baur et al. (2018), Bitcoin is not a reliable haven during times of crisis. Corbet et al. (2019) carried out an extensive survey on cryptocurrencies as a financial asset.

In order to provide the most accurate representation of the colorful nomenclature used in pertinent academic articles, this paper surveys the primary relevant literature in the field of the formation of digital currency bubble prices. An in-depth analysis of the inflationary factors affecting bitcoin values and the price development of other crucial assets is made possible by a comprehensive comprehension of big nominal price deviations from fundamental pricing. This study intends to provide more insight into bubble formation issues since a better understanding of this phenomena is beneficial for society as a whole in addition to academics, market participants, or individuals.

The most common definitions of asset bubbles and the most significant bubble creation moments in economic history are presented in Section 2. A thorough examination of the most widely used methodological approaches for determining if cryptocurrencies are in a bubble is provided in Section 3. A review of the research on the creation of price bubbles in digital, decentralized currencies is presented in Section 4. The explanation of the conclusions and their economic foundations concludes in Section 5. A brief summary of the research looked into and the bubbles found in these scholarly works are given in Tables A1 and A2 in the Appendix.

2. Asset bubbles definition and popular bubble events

Over the years, the phrase "bubble formation" has been given a variety of different, though not incompatible, definitions. A straightforward way to describe bubbles is as "systematic deviations of the market value from the fundamental value of the asset," where the latter is the net present value of the asset's expected future cash flows. A balloon might be a better metaphor for some financial advertisements, according to Van Horne (1985). Yes, it is puffed up, but not to the point where it pops. The inevitable deflation happens more gradually. "Bubbles is a fuzzy word filled with import but lacking any solid operational definition," claimed Garber in 1990. He argues that since bubbles are only financial events that we have thus far failed to comprehend, one shouldn't attempt to explain them. According to him, none of the principles can account for such discrepancies. Such a hypothesis on bubbles was supported by O'Hara (2008), who noted that it depends on the combination of agents' and markets' levels of rationality.

According to Brunnermeier and Oehmke (2013), bubbles have two phases: a run-up phase that results in the construction of bubbles and imbalances, and b crisis phase, during which risk that has been amassed manifests itself and the crisis arises.

Additionally, Shiller et al. (1984) show that mercurial investors who act on the basis of flimsy enthusiasms and bubbles control asset markets. While Kindleberger and Aliber (2011) viewed bubbles as rapid increases in an asset's market value and that the initial upwards surge sets off expectations of a series of price enlargements, Brunnermeier and Oehmke (2013) described bubbles as spectacular price increases that end in bursting. It is because of this that there is increased interest in that particular asset and a corresponding increase in demand for investments in it. This is the 'irrational exuberance' that investors are alleged to exhibit (Shiller, 2015).

For new investment assets like virtual currencies, a typical pricing pattern develops. The first coins of a new kind of currency are typically offered at a very high price. Many cryptocurrencies have an upper limit on their supply, such as Bitcoin, which will stop being produced once it hits 21 million coins. This is something to keep in mind. Until 2040, this supply will continue to rise in descending increments before remaining at that level indefinitely (Baur et al., 2018). The three most significant historical bubbles, according to Azariadis (1981) and Frehen et al. (2013), were the Dutch "tulip mania," the South Sea bubble in England, and the Mississippi Company collapse in France. Given the spectacular price increases that occurred, these are regarded as significant turning points in the history of financial and economic events. Based on a substantial body of information about financial market abnormalities, Van Horne (1985) makes the case that during the tulip mania, a single bulb may be sold for the equivalent of many years' income. He also considers the potential of bubbles and manias. As Garber (1990) supports, the Dutch tulipmania of 1634–1637 was distinguished by astronomically high prices for single bulbs of valuable and rare tulip types. It should be emphasized that even common tulip types experienced price hikes of up to 2,000% in a single month during the peak of Tulipmania in early 1637, just before the bubble burst.

According to Johannessen (2017), widespread tulip bulb stock price speculation on the stock markets in numerous Dutch towns became a common occurrence. It is interesting to note that due to market optimism in the Netherlands, the price of a bulb like this rose from between 10 and 25 guilders in 1612 to around 6,650 guilders 25 years later. This optimism was a result of both product and institutional innovation (stock exchanges). According to Johannessen (2017), the purpose of the formation of the South Sea Company was to refinance the enormous national debts that the British and French had accumulated as a result of the Spanish War of Succession. The South Sea Company's stock worth reached the staggering sum of £200 million in less than ten years. Prices rose as a result of promises of large profits in the French colonies in North America made to investors in France. According to Brunnermeier and Oehmke (2013), it is widely believed that the South Sea bubble (1720) was caused by the large number of investors from the Continent who bought South Sea Company shares in London. The company's value deteriorated and dropped to lower levels than before the bubble burst because there was actually no expectation of large trade and profits.

The Compagnie d'Occident (or "Company of the West"), founded by John Law in order to obtain the sole rights to develop the huge French holdings in the Mississippi River valley of North America, was the cause of the Mississippi bubble (1719–1722). The corporation Law used to sell its shares to the general public in exchange for publicly-issued securities from the state held the monopolistic authority over the French tobacco and African slave markets. When inflation became too much as a result of the excessive issuance of public debt, the public's mania to exchange debt for stock in the corporation subsided. As a result, the bubble burst and the French equity markets crashed. According to Frehen et al. (2013), innovation and irrational investor euphoria were the main forces behind bubble expectations in all three cases. They reject clientele-based hypotheses that link emphasis to short-sale limitations and bubble-riding.

3. Methodological Approaches for Defining, Detecting and Measuring Bubbles

3.1. Main existing literature on Detecting Bubbles

The Lucas Jr. (1978) asset pricing model serves as the foundation for academic research on the identification of asset price bubbles based on fundamentals. In order to test for price bubble behavior, a number of significant contributors have created econometric approaches along this axis. According to Blanchard and Watson (1982), bubbles can result from a variety of processes, and some bubbles can violate the variance limitations that are implied by a group of rational expectations models. According to Shiller et al. (1984), social movements and habits throughout particular time periods are what cause asset price increases. The observations of market players and human nature are the causes of investing incentives and asset price volatility. Three factors—durability, scarcity, and widespread beliefs—are necessary for the formation of bubbles, according to Tirole (1985). He makes the notion that limited supply might avoid bubbles and that scarcity is based on new units costing the same as used ones. When it comes to Bitcoin, this might be extremely logical. Additionally, he makes a distinction between the genuine bubble, which is created by the fundamentals of this market, and the financial bubble, which is dependent on market pricing. Notably, he concurs that models with overlapping generations should put more of an emphasis on speculative assets than on monetary assets. Sunspots and other "rational bubble" solutions only exhibit weak or no expectational stability in rational expectations models, according to Evans (1989), and there is only one very expectational stable solution in linear models.

In addition to asserting that negative rational bubbles in stock prices cannot arise, Diba and Grossman (1988) also argue that stock prices do not contain explosive price bubbles. If a bubble breaks, there is no chance that it will ever reappear. A rational intrinsic bubble is one that derives all of its oscillations from external economic fundamentals but not from extraneous influences. Froot and Obstfeld (1989) concentrated on such bubbles. They discover proof of US stock market bubbles that is challenging for other models to account for. Asset bubble tests, according to Gurkaynak (2008), are unable to provide sufficient information on the presence or absence of bubbles. He discovers that the inclusion of model assumptions like time-varying discount rates, risk aversion, or structural breaks only very little permits the appearance of bubbles. Furthermore, it is impossible to discern between bubbles and fundamentals that change over time or under a new regime. Overall, he contends that we may not be completely positive that a bubble actually exists even when bubble detection techniques show it to be there.

3.2. Definition of Bubbles: Intrinsic versus Extrinsic rational bubbles

When asset prices continue to rise because investors think they may be able to sell the overpriced asset at a greater price in the future, rational bubbles form (Flood and Hodrick, 1990). Investors need compensation for assuming this risk, which increases as time goes on because the risk of a bubble collapse at some point in the future increases. The constant need for bigger profits causes price inflation, which ultimately causes the bubble to burst. According to Dale et al. (2005), intrinsic rational bubbles develop when investors repeatedly and consistently make incorrect assessments of the fundamentals of an asset. This happens more frequently with products utilizing modern technology because it is more challenging to pinpoint their precise underlying worth. After extended periods of price increases, crashes typically emerge from informational dynamics. Extrinsic rational bubbles, sometimes known as "sunspots," develop when rational investors must deal with high levels of economic environment uncertainty. This is what prompts them to attribute value—in terms of price prediction—to exogenously determined elements that actually have little bearing on asset underlying values. Reliance on false information that results in subpar management abilities is the main cause of extrinsic rational bubbles.

3.3.Approaches for Detecting and Measuring Bubbles

Regarding the identification and measurement of price bubbles, there is no apparent unanimity. Deterministic temporal trends, explosive AR(1) processes, or even more intricate stochastic processes could all be manifestations of rational bubbles. There have been four main alternate techniques to characterize bubbles, among others. The first definition of a bubble is more conventional and is based on comparing the nominal value of the underlying asset to its fundamental value. It should be mentioned that, when all pertinent information has been taken into account, the fundamental value is defined as the present value of the payoffs derived from the assets (Taipalus, 2012). The asset-pricing approach therefore assumes that bubbles develop when the nominal value that corresponds with market value is less than the asset's intrinsic worth.

Foster and Wild (1999) offer a different method for modeling the fundamental value by employing the sigmoid (or logistic) curve method. When attempting to capture the various stages in a bubble's history, such as the expansion phase, the inflexion phase, and the saturation phase, this methodology is helpful. All three are regarded as typical stages in the development of price bubbles. While the inflexion phase is characterized by stability and the saturation phase by a decline in prices, the expansion phase displays positive growth. The goal of this strategy is to determine when the saturation period began. It is important to keep in mind that the positive growth phase does not actually correspond to the era of price decline. The biggest disadvantage of using the sigmoid curve approach is that it may not be as accurate when measuring during many bubbles.

The Markov-switching Augmented Dickey-Fuller (MSADF) unit root test, which finds explosive autoregressive roots, provides an approach suitable for testing regarding single or several bubbles. Hall et al. (1999) suggested this method to follow transitions from non-bubble to bubble regimes. This method's fundamental flaw is its difficulty in determining whether regimes exhibit significant volatility or explosive autoregressive behavior. The Phillips et al. (2014) and Phillips et al. (2015) approaches might be found among the widely used methods for spotting price bubbles. This article discusses a bubble test based on the notion that bubbles behave in a somewhat explosive manner, specifically an autoregressive root with the formula 1+gT(-m), where g is positive and the parameters m and c are between 0 and 1. This test supports the idea that proposes variations in pricing tendencies during upswing phases compared to tendencies during downswing phases. As a result, sub-martingale behavior is thought to differ from martingale behavior during bullish and bearish markets.

4. **Literature on Cryptocurrency Bubble Price Formation**

A growing number of empirical articles have looked into the dynamics of bitcoin market bubble prices. The majority of them have been looking at how Bitcoin's price changes, but there have also been studies on the CRIX index, other significant digital coins, and comparisons to national currencies. Additional issues, such the part played by cybercrime and illegal behavior, have also been thoroughly examined. To date, it has been identified that cryptocurrencies contain a number of pricing inefficiencies (Urquhart (2016), Sensoy (2019), Mensi et al. (2019), Corbet et al. (2019), to be in isolation from other traded assets (Corbet et al. (2018)), to present evidence of price clustering (Urquhart (2017)), pricing bubbles (Corbet et al. (2018)), regulatory ambiguity (Fry (2018)), and exceptional levels of both complex and uncomplex fraud (Gandal et al. (2018)). The value of cryptocurrencies has drawn a lot of attention, with a focus on pricing effectiveness, market dynamics, and the potential existence of a pricing bubble. While Van Vliet (2018) looked at the impact of Metcalfe's Law on the valuation of Bitcoin, Hayes (2019) discovered that the marginal cost of production plays a significant role in explaining Bitcoin prices.

According to Dwyer's (2015) research, the use of cryptocurrency technologies and a cap on production can lead to an equilibrium where a digital currency has a positive value. The impact of variables like stock market returns, currency rates, gold and oil returns, the Deferal Reserve and ECB's rates, and internet trends on Bitcoin returns for different time periods was examined by Panagiotidis et al. (2018) using a LASSO framework. The two factors that have the greatest impact on Bitcoin returns are search volume and gold returns. Fry (2018) demonstrated how liquidity problems could cause significant tails in the markets for bitcoin and other cryptocurrencies. Investigations of how different cryptocurrencies interact with one another have also been conducted. Wei (2018) discovered that, contrary to market predictions, the issuance of Tether has no effect on following Bitcoin returns, but it does have an influence on traded volumes when utilizing a VAR technique. Felix and von Eije (2019) discovered that there is an average amount of under-pricing of 123% for USA ICOs and 97% for the other nations looked at while researching ICOs. Hendrickson and Luther (2017) even looked into the procedure for outlawing Bitcoin. The authors discovered that a large enough government could outright outlaw a cryptocurrency as long as it spread sufficiently severe penalties, even without depending on punishments.

There is now a great deal of urgency to deepen our understanding of a product that has been identified as a potential improvement to and replacement for conventional cash as we know it because of the continuing expansion of cryptocurrencies and the underlying exchanges on which they trade. When compared to a number of other traditional financial instruments, Bitcoin has now matured to the point where it has a strong and liquid derivatives market (Corbet et al., 2018). One important topic of research is on the connections between cryptocurrencies and other more conventional financial markets as our understanding of FinTech develops (Goldstein et al., 2019) and the expanding utility of blockchain (Chen et al., 2019). Based on this increased potential for criminality and malpractice, regulatory authorities and policy-makers have both watched the development of cryptocurrencies with some caution. According to Foley et al. (2019), 46% of Bitcoin transactions are illicit, which amounts to approximately $76 billion annually. This is known as "black e-commerce" and is thought to be in the same area as the U.S. and European marketplaces for illegal substances. While in-depth research into the problems relating to cryptocurrencies is still being conducted, we are continuing to examine the potential means through which these novel goods might have an impact on gullible audiences. It is important to take into account their possible application by businesses looking to profit from "crypto-exuberance" (Akyildirim et al., 2019). One important problem has persisted in spite of the research's many concerns over the basic justification for investing in this novel asset class. What is the precise cost of one bitcoin unit? While taking into account the widespread application of bubble-identifying approaches, we set out to construct an evaluation of the broad estimations.

Cheung et al. (2015) use daily Bitcoin data from July 17, 2010 to February 18, 2014 and adopt the Phillips et al. (2012) methodology to investigate whether price bubbles exist in Bitcoin's largest exchange up to that point, the Mt. Gox, while taking into consideration research specifically analysing the potential for bubbles in the markets of cryptocurrencies. According to estimates from the Generalized Supremum Augmented Dickey Fuller (GSADF) statistic, the majority of bubbles only endure a few days on average. There have been three enormous Bitcoin bubbles found. Beginning on April 24, 2011, the first bubble lasts until July 3, 2011. The second one runs from January 27 through April 15, 2013. The third Bitcoin bubble in Mt. Gox, which starts on November 5, 2013, and lasts until February 18, 2014, is the biggest one. As time goes on, it is evident that bubble behavior persists for longer periods of time.

The demise of the Mt. Gox may have been caused by the previous bubble's implosion. To identify price bubbles in the US and Chinese markets, Su et al. (2018) use the Supremum Augmented Dickey Fuller (SADF) and generalized Supremum Augmented Dickey Fuller (GSADF) tests by Phillips et al. (2012). We use the weekly average prices in CNY and USD between June 16, 2011 and September 30, 2017. Econometric estimates show that severe financial crises can cause massive, long-term price increases, but domestic factors are the causes of short-term bubble behavior. Furthermore, they back the idea that investing in Bitcoin can help reduce market-specific risk. The Chinese market has been shown to have four explosive bubbles. Beginning on February 7, 2013, the first bubble lasts until April 18, 2013. The second one gets under way on November 7 and ends on December 12 of that same year. The third bubble bursts in the early months of 2017, while the final bubble starts on May 18 and deflates on September 14 of that same year. The first one, in terms of the US Bitcoin market, ends in August 2012. The three subsequent bubbles line up with those in the Chinese market. In their study of Bitcoin and Ethereum, Corbet et al. (2018) used daily data from January 9, 2009 and from August 7, 2015 to November 9, 2017, respectively. The authors use a rolling-window technique with the Supremum-, Generalized Supremum-, and Reverse Supremum Augmented Dickey-Fuller specifications to try and capture intrinsic bubbles, herd behavior, and time-varying fundamentals in discount factor models. Econometric results show that the Bitcoin bubble occurred between 2013 and 2014 at the beginning of the year. Additionally, Ethereum displays bubble behavior at the start of 2016 and in the middle of 2017. Overall, bubbles in the currencies examined are not long-lived.

Regarding Bouri et al. (2019), they analyze co-explosivity in their markets using daily data for Bitcoin, Ripple, Ethereum, Litecoin, Nem, Dash, and Stellar from August 7, 2015 to December 31, 2017. It is discovered that Bitcoin's explosivity reduces Ripple's explosivity. Additionally, rising Ripple market values are made more likely by the high prices of Ethereum, Litecoin, Nem, and Stellar. Stellar has a detrimental effect on Ethereum's explosiveness while Bitcoin, Ripple, Nem, and Dash serve to strengthen them. There is proof that the bubble of Litecoin is fueled by Bitcoin, Ripple, Nem, Dash, and Stellar. Additionally, it is discovered that five digital currencies have a favorable impact on Nem and Stellar's bubble behavior. It should be remembered that currencies with lower capitalization might have an impact on those with higher capitalization.

Geuder et al. (2019) use daily Bitcoin data that span the period from March 19, 2016, to September 19, 2018, by employing alternative estimating specifications. They use the Phillips et al. (2015) bubble detection methodology. The Log-Periodic Power Law (LPPL) model is additionally used to identify crucial intervals in bubble evolution. For parameter optimization, the latter uses a Covariance Matrix Adoption Evolution Strategy (CMAES). Three Bitcoin bubbles were present in 2016 according to Monte Carlo simulations, Supremum Augmented Dickey Fuller (SADF), and Generalized Supremum Augmented Dickey Fuller (GSADF) test statistics. More specifically, bubbles are found to have been present in May and June, at the end of October and the beginning of November, as well as in December 2016 and January 2017. Additionally, bubbles were noticed in 2017 from mid-May to early July, early August to mid-September, and mid-October to early January 2018. It is discovered that the procedure for the bubble bursting starts on December 6, 2017.

By integrating a series of forward recursive ADF unit root tests in right tails, the supremum ADF (SADF) methodology is utilized to find bubbles. The generalized SADF (GSADF) specification is preferred in the event that there are frequent episodes of booms and busts caused by swift changes in market conditions. This enables right-sided double recursive test for discovering unit roots by allowing changing in starting points and end points of recursive schemes over flexible windows. Furthermore, using a sample sequence with a defined end point but an unfixed starting point, the backward SADF (BSADF) enables performing a supremum ADF test.

A different line of inquiry into cryptocurrencies concentrates on studies using the Log-Periodic Power Low (LPPL) paradigm. In order to anticipate crashes, MacDonell (2014) uses weekly data from July 18, 2010 to August 25, 2013 and applies Autoregressive Moving Average (ARMA) techniques and the Log Periodic Power Law (LPPL) models by Johansen-Ledoit-Sornette (JLS). According to results from ARMA methods, the CBOE Volatility Index, which measures investor emotion, is what determines Bitcoin pricing. It should be emphasized that the December 2013 crash was predictably foreseen by the LPPL model. To identify price bubbles in Bitcoin and Ethereum, Bianchetti et al. (2018) used daily data covering the period from December 1, 2016, to January 16, 2018. Genetic algorithms and the Johansen, Ledoit, and Sornette (JLS) and Phillips, Shi, and Yu (PSY) models of the Log Periodic Power Law (LPPL) are the approaches used. To be more explicit, the JLS model's specifications for Ordinary Least Squares (OLS), Generalized Least Squares (GLS), and Maximum Likelihood Estimation (MLE) are used. Additionally, the PSY methodology's two versions are used. According to estimates, a Bitcoin bubble starts in the middle of December 2017 and lasts through the first half of January 2018. For Ethereum, bubble behavior began to emerge in the middle of June 2017, and a weaker bubble indicator was discovered around January 12, 2018.

A generalized Metcalfe's law and the Log Periodic Power Law Singularity (LPPLS) model are used by Wheatley et al. (2018) to forecast bubbles and crashes in the markets for digital currencies. They describe four bubbles that have emerged in the

Bitcoin market, each with a different height and length, and define bubbles as departures from the Market-to-Metcalfe value that they specify. Beginning on: August 28, 2012, April 10, 2013, December 5, 2013, and December 28, 2017, these bubbles have occurred. These findings support the idea that there is no random walk in bitcoin markets.

Based on econophysics, the Log-Periodic Power Law (LPPL) model aims to establish whether a critical point has been achieved. According to the theory, bubbles and crashes follow a specific power law with log-periodic oscillations. This model can anticipate when a bubble or crash will occur since it has a part that accounts for the market's high volatility before a crash.

To identify price bubbles, a variety of alternative estimating frameworks have been used. In order to investigate the Granger causality between Bitcoin's price and transactions as well as between Bitcoin's price and investors' appeal, Bouoiyour et al. (2014) use data from the Bitcoin Price Index (BPI), the exchange-trade ratio (ETR), and users' interest in Bitcoin. The data chosen cover the time period from December 2010 to June 2014 and are collected on a daily basis. The desirability of Bitcoin effects the Bitcoin Price Index at short- and long-run frequencies, and there is a reverse (feedback) effect at lower frequencies, revealing that bubble behavior exists in Bitcoin markets. It is discovered that this cyclical nexus lacks a constant duration. Additionally, Bouoiyour et al. (2016) analyze and explain the price movements of Bitcoin using the ground-breaking method known as Empirical Mode Decomposition (EMD). They extract data into separate Intrinsic Mode Functions (IMFs) and filter high frequency (fluctuating process) from low frequency (slowing variable components) modes using daily Bitcoin Price Index (BPI) data from December 2010 to June 2015. Moreover, Pearson correlations and analysis of component variance are used. Findings show that, in addition to Bitcoin's speculative nature, long-term fundamentals, as reflected by the low-frequency components, also play a significant role in determining price changes. To do price modeling and identify bubbles, Cheah and Fry (2015) use daily closing prices for the Bitcoin Coindesk Index for the years July 18, 2010, to July 17, 2014. They employ a price model that incorporates a Wiener process and a jump process in accordance with Johannessen (2017) to regulate whether the intrinsic rate of return and the intrinsic degree of risk are constant. They perform a BDS test to track bubble behavior and look at the bubble component. The Bitcoin market has a bubble character, according to the findings, and the random walk theory is disproved. The speculative nature of Bitcoin, fueled by its high volatility and volatile behavior, is further supported by econometric results.

Fry and Cheah (2016) create an econophysics model to study how bubbles emerge in the markets for Bitcoin and Ripple. They use data from February 26, 2013, to February 24, 2015, on market capitalization, market share, daily closing values of the Bitcoin Coindesk Index, and weekly statistics on Ripple. Exogenous and endogenous shock events affecting these currencies are taken into account. Tests for spillover and contagion effects are run, and univariate and bivariate model representations are used. Evidence shows that Ripple is overpriced in comparison to Bitcoin and that the former's influence on the latter caused recent drops in Bitcoin's price to be worsened.

Holub and Johnson (2019) look into how the 2017 bull run in Bitcoin's peer-to-peer (P2P) market was impacted by the bubble. They use daily data from January 2017 to June 2018 in their analysis. In this way, the bullish, explosive, and decreasing periods of Bitcoin's market quotes are investigated. Additionally, national currency statistics from 13 developed and emerging economies are included. Analysis of publicly accessible bid-ask spreads is given priority. Results show that spreads for the US dollar, the Hong Kong dollar, the New Zealand dollar, the Swedish krona, and the Singapore dollar are all decreasing. However, while they adhere to the belief that higher Bitcoin prices cause wider spreads, the Euro, the United Kingdom pound, the Australian dollar, the Brazilian real, the Norwegian krone, the Polish zloty, the Russian ruble, and the South African rand do not present significant falls in spreads. This supports the theory that the bubble's impact on Bitcoin pricing in the P2P market was dependent on currency and nation.

Chen and Hafner (2019) use daily data from August 8, 2014 to May 15, 2018 to examine whether sentiment-induced bubbles exist in markets for digital currencies. They perform a smooth transition autoregressive model (STAR) with regime switching and test for bubbles using a transition variable and the CRIX index. Additionally, a Beta-t-Exponential Generalized Autoregressive Conditional Heteroskedasticity (Beta-t-EGARCH) model is used to describe volatility. According to estimates, the sentiment index and volatility have a negative relationship. The period from May 2017 to April 2018 has multiple periods that have been identified. It is discovered that volatility is higher when there are bubbles.

In a more recent line of research, Corbet et al. (2019) use 5-minute data and methodologies such as Dynamic Conditional Correlations Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) to examine the relationship between Kodak returns and the Dow Jones Industrial Average (DJIA) as well as Bitcoin returns. The time frame under consideration includes the subperiods of November 22, 2017, and February 21, 2018. They show that there was a substantial correlation between Kodak and the DJIA index prior to the KodakCoin announcement, but just a modest one with Bitcoin. However, following the KodakCoin announcement, the link between Kodak and the DJIA became weaker while Kodak's tie to Bitcoin became much stronger. Kodak's return volatility also exposes the announcement's tighter connection to dangerous digital currencies.

By using the rigorous local martingale theory of financial bubbles, the non-parametric Florens-Zmirou estimator, and the Hamiltonian Monte Carlo simulation scheme for estimations, Chaim and Laurini (2019) examine if Bitcoin is a bubble. For comparison, analysis is also done using the SP500 index, the euro-dollar exchange rate, the gold-dollar pricing, and the Brent oil market price. It has been discovered that

Bitcoin only displays bubble behavior from January 2013 to April 2014. Using daily data ranging from September 2015 to January 2018, Cagli (2019) examines the explosive behavior in the market values of Bitcoin, Ethereum, Ripple, Litecoin, Stellar, Nem, Dash, and Monero. Chen et al. (2017) are the source for the methods used. Evidence suggests that, with the exception of Nem, all digital currencies display explosive behavior and strong pairwise comovement connections. More precisely, it is discovered that there are statistically significant bilateral co-explosive links between the following pairs: Ripple-Stellar, Ethereum-Litecoin, Ethereum-Dash, Bitcoin-Dash, and Ethereum-Litecoin.

Also worth mentioning is that recent academic research has centered on figuring out which model would work best for analyzing bitcoin booms and collapses. For the dynamics of Bitcoin, Cretarola and Figà-Talamanca (2019a) use a continuous time stochastic model. They offer proof that the association between market attention to Bitcoin and Bitcoin returns beyond a non-negative threshold is a sign of a bubble. Thus, it is discovered that market euphoria influences Bitcoin bubbles. These bubbles were noticeable in 2012–2013 and 2017. The model used in Cretarola and Figà-Talamanca (2019a) is expanded in Cretarola and Figà-Talamanca (2019b), which also includes a state-dependent correlation parameter between asset returns and market attention. It is discovered that, according to the modified model, the relationship between cryptocurrency prices and market interest can predict how quickly a bubble will expand. Regression analysis is used by Pyo and Lee (2020) to examine how FOMC statements affect Bitcoin returns. They consider 65 FOMC meetings that are relevant to monetary policy. Findings show that macroeconomic statements generally have no substantial effects on Bitcoin prices, however the Producer Price Index has large effects on Bitcoin prices just one day before the FOMC decision.

According to estimates made by Eom (2020) utilizing Bitcoin data from Korea and the US and the Generalized Method of Moments (GMM), the high trading volume and price volatility can account for the Kimchi premium. A clearer connection between trading volume and premium results from larger Bitcoin bubbles. Due to increased trading and fundamental uncertainty, bubbles are observed to rise. Furthermore, Shu and Zhu (2020) give proof that bubbles may be accurately detected using an adaptive multilevel time series detection methodology based on the LPPLS model and high-frequency data. Additionally, it has the ability to predict bubble collapse, even for brief bubbles. Similarly, Xiong et al. (2020) demonstrate that bubble prediction based on production cost by employing VAR and LPPL models have high predictive powers. Additionally, it is discovered that the bubble coefficient (BC) and the price-electricity cost ratio (PECR) are useful indicators. Additionally, it is asserted that the subsequent significant Bitcoin bubble is predicted to occur immediately following Bitcoin's halving in the second half of 2020.

It should be emphasized that academic research indicates that large cryptocurrencies, particularly Bitcoin but also Ethereum, are clearly in a bubble, in contrast to the remaining highly capitalized digital currencies, which are experiencing more moderate price gains. It should be noted that bubbles are observed to be more intense when the CRIX index, the Bitcoin Price Index, or the Mt.Gox values represent Bitcoin. Furthermore, it should be noted that approaches built on the SADF show that Bitcoin markets have seen many or larger bubbles.

It is crucial to try to establish a core estimate throughout time while taking into account all of the aforementioned studies in order to understand how estimations of the magnitude of a bubble in the cryptocurrency markets vary. We further seek to provide estimates both over time frequency and by type of cryptocurrency, while this research does present a central portion that offers a general overview of the approaches used to measure pricing bubbles. Figure 1 shows eight examples of monthly cryptocurrency price behavior that were compared to times when academic research had already predicted the existence of bubble-like characteristics in each respective market using the methods previously described in our research. The appendices that are attached include the collected data that was utilized to produce these statistics. We can see that every sample, with the exception of Maidsafecoin and Monero, displays consistent bubble warnings well before the significant price spikes that prevailed throughout 2016 and 2017. It's interesting to note that when each cryptocurrency's price fell throughout 2017 and into the beginning of 2018, these warnings vanished. Although there have been several cautions in a variety of trustworthy academic sources, it would seem that such advise has mostly been disregarded. A significant portion of the data presented in this systematic review views cryptocurrencies as an extraordinarily volatile product that displays numerous behavioral aspects that do not seem to be shared across conventional financial markets.

5. **Conclusions**

The body of data used to assess the likelihood of bubble price development in financial assets and gauge its size has substantially grown over the last few decades. There is already a lot of data to suggest that economic hysteria, speculative motivations, and excessive confidence lead to major deviations between asset market values and their corresponding basic values. There are several different definitions that can be used to describe bubble creation. The majority of them concur that different sizes of nominal values in respect to fair value are the result of economic units' increased interest as a result of particularly favorable conditions. According to the asset pricing concept, assets are investing tools that can be very rewarding for traders. The highly speculative nature of cryptocurrencies and the resulting rise in popularity of Bitcoin and other digital coins throughout the previous three years fueled the bubble price literature and produced some quite intriguing academic articles. Due to the difficulties that follow from persistently high price changes, interest in bubbles is surging. Different approaches are employed depending on whether there is a single bubble or several bubbles.

Additionally, different detection techniques are preferred in cases involving explosive or mildly explosive materials.

While investing in cryptocurrency is becoming a more and more common choice for businesses, there is still a lot of risk involved because of the high degree of return volatility. When virtual currency prices bubble up, it becomes harder for those currencies to serve as a unit of account and a store of value for money. According to literature on digital currency bubbles, Bitcoin has had many bubble stages, primarily between 2013 and 2017. Several bubble phases are also visible in other significant coins. The majority of research use daily data from open sources, however there have also been papers that use high-frequency data from privately held data sources. The Augmented Dickey Fuller (ADF) method has been the most often used method for locating bubbles. Additionally, the Log-Periodic Power Law (LPPL) approach is frequently applied in pertinent studies. Overall, empirical research confirm that cryptocurrencies are highly speculative, volatile, and unpredictable. By offering a comprehensive perspective on empirical academic studies of bubble price formation of digital currencies and a research road map for the future, the present study contributes to the pertinent literature. This could prove to be a very useful tool for investors, traders, regulators, and governing bodies.

Finally, it is important to consider whether the bubble-like nature of digital currencies will continue to exist without the possibility of a bust in the future. Prices will continue to rise to the extent that excessive investor confidence persists and irrational behavior predominates in investment strategies. The existence of cryptocurrencies is predicted to depend heavily on virtual currencies developed by monetary authorities (Central Bank Digital Currency, CBDC), as well as coins tied to bank deposits or government securities (stablecoins). These digital forms of liquidity could benefit from the legal tender status and be shielded from volatility and frequent upheavals if regulation or innovation in digital money increases investors' "trust" in them. The propensity for digital currencies to become more centralized may help keep bubbles in check before they collapse and trigger new crises.

Table 3.1. Overview of studies investigating the bubble character of cryptocurrencies

Authors	**Currency examined**	**Frequency of data**	**Time period examined**	**Data Source**	**Methodology**	**Conclusions about bubble existence**
Cretarola and Figà-Talamanca (2019a)	Bitcoin Ethereum	Daily	January 1, 2012-September 30, 2019 (Bitcoin)	Coinmarketcap.com	Extension of the model in Cretarola and Figà-Talamanca (2019b)	Correlation between cryptocurrencies and their market attention can indicate the speed

			August 2015-September 2019 (Ethereum)			by which a bubble boosts
Cretarola and Figà-Talamanca (2019b)	Bitcoin	Daily	January 1, 2012-January 20, 2018	www.blockchain.info	Continuous time stochastic model depending on a market attention factor	Bubble effects in 2012-2013 and 2017
Eom (2020)	Bitcoin	Daily	January 2015-September 2018	Bitcoincharts.com Coinmarketcap.com Bank of Korea	Kimchi premium estimation Generalized Method of Moments (GMM)	Cryptocurrency bubbles are loud Fundamental uncertainty leads to high trading and speculative bubbles
Pyo and Lee (2020)	Bitcoin	Daily Monthly	July 18, 2010-September 10, 2018	CryptoCompare.com www,federalreserve,gov www.bls.gov	Event-driven regression model	No significant impacts from macroeconomic announcements are found in general
Shu and Zhu (2020)	Bitcoin	Daily	January 11, 2017-April 11, 2019	Bitcoincharts.com	Adaptive multilevel time series detection methodology based on the LPPLS model	The LPPLS confidence indicator employed is an excellent tool for tracing detect bubbles and forecasting bubble crashes
Xiong et al. (2020)	Bitcoin	Daily	January 1, 2011-Decemb	-	Vector Autoregres	Models display good

			er 30, 2018		sive Model (VAR) LPPL	predictive capacities The next large Bitcoin bubble is expected to take place in the second half of 2020

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Chapter 4

Investigating the Diversifying or Hedging Nexus of Cannabis cryptocurrencies with Major Digital Currencies

1. Introduction

Since the market value of cryptocurrencies skyrocketed in 2017 there has been a significant and growing amount of interest in the space. Digital forms of liquidity, such as virtual currencies, have drawn the interest of academics, regulators, market makers, investors, and particularly speculators. The core of financial discussion over the past three years has been how to build diversified investment portfolios that include a variety of alternative cryptocurrencies in order to reduce risk. Typically, highly diversified portfolios also include gold and other conventional assets like bonds, equities, or national currencies. This happens to operate as diversifiers, hedgers, or safe havens while also lowering overall volatility.

Marijuana is the most common drug type of cannabis. In order to facilitate transactions between those involved in the cannabis sector or just for those looking to purchase marijuana, cannabis cryptocurrencies have been developed. Even though there are currently approximately 4,000 cryptocurrencies that are frequently traded, the trading of digital currencies related to cannabis is still in its infancy, despite being very promising. Seven cannabis-related coins are being traded. PotCoin is regarded as the most well-known of them all, with a market value of more over 1,300,000 US dollars. Over half of the 420 million coins that are allowed to be produced are already in use. Due to its affordable pricing, a very broad number of potential users can utilize it. Since the start of the exploding cryptocurrency bull market in 2017, PotCoin has grown in popularity.

The relationship between cannabis cryptocurrency and the three digital currencies with the biggest market capitalization—Bitcoin, Ethereum, and Ripple—is the subject of this study, which is the first of its kind. The ability of the three major cryptocurrencies to diversify and hedge against the seven cannabis-related digital currencies is emphasized. Cryptocurrencies are extremely volatile financial assets, thus GARCH parameters are used to choose the best one out of the bunch. The results show that the most widely used specifications for predicting volatilities are the GARCH and the GJR-GARCH specifications. Ripple appears to be a superior diversifier than Bitcoin and Ethereum, according to the research, although no effective hedger has been found.

The rest of this essay is organized as follows. A survey of the literature on the fundamentals of looking at the return and volatility dynamics of cryptocurrencies is presented in Section 2. The information and procedures used for the estimations are presented in Section 3. The empirical findings are presented and examined in Section 4. The overall findings of this study are presented in Section 5 along with some directions for further investigation.

2. Literature review

We focus on particular academic papers that are pertinent to our study in order to elaborate on the claims made by the pertinent strands of literature. One of the earliest influential studies, Böhme et al. (2015), addresses the decentralized nature of digital currencies and outlines both their technological and economic underpinnings. Additionally, Corbet et al. (2019) give the most comprehensive study of cryptocurrencies to date.

Alternative GARCH specifications are used by Katsiampa (2017) to investigate the best model for calculating the returns on Bitcoin. Furthermore, Dyhrberg (2016a) finds that Bitcoin exhibits a number of parallels to gold and the US dollar, as well as hedging capabilities, by using alternative GARCH specifications. Similar to this, Dyhrberg (2016b) contends that Bitcoin can undoubtedly be used as a hedge against the Financial Times Stock Exchange index by implementing GARCH models. In the short term, it can also be used for hedging against the US dollar. As a result, it shows some similarities to gold in terms of hedging. Additionally, Guesmi et al. (2019) support the idea that given their low connection with financial assets, digital currencies can effectively be used as diversifiers. Furthermore, data shows that hedging techniques incorporating gold, oil, emerging market stock, and bitcoin considerably reduce a portfolio's risk compared to a portfolio that includes these constituents but does not include Bitcoin.

By using a Time Varying Parameter Factor Augmented Autoregressive (TVP-FAVAR) connectivity technique, Antonakakis et al. (2019) support the idea that the dynamic total connectedness across various digital currencies exhibits significant dynamic fluctuation, with values ranging from 25% to 75%. It is discovered that uncertainty and connectivity are positively correlated. There is evidence to suggest that Ethereum is even more impactful than Bitcoin in terms of impact transfer. Hedging possibilities in portfolios are indicated through the use of dynamic hedge ratios and dynamic portfolio weights. Additionally, by utilizing three pairwise bivariate BEKK techniques, Katsiampa et al. (2019) discover proof of the existence of influences on shock transmission in both directions between Bitcoin and both Ethereum and Litecoin. Unidirectional shock spillovers from Ethereum to Litecoin are also found. Additionally, spillovers of bi-directional volatility are found between all three cryptocurrency pairs. The estimation of interdependencies is high overall.

Using intradaily data and an asymmetric Dynamic Conditional Correlations (ADCC) methodology, Urquhart and Zhang (2019) examine the hedging and safe haven characteristics of Bitcoin. They demonstrate that while Bitcoin exhibits diversification properties with regard to the Australian, Canadian, and Japanese currencies, it cannot be used as an intraday hedge for the CHF, EUR, or GBP. Additionally, it has been discovered that Bitcoin acts as a safe haven when the CAD, CHF, and GBP are under duress. Additionally, Beneki et al. (2019) use a multivariate BEKK-GARCH methodology and impulse response analysis to examine the volatility transmission and hedging qualities between the two main cryptocurrencies. According to their research, there are significant swaps to be found in the time-varying connection and the delayed positive response of Bitcoin volatility to a positive volatility shock on Ethereum returns. Overall, Bitcoin and Ethereum initially serve as diversifiers, but over time, their function deteriorates. In order to create an effective portfolio, Aslanidis et al. (2019) concentrate on the generalized Dynamic Conditional Correlations (DCC-GARCH) among the major digital currencies, stock and bond indices, and gold. There is little to no association between cryptocurrencies and other financial assets, according to the evidence.

Kurka (2019) focuses on the asymmetric transmission mechanisms of shocks between very liquid traditional assets and Bitcoin in another pertinent study. Findings show that there is little unconditional link between them. Furthermore, it is demonstrated that Bitcoin is ineffective as a hedge against conventional assets. Canh et al. (2019) use GARCH methods and Dynamic Conditional Correlations (DCC) to analyze the relationships between seven significant cryptocurrencies. Results from econometric analysis show that there are volatility spillovers and significant positive correlations between the various digital currencies. This demonstrates that the benefits of diversification between the examined cryptocurrencies can be quite minimal. Zhang et al. (2018) use the Multifractal Detrended Cross-Correlation Analysis (MF-DCCA) to quantify the cross-correlations between Google Trends and the Bitcoin market from their own point of view. The results show that multifractality is more prevalent over the long period than over the short term. To be more specific, it turns out that there are anti-persistent cross-correlations between Google Trends and Bitcoin returns over time.

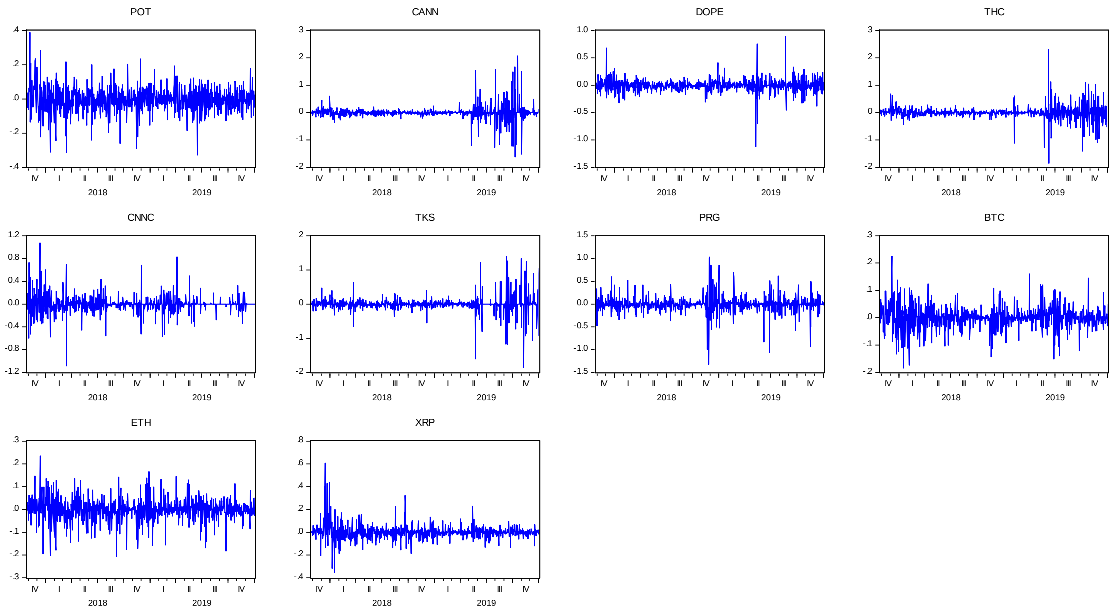
Furthermore, Yi et al. (2018) use the Least Absolute Shrinkage and Selection Operator Vector Autoregressive (LASSO-VAR) methodology to study the connectedness of static and dynamic volatility among a large number of cryptocurrencies. Econometric findings imply that although less significant ones might be net transmitters of effects, high-capitalization digital currencies are more likely to spread volatility shocks to other digital currencies. In order to develop diversification strategies, Gillaizeau et al. (2019) examine the giver and receiver impacts as well as the predictive power in cross-market Bitcoin prices using VAR models and the generalized variance decomposition approach proposed by Diebold and Yilmaz (2012). Results show that there are strong dynamic spillovers in volatility in the Bitcoin market values, especially during times of high uncertainty. Additionally, the latter increased the dynamic inefficiency of Bitcoin markets.

3. Data and Methodology

The study's estimates were made based on historical information regarding the closing values of cryptocurrencies on a daily basis. All information was taken from the www.coinmarketcap.com database, which is a dependable resource used by many important scholars. The three main cryptocurrencies under investigation—Bitcoin (BTC), Ethereum (ETH), and Ripple (XRP)—combine for more than 85% of the market capitalisation. Additionally, the coins CannabisCoin (CANN), Cannation (CNNC), DopeCoin (DOPE), PotCoin (POT), Paragon (PRG), HempCoin (THC), and Tokes (TKS) are linked to businesses that sell cannabis-based items. The information covers the time frame from 26 October 2017 to 3 January 2020. This indicates the time frame during which all cryptocurrency backed by cannabis have been legally exchanged. The disparities between all prices are translated into logarithmic terms. This study aims to investigate the effects of Bitcoin, Ethereum, and Ripple on the returns and volatility of each of the digital currencies associated to cannabis.

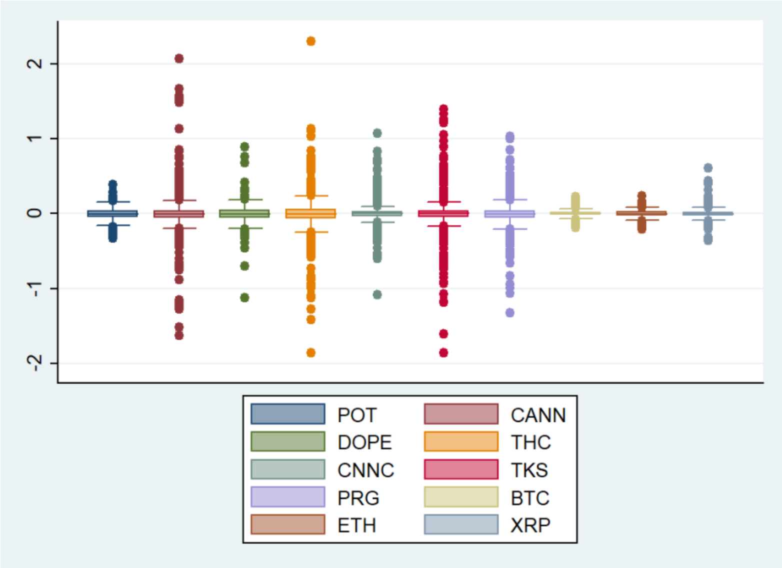
Figure 4.1. illustrates the performance of the three main digital currencies and the cannabis-related cryptocurrencies. Figure 2 also shows the boxplots for these variables.

Figure 4.1. Returns of cannabis cryptocurrencies and major cryptocurrencies



As far as the cannabis cryptocurrencies under consideration go, it is evident that PotCoin and Cannation offer extremely variable returns. Tokes and CannabisCoin are more volatile in 2019. Bitcoin and Ethereum are two of the most volatile big digital currencies, but Ripple exhibits more changes when the bull market is coming to an end and the start of the bear market in the cryptocurrency markets.

Figure 4.2. Boxplots of the returns of cryptocurrencies investigated



The majority of cannabis cryptocurrencies, despite having low mean returns, show large levels of asymmetry, as seen by the boxplots. These results suggest that GARCH specifications should take the place of conventional models in order to more accurately simulate the behavior of such digital currencies.

Similar to Katsiampa (2017), an examination of the seven cryptocurrencies backed by cannabis is conducted, and the hedging or diversifying relationships with the three digital currencies with the biggest market capitalizations are estimated. We use four alternative Generalized Autoregressive Conditional Heteroskedasticity (GARCH) specifications that are based on the ARCH model of Engle (1982) after applying the Augmented Dickey-Fuller and Phillips-Perron tests for autocorrelation. The latter are used to determine which method is best for analyzing each cryptocurrency related to cannabis. The GARCH model by Bollerslev (1986), the Exponential GARCH (EGARCH) by Nelson (1991), the Threshold GARCH (TGARCH) by Zakoian (1994) and the Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) by Glosten et al. (1993) methodologies are employed in order to find out whether volatility in cannabis-related currencies exhibits simple autoregressive, exponential or threshold behaviour or whether leverage effects exist. To determine which definition is most appropriate in each situation, the Akaike Information Criterion (Akaike, 1978) and the Bayesian Schwartz Information Criterion (Schwartz, 1987) are also used. The GARCH, EGARCH, TGARCH and GJR-GARCH models are given by equations (1), (2), (3) and (4), respectively.

$$GARCH: \; h_t^2 = \omega + \alpha u_{t-1}^2 + \beta h_{t-1}^2 \quad (1)$$

$$EGARCH: \; \log(h_t^2) = \omega + \alpha\left[\left|\frac{u_{t-1}}{h_{t-1}}\right| - \sqrt{2/\pi}\right] + \beta log(h_{t-1}^2) + \delta\frac{u_{t-1}}{h_{t-1}} \quad (2)$$

$$TGARCH: \; h_t = \omega + \alpha u_{t-1} + \alpha_1^+ \varepsilon_{\tau-1}^+ + \alpha_1^- \varepsilon_{\tau-1}^- \quad (3)$$

$$GJR-GARCH: \; h_t^2 = \omega + \alpha u_{t-1}^2 + \beta h_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} \quad (4)$$

Where h_t stands for standard deviation

ω: is the fixed term

u: represents the residuals

β: is the coefficient of variance

I: is the threshold coefficient

The AIC and SBC/BIC criteria are given by equations (5) and (6), respectively.

$$AIC = 2k - 2nL\left(\tilde{\hat{\Theta}}\right) \quad (5)$$

$$BIC = klnn - 2lnL\left(\tilde{\hat{\Theta}}\right) \quad (6)$$

4. Econometric outcomes

Estimates concerning the connections between each cryptocurrency based on cannabis and Bitcoin, Ethereum, and Ripple have been made by using four alternative GARCH specifications. For each of the seven cannabis-related digital currencies, econometric processes were carried out using STATA 16 software. By using the AIC and SBC/BIC criteria, the specification that best fits the situation has been chosen. Tables 2, 3 and 4 provide the outcomes of the model chosen in each situation.

Table 4.1. GARCH results as the optimal model concerning Paragon, HempCoin, Tokes and PotCoin (according to the AIC criterion)

		Paragon	**HempCoin**	**Tokes**	**PotCoin**
Mean equation	**BTC**	0.4173 (0.014)**	0.741 (0.000)***	0.5834 (0.000)***	0.5565 (0.000)***
	ETH	0.379 (0.043)**	0.3972 (0.042)**	0.0401 (0.746)	0.3794 (0.000)***
	XRP	0.1003 (0.296)	0.2098 (0.023)**	0.5789 (0.000)***	0.1265 (0.001)***
	Constant	-0.0101 (0.010)**	0.0003 (0.957)	-0.0033 (0.395)	-0.0028 (0.117)
Variance equation	**Arch**	0.2887 (0.000)***	0.1932 (0.000)***	0.2317 (0.000)***	0.4689 (0.000)***
	Garch	0.5418 (0.000)***	0.8488 (0.000)***	0.8687 (0.000)***	0.1283 (0.031)**
	Constant	0.0055 (0.000)***	0.0007 (0.000)***	0.0001 (0.002)***	0.0017 (0.000)***
	AIC	-796.4782	-645.1	-751.9555	-2332.78
	SBC/BIC	-763.6947	-612.3165	-719.172	

Information tests for the cryptocurrencies Paragon, HempCoin, and Tokes show that GARCH is the best methodology. To be more exact, data shows that Paragon has a small to weak positive correlation with both Bitcoin and Ethereum, with coefficients of 0.4173 and 0.379, respectively. Though it doesn't show any statistically significant values, ripple is shown to be a more promising diversifier (0.1002). The Potcoin has similar findings. Regarding the HempCoin, a strong and favorable impact from Bitcoin (0.741) and a weak to moderate impact from Ethereum (0.3972) are found. The relationship between HempCoin and Ripple (0.2098) is weaker. At a 95% confidence level, all HempCoin outcomes are statistically significant. Thus, studies suggest that Ripple is a more effective investment asset for diversification in a portfolio of digital currencies, but findings suggest that Bitcoin is the least valuable for such objectives or as a hedge against HempCoin. These econometric findings do not match predictions for the cryptocurrency Tokes, which is tied to marijuana. According to GARCH estimates, Tokes have a weak to high positive nexus with Ripple (0.5789) and Bitcoin (0.5834), respectively. This supports Ethereum's claim of being the most effective diversifier because of the very tenuous link it has (0.0401) with Tokes.

Table 4.2. EGARCH and TGARCH specifications as the optimal model concerning CannabisCoin and Cannation, respectively.

		CannabisCoin		**Cannation**
Mean equation	**BTC**	0.5827 (0.000)***	**BTC**	0.3498 (0.000)***
	ETH	0.3981 (0.001)***	**ETH**	0.0953 (0.402)
	XRP	0.1605 (0.067)*	**XRP**	0.0387 (0.717)
	Constant	-0.01 (0.006)***	**Constant**	0.0009 (0.732)
Variance equation	**Earch**	-0.0194 (0.097)*	**Abarch**	0.1408 (0.000)***
	Earch_a	0.2027 (0.000)***	**Atarch**	0.0398 (0.032)**
	Egarch	0.9895 (0.000)***	**Adgarch**	0.8797 (0.000)***
	Constant	0.0096 (0.08)*	**Constant**	0.0038 (0.000)***
	AIC	-980.6509	**AIC**	-1175.565
	SBC/BIC	-943.184	**SBC/BIC**	-1138.098

Additionally, it is clear that estimates for the CannabisCoin suggest that EGARCH is the most appropriate GARCH specification. The AIC and BIC criteria both converge on this conclusion. According to the data, there is a weak to moderate connection between Bitcoin and CannabisCoin (0.5827), a weak connection between CannabisCoin and Ethereum (0.3981), and an even weaker connection between Ripple (0.1605). The coefficients of all three coins show a favorable pattern. Results suggest that Ripple, as opposed to Bitcoin and Ethereum, is a better diversifier for

CannabisCoin. Additionally, testing using both information criteria show that TGARCH is the best methodology when it comes to the Cannation coin. Evidence suggests that Bitcoin and Cannation have a medium to weakly positive relationship (0.3498), whilst Ethereum and Ripple have a weakly positive relationship with this cannabis-based digital currency. Even while these findings are not statistically significant, they do suggest that both currencies, particularly Ripple, can act as diversifiers against Cannation.

Table 4.3. GJR-GARCH results as the optimal model concerning Dopecoin and PotCoin (according to the SBC/BIC criterion).

		DopeCoin	PotCoin
Mean equation	**BTC**	0.7733 (0.000)***	0.544 (0.000)***
	ETH	0.3405 (0.007)***	0.3771 (0.000)***
	XRP	0.0589 (0.591)	0.1356 (0.000)***
	Constant	-0.0066 (0.039)**	-0.0021 (0.275)
Variance equation	**Arch**	0.1015 (0.000)***	0.376 (0.000)***
	Tarch	0.3028 (0.000)***	0.1524 (0.066)*
	Garch	0.8392 (0.000)***	0.1705 (0.005)***
	Constant	0.0001 (0.018)**	0.0016 (0.000)***
	AIC	-1450.017	
	SBC/BIC	-1412.55	-2294.587

There is also proof that the GJR-GARCH model is the best choice for making DopeCoin estimations. According to econometric findings, Bitcoin has a significant positive impact on Dopecoin (0.7733), whilst Ethereum has a moderate to weak positive impact (0.3405). Both of these conclusions hold true in a statistically significant sample size. On the other side, Ripple is discovered to have a very weak (0.0589) favorable connection to this cryptocurrency associated with marijuana. Therefore, even if statistically non-significant, this shows improved diversifying capacities. Leverage effects are present in this relationship, according to the variance equation. Regarding the PotCoin, it is also determined that the GJR-GARCH specification is preferable. Once more, Ripple is shown to have the most potential for balancing a portfolio of cryptocurrencies tied to the cannabis industry. A statistically significant correlation (0.1356) between Ripple and PotCoin can be seen. Furthermore, the variance equation's threshold (0.1524) for enabling leverage effects is significant at a 90% confidence level.

Overall findings show that two digital currencies could be ideally evaluated by GJR-GARCH specifications and that three out of seven cannabis-related cryptocurrencies could be best examined by the traditional GARCH approach, showing leverage effects by caused by Bitcoin, Ethereum, and Ripple. Furthermore, two cannabis-related cryptocurrencies show different volatility behavior over a threshold, with one exhibiting exponential volatility behavior and the other displaying different volatility behavior, as best described by the EGARCH and TGARCH models, respectively. These results support the possibility of speculative opportunities in cannabis-related cryptocurrencies given their unpredictable volatility. It should be emphasized that Ethereum has weak to medium diversification skills, whereas Ripple is typically the best diversifier against digital currencies associated to cannabis. Additionally, it should be emphasized that Bitcoin has a strong positive correlation with cannabis-related cryptocurrencies and cannot be used as a hedge or diversifier. Therefore, the three digital currencies with the biggest capitalisation do not appear to have any effective hedgers.

5. Conclusions

Policymakers, investors, and the financial press have all recently focused their attention on digital currencies. Cryptocurrencies have come under harsh criticism from those opposed to digital forms of liquidity and investment for serving as a conduit for unlawful activity. Cannabis-related digital currencies have emerged and are growing in popularity, particularly Potcoin, which has a very large market value. This study applies the GARCH, EGARCH, TGARCH, and GJR-GARCH specifications on daily closing prices from 26 October 2017 to 3 January 2020 in order to calculate the relationship between seven cannabis-related cryptocurrencies and Bitcoin, Ethereum, and Ripple. In order to determine the model that more accurately describes the volatility of each cannabis cryptocurrency, the diversification or hedging abilities of the three digital currencies with the biggest market capitalization are therefore examined. For these reasons, the AIC and SBC/BIC criteria are effective.

This study applies the GARCH, EGARCH, TGARCH, and GJR-GARCH specifications on daily closing prices from 26 October 2017 to 3 January 2020 in order to calculate the relationship between seven cannabis-related cryptocurrencies and Bitcoin, Ethereum, and Ripple. In order to determine the model that more accurately describes the volatility of each cannabis cryptocurrency, the diversification or hedging abilities of the three digital currencies with the biggest market capitalization are therefore examined. For these reasons, the AIC and SBC/BIC criteria are effective. As a result, these three important digital currencies influence Cannation's volatility beyond a certain point. Additionally, it should be emphasized that the GJR-GARCH technique reveals that both DopeCoin and PotCoin, the two cannabis-related cryptocurrencies with the biggest market capitalization, display leverage effects.

This shows that riskier and more volatile cannabis cryptocurrencies seem to be more appealing to speculators, as evidenced by the larger demand for them. It should be noted that while Bitcoin, which is positively and slightly toward significantly tied to them, does not fall under this category, Ripple can operate as an exceptionally important diversifier in the great majority of these cannabis-related digital currencies. While none of the three major currencies offer indications of being a competent hedger, Ethereum is a poor to modest diversifier.

This study intends to shed light on the recently proposed idea of cryptocurrency connected to cannabis-producing businesses. It is examined if these digital currencies could successfully fit in a well-diversified portfolio of digital assets. Future studies could estimate how aggressive these financial products are and look into how much of them should be included in a portfolio of investments alongside traditional assets. In this regard, our research is very prognostic for Bitcoin investors.

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Chapter 5

Herding Behaviour and Cryptocurrency Price Convergence in Clubs during Bull and Bear Markets

1. Introduction

Since the astoundingly rapid growth in cryptocurrency returns during 2017, policymakers, researchers, investors, and the media have begun to pay more attention to cryptocurrencies. Their novel characteristics, including decentralized payment systems, reduced transaction costs, pseudonymity, and transaction speed, have made them very well-liked by economic units (Böhme et al., 2015). Bitcoin has been described as a form of liquidity that exists between gold and fiat money and is thought to adequately fulfill the function as a means of exchange. Furthermore, it is asserted that a subsidy given to miners in the form of new money is a major factor in the cheap transaction costs for payments made in digital currency. The overall number of coins offered will be fixed, however, as the bulk of existing cryptocurrencies show a pre-determined future path supply (Ali et al., 2014). Double spending is a problem that digital currencies address, and it is addressed by using peer-to-peer networks and open-source software (Dwyer, 2015).

The effects between financial assets of significant importance have been the subject of a significant body of literature (Beckmann and Czudaj, 2013; Das et al., 2019; El Abed and Zardoub, 2019). More particular, a variety of research have focused on market efficiency (Urquhart, 2016; Tiwari et al., 2018), market volatility (Katsiampa, 2017; Chaim and Laurini, 2018; Corbet et al., 2018; Beneki et al., 2019), and the hedging capabilities of digital coins (Dyhrberg, 2016). Additionally, a thorough survey was carried out (Corbet et al., 2019). Nevertheless, only a small number of research (Bouri et al., 2019; Kallinterakis and Wang, 2019) have examined the herding behavior of cryptocurrencies. This study strengthens that line of inquiry. Numerous academic research have looked into the herding behavior that occurs in bitcoin markets. However, most of them use established techniques, such as cross-sectional standard deviation (CSSD) and cross-sectional absolute deviation (CSAD) estimations (Ballis and Drakos, 2019; Da Gama Silva et al., 2019; Stavroyiannis and Babalos, 2019; Vidal-Tomas et al., 2019).

Herding behavior, which is based on the illogical behavior of economic agents, is a regular and notable phenomena in the financial markets. Herding phenomena are part of behavioral economics and finance that incorporate psychological factors such as framing, self-control, and justice into analysis of economics (Thaler, 2016). There is evidence to suggest that psychological variables are to blame for investors' erroneous views and choices. Thus, herding phenomena cause inefficiencies in the financial markets and give rise to bullish or bearish inclinations with regard to the nominal valuations of financial assets (Fama, 1998; Shiller, 2003). Shiller (2015) provides evidence in favor of the idea that herding behavior in financial markets causes over-enthusiasm, which causes price bubbles to form.

Herding, according to Spirou (2013), is when economic agents imitate the irrational behavior of other investors despite it being plainly obvious that these investors' judgments are totally illogical. Herding behavior typically takes the following forms: a) going in the same direction as others when making investment decisions; b) basing decisions on past choices; or c) completely copying what other investors have done. Such behavior is intimately tied to economic agents' increased risk-seeking and speculative nature. Additionally, it has a strong and favorable relationship with investors' ignorance and poor management skills. When there is market stress and economic turbulence, these phenomena become more harmful.

It should be highlighted that by examining price convergence among digital currencies using the ground-breaking methodology of Phillips and Sul (2007, 2009) in the broad range of 216 coins both in bull and bear markets, his paper contributes to the body of knowledge already available about herding and the concentration of market values. These models have gained popularity for gauging taxation (Regis et al., 2015) or the convergence of housing prices (Churchill et al., 2018). The bulk of pertinent studies on the phenomenon of herding in cryptocurrency markets use the cross-sectional absolute deviation (CSAD) and cross-sectional standard deviation (CSSD) methodologies, which is why this methodology is so novel.

We believe that this study is the first to use such methods to investigate bitcoin price segmentation and herding behavior. Our research shows that during a bull market, herding is at its worst. Additionally, it is believed that substantial herding behavior also occurs in negative markets, but in larger clusters due to club convergence among the smaller coins that make up each group. Clubs of digital currencies also group together in pairs, exhibiting secondary herding behavior. It is extremely noteworthy because this cryptocurrency study is the first to go beyond simply determining whether there is general swarming behavior or not. To provide a clearer picture of the specific clusters of transmitters and receivers of herding behavior in the markets of digital currencies, we investigate if convergence clubs are established by the clustering approach. Thus, this is the first scholarly research that allows readers to see how clusters of comparable irrationality in behavior emerge during extreme market conditions rather than just looking at the bitcoin market generally.

To that purpose, the remaining portions of the essay are organized as follows. The literature study on the herding behavior of cryptocurrencies is presented in Section 2. Section 3 contains the approach and data. Additionally, Section 3 presents and examines the findings and offers the economic ramifications. Section 5 comes to a conclusion and offers directions for additional investigation.

2. Literature review

In their groundbreaking study, Christie and Hwang (1995) use the CSSD approach to support their claim that herding is expected to be more effective in times of economic hardship. Additionally, by examining the cross-sectional variability of factor sensitivity, Hwang and Salmon (2004) concentrate their investigation on market-wide herding. They demonstrate that during bull and downturn markets in the US, UK, and Korea, investors tended to flock to the market portfolio.

Numerous academic publications have looked into the herding tendencies that occur in stock markets. According to the key work by Chang et al. (2000), Japan had weaker herding behavior while significant herding phenomena were observed in South Korea and Taiwan. Furthermore, neither the US nor Hong Kong had any indication of such a phenomenon. Furthermore, Chiang and Zheng (2010) demonstrate that herding was noticeable in developed non-US stock markets and in Asian nations between 1988 and 2009, but not in the economies of Latin American nations. Herding took place in both bullish and bearish market settings. While BenSada (2017) contends that herding phenomena occur in virtually every sector of the US stock market during stressful times, Demirer et al. (2010) support the idea that herding in Taiwan is more pronounced during bear markets. By offering evidence that the Chinese stock market exhibits herding behavior, which is more pronounced during bad markets, Gong and Dai (2017) support earlier findings. Additionally, BenMabrouk and Litimi (2018) provide evidence that sectoral herding is more pronounced in the US during bearish trends in the oil market.

According to Galariotis et al. (2016), the European government bond market values were not affected by herding before or after the crisis in the European Union, but only during it. Further evidence that institutional herding is stronger in the corporate bond market when it comes to speculative-grade bonds is provided by Cai et al. (2019). Additionally, it is discovered that herding is worse during times of financial stress. Regarding research examining irrational behavior in commodity markets, Cakan et al. (2019) find that there are regular shifts between herding and non-herding behavior in commodity markets in Brazil, Turkey, and particularly in Russia. Higher oil speculation is observed to result from more intense herding. Júnior et al. (2019) on the other hand, support the idea that inverse herding occurs when it comes to food items.

Herding phenomena in derivatives markets have also been under scrutiny. **McAleer and Radalj (2013)** examine nine markets of the Commodity Futures Trading Commission (CFTC) and support that herding takes place among small traders as regards the Canadian and British currencies, gold, the S&P500 and the Nikkei225 futures. Besides that, **Boyd et al. (2016)** investigate thirty-two US futures markets and support that such phenomena exist in a medium level. Moreover, **Babalos et al. (2015)** look into US-listed Real Estate Investment Trust (REIT) stocks and show evidence that negative herding phenomena take place during extreme volatility regimes but turn into positive under during bear markets for the great majority of REIT sectors. In a somewhat different perspective, **Akinsomi et al. (2018)** detect a linear nexus between volatility and herding behaviour as concerns Turkish REITs, while herding is more obvious during stressed periods.

The subjects of a large number of academic studies have been the factors that influence market prices in the cryptocurrency marketplaces. One of the most intriguing areas of academic study on cryptocurrencies is herding phenomenon in markets for digital currencies. This has led to a credible and rapidly expanding body of pertinent empirical study in pertinent research articles.

The cross-sectional absolute deviation (CSAD) methodology is used by Bouri et al. (2019) to examine herding phenomena over subperiods from early 2016 to late 2019. Examinable digital currencies include Bitcoin, Ethereum, Ripple, Litecoin, Stellar, Dash, Nem, Monero, Bytecoin, Verge, Siacoin, BitShares, Decred, and Dogecoin. They demonstrate that herding occurs, while its severity varies across time. The Probit model is used to demonstrate that herding intensifies during times of more uncertainty. The 2019 study by Kallinterakis and Wang, which also adopts dummies concerning high volume and high volatility, uses the CSAD approach. A significant amount of herding behavior is revealed. Herding is also seen to be more pronounced during bull markets. There is a claim that this behavior cannot just be attributed to cryptocurrencies with huge market capitalization. According to their viewpoint, Kaiser and Stöckl (2019) also use the CSAD approach to support their claim that Bitcoin is a "transfer currency" and that the cryptocurrency market produces highly irrational behavior. The significant price swings in the market for digital currencies can be attributed to the strong herding phenomenon.

The cross-sectional standard deviation (CSSD) and the CSAD specifications are also used by Ballis and Drakos (2019) to identify the presence of herding behavior in the markets for Bitcoin, Ethereum, Litecoin, Monero, and Dash. They contend that, in contrast to bad situations, market dispersion occurs more quickly during bull markets. They also highlight how asymmetrical herding behavior is in bitcoin markets. Furthermore, the approaches used by Da Gama Silva et al. (2019) are the same as those used in the adaptations of the Forbes and Rigobon (2002) test and the Hwang and Salmon (2004) model. Based on their research, they support the idea that extreme adverse herding phenomena are brought to the fore during bear markets and times of elevated risk aversion. Similar to Stavroyiannis and Babalos (2019), who use quantile regressions, time-varying parameter (TVP) schemes, Ordinary Least Squares (OLS), and CSSD and CSAD specifications to explore herding behavior from both a static and dynamic perspective. They contend that herding is more potent in bull markets than in bear ones. Vidal-Tomas et al. (2019) adopt cap-weighted market portfolios in addition to the CSSD and CSAD techniques. According to their findings, herding behavior is more pronounced in down markets than bull markets. It should be underlined that only when Ripple, Litecoin, Dash, and Stellar join Bitcoin in this phenomenon can herding tendencies be created.

Overall, it can be claimed that the vast bulk of empirical scholarly articles about cryptocurrencies support the idea that herding phenomena are more intense during down markets than they are during bullish ones. The CSSD and CSAD are the approaches that are used the most frequently, while Probit models, quantile regressions, time-varying schemes, and weighted portfolios have also been used.

3. Data and Methodology

216 coins' daily closing prices are taken from the coinmarketcap.com database with no missing information. Data is divided into two subperiods. According to Wheatley et al. (2018), the bull market began on January 1, 2017, and it lasted until December 18, 2017, when the Bitcoin bubble burst. The bear market also runs from December 19, 2017, until December 15, 2018, when the decline in Bitcoin prices came to an end. The currencies under investigation and their symbols are shown in Table 5.1. These are examples of digital currencies with high and medium capitalizations that are very indicative of the cryptocurrency market and are also the ones that investors trade the most. This is owing to the fact that they have continued to trade since their inception, as opposed to the other digital currencies that are constantly being generated and forced off the market due to their extremely low trading volume. The returns of digital currencies are estimated using logarithmic differences.

Table 5.1. Cryptocurrencies selected for club convergence estimations.

Bitcoin.(BTC)	EDRCoin.(EDRC)	Gulden.(NLG)	Myriad.(XMY)	Creditbit.(CRB)	CrevaCoin.(CREVA)	FedoraCoin.(TIPS)	Maxcoin.(MAX)	Joincoin.(J)
Ethereum.(ETH)	Ardor.(ARDR)	Vertcoin.(VTC)	Omni.(OMNI)	Shift.(SHIFT)	Stealth.(XST)	GlobalBoost-Y.(BSTY)	Swing.(SWING)	Trollcoin.(TROLL)
Tether.(USDT)	PotCoin.(POT)	Nexus.(NXS)	Bela.(BELA)	Magi.(XMG)	VeriumReserve.(VRM)	Veros.(VRS)	MintCoin.(MINT)	Neutron.(NTRN)
Litecoin.(LTC)	Syscoin.(SYS)	Primecoin.(XPM)	Pinkcoin.(PINK)	OKCash.(OK)	OBITS.(OBITS)	FairCoin.(FAIR)	NoLimitCoin.(NLC2)	Xriba.(XRA)
Monero.(XMR)	Golem.(GNT)	Xaurum.(XAUR)	Curecoin.(CURE)	Adzcoin.(ADZ)	Incent.(INCNT)	First_Bitcoin.(BIT)	Zeitcoin.(ZEIT)	ParallelCoin.(DUO)
Dash.(DASH)	HyperSpace (AMP)	Revolution VR.(RVR)	Bytecoin.(BCN)	PostCoin.(POST)	Pepe Cash.(PEPECASH)	Elcoin.(EL)	Cryptojacks.(CJ)	Francs.(FRN)
Ethereum Classic.(ETC)	BlackCoin.(BLK)	BitCrystals.(BCY)	FLO.(FLO)	MonetaryUnit.(MUE)	Karbo.(KRB)	Pakcoin.(PAK)	Eternity.(ENT)	FujiCoin.(FJC)
Ripple.(XRP)	Decred.(DCR)	FoldingCoin.(FLDC)	SingularDTV.(SNGLS)	Internet_of_People.(IOP)	Safex Token.(SFT)	HempCoin.(THC)	AudioCoin.(ADC)	Elite.(1337)
Zcash.(ZEC)	NavCoin.(NAV)	Novacoin.(NVC)	Capricoin.(CPC)	Diamond.(DMD)	Digitalcoin.(DGC)	Titcoin.(TIT)	Dimecoin.(DIME)	SongCoin.(SONG)
Factom.(FCT)	Namecoin.(NMC)	HiCoin.(XHI)	PIVX.(PIVX)	vSlice.(VSL)	Golos.(GOLOS)	Quark.(QRK)	Hush.(HUSH)	Hodlcoin.(HODL)
MaidSafeCoin.(MAID)	Emercoin.(EMC)	Zclassic.(ZCL)	Auroracoin.(AUR)	WorldCoin.(WDC)	Blocknet.(BLOCK)	Blakecoin.(BLC)	Ixcoin.(IXC)	DigitalPrice.(DP)
Dogecoin.(DOGE)	Counterparty.(XCP)	Obyte.(GBYTE)	MonaCoin.(MONA)	BitSend (BSD)	Deutsche_eMark.(DEM)	bitBTC.(BITBTC)	2GIVE.(2GIVE)	AnarchistsPrime.(ACP)

Augur.(REP)	LEOcoin.(LEO)	SIBCoin.(SIB)	Global_Currency_Reserve.(GCR)	Sequence.(SEQ)	Bata.(BTA)	BERNcash.(BERN)	NevaCoin.(NEVA)	BowsCoin.(BSC)
NEM.(XEM)	LBRY Credits.(LBC)	SolarCoin.(SLR)	Aeon.(AEON)	CannabisCoin.(CANN)	Advanced_Technology_Coin.(ARC)	Memetic/Pepe Coin.(MEME)	LanaCoin.(LANA)	Pura.(PURA)
Stellar.(XLM)	FirstBlood.(1ST)	I/O_Coin.(IOC)	bitUSD.(BITUSD)	Crown.(CRW)	Verge.(XVG)	Orbitcoin.(ORB)	AllSafe.(ASAFE)	Anoncoin.(ANC)
BitShares.(BTS)	DigiByte.(DGB)	Viacoin.(VIA)	Startcoin.(START)	Terracoin.(TRC)	GoldBlocks.(GB)	Cryptonite.(XCN)	TajCoin.(TAJ)	HyperStake.(HYP)
Lisk.(LSK)	Expanse.(EXP)	BitBay.(BAY)	Unobtanium.(UNO)	TrumpCoin.(TRUMP)	Moin.(MOIN)	ExclusiveCoin.(EXCL)	BlueCoin.(BLU)	FuzzBalls.(FUZZ)
GameCredits.(GAME)	Zcoin.(XZC)	Radium.(RADS)	NuBits.(USNBT)	ReddCoin.(RDD)	Atomic_Coin.(ATOM)	Sphere.(SPHR)	Syndicate.(SYNX)	PopularCoin.(POP)
Nxt.(NXT)	Clams.(CLAM)	Rubycoin.(RBY)	CloakCoin.(CLOAK)	Rise.(RISE)	DopeCoin.(DOPE)	Prime-XI.(PXI)	Rimbit.(RBT)	NewYorkCoin.(NYC)
Steem.(STEEM)	NEO.(NEO)	Einsteinium.(EMC2)	Bitcoin_Plus.(XBC)	TransferCoin.(TX)	SaluS.(SLS)	MojoCoin.(MOJO)	SecureCoin.(SRC)	Motocoin.(MOTO)
Siacoin.(SC)	Steem_Dollars.(SBD)	Feathercoin.(FTC)	LoMoCoin.(LMC)	PutinCoin.(PUT)	Pesetacoin.(PTC)	HEAT.(HEAT)	SmartCoin.(SMC)	Comet.(CMT)
Stratis.(STRAT)	Burst.(BURST)	GridCoin.(GRC)	EverGreenCoin.(EGC)	ArtByte.(ABY)	Groestlcoin.(GRS)	BitBar.(BTB)	Acoin.(ACOIN)	Pandacoin.(PND)
Peercoin.(PPC)	bitCNY.(BITCNY)	VeriCoin.(VRC)	Yocoin.(YOC)	Zetacoin.(ZET)	WhiteCoin.(XWC)	Espers.(ESP)	AquariusCoin.(ARCO)	LiteDoge.(LDOGE)
Waves.(WAVES)	DigixDAO.(DGD)	DigitalNote.(XDN)	e-Gulden.(EFL)	Pascal Coin.(PASC)	SpreadCoin.(SPR)	Bolivarcoin.(BOLI)	Elementrem.(ELE)	Advanced_Internet_Blocks.(AIB)

The method developed by Phillips and Sul (2007) is used to test for currency convergence clubs in both bull and bear cryptocurrency markets. This methodology accounts for the possibility of groups with similar traits in terms of their convergence pathways. This enables us to understand if club convergence—herding behavior in the form of alternative cryptocurrency market prices—occurs under advantageous or unfavorable circumstances. T-statistic readings less than -1.65 imply club convergence.

Our investigation looks into whether market valuations for digital currencies converge under incredibly favorable or unfavorable market situations. The novel analytical approach of Phillips and Sul (2007, 2009) is employed for these estimations in order to use the log-t test to capture heterogeneity among panel data. The model can be written as follows given a panel data set with the element $X_{i,t}$ (market values of cryptocurrencies):

$$X_{i,t} = \delta_{i,t}\mu_t \qquad (1)$$

Where $\delta_{i,t}$ represents time-variation of systemic (idiosyncratic) factor loading that shows the deviation of cryptocurrency's i market value from the common path μ_t. The algebraic form of the factor $\delta_{i,t}$ can be given as:

$$\delta_{i,t} = \delta_i + \sigma_i\psi_{i,t}L(t)^{-1}t^{-a} \qquad (2)$$

Where $\psi_{it} \sim iid(0,1)$ and δ_i is fixed. It should be noted that $L(t)$ is a varying function and that when $t \to \infty$ then $L(t) \to \infty$. If the null hypothesis of convergence holds then there is convergence of $\delta_{i,t}$ to δ_i for every $a \geq 0$. Thereby, the null hypothesis is given as:

$$H_o: \delta_\iota = \delta_\iota \; and \; a \geq 0; \;\; H_1: \delta_\iota \neq \delta_i \; for \; some \; i \frac{and}{or} a < 0 \qquad (3)$$

Furthermore, emphasis should be paid in that the proposed methodology takes into consideration a transition coefficient so as to test for the convergence in the panel data. This coefficient is called the relative transition parameter, is indicated as $h_{i,t}$ and is given as follows:

$$h_{i,t} = \frac{X_{i,t}}{N^{-1}\sum_{i=1}^{N} X_{i,t}} = \frac{\delta_{i,t}}{N^{-1}\sum_{i=1}^{N} \delta_{i,t}} \qquad (4)$$

Moreover, based on the cross-sectional variance (H_t), Phillips and Sul (2007, 2009) construct the cross-sectional ratio (H_1/H_t) for the purposes of creating the $logt$ regression pattern. They use this pattern in order to test the null hypothesis as displayed in (3). The general presentation of this ratio can be given as:

$$log\left(\frac{H_1}{H_t}\right) - 2\log(t) = \hat{c} + \hat{\gamma}\log t + u_t$$

$$where \; t = [rT], [rT] + 1, \ldots, T \;\; when \; r > 0 \qquad (5)$$

As concerns (5), let us suppose that $L(t) = \log(t+1)$ and that $\hat{\gamma} = \hat{\alpha}$, where $\hat{\alpha}$ constitutes the estimate of a in the null hypothesis. Additionally, based on Phillips and Sul (2007, 2009) we adopt that $r = 0.3$, as is found from Monte Carlo simulations. In order to be able to form convergence clubs and include cryptocurrencies into the appropriate ones, four steps are followed. Firstly, the digital currencies are ordered based on their last observation. Secondly, the convergence statistic (t_ω) is estimated for $\log t$ regressions by relying on the ω highest-ordered members as found by the first step and abiding by the constraint that $2 \leq \omega \leq N$. The maximum of higher than -1.65 values of (t_ω) is what directs which will be the size of the group. If and only if the t-statistic is positive, the group members are added one by one in the third phase. The fourth stage involves repeating processes 1 through 3 for the remaining cryptocurrencies until no more clubs can be formed. It should be underlined that the four-step method by Phillips and Sul (2009) enables the discovery of further convergence clubs as well as their transition paths once the convergence clubs have been formed.

4. Empirical results

Econometric analyses have been carried out to analyze the outcomes of bull and bear markets and to determine whether convergence among large- and medium-capitalization cryptocurrencies occurs during periods of extreme economic situations. For this reason, the estimating processes for the two time periods under consideration were carried out individually. Results of the convergence tests conducted throughout the bull and bear markets are shown in Tables 5.2 and 5.3, respectively.[1].

Two convergence clubs are discovered by the club-clustering algorithm during the increasing trends in cryptocurrency markets. Notably, the bulk of the examined digital currencies are found in the first club. This very big club displaying herding behavior includes all of the major cryptocurrencies, including Bitcoin, Ethereum, Ripple, Litecoin, and the Tether stablecoin. The only cryptocurrencies that make up the second club of clustering, on the other hand, are Einstenium, Yocoin, DigitalCoin, GoldBlocks, FedoraCoin, Veros, SecureCoin, Joincoin, and AnarchistsPrime. The fundamental trait of the cryptocurrencies in this second club is that they have shown themselves to be significantly more profitable during the down market than the bull market of cryptocurrencies as a whole. They chose not to follow the sharp rise in returns of Bitcoin and other prominent cryptocurrencies during the bull market because of this. It is amazing how these digital currencies differ from traditional cryptocurrencies in that they serve other purposes besides speculation, such as financing scientific research (Einstenium), serving as a safe haven asset (GoldBlocks), or having political motivations (AnarchistsPrime). As a result, they do not exhibit the irrational behavior of the masses. Out of the 216 cryptocurrencies examined overall,

[1] For our estimation we have evaluated the R-codes yielded by Schnurbus et al. (2017).

207 display herding behavior, forming the sizable cluster known as group 1. It may be argued that during periods of market growth, the dramatic price increases of the vast majority of cryptocurrencies were driven by Bitcoin and the other three digital currencies with the greatest market capitalizations. These results are consistent with Kallinterakis, Wang, Stavroyiannis, and Babalos (2019) and Stavroyiannis and Babalos (2019), but they are at odds with pertinent academic research that suggests that the bull period exhibits weak herding behavior (Ballis and Drakos, 2019; Da Gama Silva et al., 2019).

A striking number of significant findings arise during the bear market of digital forms of investing, in addition to those pertaining to the bull phase. It's interesting to note that nine separate cryptocurrency convergence groups are exposed during times of market stress. One or more of the main cryptocurrencies that make up the core of each of these clubs attract lesser-capitalized digital currencies are present in each club. As can be seen, club 4 attracts the most cryptocurrencies compared to the other clubs due to the inclusion of Bitcoin, Ethereum, Litecoin, Monero, Dash, Ethereum Classic, Zcash, MaidSafeCoin, Augur, BitShares, Steem, and Siacoin. Notably, this group includes roughly half of the researched digital currencies. According to Phillips and Sul's technique (2007, 2009), strong herding phenomena are therefore also observed during bear markets. The segmentation into clubs, however, is considerably more obvious as herding phenomena are discovered to effect each cryptocurrency differently throughout the range of cryptocurrencies under consideration.

Aside from club 4, it is possible to see how small club 3 formed. Its defining characteristic is that it combines Terracoin and Quark, two less significant cryptocurrencies, with Ripple and Stellar, two major players in the cryptocurrency industry. The fact that Ripple and Stellar do not belong to the group of leading cryptocurrencies, such as Bitcoin, Ethereum, Litecoin, Monero, Dash, Ethereum Classic, Zcash, MaidSafeCoin, Augur, BitShares, Steem, and Siacoin, which attract the majority of the other cryptocurrencies, should be emphasized during bear markets. It has been discovered that Ripple and Stellar's herding abilities are constrained under pressure. However, it should be emphasized that this small club (club 3) can be combined with club 4 to form a broader group that includes the major digital currencies and about half of the currencies under investigation. This is crucial since it has been seen that severe clustering and herding phenomena occur during bear markets and that not all major cryptocurrencies actively pursue medium-capitalization digital currencies. Nevertheless, when small clusters demonstrate herding behavior by trailing large clusters, convergence between groups is eventually attained. Each and every result is statistically significant.

Another group, known as club 1, has also formed and comprises of nine lesser-known digital currencies with high or medium capitalization together with four large cryptocurrencies: Dogecoin, Decred, bitCNY, bitUSD (which are less significant than those at clubs 3 and 4), and the key stablecoin Tether. There is no predicted statistically significant convergence between them. Additionally, the poorly capitalized AllSafe and Advanced_Internet_Blocks, which are regarded as assets that advance the financial and technological sectors, form the very small club 2. It is important to note that under pressured market conditions, digital currencies with similar objectives tend to group and create distinct clubs from those with more traditional objectives. This supports the claim that "following a digital currency is like knowing the whole market of cryptocurrencies," which investors find difficult to accept in an environment where incentives for risk aversion are higher and uncertainty plays a significant role in decision-making. This is also the cause of the statistically insignificant attempt to combine clubs 1 and 2 into one larger club.

Furthermore, the highest-capitalized cryptocurrencies in club 6 are NEM, Lisk, Stratis, Potcoin, and Syscoin. The group is completed by another eighteen digital currencies with low capitalization. Once again, it is seen that a small number of important cryptocurrencies that are not among the top ones are able to bring together a fair number of unimportant alternative digital currencies into a sizable convergence club. The same is true of Club 5, where the largest cryptocurrencies are Nxt and DigitDao, with 28 additional cryptocurrencies making up the group. It should be noted that the majority of Club 6 currencies fall in between the high-cap and medium-cap categories. For the vast majority of cryptocurrencies in club 5, the same is true. Perhaps not unexpectedly, econometric projections show that clubs 5 and 6 statistically significantly combine into a larger herding phenomena.

It is imperative to note that the lowest-priced large-cap digital currencies tend to draw buyers mostly from the large-cap and medium-cap categories, roughly speaking. Contrarily, studies on clubs 4 and 3 show that the highest-cap cryptocurrencies are members of convergence clubs that primarily consist of large-cap or medium-cap digital currencies during downturn markets.

The two main cryptocurrencies in Club 7 are Hyperspace and LBRY, which are joined by Zclassic, Dopecoin, and fifteen medium-cap digital currencies. Three digital currencies—a significant one (Factom), a large-cap (Expanse), and a medium-cap (Magi)—are all that Club 8 is found to hold. These two clubs support prior clubs' results that, during bad markets, higher-cap digital currencies draw lower-cap and more numerous ones into convergence. Additionally, econometric projections show that Clubs 7 and 8 combine to form a single, larger club. As a result, following the development of the initial cluster, herding becomes increasingly focused.

Similar to this, Club 9 is made up of eleven medium-cap digital currencies and one large-cap cryptocurrency called GameCredits. It is noteworthy that the lower-level large-cap cryptocurrencies Global_Currency_Reserve and PutinCoin show no convergence with any of the large-cap or medium-cap digital currencies. These assets are more complex than simple cryptocurrencies since they might appear to uninformed investors to be on the verge of reaching the "legal tender" attribute compared to other cryptocurrencies. Economic agents may not have followed irrational behavior coming from other cryptocurrency marketplaces when making investment decisions concerning these two due to the former's and latter's national and international outlooks. The remaining 214 large-cap or modest-cap digital currencies may have been viewed as not even weak alternatives or complements to them.

Overall, the evidence shows that Club 4 serves as the primary core of all significant cryptocurrencies and of severe and widespread herding behavior during the weak market. Additionally, smaller clusters are found, each of which shows a significant number of medium-cap cryptocurrencies as well as a few substantial ones. The fact that five medium-sized clubs and four minor clubs, including the non-convergence club, have been exhibited in addition to Club 4 should be stressed. According to Phillips and Sul (2009), the convergence of Club 4—which includes Bitcoin, Ethereum, Litecoin, Monero, Dash, Ethereum Classic, Zcash, MaidSafeCoin, Augur, BitShares, Steem, and Siacoin—and Club 3—which contains Ripple and Monero—creates the largest of all secondary clusters. Club 1, which includes the biggest stablecoin (Tether), does not show statistically significant convergence. It should be highlighted that during the bad market, several clubs are using cannabis-based cryptocurrencies like CannabisCoin, HempCoin, PotCoin, and DopeCoin.

Estimates have unmistakably shown that herding affects digital currencies more broadly as a big club of 207 cryptocurrencies is formed. Notably, herding intensifies during downturns, though it does so in a totally different way. Herding occurs inside smaller groups, and these clubs also engage in herding behavior among themselves, although not to the extent necessary to produce the nearly universal irrationality seen during bull markets. This supports the idea that investor apprehension breeds uncertainty about whether large cryptocurrencies can accurately predict the market values of all cryptocurrencies over time. The most significant digital assets are split up into lesser-significant assets. The dominant cryptocurrencies, as seen in Clubs 3 and 4, remain in the lead, although their herding ability has decreased.

Table 5.2. Convergence Clubs during the Bullish period.

Category	**log t**	**t-stat**		**New club**	**Final classification**	**log t**	**t-stat**
Full sample	-2.796	-1.309					

Club 1 [BTC, ETH, USDT, LTC, XMR, DASH, ETC, XRP, ZEC, FCT, MAID, DOGE, REP, XEM, XLM, BTS, LSK, GAME, NXT, STEEM, SC, STRAT, PPC, WAVES, EDRC, ARDR, POT, SYS, GNT, AMP, BLK, DCR, NAV, NMC, EMC, XCP, LEO, LBC, X1ST, DGB, EXP, XZC, CLAM, NEO, SBD, BURST, BITCNY, DGD, NLG, VTC, NXS, XPM, XAUR, RVR, BCY, FLDC, NVC, XHI, ZCL, GBYTE, SIB, SLR, IOC, VIA, BAY, RADS, RBY, FTC, GRC, VRC, XDN, XMY, OMNI, BELA, PINK, CURE, BCN, FLO, SNGLS, CPC, PIVX, AUR, MONA, GCR, AEON, BITUSD, START, UNO, USNBT, CLOAK, XBC, LMC, EGC, EFL, CRB, SHIFT, XMG, OK, ADZ, POST, MUE, IOP, DMD, VSL, WDC, BSD, SEQ, CANN, CRW, TRC, TRUMP, RDD, RISE, TX, PUT, ABY, ,ZET, PASC, CREVA, XST, VRM, OBITS, INCNT, PEPECASH, KRB, SFT, GOLOS, BLOCK, DEM, BTA, ARC, XVG, MOIN, ATOM, DOPE, SLS, PTC, GRS, XWC, SPR, BSTY, FAIR, BIT, EL, PAK, THC, TIT, QRK, BLC, BITBTC, BERN, MEME, OR, B, XCN, EXCL, SPHR, PXI, MOJO, HEAT, BTB, ESP, BOLI, MAX, SWING, MINT, NLC2, ZEIT, CJ, ENT, ADC, DIME, HUSH, IXC, X2GIVE, NEVA, LANA, ASAFE, TAJ, BLU, SYNX, RBT, SMC, ACOIN, ARCO, ELE, TROLL, NTRN, XRA, DUO, FRN, FJC, X1337, SONG, HODL, DP, BSC, PURA, ANC, HYP, FUZZ, POP, NYC, MOTO, CMT, PND, LDOGE, AIB]	-0.713	-0.577		1 + 2	Club 1	-2.796	-1.309
Club 2 [EMC2, YOC, DGC, GB, TIPS, VRS, SRC, J, ACP]	1.864	1.945					

Table 5.3. Convergence Clubs during the Bearish period.

Category	log t	t-stat		New club	Final classification	log t	t-stat
Full sample	0.314	0.118					
Club 1 [USDT, DOGE, DCR, BITCNY, XPM, CPC, BITUSD, UNO, DGC, XWC, BSTY, VRS, MAX, ARCO]	5.934	4.150		1 + 2	**Club 1**	7.027	8.681
Club 2 [ASAFE, AIB]	-1.359	-0.919					
Club 3 [XRP, XLM, TRC, QRK]	-1.719	-1.396		3 + 4	**Club 2**	-0.009	-0.003
Club 4 [BTC, ETH, LTC, XMR, DASH, ETC, ZEC, MAID, REP, BTS, STEEM, SC, PPC, WAVES, EDRC, ARDR, GNT, BLK, NAV, NMC, EMC, LEO, DGB, CLAM, NEO, SBD, BURST, NLG, VTC, NXS, XAUR, NVC, VIA, BAY, RADS, RBY, GRC, XMY, BELA, BCN, FLO, SNGLS, MONA, AEON, YOC, EFL, SHIFT, ADZ, POST, DMD, WDC, SEQ, CANN, TRUMP, RDD, ABY, ZET, PASC, CREVA, XST, INCNT, SFT, BLOCK, DEM, SLS, PTC, GRS, PASC, FAIR, BIT, EL, PAK, BLC, BITBTC, BERN, ORB, XCN, BTB, ESP, BOLI, MINT, ZEIT, DIME, 2GIVE, NEVA, LANA, TAJ, BLU, RBT, SRC, ACOIN, J, TROLL, XRA, DUO, FJC, 1337, ANC, FUZZ, POP, NYC, MOTO, CMT, PND, LDOGE]	0.075	0.029					
Club 5 [NXT, DGD, RVR, BCY, XHI, IOC, VRC, PINK, AUR, START, XBC, MUE, CRW, RISE, PEPECASH, KRB, ARC, GB, THC, SWING, NLC2, CJ, ADC, IXC, SMC, ELE, FRN, SONG, HODL, DP]	1.099	0.413		5+ 6	**Club 3**	0.045	0.013
Club 6 [XEM, LSK, STRAT, POT, SYS, XCP, 1ST, XZC, EMC2, FTC, XDN, PIVX, CLOAK,	0.405	0.137					

EGC, BSD, VRM, XVG, MOIN, ATOM, TIT, EXCL, SPHR, PURA]							
Club 7 [AMP, LBC, FLDC, ZCL, GBYTE, SLR, OMNI, USNBT, LMC, OK, TX, OBITS, GOLOS, BTA, DOPE, SPR, MEME, MOJO, SYNX]	0.445	0.166		7 + 8	**Club 4**	-0.093	-0.030
Club 8 [FCT, EXP, XMG]	-1.363	-0.896					
Club 9 [GAME, SIB, CRB, IOP, VSL, PXI, HEAT, ENT, HUSH, NTRN, ACP, BSC]	0.545	0.206		5	**Club 5**	-1.038	-0.508
No convergence [GCR, PUT]	-3.667	-2.775					

5. Conclusions

Academic research in economics and finance has placed a high priority on examining the herding behavior of financial assets. In view of the escalating liquidity needs on a global scale, cryptocurrencies represent contemporary and highly inventive kinds of investments that could offer beneficial answers. Uninformed investors' irrational behavior has received a lot of attention and has also been observed in the markets for digital currency. This paper advances research by examining the convergence into clubs by using cluster analysis and draws on the empirical work that has already been done on herding behaviors in bitcoin markets.

This study examines the herding behavior of 216 digital currencies with high and medium capitalizations over the course of two subperiods. Initially, there was the bull market that lasted from January 1, 2017, until December 18, 2017, when the Bitcoin bubble burst. Second, there was the bear market, which lasted from December 19, 2017, to December 15, 2018, when the sharp decline in Bitcoin prices came to a stop. For the purposes of our econometric estimations, the extremely creative convergence analysis from Phillips and Sul (2007) was used as the approach. The model developed by Phillips and Sul (2009) also looks at group convergence.

According to econometric results, bull markets exhibit severe herding behavior, resulting in the formation of both a very big convergence club (207 cryptocurrencies) and a smaller one. While segmentation occurs, the herding phenomenon persists and nine clubs are formed during bear markets. Major digital currencies continue to play a major role, but herding effect transmitters and receivers are divided into these groups. The bulk of the top cryptocurrencies are discovered to be part of Club 4 (Bitcoin, Ethereum, Litecoin, Monero, Dash, Ethereum Classic, Zcash, MaidSafeCoin, Augur, BitShares, Steem, and Siacoin), and it is discovered that Club 4 has merged with Club 3, which is made up of Ripple and Stellar among other cryptocurrencies.

It should be emphasized that the lowest of the large-cap digital currencies can draw investors primarily from the large-cap and medium-cap categories, roughly in that order. On the other hand, during bear markets, the highest-cap cryptocurrencies belong to convergence clubs that are primarily made up of pure large-cap or pure medium-cap digital currencies. In addition to Club 4, estimates have been made for five medium-sized clubs, four minor clubs, and the non-convergence club. There is no statistically significant convergence in the group containing the Tether stablecoin. The uniform irrationality of investors that exists during prosperous eras is prevented by investor fear sentiments during bear markets, it should be stressed.

This study advances knowledge of the factors that affect bitcoin market values both during bull and bear markets. This study advances research by concentrating on convergence among digital currencies and sheds light on irrational behavior on the part of ignorant investors during extreme moments. In a secondary level, convergence between clubs is also investigated. The interested reader has a more comprehensive understanding of how fear and risk aversion prohibit investing decisions from being made uniformly based on the market behavior of important assets. In order to shed more light on herding phenomena, avenues for further research in cryptocurrency price segmentation could involve evaluation with a wider spectrum of digital currencies or with other convergence inquiry approaches.

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Chapter 6

Policy Implications and Conclusions

This post-doctoral thesis sheds light on numerous issues about modern and digital forms of liquidity and investment and which influential factors affect their optimal synthesis in order to construct portfolios with the best feasible risk-adjusted performance. The aim of this thesis is to widen to the best achievable extent the knowledge about the spillover impacts and the efficiency in cryptocurrency markets, the bubble character of such innovative investments, and the driving forces of market values of sophisticated digital assets. Moreover, the herding behaviour that appears among cryptocurrencies and separates them into groups during flourishing or crisis periods is under scrutiny. For the purposes of achieving this, analytical theoretical analysis is employed as well as the systematic reviews that provide a bird's-eye view on the variables used, the linkages examined, the methodologies adopted and the outcomes estimated by the full spectrum of relevant academic research. Furthermore, the empirical chapters of this thesis employ a spectrum of GARCH-based modern specifications in order to better explore the returns and volatility of such risky assets as cryptocurrencies. Apart from this, the innovative methodology of Phillips and Sul (2009) is applied to reveal the intensity and the group dynamics of club convergence among large-cap, medium-cap, and smaller-cap cryptocurrencies. This serves for better detecting the existence of herding phenomena that are the driving forces of irrational decision-making by investors and constitute the source of bubble phenomena during bull markets while result into bubble burst during bear markets.

More particular, it is shown that Bitcoin continues to be the most popular cryptocurrency, the most significant giver in terms of virtual currency, and the biggest recipient of spillover effects in terms of high-capitalization cryptocurrencies and other assets. As recipients of Bitcoin's spillovers, currencies like Ethereum, Litecoin, and Ripple are discovered to have close ties to the digital currency. There is evidence that volatility spillovers occur more frequently but that return spillovers are more pronounced. It is argued that herding behavior could be sustainable in the markets for digital currencies, with Bitcoin continuing to be the main driver of this phenomena. Because virtual coins and traditional assets are interconnected, portfolio managers may be able to reduce risk by creating diversified portfolios with the right mix of assets. Spillover effects are a sign that the cryptocurrency markets are moving in the direction of greater integration with the international financial markets.

As concerns studying efficiency in cryptocurrency markets, it is supported that weak-form efficiency is mostly examined, which determines whether prices represent the information contained in the previous series of prices. The majority of the scholarly studies that were analyzed argue against the validity of the Efficiency Market Hypothesis. As dependence on previous returns becomes apparent, long memory in bitcoin time series is detected. There is a wide range of tests used, including the Hurst exponent, the Bartels test, the Variance Ratio test, and its parameters.

Investors can thus forecast future returns using information from the past. This makes it possible for traders to employ winning techniques with very little risk. Notably, long-range dependence that results in inefficiency is shown to diminish over time.

When it comes to bubble price development, it is supported that economic hysteria, speculative motivations, and excessive confidence lead to major deviations between asset market values and their corresponding basic values. Different sizes of nominal values in respect to fair value are the result of economic units' increased interest as a result of particularly favorable conditions. Intriguingly, digital assets are considered to be very rewarding for investors and this has caused interest in bubbles to surge despite virtual currency prices bubbling up, which renders harder for those currencies to serve as a unit of account and a store of value for money. Bitcoin is found to have many bubble stages, primarily between 2013 and 2017. Several bubble phases are also visible in other significant coins. The majority of research use daily data from open sources, however there have also been papers that use high-frequency data from privately held data sources. The Augmented Dickey Fuller (ADF) method has been the most often used method for locating bubbles. Additionally, the Log-Periodic Power Law (LPPL) approach is frequently applied in pertinent studies. Overall, empirical research confirm that cryptocurrencies are highly speculative, volatile, and unpredictable. It should be underlined that the existence of cryptocurrencies is predicted to depend heavily on virtual currencies developed by monetary authorities (Central Bank Digital Currency, CBDC), as well as coins tied to bank deposits or government securities (stablecoins). These digital forms of liquidity could benefit from the legal tender status and be shielded from volatility and frequent upheavals if regulation or innovation in digital money increases investors' "trust" in them. The propensity for digital currencies to become more centralized may help keep bubbles in check before they collapse and trigger new crises.

Regarding the riskier and more volatile types of cryptocurrencies, such as cannabis cryptocurrencies, they are attractive to speculators and enjoy high demand. Ripple is found to be an exceptionally important diversifier in the great majority of these cannabis-related digital currencies while Bitcoin is less connected with them and Ethereum is a poor to modest diversifier. Moreover, by focusing on club convergence among digital currencies, it is revealed that bull markets generate very powerful herding phenomena, leading to the construction of both a very big convergence club (207 cryptocurrencies) and a smaller one. Despite segmentation appearing, the herding behaviour persists and nine clubs are brought about during bear markets. Major digital currencies keep on playing a major role, but herding impacts generators and receivers are split into these groups. The largest portion of the top cryptocurrencies are discovered to be part of the Bitcoin, Ethereum, Litecoin, Monero, Dash, Ethereum Classic, Zcash, MaidSafeCoin, Augur, BitShares, Steem, and Siacoin club and it is estimated that this club has merged with the club of Ripple and Stellar among other cryptocurrencies. Remarkably, the lowest of the large-cap digital currencies can attract investors mainly from the large-cap and medium-cap categories. On the other hand, during bear markets, the highest-cap cryptocurrencies make part of convergence clubs that are mostly synthesized of pure large-cap or pure medium-cap digital currencies. Notably, no statistically significant convergence in the group about the Tether stablecoin is detected. Investor fear sentiments during bear markets are found to replace the uniform optimistic irrationality and greediness of investors during flourishing eras.

Overall conclusions

In this post-doctoral thesis, it is demonstrated that Bitcoin remains the most popular cryptocurrency, the largest giver of impacts towards virtual currencies, and the largest recipient of spillover effects in terms of high-capitalization cryptocurrencies and other assets. As a result of Bitcoin's spillovers, currencies such as Ethereum, Litecoin, and Ripple have been identified to have close linkages to the digital money. It is found that volatility spillovers are more common, but return spillovers are more severe. Overall, the data speak to the prospect of long-term herding behavior in digital currency markets, with Bitcoin remaining the primary driver of this phenomenon. Portfolio managers may be able to mitigate risk by constructing diversified portfolios with the proper mix of assets because virtual currency and traditional assets are interconnected. Spillover effects indicate that cryptocurrency marketplaces are moving toward deeper integration with international financial markets. Moreover, long-term dependency, which leads in inefficiency, has been found to lessen with time in Bitcoin markets as well as in the cryptocurrency industry in general. This provides useful information and promotes a more spirited discussion about the future of digital currency. These coins are extremely complex investment vehicles that have attracted a large number of new investors and are expected to play an important role in the future of finance.

This thesis provides insights into the major issue of cryptocurrency optimal allocation that has gained increasing attention and has resuscitated arousing interest due to modern crises that render investors more vulnerable to losses stemming from conventional investment assets. The findings of this thesis are useful as the issue is tightly connected with the financial system, financial and capital markets, and the real economy. It provides a solid and multi-prismatic analysis of the main determinants of cryptocurrency performance (diversifying or hedging character, spillover impacts, level of efficiency, club convergence that fortifies herding behaviour) and informs about the main generators and receivers of cryptocurrencies' influential effects. Furthermore, it offers a more profound understanding of the main concepts that are related with such innovative forms of liquidity which are characterized by 'bubbly' nominal prices and low fundamental values. Moreover, this dissertation provides a complete synthesis of empirical findings in the highly-proliferating bulk of relevant literature. This enables policymakers to estimate in a more accurate manner the level by which financial stability is threatened by the crypto volatility infused in the financial system. Additionally, it strengthens the arsenal of investors in their effort to distinguish difficultly-discernible signs for the evolution of market prices of cryptocurrencies and how large is the volatility that characterizes them. Thereby, the optimal weights of modern and traditional asset allocation could be more safely estimated and the personal and the overall wealth levels could be fortified by taking into consideration the outcomes and conclusions of this thesis.