UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

Overreaction in Bitcoin before and during COVID-19

Master's degree Project in Finance

Gothenburg University - School of Business, Economics and Law
Supervisor: Viktor Elliot

Georgios Kirkinezos & Endri Skora
Gothenburg, Sweden

Spring 2021

Contents

Abstract

In recent years, Bitcoin has attracted a lot of interest from the media, academics and investors, but there is still skepticism and a lack of knowledge about how this cryptocurrency performed in the years leading up to and through the COVID-19 pandemic. The spread of COVID-19 in 2020, means that Bitcoin has been put to test under extreme financial conditions for the first time, and this thesis exploits this period to analyze how the COVID-19 crisis affected Bitcoin investors. As such, our thesis contributes to an understanding of how cryptocurrencies and especially Bitcoin investors react under high uncertainty. Using quantile autoregressive (QAR) models, we investigate the persistence of daily and weekly Bitcoin returns for the PreCOVID-19 and the DuringCOVID-19 periods on the return distributions. We found that lower quantiles of the daily DuringCOVID-19 return distribution have positive correlation with previous negative returns. These findings point to overreaction in the Bitcoin market: investors overreact during days (DuringCOVID-19) where the Bitcoin price falls sharply. Additionally, stronger dependencies between returns were observed from DuringCOVID-19 data, suggesting higher investors' overreaction during that period.

Keywords: Cryptocurrencies, Bitcoin, COVID-19, investors, Cryptocurrency Market, Returns, Quantile Autoregressive Model (QAR)

1. Introduction

1.1 Operations of Cryptocurrencies/Bitcoin and Blockchain Technology

Cryptocurrencies became one of the foremost traded financial assets within the last decade. They are a rapidly increasing alternative asset class that has piqued the attention of many individual and institutional investors due to its potential unique characteristics, such as its safe haven position during crises, a potential hedge for other assets as well as a tool for portfolio diversification (Brière, Oosterlink & Szafarz, 2015). The cryptocurrency market has attracted attention from researchers, investors, policymakers, and governments. The market efficiency of cryptocurrencies has been a hotly debated research topic for years (Tran & Leirvik, 2019). Cryptocurrency markets represent a complicated system in the sphere of economics and finance, and it is vital to further develop our understanding of the way in which these markets operate (Giudici, Milne & Vinogradov, 2020). Cryptocurrencies undeniably have a variety of possible economic advantages to both developers and customers (Bunjaku, Gjorgieva-Trajkovska & Miteva-Kacarski, 2017). The size of the cryptocurrency market is increasing at a standard rate as a consequence of the decline of the public trust in the central banking system since the global financial crisis (Ward & Rochemont, 2019), the innovation of smartphones technology (Mikhaylov, 2020), legalization of cryptocurrencies to be used for payment and trading purposes in many countries worldwide, and the acknowledgment and acceptance of payments from some of the largest companies around the world like Tesla, Microsoft, Starbucks, Amazon, Visa in early 2021.

With the emergence of Bitcoin in early 2009 and the invention of its decentralized technology (the so-called blockchain), several virtual currency altcoins were launched. Crypto markets have quickly become a new digital asset field worthy of consideration for investors, regulators, and academics (Böhme, Rainer, Christin, Edelman & Moore, 2015). We focus on Bitcoin as a form of asset. The idea of Bitcoin relies on the utilization of a peer- to-peer network and a distributed ledger technology that makes online payments potential without an institution acting as a 3rd party (Nakamoto, 2008). The system is decentralized and in order to switch the intermediary and establish trust, Bitcoin enforces attributes corresponding to cryptological proof, digital signatures and proof-of-work. The transactions are validated by miners, which manufacture blocks and add them to a ledger that eventually forms a blockchain. This validation is formed by finding an algorithm, which becomes tougher to try to calculate with time because the ledger becomes longer. This technique of validation makes it rather tough to commit fraud. Moreover, all the transactions and ledgers are publicly available, while anonymity is kept through the assistance of encrypted identities. Companies like MicroStrategy and Square have been betting big on Bitcoin as an investment according to Matt Hussey (Nov 8, 2020). The principal determinants of Bitcoin prices are generally accepted to be a fundamental supply and demand element (Kristoufek, 2015); investors' involvement (Ciaian, Rajcaniova, & Kancs, 2016); macroeconomic and financial improvements (Panagiotidis, Stengos, & Vravosinos, 2019); and technical considerations (Adjei, 2019).

1.2 Bitcoin as an asset and not a currency

Baur et al. (2015) and Wolla et al. (2018) argue that Bitcoin is more an investment asset than a currency. According to Jeffrey Dorfman (May 17, 2017), Bitcoin is not a currency because it has two major flaws: its value fluctuates and transaction execution is slow. Because of the volatility of currency prices, an investor cannot reliably forecast the value of future profits. From the instability, savings are less valuable, and as a result, less investment is made. In addition, Bitcoin transfers are processed very slowly to protect the blockchain, which is what makes cryptocurrencies like Bitcoin so secure. In fact, due to a daily cap on the amount of transactions that can be completed, completing a basic transaction can take days. Because of opposition to change these laws by citizens that like Bitcoin's anonymity and traceability, it may never become a commonly utilized currency. Its value in daily usage is negated by its security. With these disadvantages, Jeffrey Dorfman (May 17, 2017) argued that the only incentive to own Bitcoins is to speculate about its asset valuation or to use them to hide trades from others, rather than to use them as a currency. Additionally, he underlines that Bitcoin cannot be considered a currency until its value is stable. Rather, it is a commodity asset, such as gold or silver, that is traded in the hopes of increasing in value and yielding a trading profit. There is nothing wrong with speculation; speculators' activities help to increase market liquidity and assess commodity market valuation. However, the commodity being priced typically has a practical application compared to Bitcoin, gold may be invested in or used to produce jewellery or electrical components. Bitcoin's behavior is more similar to technology-based products, emerging asset classes, or bubble events, rather than a currency (White, Marinakis, Islam & Walsh, 2020).

1.3 Bitcoin before and during COVID-19 appearance

The World Health Organization (WHO) Director (11 March 2020) confirmed the pandemic status of COVID-19 on March 11, 2020. (COVID-19). The virus was first identified in December 2019 in Wuhan, China, according to Wikipedia (2019). Tens of thousands of people became infected and over a thousand died in the first five weeks of the pandemic. Owing to the expected global economic recessions in the coming years, the WHO announcement sent financial markets around the world into a tailspin. The COVID-19 epidemic, quickly spread across the world, infecting millions of people and killing thousands. The COVID-19 pandemic is still holding strong at the time of writing, and the full scope of the tragedy has yet to be established. Countries are imposing a variety of restrictions, including travel bans, school closures, and curfews, which affect the lives of billions of people. In accordance with Wikipedia (2020), China, on January 23, 2020, was the first to introduce restrictions, followed by other East Asian countries such as Vietnam. Significantly Europe, North America, and Africa waited much longer to implement stricter restrictions. The severity of border and intra-national restrictions varies to geographical regions and restrictions are not stable through time. The pandemic kept people at home but not from continuing with their daily lives. For pending transactions, all transfers, receipts, and trading practices required a safe, decentralized, and fast payment mode.

Many financial analysts and researchers are interested in the impact of COVID-19 on financial markets. COVID-19's effect on financial markets has been extensively studied during the last months, with findings indicating that it is linked to a drop in asset prices and a rise in market volatility (Ali, Alam, & Rizvi, 2020; Apergis & Apergis, 2020; Gil-Alana & Monge, 2020). Corbet et al. (2020) investigates the relationship between Chinese financial markets and Bitcoin volatility. Bitcoin was significantly influenced by the coronavirus spread in 2020, losing half its value in days, dropping from 9,000 USD on March 7 to about 4,000 USD on March 13 according to data from Yahoo Finance. Our research examines the behaviour of Bitcoin's price and returns before and during the COVID-19 pandemic, which is the first major global disruption experienced since Bitcoin was introduced. The extraordinary price fluctuations seen as a consequence of COVID-19, caught our attention and motivated a further probing into the possibility of investor overreaction.

Overreaction by investors, if it exists, could result in the creation of dependency behaviours in Bitcoin returns, meaning inefficiency. Investigations of the PreCOVID-19 period finds a run of results when assessing Bitcoin’s price behaviour. Baur et al. (2015) by working on information from July 2010 to June 2015, discovered that Bitcoin may without a doubt be utilized as a speculative investment and not as an alternative currency and medium of exchange. After the inception of blockchain investing, COVID-19 has led to the first widespread bear market. As a result, it is interesting to examine the cryptocurrency market's movements, especially the behaviour of Bitcoin during and before the COVID-19 crisis. In several studies of COVID-19's effect on financial markets (Zhang, Hu & Ji, 2020; He, Sun, Zhang & Li, 2020; Ashraf, 2020; Albulescu, 2020), traditional statistical methods such as parametric models are used. Many of these approaches have been extensively investigated in the finance literature.

The price of Bitcoin can be observed in Figure 1 and Figure 2, where, for the PreCOVID period, the Bitcoin’s price spiked on the 26th of June 2019 and reached a value of $13,016 and for the DuringCOVID period the Bitcoin’s price spiked on 21st February 2021 and reached the value of $57,539. The lack of statistically meaningful correlations in 2019, when traditional financial instruments were unaffected, was more likely attributed to a market cap asymmetry between cryptocurrencies and traditional stocks, which favours the latter, and is also too small to have a significant effect on other markets. According to Baur and Dimpfl (2018), cryptocurrency volatility grows more in response to positive shocks than in response to negative shocks, suggesting an asymmetric effect that differs from that seen in stocks. Traditional markets, on the other hand, will easily affect the cryptocurrency industry as they become volatile. This is exactly what occurred in March and June of 2020. In addition, during the COVID-19 pandemic, Bitcoin has risen from around $7,000 on January 1st of 2020, to around $17,000 on November 27th of 2020. Bitcoin has risen sharply from $10,665 on September 25th of 2020, to $19,028 on November 25th of 2020, before plummeting to about $17,000.

The repeated mentions of certain abrupt price declines, such as the following, prompted an examination of Bitcoin's intraday price dynamics in 2020 and a comparison to a period prior to COVID-19, to determine if Bitcoin's price behaviour in 2020 is truly extraordinary. Some of the largest price movements are listed below:

- **20th February 2020:** "After peaking at about $10,300, Bitcoin plummeted to $9,300 only a few hours later."
- **13th March 2020:** Bitcoin's price has fallen 20% in the last two days, from $9,000 to as little as $4,100 due to the WHO announcement of COVID-19 being a pandemic."
- **21st May 2020:** "Bitcoin investors are bracing for a bumpy ride after the price of bitcoin dropped almost 10% in the last 24-hour trading time."
- **2nd June 2020:** "Bitcoin's price collapsed by over $800 in less than five minutes on Tuesday, sending the wider cryptocurrency sector into the red."
- **15th June 2020:** "Cryptocurrency has declined by $2,000 in one of the worst crashes of its history."
- **21st February 2021:** "Bitcoin's price rose to $57,539."
- **13th April 2021**: "Bitcoin reached its highest peak so far at $63,503."

These price movements suggest that Bitcoin's price behaviour in 2020 and early 2021 is out of the ordinary, and that abrupt price swings are a consequence of existing market dynamics fuelled by COVID-19.

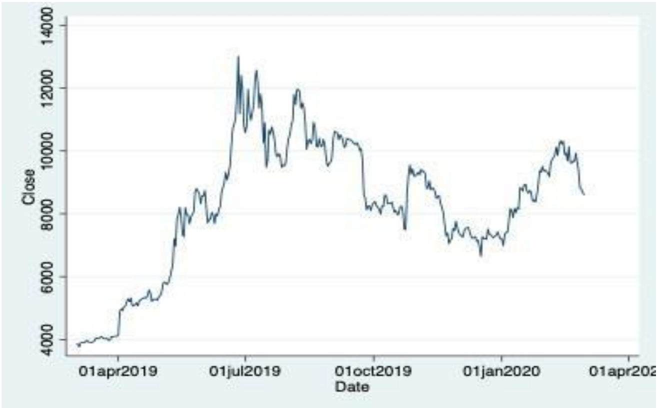

Fig. 1: Level of Bitcoin over PreCOVID period (02/03/2019 - 29/02/2020).

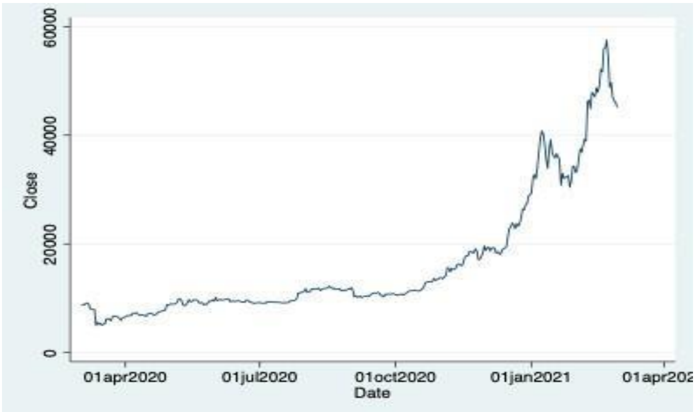

Fig. 2: Level of Bitcoin over DuringCOVID period (02/03/2020 - 28/02/2021).

1.4 Purpose of the Thesis, Method and Summary Results

As authors of this thesis, we want to investigate the long-term economic consequences of COVID-19, including its effect on securities returns. In response to this, we investigate the logarithmic returns of Bitcoin since a logarithmic return decreases the time series' variance, making it easier to match the model in question and for normality reasons to measure all factors in a metric that is comparable. COVID-19, according to analysts and investors, has caused a rethinking of Bitcoin's appeal as a speculative asset (Pagano & Sedunov, 2020), and also as a gold substitute according to Fed Chairman Jerome Powell (March 22, 2021). As reported by Goodell (2020), the COVID-19 pandemic will have a major effect on financial economies, institutions and industries. Ashish Agarwal (May 23, 2020) underlines that unlike fiat assets, Bitcoins have a limited supply to preserve their worth. The blockchain system is set up in such a manner that there will only be a fixed number of coins to mine, and there is no risk that economic disruptions, such as the one COVID-19 is causing, will affect the valuation of these crypto assets. Despite the rising interest in Bitcoin among academics, no one has investigated the topic of investors' reactions to the price trend of Bitcoin before and during COVID-19, to our knowledge. Using the quantile autoregressive (QAR) model, first developed by Koenker and Xiao (2006) and later used by Baur et al. (2012) to examine stock market return autocorrelation, our thesis tries to add to this growing literature by exploring the existence of investors' overreaction to price movement of Bitcoin as a stock, at various points in the return distribution. There are several reasons to think COVID-19 would affect financial market conditions, both during the pandemic and in terms of potential expectations and behaviors. This study's key contribution is an effort to assess the effect of COVID-19 on the reaction of Bitcoin returns and thus the investor’s reaction before and during the pandemic. The methodology is based on the Chevapatrakul and Mascia (2019), where they examined the persistence of returns on Bitcoin at different parts of the return distributions.

Our thesis aims to answer the question if Bitcoin investors overreact at times of financial distress such as the COVID-19 pandemic compared to stable periods of the cryptocurrencies market. Our focus on Bitcoin was because it seemed as the ‘miracle’ of the COVID-19 pandemic, for most time it offered great positive returns and achieved new highs in its price. In accordance with Vikram Khanna (July 29, 2020), stock markets have also increased in value, but their increases pale in comparison to the best-performing crypto assets, thus COVID-19 has made cryptocurrencies hot. Our hypothesis is that investors’ behavior will be more sensitive in the COVID-19 period compared to the more stable previous year. Borgards et al. (2020) found proof that price overreactions are common in the Bitcoin market at all frequencies, confirming the overreaction theory. Despite the fact that cryptocurrency and stock markets are fundamentally different, the results are typically equivalent. However, since greater overreactions are the most important component for success, the returns of an overreaction trading method are substantially greater for cryptocurrencies.

The graph of Bitcoin has seen an upward trend in terms of both prices and returns, during the COVID-19 timeframe and before it. This study also confirmed Bitcoin's upward trajectory and the strong correlation between COVID-19 and Bitcoin returns. Bitcoin is important because it has the characteristics of being anonymous, virtual and cashless. According to Hou, Liu and Jie (2021), the stability of Bitcoin would increase investors' confidence and the users' trust. The QAR model's results suggest that investors overreact to price changes in Bitcoin when returns are significantly persistent at daily frequencies where returns are placed at the tails of the distribution. Specifically, while DuringCOVID returns at the daily frequency are in the lower quantiles of the distribution, investors tend to overreact. Our explanation of the former is that during days of pessimistic feelings, as rates collapse due to depressive emotions, market participants hurry to leave the market, causing the Bitcoin market to fall much more. At the daily and weekly PreCOVID and weekly DuringCOVID frequency, we have no evidence of clear overreaction rather than a slight reaction.

2. Literature Review

2.1 Bitcoin as a currency/diversifier

The question of whether Bitcoin should be classified as a money or a commodity has been debated in recent years. For an item to be categorized as a currency, it must have features such as a medium of exchange, a store of value, and a unit of account (Bariviera et al. 2017). To investigate this, Bariviera et al. (2017) analysed the dynamics of Bitcoin and other major currencies, concluding that Bitcoin lacks the aforementioned characteristics and, as a result, should not be categorized as a currency. Bitcoin, on the other hand, appears to be a speculative asset, according to some (Bariviera et al. 2017). Yermack (2015) follows a similar line of argument and suggest that Bitcoin fails at major characteristics of a currency such as the medium of exchange, unit of account, and store of value. It is difficult to identify the true value of a speculative asset, which is its typical characteristic (Bariviera et al. 2017). This is related to the generation of the price bubble (Shiller 1990; Blau 2018) and is followed by huge volatilities in a global spectrum as mentioned by Tao et al. (2018). Ciaian et al. (2016) claimed that Bitcoin cannot become a currency if its price continues to rely on speculating investments and be a subject of extreme volatility.

Similarly, another strand of literature related to Bitcoin's international diversification and hedging potential is being rapidly discussed by academics. For example, utilizing the multivariate quantile model, Wang et al. (2019) analyzed the danger overflow impact from the U.S EPU index to Bitcoin. U.S EPU index is the Economic Policy Uncertainty Index for the United States. Wang et al. (2019) concluded that the consequences are unimportant/ immaterial, implying that Bitcoin can serve as a safe haven and a diversifier against EPU shocks. Also, they analyzed Bitcoin and gold by exploring their fence or place of refuge parts against EPU. The authors utilize the GARCH model and quantile regression with dummies, and the outcomes demonstrate the accompanying outcomes. To begin with, both assets are unsuccessful on average to act as a reliable hedge or safe haven against the EPU. Second, considering volatile economic situations, Bitcoin and gold both act weakly against uncertainty shocks. Third, Bitcoin is stronger against EPU stuns than gold. As a conclusion, we have seen some signs that Bitcoin can act as a safe-haven asset and a diversifier against EPU shock but on the other hand some other studies say that Bitcoin acts weakly against uncertainty shocks.

2.2 Bitcoin Uncertainty (return-drivers), Volatility and Efficiency

As of late, an examination point that has gotten mainstream among researchers is the impact of uncertainty on Bitcoin returns. Several empirical researches have looked at the effects of uncertainty on Bitcoin returns to see how successful it is at hedging. Aysan et al. (2019) investigated the influence of geopolitical risks on Bitcoin returns and volatility. Researchers utilized the GPR (Geopolitical Risk) index created by Caldara and Iacoviello (2018) to quantify terrorism, wars, and pressures among states. The GPR index reflects the results of automated text searches of the electronic archives of 11 domestic and international newspapers. Utilizing the Bayesian graphical underlying vector autoregressive model, Aysan et al. (2019) find that GPR has a predictive force on value volatility and Bitcoin returns, in this manner, implying Bitcoin's capacity to function as a helpful supporting instrument on occasion of higher global geopolitical risks. The literature shows that the variables deciding Bitcoin price are especially not quite the same as those of regular resources, for e.g., web or google search (Glaser et al., 2014), the absolute number of unique Bitcoin exchanges each day (Ciaian, Rajcaniova & Kancs, 2016), data on media and google patterns (Garcia, Tessone, Mavrodiev & Perony, 2014). Certain extraordinary factors additionally decide Bitcoin cost, e.g., energy costs (Hayes, 2017), social conclusion (Kristoufek, 2015; Bouoiyour & Selmi, 2015), innovation (Li & Wang, 2017), the proportion of trade exchanged volume and the hash rate (Bouoiyour & Selmi, 2015). On exploring the expected drivers of Bitcoin, Panagiotidis, Stengos and Vravosinos (2018) analyzed the determinants of Bitcoin returns by considering 21potential factors that could drive Bitcoin returns. Utilizing the least absolute shrinkage and selection operator (LASSO) regression, the authors reason that search power, gold returns and policy uncertainty are the main drivers for Bitcoin returns.

Likewise, Gozgor et al. (2019) investigated the exchange strategy uncertainty index and the Bitcoin returns of the United States. They concluded that the trade policy uncertainty index is positively related with Bitcoin's returns using Wavelet Power Spectrum, Wavelet Coherency, and Cross-Wavelet Techniques, in conditions extreme uncertainty Bitcoin perish as a hedge instrument. In a similar study they also studied volatility and effectiveness of Bitcoin in regards to the geopolitical risks (GPR) and conluded to a clear hedging impact The relation between global financial stress and Bitcoin returns is researched by Bouri et al. (2018), instead of utilizing volatility indexes, they employed the global financial stress index to represent global stress (since the former better captures global stress). By using a Copula-based approach to dependency and causation, Bitcoin showed persistence in returns at periods of financial distress. Bouri et al. (2017) utilized volatility records of 14 progressed and created securities exchanges as an intermediary for global uncertainty to inspect whether Bitcoin is useful as a hedging tool against global uncertainty. The results indicate that Bitcoin can be used only slightly better against uncertainty at higher quantiles limited role on developments of Bitcoin returns.

Within the previous literature, concerning asset markets in general, investments in cryptocurrencies are usually defined by high expected returns (Elendner et al., 2017) and with the presence of high volatility has been shown to be a sign of a bubble (Cheung, Roca, & Su, 2015). In fact, the volatility of Bitcoin has been shown to be higher than the average volatility for 51 alternative currencies (Blau, 2018), and higher than of traditional assets (Dwyer & Gerald ,2015). A comparison with the S&P 500 index found Bitcoin to be 26 times more volatile (Baek & Elbeck, 2015). Oil and gold found to be less volatile than Bitcoin in a study by Chaim and Laurini (2019.) The excess return and volatility give proof of a speculative asset and a bubble (Corbet, Meegan, Larkin, Lucey & Yarovaya, 2018; Cheah & Fry, 2015),with regulatory pressure and market abuse, like suspicious trading activities on some trading platforms (Gandal, Hamrick, Moore & Oberman, 2018). Zhang and Li (2020) further investigate whether the idiosyncratic volatility is priced in the returns of cryptocurrencies and find a positive relationship between the idiosyncratic volatility and the returns of cryptocurrencies. Modeling Bitcoin volatility is a common subject among financial academics. Several researches examined durability and spillovers of Bitcoin's volatility using various models. However, because of their ability to depict Bitcoin's conditional volatility, the majority of these experiments have used GARCH-based models, with the negative of providing poor risk forecasts (Ardia et al. 2019).

Urquhart (2016) investigates the market efficiency of Bitcoin and discovers that the returns are highly inefficient when considering the entire time period of 1st August of 2010 to 31st July of 2016. Some experiments show that Bitcoin evolve to become more efficient in the latter periods of studies and cryptocurrencies in their majority are considered to be weakly persistent, rather than following a random walk (Caporale, Gil-Alana, & Plastun, 2018). The degree of persistence, on the other hand, seems to vary with time. These features contradictthe market's efficiency (Bouri et al. 2019; Caporale, Gil-Alana & Plastun, 2018). Furthermore, Bouri et al. (2019) claim that there is a predictable component in Bitcoin's price movements. This suggests that there is a chance of anticipating volatility, which provides a hedging advantage by allowing investors to profit from market inefficiencies. In contrary to such conclusions, Alvarez-Ramirez, Rodriguez, and Ibarra-Valdez (2018) contend that there is evidence of efficiency in the Bitcoin market, but they emphasize that the efficiency is only visible for a limited length of time. Sensoy (2018) in his research claimed that liquidity is a positive factor while volatility is a negative factor for Bitcoin's efficiency.

It takes time for information about the COVID-19 to be expressed in Bitcoin markets, highlighting the inefficiencies that this means. The adjustment of Bitcoin values, according to Bouoiyour and Selmi (2020), is incompatible with the EMH (efficient market hypothesis). Bitcoin, in particular, is far from being efficient due to its speculative and unpredictable nature. They reveal that investors seeking Bitcoin as a safe haven in uncertain times are fueling the present positive trend. However, they discover that COVID-19 increases Bitcoin volatility asa result of investors looking for other asset classes in the wake of the coronavirus outbreak. They find that it takes time for information about the COVID-19 to be reflected in the Bitcoinprice, illustrating the inefficiencies it provides, similar to the findings of Jana and Das 2020, Albulescu 2020, Kayal and Rohilla 2019 and Urquhart 2016. Nadarajah and Chu (2017) repeat Urquhart (2016)'s findings, demonstrating that a transition of returns leads to an effectivemarket.

Given the extraordinary nature of the COVID-19, researchers investigated how it impacted cryptocurrency markets, especially in light of the disagreeing behavioral evidence. Lahmiri and Bekiros (2020a) studied the improvement of informational efficiency in 45 cryptocurrency marketplaces, including the CCI30 index and 16 global stock markets, from September 2019 to April 2020. When compared to international stock markets, they claimed that cryptos displayed higher volatility and irregularity during COVID-19.

2.3 Cryptocurrency Market/Bitcoin reaction on COVID-19 pandemic

It is hard to discover a case of comparable monetary markets' reaction within the modern history (Ashraf, 2020; Zhang et al., 2020). Periods of extraordinary monetary push can cause spillover impacts within the cryptocurrency markets (Ji, Bouri, Lau, & Roubaud, 2019). A later consideration recommends that the direction of disease in case of financial disasters is from conventional to crypto-markets, and investors maintain a strategic distance from crypto-assets within the times of financial distress (Matkovskyy & Jalan, 2019). Stress within the global financial markets can cause noteworthy changes within the upper and lower dispersions of the returns of cryptocurrencies such as Bitcoin, shown by the copula-based quantile models (Bouri, Gupta, Lau, Roubaud & Wang, 2018). During the early days of COVID-19, Bitcoin displayed a high relationship with the value markets and dropped in value in pairs with the other financial markets. Furthermore, as compared to traditional stocks, cryptocurrencies are seen to react more strongly to bad news (Borgards & Czudaj, 2020). On the other hand, a number of investigations discover that the behavior of cryptocurrencies is diverse as compared with the conventional resources, commodities, and currencies, and investors' excitement driven by extraordinary news and occasions (both positive and negative) causes an increment within the crypto-markets' returns (Liu & Tsyvinski, 2018; Rognone, Hyde, & Zhang, 2020).

During January to mid-March 2020, Jabotinsky et al. (2020) looked into how the market price and trade rate of the top 100 cryptocurrencies associated with the number of COVID-19 cases and deaths worldwide with two major results. They discovered a connection between the number of new COVID-19 cases (as well as deaths) and cryptocurrency market capitalization, indicating an upward trend in the market. And secondly, they discovered that the relationship between virus spread and cryptocurrency investment in their study time frame had a U-shaped pattern, i.e., more coronavirus cases contributed to greater cryptomarket investments at first, but then the impact reversed. It is likely that investors briefly panicked and withdrew from traditional markets, only to return after the scope of the situation became clearer. Due to the aforementioned advantages of cryptocurrencies, such actions could be justified in the risk-hedging context. However, this finding may be the product of either pump-and-dump schemes or other illegal activity.

2.3.1 Bitcoin does not act as a safe-haven during COVID-19

Conlon and McGee (2020) explore the diversification effects of buying Bitcoin during COVID-19 in order to better understand this significant development of capital markets. Their results indicate that Bitcoin does not act as a safe haven during the early phase of COVID-19. They prove it by adding Bitcoin and S&P 500 index in the same portfolio and the outcomes of their portfolio analysis indicate that Bitcoin does not behave as a safe haven commodity, in fact, Bitcoin adds to the portfolio's downside risk. Furthermore, it seems that Bitcoin and the S&P 500 index have moved together during COVID-19 (Yousaf & Ali 2021), which is not consistent with an asset serving as a safe haven (Baur & Lucey 2010). Ji, Zhang, and Zhao (2020) aim to identify safe haven assets by adding one asset after another to a mean-variance portfolio and then analyzing the impact on the return distribution, with a particular emphasis on the left tail. During this time span, only gold and soybeans have the property of becoming a safe haven asset. The proof suggests that the latest pandemic has had a negative impact on global capital markets. Unfortunately, this has resulted in increased uncertainty and, as a result, danger (Zhang, Hu, & Ji 2020). As a result, investors all over the world have suffered significant losses. Zhang, Hu, and Ji (2020) investigated the connection between these extraordinary threats in the financial markets and the pandemic, they viewed gold as good hedger and diversifier during the pandemic but reject the idea of Bitcoin being a commodity.

2.3.2 Bitcoin as "Digital Gold"/Currency During COVID-19

A few analysts have tried to archive the influence of this flare-up on the Bitcoin returns and found that it performed ineffectively amid this circumstance and showed a high relationship with the equity markets (Conlon & McGee, 2020). Klein et al. (2018) claimed that Bitcoin does no act as a hedger for equity market and overall reported different behavior than gold. The findings of Ali et al. (2020) point to a growing fear and rapidly deteriorating market condition as COVID-19 progressed from epidemic to pandemic. The situation has gotten worse as the global spread has expandedbeyond geographical and continental boundaries, with even safer commodities like gold seeing negative returns as COVID-19 spreads to the US, despite being the least volatile. Their findings lean towards Bitcoin having a diversifying while gold acts as a hedger role for the oil market. The COVID-19 outbreak is said to have harmed cryptocurrency performance, especially Bitcoin and Ethereum, but they recovered quickly by the end of March2020 (Naeem et al., 2021). Their view of the cryptocurrency market is that low returns relate to low trading volumes and liquidity problems. Because of the severity of the pandemic, according to Wisniewski et al. (2021), consumers favor cashless transactions when they believe that handling cash presents a higher risk of infection. During COVID-19, divergent implementations were created to stop cash payments. People's psychological attitudes about Bitcoin are influenced by their sense of safety. The cryptocurrency is advertised on social media, and every social media user is informed about it. Human psychology is influenced by social movements, whether positively or negatively; it is up to trending knowledge to determine this (Tausczik & Pennebaker, 2010; Zhang et al., 2014; De Choudhury et al., 2016). Mnif and Jarboui (2021) found that the efficiency of Bitcoin increases during the pandemic and support a drop in herd bias during that time.

3. Methodology

The approach to investigate the persistence and overreaction on Bitcoin's returns in this thesis is the quantile autoregression (QAR) analysis and this is done in accordance with the methodology used by Chevapatrakul and Mascia (2019). We consider this method to be the most appropriate since a simple linear autoregression would focus on the mean of the response variable at each value of the predictors. Simple linear autoregression provides a grand description of the averages of the distributions that refer to the series of the independent variables (Hao and Naiman, 2007). Quantile regression aims to provide a more detailed approach by computing several different regression curves corresponding to the different percentage points of the distributions, giving a more complete image of the set (Hao and Naiman, 2007). The quantile autoregressive model can capture systematic influences of conditioning variables on the location, scale, and shape of the conditional distribution of the response variable. Thus, it constitutes a significant extension of classical constant coefficient linear time series models in which the effect of conditioning is confined to a location shift. The model may be thought of as a variant of the generic random-coefficient autoregression model with highly dependent coefficients (Koenker & Xiao, 2006).

The model is the first-order conditional quantile autoregressive QAR(1) - model:

$$q_c(R_t \mid \Omega_{t-1}) = \alpha_c + \beta_c R_{t-1} \qquad (1)$$

In equation (1), $q_t(\cdot)$ denotes the conditional quantile function at the τ-th quantile with $\tau \in (0, 1)$, $R_t = \ln(P_t / P_{t-1}) \times 100$ is the Bitcoin return at the end of period t, calculated from the closing prices at time t and t-1, and Ω_{t-1} is the information set publicly available to the market participants at the end of period t-1. For the information set times-one lagged returns were used. The estimates of both α_c and β_c in equation (1) can be obtained by solving the minimisation problem of formula (2):

$$\min_{\alpha_r, \beta_r} \sum_{t=1}^{T} [\rho_c(R_t - \alpha_c - \beta_c R_{t-1})] \qquad (2)$$

where T is the total number of observations, $\rho_\tau(z) = z(1[z\ 0])$ and $1[z\ 0] = 1$ if $z \leq 0$ and 0 otherwise. Contrast of the least squares estimation minimization problem we encounter in classical linear regression, here we have the difference of the ρ_τ component which is the indicator of a corresponding quantile group.

Bitcoin's returns were separated based on quantiles, which corresponded to different states of the asset. The groups that contain the lower quantiles correspond to the bad states of Bitcoin, since they include the lowest returns. The groups with the higher quantiles contain the highest Bitcoin's returns and correspond to good states of the asset. The quantile group where τ =0.1 contains returns from the tenth percentile and the quantile group that τ=0.9, which has the highest returns, includes the returns from the 90th percentile. The intercept α_c is the expected mean value of Bitcoin's returns for the τ-quantile group. The regression coefficient β_c informs us about the movement of Bitcoin's returns. A positive coefficient in a quantile group with negative returns (low quantiles), indicates that the returns aligns with the movement of the previous period and thus, returns are decreasing. A negative coefficient in low quantiles, indicates opposite movement and that returns are increasing. On higher quantiles that have positive intercepts, negative coefficients lead to the opposite movement and return decrease and positive coefficients continue the increase in returns.

The QAR methodology appeals to us because it allows for a more in-depth examination of investor behavior under various market conditions as proxied by the position of the return on its delivery. When the response distribution is asymmetric, extremes are noteworthy, or the response variance fluctuates with the predictors, quantile regression offers a reliable estimate of the connection at the target quantile (Das, Krzywinski & Altman, 2019). While more conventional methodologies will encourage one to examine the effect of lagged returns on current returns at their conditional mean, the approach used in this thesis allows us to investigate the impact of a lagged Bitcoin return on the different percentiles of the current Bitcoin return. Those models can capture systemic effects of conditioning variables on the location, scale, and shape of the conditional distribution of the answer, and thus represent a major advancement over traditional constant coefficient linear time series models in which the effect of conditioning is limited to a location swift (Koenker & Xiao, 2006). Our assumption on Bitcoin's investors behavior is that when returns are found to be either very low or extremely high before and after a pandemic, Bitcoin investors may not behave rationally as Borgards et al. (2020) suggests. Furthermore, in order to see how investment horizons impact response, we run tests on Bitcoin data at daily and weekly frequencies.

We run two QAR(1) processes where we get the results for the two time periods. The concept of sample quantiles is extended to linear and nonlinear regression models, with the least absolute variance estimate as a special case. The history of time series advances in quantile models is explored in (Koenker & Xiao, 2006; Koenker, 2017) for the class of quantile Autoregressive (QAR) models and our thesis follows the previous research on detecting overreaction in the Bitcoin market: a quantile autoregression approach (Chevapatrakul & Mascia, 2019). As mentioned in those research papers the QAR(1) has more advantages than an AR(1), because it separates and analyses the data in different sentiments, giving more depth and insight in the findings. However, AR(1) results are still presented in the research for comparison reasons. Such QAR models are appealing because they enable one to catch the autoregressive coefficients as monotone functions of a single, scalar random variable "systematic influences of conditioning variables on the location, scale and shape of the conditional distribution of the response, and therefore constitute a significant extension of classical constant coefficient linear time series models in which the effect of conditioning is confined to a location shift." (Koenker & Xiao 2006, p.1).

In addition, we use bootstrapped standard errors since this method is preferred because it makes no assumptions regarding the result distribution (Hao & Naiman, 2007). Hao and Naiman (2007) point out that the asymptotic procedure's predictions are often violated, and even though they are, solving for the constructed scale's standard error and skewness changes is difficult. A small sample may have two main methodological issues: inherent distributional assumptions being violated and the inclusion of outliers in the dataset. Since this robust strategy blends the analytical benefits of bootstrapping with the advantages of quantile regression, bootstrapped quantile regression is an appropriate statistical solution to minimize these issues due to the fact that we have a small sample for the periods. We also run Wald tests to investigate the hypothesis that the slope coefficients are identical at the different quantiles for both periods. The results showed significant differences and thus rejected the hypothesis of identical co-movement in the coefficients.

3.1. Data

The data was collected from https://finance.yahoo.com and contains the Bitcoin closing prices, from 1st March of 2019 to 28th February of 2021, a time period of two years. The purpose of this thesis is to compare two different time periods regarding COVID-19. For that reason we separated our data sample into two equal size subsamples. The first subsample is named PreCOVID-19 and contains the Bitcoin closing prices from 1st March 2019 to 29th February 2020. By computing the logarithmic returns (Rt = ln(Pt/Pt 1) × 100), we obtain a total of 365 daily and 51 weekly, return observations for the PreCOVID period and a total of 357 daily and 51 weekly, return observations for the DuringCOVID period. We did not analyze monthly frequencies because a one year time period has very few observations and our results would not be economically relevant. We present the summary statistics of the Bitcoin PreCOVID-19 returns for the various frequencies in Table 1. The time series plots of PreCOVID returns are shown in Figure 3. This specific time period was selected because March 2020 was when the WHO classified COVID-19 as a pandemic, so the time before is considered a PreCOVID-19 period. On 11th March 2020 the World Health Organization (WHO) made the assessment that COVID-19 can be characterized as a pandemic and this corresponds with the next time subsample.

In addition, the second subsample is named During COVID-19 period and contains the data that was gathered from 1st March of 2020 to the 28th February of 2021, it corresponds to one year which we consider the most depicted period of the COVID-19 at least at the time the thesis was written. From the prices we obtain the logarithmic returns and we get daily and weekly variations of returns. We present the summary statistics of the Bitcoin DuringCOVID-19 returns for various frequencies in Table 2. The time series plots are shown in Figure 4.

Table 1. Descriptive statistics. This table reports the means, standard deviations, minima, maxima, skewness, kurtosis and quantiles for daily and weekly returns on Bitcoin for PreCOVID-19 period. The sample period is between 01/03/2019 and 29/02/2020.

	Daily	Weekly
Number of Observations	357	51
Mean	0.45	3.37
Standard Deviation	4.45	10.96
Skewness	-3.02	-1.34
Kurtosis	37.72	7.1
Minimum	-46.47	-40.79
25th quantile	-1.11	-1.05
Median	0.32	3.03
75th quantile	2.09	10.97
Maximum	17.18	22.49

Table 2. Descriptive statistics. This table reports the means, standard deviations, minima, maxima, skewness, kurtosis and quantiles for daily and weekly returns on Bitcoin for the DuringCOVID-19 period. The sample period is between 01/03/2020 and 28/02/2021.

	Daily	Weekly
Number of Observations	357	51
Mean	0.45	3.37
Standard Deviation	4.45	10.96
Skewness	-3.02	-1.34
Kurtosis	37.72	7.1
Minimum	-46.47	-40.79
25th quantile	-1.11	-1.05
Median	0.32	3.03
75th quantile	2.09	10.97
Maximum	17.18	22.49

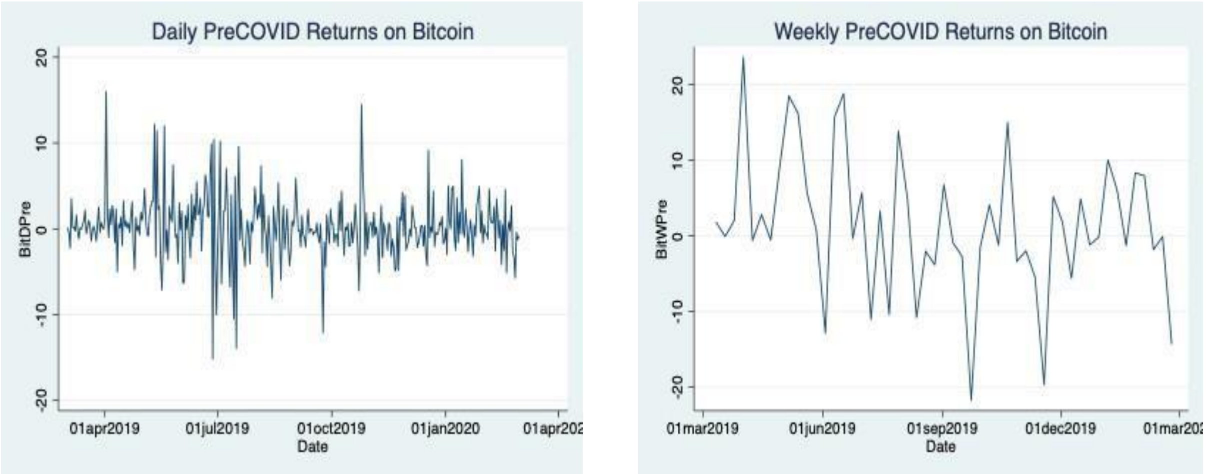

Fig. 3. Time series plots of daily and weekly returns on Bitcoin for PreCOVID-19 period of 01/03/2019 and 29/02/2020.

3.2 PreCOVID-19 Findings

The distributions of Bitcoin returns show up to have exceptionally expansive standard deviations at all the frequencies. Extraordinary price fluctuation is obvious within the data. The highest daily loss of around -15.18% was observed between 26th and 27th of June 2019 and the highest daily gain of 16% was realised between 1st and 2nd of April 2019. About the weekly returns, the highest weekly loss of around -21.72% was observed between 16th and 23th of September 2019 and the highest weekly gain of 23.61% was realized between 25th March and 1st of April 2019. When it comes to the standard deviation, the weekly Bitcoin PreCOVID returns have the highest (9.31) followed by daily(3.54) returns as expected since Bitcoin has high volatility. The return distribution is slightly positively skewed at the daily frequency while it is slightly negatively skewed at the weekly frequency. This is a result that confirms that Bitcoin PreCOVID returns have not experienced extreme negative or positive values. Moreover, daily and weekly returns have non-zero and positive kurtosis. Daily mean log returns are the lowest (0.22%) compared to the weekly (1.52%). The p-value for the Jarque–Bera test statistic for the daily Bitcoin PreCOVID returns is zero (0.000088), indicating rejection of the null hypothesis of normality. For weekly PreCOVID returns the p-values for the Jarque-Bera test statistics are (0.8494) and kurtosis-skewness have values different from zero, indicating acceptance of the null hypothesis of normality. As a preparatory check for the presence of return autocorrelation, we perform a data-driven Portmanteau test, presented by Escanciano and Lobato (2009), on the time series of Bitcoin PreCOVID returns. The Escanciano–Lobato insights for the daily and weekly returns are 42.293 and 1.258 with the p-values of 0.372 and 1, respectively. The evidence points to the nonappearance of autocorrelation in all the return arrangements, recommending effectiveness at all the frequencies under examination.

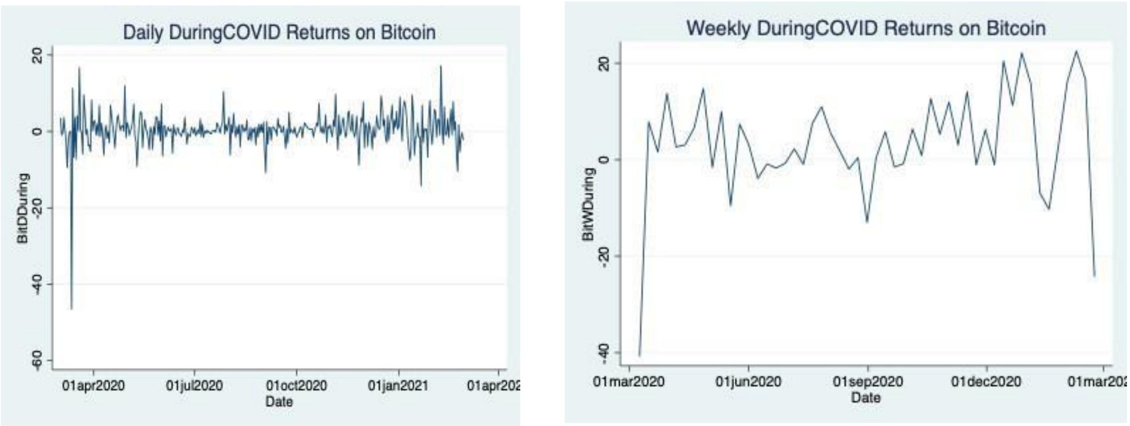

Fig. 4. Time series plots of returns on Bitcoin. Figures above show time series plots of daily and weekly returns on Bitcoin for DuringCOVID-19 period of 01/03/2020 and 28/02/2021

3.3 DuringCOVID-19 Findings

In contrast to the Bitcoin PreCOVID returns, in the period during COVID-19 the mean returns are double in value for each corresponding frequency. The standard deviation remained at similar levels, where daily and weekly returns during the pandemic are higher than the previous period. The highest daily loss occurred 12th of March 2020 with a tremendous 46.47% loss, this loss coincides with the WHOs declaration of COVID-19 being a pandemic which shocked most markets worldwide. The cryptocurrency market was not an exception and the Bitcoin investors saw an extreme drop in Bitcoin value. Bitcoin quickly bounced back over the next few days, but that event was a characteristic example of the uncertainty that dominated the markets during the early phase of COVID-19. Standard deviation remained in similar levels with the PreCOVID period, where again the highest value was observed for weekly returns (10.96), followed by daily returns (4.45). The highest daily return was 17.18 and occurred 08/02/2021 which was an extreme positive jump in an already long-time upward trend. From the end summer of 2020, Bitcoin values continued to increase rapidly. For the weekly returns the maximum return value (22.49) happened in the same week as the daily high. The p-value for the Jarque-Bera test statistic is zero for the daily and weekly returns, indicating rejection of the null hypothesis of normality. The Escanciano–Lobato insights for the daily and weekly returns are 29.8727 and 6.1076 with the p-values of 0.879 and 0.9998, respectively. The results suggest the nonappearance of autocorrelation in all the return arrangements, recommending effectiveness at all the frequencies under examination.

4. Results

To begin with, findings for the AR(1) models indicate that the behavior of Bitcoin returns at the means at all frequencies under consideration is compatible with a white noise operation, which is consistent with the results of the Portmanteau tests mentioned in the previous section. The null hypothesis in the Portmanteau test is that the variable follows a white noise process. A p-value less than the significance level (the probability of rejecting a true null hypothesis, commonly set at 0.05) indicates we reject the null hypothesis and conclude that the variable is not white noise, just as in any other statistical inference. If the p-value is bigger than the significance level (0.05), we do not reject the null hypothesis and this is evidence of absence of autocorrelation in all the return series, suggesting efficiency at all the frequencies under investigation.

Table 3. Quantile regression results for PreCOVID period. We set τ = 0.1, 0.2, …, 0.9 . Numbers in parentheses are standard errors.

QAR(1)/AR(1) PreCOVID Results

τ	Daily		Weekly	
	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\alpha}$	$\hat{\beta}$
Mean	0.22	-0.004	1.36	0.09
	(0.19)	(0.06)	(1.34)	(0.15)
0.1	-3.4	0.004	-13.46	0.54
	(0.42)	(0.11)	(3.45)	(0.43)
0.2	-1.97	-0.03	-3.77	0.027
	(0.25)	(0.09)	(3.1)	(0.22)
0.3	-0.93	-0.005	-1.58	0.04
	(0.22)	(0.06)	(0.78)	(0.17)
0.4	-0.4	-0.02	-1.03	0.019
	(0.16)	(0.06)	(0.98)	(0.19)
0.5	0.11	-0.02	-0.046	-0.016
	(0.15)	(0.08)	(0.82)	(0.19)
0.6	0.64	0.009	2.32	-0.09
	(0.17)	(0.08)	(0.97)	(0.17)
0.7	1.33	0.02	5.44	0.012
	(0.21)	(0.07)	(1.44)	(0.16)
0.8	2.26	0.03	7.14	0.096
	(0.27)	(0.04)	(1.99)	(0.22)
0.9	3.64	0.04	15.14	0.12
	(0.5)	(0.08)	(2.38)	(0.34)

We now zoom in the QAR(1) models' results. It is notable in the daily Bitcoin PreCOVID returns that the coefficients β_c have small values and thus do not support an overreaction hypothesis which means that the lagged returns do not have strong effects on Bitcoin's returns. The highest dependency of daily PreCOVID returns is observed at the highest quantile with the coefficient's value being 0.04, which is weak. The highest coefficients for the whole PreCOVID sample is observed at the weekly frequency for the 0.1 quantile, with a positive value of 0.54 and 0.12 at the 0.9 quantile. Those two extremes show high dependency, however their closest sentiments have weak dependency and do not support the overreaction hypothesis. Bitcoin DuringCOVID returns tend to be more predictable at the 10th quantile and to have less of an impact at the median and in the high quantiles, according to estimates in the third column of Table 4 – a result of overreaction of prices in an inefficient sector (Lehmann, 1990). Those results are interpreted through the magnitude of the β_c coefficients, which show the strong or weak dependency of the returns with the lagged returns. The positive return dependency at the 10th quantile which is 0.1, in combination with the expected daily return being roughly -3.57%, means that the negative returns will continue to decrease. One possible explanation is that during times of negative market sentiments, tumbling Bitcoin value leads investors to overreact, racing for exit and therefore allowing prices to drop. While the size of the predicted parameter is small and therefore not economically significant, the estimates of the median suggest statistically significant negative return autocorrelation and possibly verify the uncertainty due to the pandemic. The highest 90th quantile of the daily DuringCOVID data has an expected mean return of 4.77, the coefficient is -0.14 suggesting an opposite movement, a decrease in the returns, the rest high quantiles have similar results. This effect can be possibly explained by the investor's fear of a drop in the price of Bitcoin since it is already in a high price spot and further increase may be considered unlikely to happen. However, the magnitude of the median and high quantiles coefficients are much smaller compared to the coefficient of the 10th quantile and thus this is not a strong result. Weekly DuringCOVID returns have similar behaviour in the low quantiles with the corresponding daily returns, but in the median and high quantiles follow an opposite direction. At high quantiles of the weekly DuringCOVID returns, positive coefficients are observed which support a view of investors' optimism in increasing weekly returns.

Table 4. Quantile regression results. This table reports the quantile regression results for the DuringCOVID period for the model shown in the beginning of the methodology and data part. We set τ = 0.1, 0.2, ..., 0.9 . Numbers in parentheses are standard errors.

QAR(1)/AR(1) DuringCOVID Results

τ	**Daily**		**Weekly**	
	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\alpha}$	$\hat{\beta}$
Mean	0.49	-0.009	2.88	0.13
	(0.24)	(0.05)	(1.64)	(0.15)
0.1	-3.57	0.1	-9.26	0.15
	(0.64)	(0.17)	(7.06)	(0.54)
0.2	-1.52	-0.01	-1.14	-0.07
	(0.33)	(0.09)	(2.31)	(0.25)
0.3	-0.59	-0.09	-0.83	0.04
	(0.21)	(0.07)	(1.35)	(0.2)
0.4	-0.05	-0.13	1.13	0.05
	(0.13)	(0.07)	(1.52)	(0.21)
0.5	0.43	-0.13	2.86	0.03
	(0.1)	(0.06)	(1.88)	(0.21)
0.6	0.94	-0.11	5.97	-0.05
	(0.12)	(0.05)	(1.79)	(0.27)
0.7	1.65	-0.11	8.59	0.13
	(0.16)	(0.06)	(1.75)	(0.23)
0.8	2.91	-0.17	12.52	0.14
	(0.26)	(0.09)	(1.88)	(0.21)
0.9	4.77	-0.14	13.75	0.15
	(0.63)	(0.13)	(1.68)	(0.2)

The quantile processes are seen in Fig. 5.1 to graphically highlight the pattern of return dependency. The dotted black line in each figure depicts the estimations of β_τ, while the grey color depicts the 90% confidence interval measured using a bootstrapped quantile regression model. The estimations of β_τ and its corresponding 90% confidence interval, drawn in the figures, are taken from the AR(1) process, as are the red solid and red dotted lines.From Fig.5.1 and Fig.5.2 the overreaction hypothesis, can be visually explained by the smooth distribution line at the daily DuringCOVID returns. High slopes combined with smooth lines support overreaction, corners and low slopes in the distribution line suggest no overreaction. High slopes relate to the coefficients' change, and thus dependency changes in different sentiments and the smooth lines ensure not to have severe differences in neighboring quartiles.

We can see from the estimated quantile processes that for the daily PreCOVID returns we find no evidence of return dependence as can be seen from the quantile process. The slope of the distribution line is low, so there is no trend in this case and its' highest dependency appears in the lowest quantile but is insignificant when compared to the corresponding quantile of the daily DuringCOVID returns. This comparison suggests that investors' overreaction is more sensitive in the pandemic era. For the weekly PreCOVID returns positive autocorrelation is observed in the extremes. The corners at the distribution line and the spike from the extreme autocorrelation at the 0.1 quantile do not support an overreaction view.

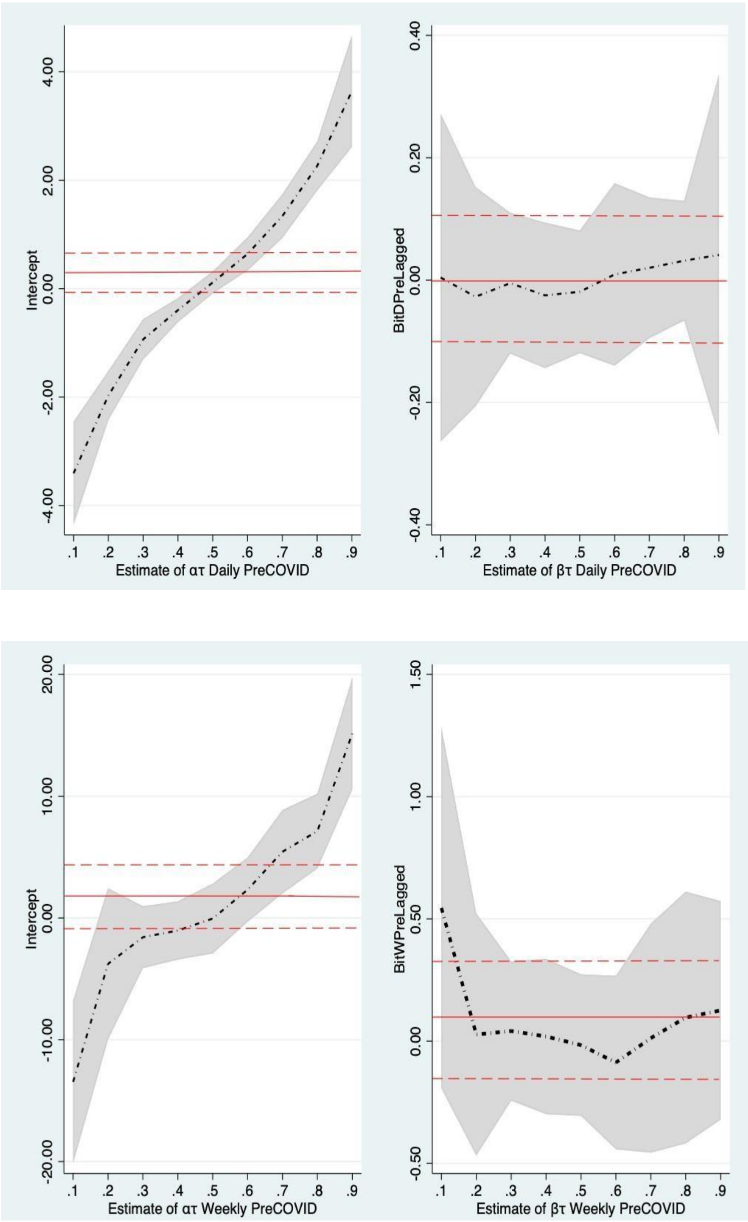

Fig. 5.1: Estimates of ατ and βτ for the PreCOVID used the daily and weekly observations. The 90% confidence intervals of the estimated quantile regression parameters are depicted by the gray shade areas. The red solid line represents the estimated parameter for the AR(1) model and the corresponding 90% confidence interval shown by the dotted lines.

For the daily DuringCOVID returns distribution, from Fig.5.2 we notice that the left tail has a statistically important positive return autocorrelation and a lesser negative autocorrelation at median and high quantiles. A down sloping trend and a smooth distribution line is visual to strongly support overreaction in the lowest quantiles. For the weekly PreCOVID returns distribution we see no evidence of return dependence according to the quantile process. Weekly DuringCOVID returns distribution line has many corners, so an overreaction trend does not exist, and has an opposite slope than daily DuringCOVID returns distribution at median and high quantiles. This could be because investors view different daily and weekly returns and have different approaches to investments with different frequencies. We have mentioned that our weekly data is small in size, and their results may not be significant.

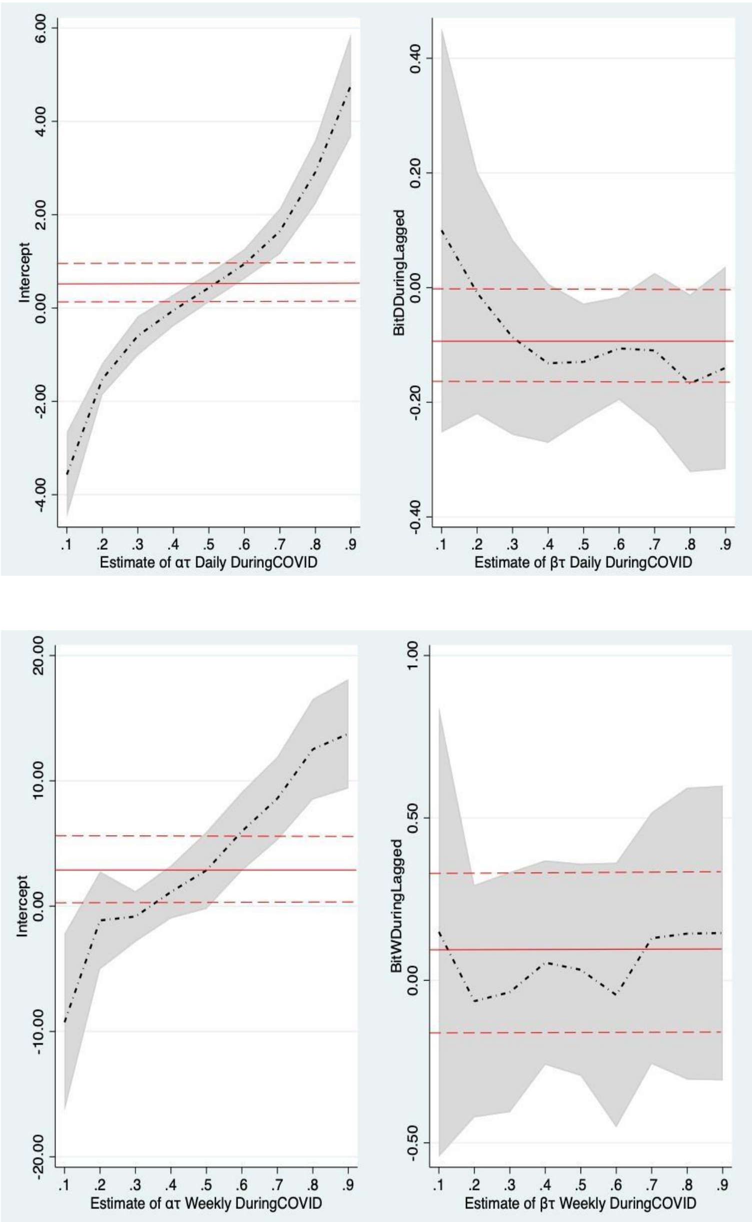

Fig. 5.2: Estimates of ατ and βτ for the DuringCOVID period used the daily and weekly observations. The 90% confidence intervals of the estimated quantile regression parameters are depicted by the gray shade areas.

The red solid line represents the estimated parameter for the AR(1) model and the 90% confidence interval is shown by the dotted lines.

According to the classical theory of linear regression, the conditional quantile functions of the response variable, y, provided covariates x, are all parallel to one another, meaning that the slope coefficients of different quantile regressions would be similar. The direction of the response distribution is shifted by covariate results, but the size and shape remain unchanged. However, as we have seen, quantile regression slope estimates frequently differ significantly between quantiles in practice, so checking for equality of slope parameters across quantiles is an urgent and fundamental issue of inference in quantile regression. Koenker and Bassett (1982a) proposed a couple of basic tests for this reason. Our hypothesis is accommodated by the Wald test. Slope estimates often vary across quantiles, implying that it is important to test for equality of slopes across quantiles. Wald tests designed for this purpose were suggested by Koenker and Bassett (1982a); Koenker and Bassett (1982b); Koenker and Machado (1999). The hypothesis is that the slope coefficients at different quantiles are the same for the PreCOVID and DuringCOVID period. The null hypotheses for the tests are as follows: $\beta_{0.10}=\beta_{0.90}$, $\beta_{0.10}=\beta_{0.50}$, $\beta_{0.50}=\beta_{0.90}$, $\beta_{0.25}=\beta_{0.75}$, $\beta_{0.10}=\beta_{0.25}=\beta_{0.50}=\beta_{0.75}=\beta_{0.90}$. Tables 5 and 6 display the F-statistics along with their related p-values. The findings indicate that none of the differences are statistically significant for the PreCOVID and the DuringCOVID period. However, the difference between β_c estimated at the 10th against the median would be taken as statistically significant at the weekly frequencies since it is very close (0.12) to the statistically significance level (0.1). The daily DuringCOVID frequencies between $\beta\tau$ estimated at the 10th against the median follow the same direction of significance either. From the Wald-test results, we conclude that due to the lack of appropriate amount of data for the Pre and DuringCOVID period, we do not have a significant result from this test. Taking into consideration the results of the Wald test coming from our limited data, with much more data in the future about these two periods the results of the Wald test would be more helpful and indicative

Table 5. Slope equality test results for PreCOVID period. This table reports the results from the slope equality test of Wald.

H0	**Daily**			**Weekly**		
	F	**Df**	**p-value**	**F**	**Df**	**p-value**
$Q_{0.10}=Q_{0.90}$	0.10	1	0.75	1.03	1	0.32
$Q_{0.10}=Q_{0.50}$	0.03	1	0.86	2.47	1	0.12
$Q_{0.50}=Q_{0.90}$	0.61	1	0.44	0.46	1	0.5
$Q_{0.25}=Q_{0.75}$	0.13	1	0.72	0	1	0.74
$Q_{0.10}=Q_{0.25}=Q_{0.50}=Q_{0.75}=Q_{0.90}$	0.47	4	0.76	0.89	4	0.47

Table 6. Slope equality test results for DuringCOVID period. This table reports the results from the slope equality test of Wald.

H0	**Daily**			**Weekly**		
	F	**Df**	**p-value**	**F**	**Df**	**p-value**
$Q_{0.10}$=$Q_{0.90}$	1.23	1	0.27	0	1	0.997
$Q_{0.10}$=$Q_{0.50}$	1.80	1	0.18	0.02	1	0.88
$Q_{0.50}$=$Q_{0.90}$	0.01	1	0.92	0.31	1	0.58
$Q_{0.25}$=$Q_{0.75}$	0.37	1	0.54	0.68	1	0.41
$Q_{0.10}$=$Q_{0.25}$=$Q_{0.50}$ =$Q_{0.75}$=$Q_{0.90}$	0.47	4	0.76	0.39	4	0.82

5. Conclusion

This paper adds to the existing body of research about Bitcoin and its investors' behavior during COVID-19 pandemic. The findings suggest overreaction in the PreCOVID and DuringCOVID periods at various parts of the return distribution. At the daily frequency for the DuringCOVID time, investors overreact to negative returns and due to pessimism push further down Bitcoin's price. At the weekly frequency for the DuringCOVID time, investors show an optimistic overreaction to positive returns, that increase more Bitcoin's price. For the lower frequency of daily DuringCOVID returns, the results suggest a negative overreaction on the lower quantiles and for the higher frequency of weekly DuringCOVID returns, the results suggest a slight positive overreaction on the higher quantiles which corresponds to previous literature such as the paper by Chevapatrakul and Mascia (2019). Furthermore, we found evidence that, during the COVID- 19,the overreaction magnitude is enlarged. The QAR estimated parameters of DuringCOVID-19 show stronger dependency in the lower quantiles of daily returns and in the higher quantiles of the weekly returns, no significant differences are observed in other parts of the return distributions.

What sets this study apart from others is that the investigation would be limited to Bitcoin for both the pre- and post-COVID periods. Since the virus is still active at the time of writing this thesis, the data used may produce findings that vary as the effects of the virus at various times are analyzed in the future. As a result, this study will be one of the first academic contributions to a deeper understanding of Bitcoin returns and investor's overreaction in the period of extreme economic turbulence, especially the Novel Coronavirus. The effect of Bitcoin prices and COVID-19 on growth is fascinating. It remains to be seen if this trend persists, but it shows no signs of slowing down. Because of the competitive nature of the cryptocurrency market, it is difficult to say how long the recent increase in Bitcoin's value will last. Bitcoin, as a virtual currency could be important because it has the characteristics of being an anonymous, virtual, cashless, and decentralized currency. The idea that cryptocurrencies may be exchanged from anywhere in the world helps to eliminate some of the anonymity issues that can occur if local governments impose exchange restrictions as part of a lockdown. As a consequence, when opposed to substitutes, cryptocurrencies appear more appealing. Furthermore, investors who are concerned that a recession could prompt central banks or government agents to intervene in the market may choose to invest in the decentralized cryptomarket. To put it another way, since cryptocurrencies are not regulated by a central authority but rather function autonomously, they can help investors mitigate political risk and thus become more appealing. And Bitcoin's stability if achieved would inspire trust in both investors and users.

Forces, on the other hand, could drive demand down. In a time of crisis, cryptocurrencies may become highly correlated with conventional financial markets (even though there is no such connection in normal times), making the advantage of switching to crypto insignificant. Worse, the confusion created by a pandemic could result in at least two dangerous behaviors that could result in significant losses. To begin, sophisticated investors can manipulate the price of cryptocurrencies ("pump-and-dump" schemes) by artificially inflating demand in order to attract unsophisticated investors, who would then sell their holdings once the price has risen sufficiently. This seems possible if people engage in herding activity, that is, buying cryptocurrencies simply because others are doing so. Second, cryptocurrencies were accused of encouraging illegal activities long before the pandemic. As a result, the same characteristics that make cryptocurrencies appealing during a crisis often make them appealing to criminals (especially if crime is more attractive during the turbulence of the pandemic). People may be afraid that using cryptocurrency would expose them to criminal allegations of money trafficking, so they stop trading. We now realize that the cryptomarket has thrived, implying that the first set of consequences has won out in the long run. However, much of the mystery surrounding COVID-19 has been dispelled, thanks to the development of vaccines and advances in medical care.

What is clear is that the pandemic has had a huge impact on consumer behaviour, which is unlikely to improve anytime soon. Bitcoin is going to begin to become more popular as the transition to the digital realm accelerates. Since digital, fiat, or online capital is reliant on the internet, investors' inability to access it becomes a source of failure. Bitcoin has a lot of advantages, but because of its unpredictability, it can lead to bankruptcy. Future studies should look at the policies and initiatives that could have affected Bitcoin's prices and returns. With our thesis, we take the initiative to give the impetus to future researchers to study the overreaction of investors in Bitcoin or cryptocurrencies in the COVID-19 period. This thesis is limited to the period before and during COVID-19 and there will be more sufficient data for such a study in the future. So, future research could add analysis on the post era of COVID-19. Other suggestions for future research on the topic should be the investigation on a larger time horizon for the two periods. For the PreCOVID era one has sufficient data from previous years, but as this thesis was written within the first year of COVID-19, the sample for the DuringCOVID data was limited. While our daily data may provide a sufficient analysis, the weekly data has small size and as a result may provide imprecise and faulty results. With a bigger data sample for the period of the pandemic, researchers can have more trustworthy results for all daily and weekly frequencies and possibly try to insert an analysis on monthly returns.

6. References

Adjei, F. 2019. Determinants of Bitcoin expected returns. Journal of Finance and Economics 7 (1):42–47. doi:10.12691/jfe-7-1-5.

Albulescu, C. (2020). Coronavirus and financial volatility: 40 days of fasting and fear. ArXiv Preprint ArXiv:2003.04005.

A. Mikhaylov. (2020). Cryptocurrency Market Analysis from the Open
Innovation Perspective

Ali, M. , N.Alam, and S. A. R.Rizvi . 2020. Coronavirus (COVID-19) — An epidemic or pandemic for financial markets. Journal of Behavioral and Experimental Finance 27:100341. doi:10.1016/j.jbef.2020.100341.

Alvarez-Ramirez, J., Rodriguez, E., & Ibarra-Valdez, C. (Feb. 2018). Long-range correlations and asymmetry in the Bitcoin market, Physica A: Statistical Mechanics and its Applications, vol. 492, pp. 948–955.

Apergis, E. , and N.Apergis . 2020. Can the COVID-19 pandemic and oil prices drive the US partisan conflict index? Energy Research Letters 1 (1):13144. doi:10.46557/001c.13144.

Ardia D, Bluteau K, Ruede M, 2019. Regime changes in Bitcoin GARCH volatility dynamics

Aysan AF, Demir E, Gozgor G, Lau CKM. Effects of geopolitical risks on the bitcoin returns and volatility. Res Int Bus Finance. (2019) 47:511–8. doi: 10.1016/j.ribaf.2018.09.011

Baek, C. & Elbeck, M. (2015). Bitcoins as an investment or speculative vehicle? A first look, Applied Economics Letters, vol. 22 (1).

Bariviera, Aurelio F. et al. (2017). Some stylized facts of the Bitcoin market, Physica A: Statistical
Mechanics and its Applications, vol. 484.

Baur, D., Hong, K. & Lee, A.D. (2015), “Bitcoin: Currency or Asset?”,. Available on SSRN at hllps://ssrn.com/abstract=2736020.

Baur, Dirk & Dimpfl, Thomas. (2018). Asymmetric volatility in cryptocurrencies. Economics Letters. 173. 10.1016/j.econlet.2018.10.008.

Baur DG, Dimpfl T, Kuck K. Bitcoin, gold the US. dollar – A replication and extension. Finance Res Lett. (2018) 25:103–10. doi: 10.1016/j.frl.2017.10.012

Baur DG, Hong K, Lee AD. Bitcoin: medium of exchange or speculative assets? J Int Financ Mark Insti Money. (2018) 54:177–89. doi: 10.1016/j.intfin.2017.12.004

Baur, Dimpfl, Jung, 2012, D.G. Baur, T. Dimpfl, R.C. Jung, Stock return autocorrelations revisited: a quantile regression approach, J. Empir. Finance, 19 (2) (2012), pp. 254-265

Baur, Dirk G & Lucey, Brian M (2010). Is Gold a Hedge or a Safe Haven? An Analysis of Stocks,
Bonds and Gold, pp. 217–229.

Blau, Benjamin M. (2018). Price dynamics and speculative trading in Bitcoin, Research in International Business and Finance, vol. 43.

B.N. Ashraf
Stock markets' reaction to COVID-19: Cases or fatalities?
Research in International Business and Finance (2020), p. 101249

B.N. Lehmann
Fads, martingales, and market efficiency
Quart. J. Econ., 105 (1990), pp. 1-28

Brière M, Oosterlinck K, Szafarz A. Virtual currency, tangible return: portfolio diversification with bitcoin. J Asset Manage. (2015) 16:365–73. doi: 10.1057/jam.2015.5

Böhme, Rainer, Nicolas Christin, Benjamin Edelman, and Tyler Moore. 2015. "Bitcoin: Economics, Technology, and Governance." Journal of Economic Perspectives, 29 (2): 213-38.

Borgards O. ,Czudaj R.L.
The prevalence of price overreactions in the cryptocurrency market (2020).

Bouoiyour J, Selmi R. What does bitcoin look like? Ann Econ Finance. (2015) 16:449–492.

Bouoiyour, J., & Selmi, R. (2020). Coronavirus Spreads and Bitcoin's 2020 Rally: Is There a Link?

Bouri E, Azzi G, Dyhrberg AH. On the Return-Volatility Relationship in the Bitcoin Market Around the Price Crash of 2013. Economics Discussion Papers No. 41 (2016). doi: 10.2139/ssrn.2869855

Bouri, Elie et al. (2019). Modelling long memory volatility in the Bitcoin market: Evidence of persistence and structural breaks, International Journal of Finance and Economics, vol. 24 (1).

Bouri E, Gil-Alana LA, Gupta R, Roubaud D. Modelling long memory volatility in the bitcoin market: evidence of persistence and structural breaks. Int J Finance Econ. (2019) 24:412–26. doi: 10.1002/ijfe.1670

Bouri E, Gupta R, Lau CKM, Roubaud D, Wang S. Bitcoin and global financial stress: a copula-based approach to dependence and causality-in-quantiles. Q Rev Econ Finan. (2018) 69:297–307. doi: 10.1016/j.qref.2018.04.003

Bouri E, Gupta R, Tiwari AK, Roubaud D. Does bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. Finance Res Lett. (2017) 23:87–95. doi: 10.1016/j.frl.2017.02.009

Bouri E, Molnár P, Azzi G, Roubaud D, Hagfors LI. On the hedge and safe haven properties of bitcoin: is it really more than a diversifier? Finance Res Lett. (2017) 20:192–8. doi: 10.1016/j.frl.2016.09.025

Bouri E, Shahzad SJH, Roubaud D. Co-explosivity in the cryptocurrency market. Finance Res Lett. (2019) 29:178–83. doi: 10.1016/j.frl.2018.07.005

Ciaian P, Rajcaniova M, Kancs A, (2016) The digital agenda of virtual currencies: Can Bitcoin become a global currency

Caldara D, Iacoviello M. Measuring Geopolitical Risk. Board of Governors of the Federal Reserve Board Working Paper (2018). doi: 10.17016/IFDP.2018.1222

Caporale, Guglielmo Maria, Gil-Alana, Luis, & Plastun, Alex (Dec. 2018). Persistence in the cryptocurrency market, Research in International Business and Finance, vol. 46, pp. 141–148.

Chaim, Pedro & Laurini, Márcio P. (Mar. 2019). Is Bitcoin a bubble?, Physica A: Statistical Mechanics and its Applications, vol. 517, pp. 222–232.

Cheah, E. T. , and J.Fry . 2015. Speculative bubbles in bitcoin markets? An empirical investigation into the fundamental value of bitcoin. Economics Letters 130:32–36. doi:10.1016/j.econlet.2015.02.029.

Cheung, Adrian., Roca, Eduardo., & Su, Jen Je. (May 2015). Crypto-currency bubbles: an application of the Phillips–Shi–Yu (2013) methodology on Mt. Gox bitcoin prices, Applied Economics, vol. 47 (23), pp. 2348–2358.

Chu J, Chan S, Nadarajah S, Osterrieder J. GARCH modelling of cryptocurrencies. J Risk Financ Manage. (2017) 10:17. doi: 10.3390/jrfm10040017

Ciaian, P. , M.Rajcaniova, and D. A.Kancs . 2016. The economics of Bitcoin price formation. Applied Economics 48 (19):1799–815. doi:10.1080/00036846.2015.1109038.

Claudiu Tiberiu Albulescu . 2020. COVID-19 and the United States financial markets' volatility

Corbet S, Meegan A, Larkin C, Lucey B, Yarovaya L. Exploring the dynamic relationships between cryptocurrencies and other financial assets. Econ Lett. (2018) 165:28–34. doi: 10.1016/j.econlet.2018.01.004

Corbet, S., Hu, Y., Lucey, B. M., Oxley, L., 2020b. Aye Corona! The Contagion Effects of Being Named Corona during the COVID-19 Pandemic

D. Shen, A. Urquhart, P. Wang
A three-factor pricing model for cryptocurrencies
Finance Research Letters., 34 (2019), Article 101248

D. Zhang, M. Hu, Q. Ji Financial markets under the global pandemic of COVID-19 Finance Research Letters, 101528 (2020)

Das Kiranmoy, Krzywinski Martin and Altman Naomi
Quantile regression robustly estimates the typical and extreme values of a response (2019).

De Choudhury, M., Kiciman, E., Dredze, M., Coppersmith, G., and Kumar, M. (2016). "Discovering shifts to suicidal ideation from mental health content in social media," in Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems, San Jose, CA, 2098–2110. doi: 10.1145/2858036.2858207

Demir E, Gozgor G, Lau CKM, Vigne S. Does economic policy uncertainty predict the bitcoin returns? An empirical investigation. Finance Res Lett. (2018) 26:145–9. doi: 10.1016/j.frl.2018.01.005

Dyhrberg AH. Bitcoin, gold and the dollar –a GARCH volatility analysis. Finance Res Lett. (2016) 16:85–92. doi: 10.1016/j.frl.2015.10.008

Dyhrberg AH. Hedging capabilities of bitcoin. Is it the virtual gold? Finance Res Lett. (2016) 16:139–44. doi: 10.1016/j.frl.2015.10.025

Dwyer, Gerald P. (2015). The economics of Bitcoin and similar private digital currencies, Journal of Financial Stability, vol. 17, pp. 81–91.

E. Bouri, R. Gupta, A.K. Tiwari, D. Roubaud
Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. (2017), vol. 23, issue C, 87-95

El Sayed A, Gozgor G, Lau CKM. Causality and dynamic spillovers among cryptocurrencies and currency markets. Int J Finance Econ Forthcom. (2021). doi: 10.1002/ijfe.2257

Elendner, Hermann et al. (Aug. 2017). The Cross-Section of Crypto-Currencies as Financial Assets: Investing in Crypto-Currencies Beyond Bitcoin, Handbook of Blockchain, Digital Finance, and Inclusion, Volume 1: Cryptocurrency, FinTech, InsurTech, and Regulation, vol. 1, pp. 145–173.

Engle RF, Ghysels E, Sohn B. Stock market volatility and macroeconomic fundamentals. Rev Econ Stat. (2013) 95:776–97. doi: 10.1162/REST_a_00300

Flamur Bunjaku, Olivera Gjorgieva-Trajkovska, Emilija Miteva-Kacarski.2017. CRYPTOCURRENCIES – ADVANTAGES AND DISADVANTAGES

Gandal N, Hamrick JT, Moore T, Oberman T. Price manipulation in the bitcoin ecosystem.J Monet Econ. (2018) 95:86–96. doi: 10.1016/j.jmoneco.2017.12.004

Garcia D, Tessone C, Mavrodiev P, Perony N. The digital traces of bubbles: feedback cycles between socio-economic signals in the bitcoin economy. J R Soc Interface. (2014) 11:1–8. doi: 10.1098/rsif.2014.0623

Gil-Alana, L. A. , and M.Monge . 2020. Crude oil prices and COVID-19: Persistence of the shock. Energy Research Letters 1 (1):13200. doi:10.46557/001c.13200

Giudici, G., Milne, A. & Vinogradov, D. Cryptocurrencies: market analysis and perspectives. J. Ind. Bus. Econ. 47, 1–18 (2020). https://doi.org/10.1007/s40812-019-00138-6

Glaser F, Zimmermann K, Haferkorn M, Weber MC, Siering M. Bitcoin-asset or currency? Revealing users' hidden intentions. revealing users' hidden intentions. In ECIS Conference 2014. Paper No. 2425247 (2014).

Gozgor G, Tiwari AK, Demir E, Akron S. The relationship between bitcoin returns and trade policy uncertainty. Finance Res Lett. (2019). 29:75–82. doi: 10.1016/j.frl.2019.03.016

Hayes AS. Cryptocurrency value formation: an empirical study leading to a cost of production model for valuing bitcoin. Telemat Informat. (2017) 34:1308–21. doi: 10.1016/j.tele.2016.05.005

Yousaf, Imran & Ali, Shoaib. (2021). Linkages between Stock and Cryptocurrency Markets during the Covid-19 Outbreak: An Intraday Analysis. The Singapore Economic Review. 10.1142/S0217590821470019.

J. Fry, E.T. Cheah
Negative bubbles and shocks in cryptocurrency markets
International Review of Financial Analysis, 47 (2016), pp. 343-352

J.C. Escanciano, I.N. Lobato
An automatic Portmanteu test for serial Autocorrelations

Jabotinsky, Hadar Yoana and Sarel, Roee, How Crisis Affects Crypto: Coronavirus as a Test Case (March 22, 2020).

Jakub, B. (2015). Does Bitcoin follow the hypothesis of efficient market. 4 (2), 10-23.

Jana, R. K., & Das, D. (2020). Did Bitcoin act as an antidote to the Chinese equity market and booster to Altcoins during the Novel Coronavirus outbreak? Available at SSRN 3544794.

JianPing Hou , Jingyi Liu, YingJiang Jie (2021). Examining the Psychological State Analysis Relationship Between Bitcoin Prices and COVID-19. https://doi.org/10.3389/fpsyg.2021.647691

Ji Q, Bouri E, Gupta R, Roubaud D. Network causality structures among bitcoin and other financial assets: a directed acyclic graph approach. Department of Economics Working Paper, No. 201729; University of Pretoria. (2017). doi: 10.1016/j.qref.2018.05.016

Ji, Qiang, Zhang, Dayong, & Zhao, Yuqian (Oct. 2020). Searching for safe-haven assets during the COVID-19 pandemic, International Review of Financial Analysis, vol. 71.

Katsiampa P. Volatility estimation for bitcoin: a comparison of GARCH models. Econ Lett. (2017) 158:3–6. doi: 10.1016/j.econlet.2017.06.023

Kayal, P., & Rohilla, P. (2019). Bitcoin in the Literature of Economics and Finance: A Survey. Available at SSRN 3441652.

Kristoufek, L. 2015. What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis. PLoS One 10 (4):e0123923. doi:10.1371/journal.pone.0123923.

Koenker, Roger. 2017. Quantile regression: 40 years on. Annual Review of Economics 9: 155–76

L. Rognone, S. Hyde, S.S. Zhang
News sentiment in the cryptocurrency market: An empirical comparison with Forex

International Review of Financial Analysis, 69 (2020), p. 101462

L Hao, DQ Naiman, DQ Naiman. Quantitative Applications in Social Sciences (book) (2007)

Lahmiri S, Bekiros S (2020a) The impact of COVID-19 pandemic upon stability and sequential irregularity of equity and cryptocurrency markets. Chaos Solitons Fractals 109936

Li X, Wang CA. The technology and economic determinants of cryptocurrency exchange rates: the case of bitcoin. Deci Support Syst. (2017) 95:49–60. doi: 10.1016/j.dss.2016.12.001

Liu Y., Tsyvinski A.
Risks and returns of cryptocurrency (no w24877)
National Bureau of Economic Research (2018)

Mnif E, Jarboui A, COVID-19, bitcoin market efficiency, herd behaviour (2021)

Moser M, Bohme R, Breuker D. An inquiry into money laundering tools in the Bitcoin ecosystem. eCrime Researchers Summit (eCRS). (2013). doi: 10.1109/eCRS.2013.6805780

Nadarajah, Saralees & Chu, Jeffrey (Jan. 2017). On the inefficiency of Bitcoin, Economics Letters, vol. 150, pp. 6–9

Naeem, M.A., Bouri, E., Peng, Z., Shahzad, S.J.H., Vo, X.V.J.P.A.S.M., & Applications, i. (2021). Asymmetric efficiency of cryptocurrencies during COVID19. 565, 125562

Orla Ward, Sabrina Rochemont. Understanding Central Bank Digital
Currencies (CBDC) (2019)

Pagano, Michael S. and Sedunov, John, Bitcoin and the Demand for Money: Is Bitcoin More Than a Speculative Asset? (June 11, 2020). Available at SSRN: https://ssrn.com/abstract=3293998 or http://dx.doi.org/10.2139/ssrn.3293998

Panagiotidis, T. , T.Stengos, and O.Vravosinos . 2019. The effects of markets, uncertainty and search intensity on bitcoin returns. International Review of Financial Analysis 63:220–42. doi:10.1016/j.irfa.2018.11.002.

Panagiotidis T, Stengos T, Vravosinos O. On the determinants of bitcoin returns: a LASSO approach. Finance Res Lett. (2018) 27:235–40. doi: 10.1016/j.frl.2018.03.016

P He, Y Sun, Y Zhang, T Li .2020. COVID–19's impact on stock prices across different sectors—An event study based on the Chinese stock market

Q. Ji, E. Bouri, C.K.M. Lau, D. Roubaud
Dynamic connectedness and integration in cryptocurrency markets
International Review of Financial Analysis, 63 (2019), pp. 257-272

Q. Ji, et al.
Searching for safe-haven assets during the COVID-19 pandemic
International Review of Financial Analysis (2020), p. 101526

R. Koenker, Z. Xiao, Quantile autoregression, J. Am. Stat. Assoc., 101 (475) (2006), pp. 980-990

R. Matkovskyy, A. Jalan
From financial markets to Bitcoin markets: A fresh look at the contagion effect
Finance Research Letters, 31 (2019), pp. 93-97

S.R. Baker, N. Bloom, S.J. Davis, K.J. Kost, M.C. Sammon, T. Viratyosin
The unprecedented stock market impact of COVID-19 (no. w26945)
National Bureau of Economic Research (2020)

Scott A. Wolla (2018). Bitcoin: Money or Financial Investment?

Sensoy A. (2018) The inefficiency of Bitcoin revisited: A high frequency analysis with alternative currencies

Shiller, Robert J. (1990). Market Volatility and Investor Behavior, The Hundred and Second Annual Meeting of the American Economic Association, vol. 80 (2).

T. Conlon, R. McGee
Safe haven or risky hazard? Bitcoin during the COVID-19 bear market
Finance Research Letters, 101607 (2020)

T. Klein, et al.
Bitcoin is not the new gold–a comparison of volatility, correlation, and portfolio performance
International Review of Financial Analysis, 59 (2018), pp. 105-116

Tausczik, Y. R., and Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. J. Lang. soc. Psychol. 29, 24–54. doi: 10.1177/0261927X09351676

Thanaset Chevapatrakul,Danilo V. Mascia. Detecting overreaction in the Bitcoin market: A quantile autoregression approach. Finance Research Letters (2019)

Tran, Vu & Leirvik, Thomas. (2019). Efficiency in the Markets of Crypto-Currencies. Finance Research Letters. 35. 101382. 10.1016/j.frl.2019.101382.

Urquhart, Andrew (Nov. 2016). The inefficiency of Bitcoin, Economics Letters, vol. 148, pp. 80–82.

Vasek M, Moore T. There's no free lunch, even using Bitcoin: tracking the popularity and profits of virtual currency scams. In: International Conference on Financial Cryptography and Data Security Berlin: Springer (2015). p. 44–61.

Wang GJ, Xie C, Wen D, Zhao L. When bitcoin meets economic policy uncertainty (EPU): measuring risk spillover effect from EPU to bitcoin. Finance Res Let. (2019) 31:489–97. doi: 10.1016/j.frl.2018.12.028

Wisniewski, Tomasz & Polasik, Michal & Kotkowski, Radosław & Polski, Narodowy & Moro, Andrea. (2021). Switching from Cash to Cashless Payments during the COVID-19 Pandemic and Beyond. 10.13140/RG.2.2.30511.25766.

Wu S, Tong M, Yang Z, Derbali A. Does gold or bitcoin hedge economic policy uncertainty? Finance Res Lett. (2019) 31:171–8. doi: 10.1016/j.frl.2019.04.001

White,Marinakis,Islam and Walsh 2020. Is Bitcoin a currency, a technology-based product, or something else?

Yermack, David (2015). Chapter 2 - Is Bitcoin a Real Currency? An Economic Appraisal, Handbook of Digital Currency. Ed. by David Lee Kuo Chuen. San Diego: Academic Press, pp. 31 –43.

Zhang, L., Huang, X., Liu, T., Li, A., Chen, Z., and Zhu, T. (2014). "Using linguistic features to estimate suicide probability of Chinese microblog users," in Proceedings of the International Conference on Human Centered Computing (Springer: Cham), 549–559. doi: 10.1007/978-3-319-15554-8_45

Zhang, Wei & Li, Yi (2020). Is idiosyncratic volatility priced in cryptocurrency markets?, Research in International Business and Finance, vol. 54.

Websites

https://www.forbes.com/sites/jeffreydorfman/2017/05/17/bitcoin-is-an-asset-not-a-currency/?sh=771fe4532e5b

https://www.economist.com/

https://www.euronews.com/2021/04/07/paying-with-cryptocurrencies-these-are-the-major-companies-that-accept-cryptos-as-payment

https://news.bitcoin.com/fed-chairman-jerome-powell-bitcoin-substitute-for-gold/

https://finance.yahoo.com/

Nakamoto, Satoshi (2008). Bitcoin: A Peer-to-Peer Electronic Cash System https://decrypt.co/47566/is-bitcoin-an-asset-a-commodity-or-a-currency

https://www.straitstimes.com/opinion/covid-19-has-made-crypto-hot-again

https://www.statista.com/statistics/863917/number-crypto-coins-tokens/#:~:text=How%20many%20cryptocurrencies%20are%20there,of%20digital%20coins%20in%202013.

https://www.weforum.org/agenda/2021/02/how-common-is-cryptocurrency/

https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19 -- 11-march-2020

https://en.wikipedia.org/wiki/COVID-19_pandemic

https://en.wikipedia.org/wiki/COVID-19_lockdowns

7. Appendix

Tables of AR(1) analysis in STATA

Table 7a, AR(1) of PreCOVID daily returns

Source	SS	df	MS		
				Number of obs =	365
				F(1, 363) =	0.01
Model	.06588708	1	.06588708	Prob > F =	0.9424
Residual	4572.03009	363	12.5951242	R-squared =	0.0000
				Adj R-squared =	-0.0027
Total	4572.09597	364	12.5607032	Root MSE =	3.549

BitDPre	Coef.	Std. Err.	t	P>|t|	[90% Conf.	Interval]
BitDPreLagged	-.0042826	.0592114	-0.07	0.942	-.1019259	.0933608
_cons	.2204215	.1862052	1.18	0.237	-.0866424	.5274854

Table 7b, AR(1) of PreCOVID weekly returns

Source	SS	df	MS		
				Number of obs =	51
				F(1, 49) =	0.36
Model	31.3095451	1	31.3095451	Prob > F =	0.5532
Residual	4302.67523	49	87.8096986	R-squared =	0.0072
				Adj R-squared =	-0.0130
Total	4333.98478	50	86.6796955	Root MSE =	9.3707

BitWPre	Coef.	Std. Err.	t	P>|t|	[90% Conf.	Interval]
BitWPreLagged	.0876195	.146735	0.60	0.553	-.1583891	.3336281
_cons	1.361863	1.340187	1.02	0.315	-.8850287	3.608755

Table 7c, AR(1) of DuringCOVID daily returns

Source	SS	df	MS			
				Number of obs	=	354
				F(1, 352)	=	2.78
Model	55.2779587	1	55.2779587	Prob > F	=	0.0963
Residual	6995.86991	352	19.8746304	R-squared	=	0.0078
				Adj R-squared	=	0.0050
Total	7051.14787	353	19.9749231	Root MSE	=	4.4581

BitDDuring	Coef.	Std. Err.	t	P>|t|	[90% Conf.	Interval]
BitDDuringLagged	-.0888562	.0532797	-1.67	0.096	-.1767248	-.0009877
_cons	.4905724	.2380535	2.06	0.040	.0979759	.8831688

Table 7d, AR(1) of DuringCOVID weekly returns

Source	SS	df	MS			
				Number of obs	=	51
				F(1, 49)	=	0.76
Model	91.7439745	1	91.7439745	Prob > F	=	0.3876
Residual	5915.84557	49	120.731542	R-squared	=	0.0153
				Adj R-squared	=	-0.0048
Total	6007.58954	50	120.151791	Root MSE	=	10.988

BitWDuring	Coef.	Std. Err.	t	P>|t|	[90% Conf.	Interval]
BitWDuringLagged	.131391	.1507256	0.87	0.388	-.1213082	.3840901
_cons	2.875572	1.63838	1.76	0.085	.1287443	5.6224

Tables of QAR(1) analysis in STATA

Table 8a, QAR(1) of PreCOVID daily returns

BitDPre	Coef.	Bootstrap Std. Err.	t	P>|t|	[90% Conf.	Interval]
q10						
BitDPreLagged	.0041511	.1595166	0.03	0.979	-.2589016	.2672039
_cons	-3.404648	.4121637	-8.26	0.000	-4.084332	-2.724965
q20						
BitDPreLagged	-.027228	.0847661	-0.32	0.748	-.1670125	.1125565
_cons	-1.970487	.1723856	-11.43	0.000	-2.254761	-1.686212
q30						
BitDPreLagged	-.0049951	.0268699	-0.19	0.853	-.0493053	.0393151
_cons	-.9350925	.1226388	-7.62	0.000	-1.137331	-.7328535
q40						
BitDPreLagged	-.0249716	.0474607	-0.53	0.599	-.1032372	.0532941
_cons	-.396162	.1072803	-3.69	0.000	-.5730739	-.2192502
q50						
BitDPreLagged	-.0190922	.0581584	-0.33	0.743	-.1149989	.0768145
_cons	.1148464	.0782317	1.47	0.143	-.0141625	.2438553
q60						
BitDPreLagged	.0092546	.0706967	0.13	0.896	-.1073287	.1258378
_cons	.640258	.1136691	5.63	0.000	.4528106	.8277054
q70						
BitDPreLagged	.0201065	.055159	0.36	0.716	-.0708541	.1110672
_cons	1.337003	.189185	7.07	0.000	1.025025	1.648981
q80						
BitDPreLagged	.0317569	.0507062	0.63	0.532	-.0518608	.1153745
_cons	2.259854	.2007576	11.26	0.000	1.928793	2.590916
q90						
BitDPreLagged	.0411432	.1294706	0.32	0.751	-.1723619	.2546483
_cons	3.64327	.5496815	6.63	0.000	2.736811	4.549729

Table 8b, QAR(1) of PreCOVID weekly returns

BitWPre	Coef.	Bootstrap Std. Err.	t	P>|t|	[90% Conf.	Interval]
q10						
BitWPreLagged	.54459	.3898128	1.40	0.169	-.1089509	1.198131
_cons	-13.46152	3.830325	-3.51	0.001	-19.88325	-7.039784
q20						
BitWPreLagged	.0268937	.3744683	0.07	0.943	-.6009214	.6547088
_cons	-3.771301	4.146703	-0.91	0.368	-10.72346	3.180858
q30						
BitWPreLagged	.0413582	.2990372	0.14	0.891	-.4599929	.5427093
_cons	-1.578089	2.659973	-0.59	0.556	-6.037669	2.88149
q40						
BitWPreLagged	.0190221	.2241399	0.08	0.933	-.3567598	.3948041
_cons	-1.028878	1.644123	-0.63	0.534	-3.785333	1.727578
q50						
BitWPreLagged	-.0163101	.1859296	-0.09	0.930	-.3280305	.2954104
_cons	-.0459586	1.398233	-0.03	0.974	-2.390167	2.29825
q60						
BitWPreLagged	-.0876129	.1874583	-0.47	0.642	-.4018962	.2266704
_cons	2.324648	1.593805	1.46	0.151	-.3474473	4.996744
q70						
BitWPreLagged	.0121721	.1879058	0.06	0.949	-.3028616	.3272057
_cons	5.441668	2.196641	2.48	0.017	1.758887	9.124448
q80						
BitWPreLagged	.0964264	.2423547	0.40	0.692	-.3098936	.5027464
_cons	7.137139	3.095605	2.31	0.025	1.9472	12.32708
q90						
BitWPreLagged	.1256647	.2267104	0.55	0.582	-.2544269	.5057563
_cons	15.14007	2.893936	5.23	0.000	10.28824	19.9919

Table 8c, QAR(1) of DuringCOVID daily returns

BitDDuring	Coef.	Bootstrap Std. Err.	t	P>|t|	[90% Conf.	Interval]
q10						
BitDDuringLagged	.1000038	.172726	0.58	0.563	-.1848549	.3848624
_cons	-3.566824	.5350228	-6.67	0.000	-4.44918	-2.684468
q20						
BitDDuringLagged	-.0091415	.0880349	-0.10	0.917	-.1543281	.1360452
_cons	-1.522645	.2650753	-5.74	0.000	-1.959806	-1.085485
q30						
BitDDuringLagged	-.0866033	.0545165	-1.59	0.113	-.1765115	.0033049
_cons	-.5943321	.1518629	-3.91	0.000	-.8447834	-.3438807
q40						
BitDDuringLagged	-.1319256	.0520206	-2.54	0.012	-.2177177	-.0461335
_cons	-.0511831	.1350042	-0.38	0.705	-.2738313	.171465
q50						
BitDDuringLagged	-.1294938	.0472207	-2.74	0.006	-.2073698	-.0516177
_cons	.4338359	.1258289	3.45	0.001	.2263196	.6413522
q60						
BitDDuringLagged	-.1059943	.046511	-2.28	0.023	-.1826999	-.0292887
_cons	.942859	.1391307	6.78	0.000	.7134055	1.172313
q70						
BitDDuringLagged	-.109594	.0585335	-1.87	0.062	-.2061271	-.0130609
_cons	1.645163	.1535384	10.71	0.000	1.391949	1.898378
q80						
BitDDuringLagged	-.1669288	.0586306	-2.85	0.005	-.263622	-.0702355
_cons	2.911897	.2987573	9.75	0.000	2.419189	3.404606
q90						
BitDDuringLagged	-.1398229	.0977242	-1.43	0.153	-.300989	.0213433
_cons	4.770632	.4681005	10.19	0.000	3.998644	5.542621

Table 8d, QAR(1) of DuringCOVID weekly returns

BitWDuring	Coef.	Bootstrap Std. Err.	t	P>|t|	[90% Conf.	Interval]
q10						
BitWDuringLagged	.1491538	.7323677	0.20	0.839	-1.078698	1.377005
_cons	-9.26417	8.244604	-1.12	0.267	-23.08667	4.558328
q20						
BitWDuringLagged	-.0640572	.3894294	-0.16	0.870	-.7169554	.5888409
_cons	-1.138855	3.110509	-0.37	0.716	-6.353782	4.076071
q30						
BitWDuringLagged	-.0363023	.1724562	-0.21	0.834	-.325434	.2528293
_cons	-.8275318	1.033731	-0.80	0.427	-2.560634	.9055702
q40						
BitWDuringLagged	.0547328	.198561	0.28	0.784	-.2781648	.3876304
_cons	1.13469	1.222489	0.93	0.358	-.914874	3.184255
q50						
BitWDuringLagged	.0326465	.1535872	0.21	0.833	-.2248503	.2901432
_cons	2.859013	1.758914	1.63	0.110	-.0898955	5.807921
q60						
BitWDuringLagged	-.0450747	.16301	-0.28	0.783	-.3183693	.2282199
_cons	5.97004	2.02818	2.94	0.005	2.569693	9.370386
q70						
BitWDuringLagged	.1300283	.1631989	0.80	0.429	-.143583	.4036396
_cons	8.593864	2.557138	3.36	0.002	4.306692	12.88104
q80						
BitWDuringLagged	.143855	.1380614	1.04	0.303	-.087612	.3753219
_cons	12.51977	2.441941	5.13	0.000	8.425728	16.61381
q90						
BitWDuringLagged	.1457718	.1916883	0.76	0.451	-.1756034	.4671471
_cons	13.75449	2.305973	5.96	0.000	9.888412	17.62057