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Potential drivers of Bitcoin returns

Evidence within a LASSO framework

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Kirmizis Panteleimon

Abstract

This thesis examines the relationship between bitcoin returns and 36 potential explanatory variables. We first present in brief how bitcoin operates, its history, and its uses. Afterward, we present an extensive review of the literature. We use a GARCH filter in order to deal with the effects of volatility clustering in our models. To capture the effects of technical factors, market forces of bitcoin's supply and demand, investors' attractiveness to bitcoin, and global macroeconomic and financial indicators, we employ a LASSO regression due to its ability to perform both variable selection and regularization in the analysis. We estimate models for the period 2013-2020 (full sample), and 3 sub-periods of it separately. Our results reveal policy uncertainty and exchange rates as the most consistent, important drivers of bitcoin returns.

Keywords – Bitcoin, Returns, Determinants, LASSO regression, Bachelor Thesis

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1 Introduction

Since its introduction in 2008, bitcoin has attracted the interest of both the investment and the research world. The unique technology and structure, the nature of a digital currency, and most importantly the capacity to yield profits due to its properties of high volatility are all reasons that have kept bitcoin in the midst of attention of various fields in the last decade. In this paper, we focus our research on the economic and investment perspective of bitcoin and we examine how a number of factors affect bitcoin returns.

This ever-increasing interest in bitcoin has resulted in substantial literature that examines bitcoin in general and bitcoin price formation in particular. Several factors driving bitcoin prices and explaining its volatility have been identified over time, even though evidence is provided that the information content of exogenous factors is time-varying and model-dependent. Even the most extensively proven determinants of bitcoin returns cannot be unequivocally accepted regardless of the model adopted.

This thesis investigates 36 potential explanatory variables of bitcoin returns in order to determine the drivers of bitcoin price. Following the existing empirical literature, we include technical factors, variables that proxy the market forces of bitcoin's supply and demand, variables that proxy investors' attractiveness to bitcoin, and global macroeconomic and financial indicators. We investigate data for the period 2013-2020 as well as for 3 sub-periods of it separately. We use a GARCH filter in order to deal with the effects of volatility clustering in our models. Then, we employ a LASSO regression due to its ability to perform both variable selection and regularization in the analysis. Policy uncertainty and exchange rates are found to be the most consistent, significant determinants of bitcoin returns.

Our paper closely follows the notion and methodology of the work of Panagiotidis et al. (2018). Nevertheless, this is the first paper to our knowledge that examines the determinants of bitcoin returns within a LASSO framework while including a GARCH filter. The structure of the thesis follows as: Chapter 2 contains information that we believe is necessary for better understanding the nature of bitcoin, while it also reviews the literature. Chapter 3 describes the data selected, and Chapter 4 presents the methodology (LASSO regression and GARCH model). The empirical results are displayed in Chapter

5, while in Chapter 6, the said results are compared to existing results of the literature. Finally, in Chapter 7, the concluding remarks can be found.

2 Theoretical Review

2.1 Understanding Bitcoin

Bitcoin introduced the idea of a decentralized, peer-to-peer digital currency. It was initiated by Nakamoto (2008), in an effort to create an electronic cash system free of trusted third parties, such as financial institutions. To achieve a trustworthy, peer-to-peer system Nakamoto had to cope with the double-spending problem. In order to prove the chronological order of transactions, therefore solving the double-spending problem, he proposed using the blockchain mechanism. This technology works as a public ledger for transactions, where they are permanently recorded and viewable to anyone. With each transaction being hashed into an ongoing chain of previous hashed transactions, a timestamp network is being created. The system's security is guaranteed by cryptographic algorithms, as long as the majority of the CPU power is controlled by honest nodes.

The structure of bitcoin has given it a plethora of advantages. To begin with, the decentralized nature of bitcoin eliminates any need for bank intermediation. Furthermore, bitcoin allows transactions to take place anywhere and at any time, thus eliminating any geographical or temporal constraints. In addition, it offers low transaction fees, although higher fees can prioritize confirmation of the transaction. Also, bitcoin provides a high level of security through anonymity and transparency, as all information concerning transactions is publicly available. Nonetheless, bitcoin has also some disadvantages, namely its degree of acceptance and its ongoing development. Consumers and businesses seem hesitant to use bitcoin, even though an upward trend has been observed in the number of consumers and businesses using bitcoin and accepting payments by bitcoin respectively, as well as in the transaction frequency in the digital currencies market [Kondor et al. (2014), Polasik et al. (2015), Dyhrberg (2016b)]. Bitcoin is still maturing as a technology. Its software is often modified to become more secure, while new features are being developed with the purpose of making bitcoin more accessible to the masses.

The impressive price development and high volatility is another factor that creates reluctance among consumers towards bitcoin. Bitcoin has a limited and finite supply-the number of coins is determined by an algorithm and will become stable after reaching 21 million; therefore, relatively small activities can significantly alter the price. At the time of its initiation in 2009, bitcoin had zero value. In July 2010, bitcoin rose from around \$0.0008 to \$0.08 signifying the first real price increase. Between April 2011 and April 2013, the price of bitcoin had increased by a factor of 100. On November 19, 2013, the price of bitcoin decreased by nearly 20% before rising, breaking for the first time the threshold of \$1,000, on November 28 of the same year. On December 7, 2013, the price of bitcoin plummeted again, this time by almost 15%. The late 2013 period, where the value of the currency increased from \$100 to over \$1,100, is referred to as the "Bitcoin Boom". Over the following years, prices continued to fluctuate but maintained at relatively low levels. From 2015 to 2017, bitcoin prices slowly and steadily increased. The period between January 2017 and December 2017, was marked by sharp rises, leading to historically high price levels of more than \$19,700 on December 17, 2017. The months followed saw a significant decline in prices, with a lowest of almost \$3,200 in December 2018, confirming the suspicions of some investors of a "Bitcoin Bubble". Since then, prices have recovered and, keeping their volatile nature, managed to surpass once again the value of \$19,000 in November 2020. In mid-December 2020, bitcoin surpassed for the first time the pricing of \$20,000. The year 2020 ended at an all-time high price of \$28,928.

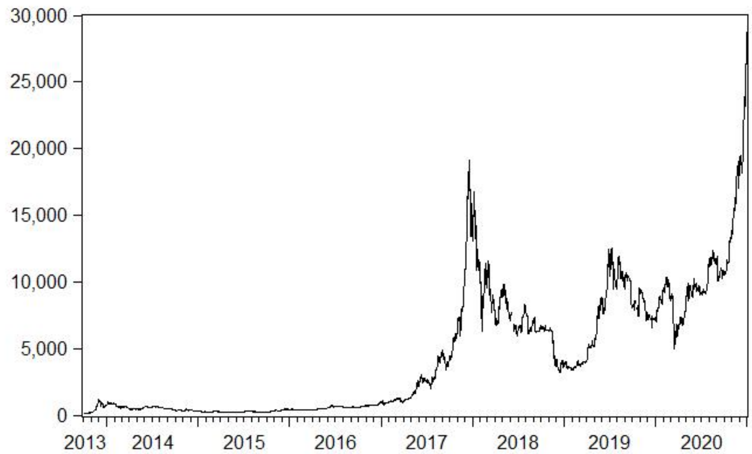

Figure 2.1: Bitcoin historical prices 1/10/2013 - 31/12/2020

2.2 Uses of Bitcoin

It is to our belief that in order to fully understand bitcoin from an economic point of view one ought to first study extensively the uses of bitcoin both as a currency and as an investment instrument. In this section, we introduce the concepts of bitcoin as a currency and as an investment tool, specifically, its speculative, diversifying, hedging, and even in some cases safe haven properties. For each case, we present the economic theory and then we refer to the results of previous related empirical work.

2.2.1 Bitcoin as a Currency

Bitcoin was built to work fundamentally as an alternative currency that could be used in e-commerce. Money is typically defined by economists as an economic unit that is generally accepted as a form of payment for goods and services. Money, commonly referred to as currency, is the primary medium of exchange in the modern world and is usually issued by a government in the form of paper or coins. Generally, monetary base, the total amount of a currency that is either in the hands of the public or in the commercial bank deposits, is divided into two categories: “commodity money” and “fiat money”. By definition, commodity money consists of a good of trade that also has another use other than that of being a medium of exchange and is the original form of money. This type of money is naturally scarce, as it commands a positive real value, the worth of a commodity backing it, while it also has a considerable marginal cost of production. Gold, silver, and other metals can all be considered examples of commodity money. On the contrary, fiat money is uniformly worthless in itself, having no nonmonetary value as it has an insignificant marginal cost. It is government-issued currency that is not backed by a physical commodity, and its value is derived from supply and demand. It follows that fiat money is not naturally scarce as its supply is monitored and controlled by a government. Most modern money is fiat money, including the U.S. dollar, the euro, the yuan, and more major currencies. Selgin (2015), introduces a new category and defines bitcoin as “synthetic commodity money”, a combination of commodity money and fiat money. Bitcoin shares similarities with commodity money in being naturally scarce, as well as with fiat money in having no nonmonetary value. Dyhrberg (2016a), comes to similar conclusions, finding many similarities between bitcoin, and both gold and the dollar, concluding that it is a hybrid between a currency and a commodity.

Seemingly, bitcoin justifies its role as a currency as it is being used to pay for goods and services alongside standard fiat currencies. However, questions have been raised about the usefulness of bitcoin as a currency. According to economic theory, money has three main functions; It performs as a medium of exchange, a store of value, and a unit of account [Jevons (1876)]. As a medium of exchange, bitcoin has not yet cemented its feasibility worldwide. According to a survey by HSB (2020), only 36% of small and mid-sized businesses in the US accepted cryptocurrency, while in some countries the use of cryptocurrency remains illegal [Dumitrescu (2017)]. The lack of liquidity is another feature that creates ambiguity about the usefulness of bitcoin as a medium of exchange [Yermack (2015), Loi (2018)]. As a store of value, bitcoin encounters two main problems. The first is the inadequate security of the "digital wallets" that store bitcoins, which has led to numerous digital breaches and thefts since the introduction of bitcoin [Yermack (2015), Krombholz et al. (2017)]. The second is the high risk created by bitcoin's excessive fluctuations (Figure 2.2 presents the volatility of Bitcoin). Several pieces of research have shown that the volatility of bitcoin, hence its risk as well, extensively surpass that of forex pairs, commodities, stock indices, and even most single stocks [Baur and Dimpfl (2017), Baur et al. (2018a)]. Lastly, bitcoin is not practical as a unit of account due to its high value and volatility. In most transactions concerning common retail goods, prices are required to be quoted out to decimals or to smaller sub-units, creating confusion to both participating parties. Also, high volatility discomforts price comparisons, while it increases businesses' "menu costs".

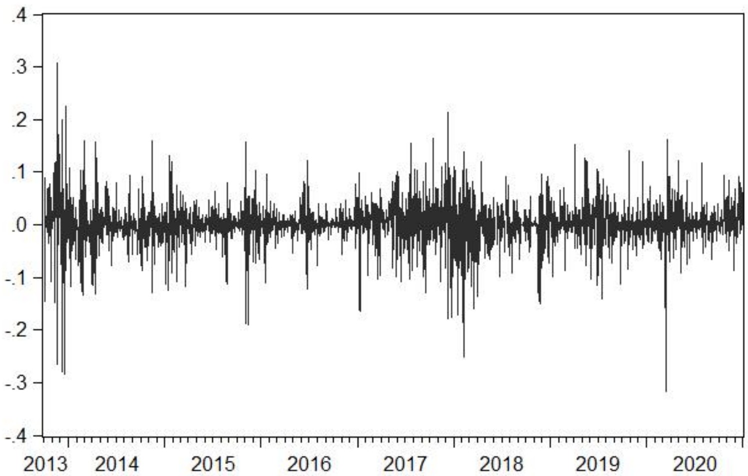

Figure 2.2: Bitcoin Volatility 1/10/2013 - 31/12/2020

Theoretically, if bitcoin's main use is that of a medium of exchange, it should compete with fiat currency. If bitcoin manages to become as widely accepted as fiat currency in a market, then the two currencies will coexist, creating a dual currency economy. Gresham-Copernicus law is a monetary principle that describes the effect of a multiple currency economy. Specifically, it states that when two forms of money operate in a market the one with the most value, in the sense of a better store of value, will gradually disappear from circulation. The result will be such, as the superior currency will be held on while the less valuable will be used in transactions. The previous statement is known as "Bad money drives out good". Good money can be described as money that shows no great difference between its nominal and real value. What remains uncertain is if bitcoin will become good or bad money. For the moment, we cannot define bitcoin as a currency, even though sometimes it seems to behave according to standard economic theory, such as the quantity theory of money [Kristoufek (2014)].

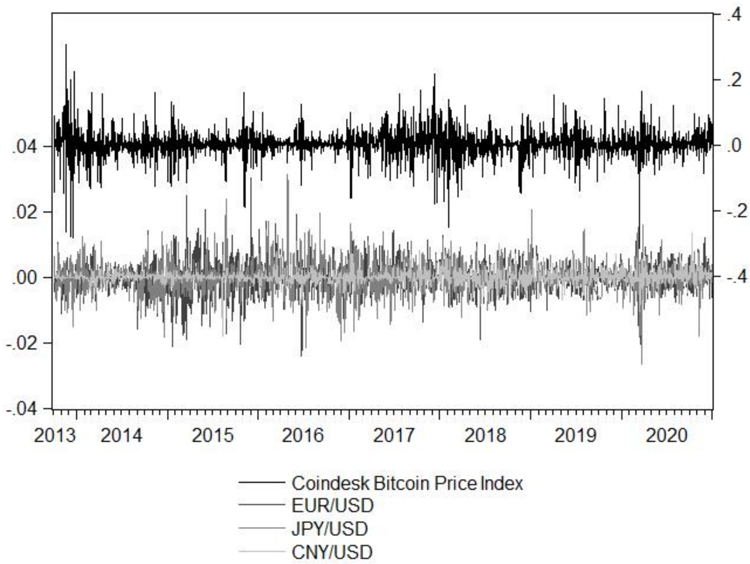

Figure 2.3: Bitcoin and exchange rates returns

2.2.2 Bitcoin as an Investment Asset

In addition to its operation as a payment system, bitcoin also acts as an investment asset. Investment assets include both tangible and intangible instruments obtained by investors for the purposes of generating additional income, on a short- or long-term basis, or held for speculation in anticipation of a future increase in value. In general, investing is used to enhance investors' wealth. Most asset classes, or investment vehicles, can be identified as money-market instruments, fixed income securities, common stocks, or speculative investment vehicles. Money-market instruments, such as cash equivalents, are short term investment vehicles with a maturity of one year or less. Fixed income securities include preferred stocks and bonds and have a fixed return up to a specific date. Common stocks represent either the ownership interest of companies or the equity of the stockholders. Lastly, financial derivatives such as futures, forwards, and options, as well as commodities, are considered speculative investment vehicles. Other investment tools not included in the preceding categories are various types of funds and real estate.

Each asset class is composed of a certain set of characteristics which make it vary from other asset types. The multiple natures of financial assets allow them to be more or less suitable for, and therefore be utilized by, different types of investors and strategies. Investors select assets based on their properties and use them to satisfy their goals, risk tolerance, and future needs. As already mentioned, it has been observed that bitcoin can be used as an investment asset. Ron and Shamir (2013) indicate that more than 70% of addresses do not participate in outgoing transactions but only receive bitcoins. Baur et al. (2018b) showcase that nearly a third of bitcoins are held for investment purposes, while there is only a minuscule number of users, that use it as a medium of exchange. The different uses of bitcoin have excessively been investigated in the literature and bitcoin appears to have speculative, hedging, diversifying, and even in some cases safe haven features.

Bitcoin as a Speculative Asset

We noted earlier that bitcoins have a great deal of risk, revealed by the high volatility of the bitcoin price, potentially allowing for important returns. Investors might choose to speculate on bitcoin in the hopes that it will "beat the market". Speculation, or speculative trading, is described as an investment with an exceptionally high risk. It is typically related to the short-term investment horizons as the investor is usually focused on price fluctuations. In other words, speculators purchase the salable securities with the hope of a quick profit based on rapid market value changes, ignoring any long-term investing. With speculation, the substantial risk of losing value must be offset by the possibility of high earnings. Without the prospect of significant gains or other major value, there would be little motivation to conduct this financial transaction. Speculators invest in risky assets, which can be for example Initial Public Offerings (IPOs) or a volatile commodity. They often are active traders who in order to reduce the undertaking risk they use hedging strategies. It must be noted that the degree of speculation may depend on the nature of the asset, the expected holding period, and the possible amount of leverage. Other than that, it is easily understandable that the greater the risk, the more speculative the asset. At this point, we consider it necessary to mention a common misconception around speculation. It is sometimes perceived that the term gambling is used instead of speculation. Even though, speculation and gambling are both used to increase wealth under conditions of uncertainty it is critical to understand that in investing these two terms have major differences. Gambling refers to a bet or wager on an uncertain outcome for enjoyment. It involves a game of chance where the parties assign the same probabilities to the possible outcomes. Conversely, speculation involves taking a considerable risk for a commensurate gain. Speculators conduct research before entering a financial transaction where the parties of the transaction have heterogeneous expectations.

The immense level of volatility on bitcoin's prices leads economists to reasonably acknowledge that bitcoin is used as a speculative asset. To our knowledge, MacDonell (2014) is the first to prove the speculative characteristics of bitcoin. Using an autoregressive moving average (ARMA) model he concludes that a primary driver of bitcoin prices is speculation by investors.

By analyzing several fundamental economic variables Baek and Elbeck (2015) suggest that the bitcoin returns are determined by buyers and sellers. The findings, also, show that bitcoins are by far riskier than the S&P 500 Index, implying that bitcoins act as a speculative vehicle.

Baur and Dimpfl (2017) examine bitcoin compared to major currencies. The results reveal up to 30 times larger volatility of bitcoin markets, implying that bitcoin has limited capabilities to function as a currency and might better be classified as a speculative investment.

The aforementioned implication also matches the findings of Yermack (2015), who studies the relationship of bitcoin with the other currencies and with gold and finds almost zero correlation.

Additionally, Kristoufek (2014) examines potential drivers of bitcoin price, using wavelet coherence analysis. He comes to the conclusion that, in the long term, bitcoin carries features of both a speculative and a standard financial asset, forming a totally unique asset.

Hencic and Gouriéroux (2015) study the dynamics of the Bitcoin/USD exchange rate. Through the analysis, they observe episodes of local trends in bitcoin prices which they interpret as speculative bubbles. Moreover, they consider the use of bitcoin in speculative trading as one of the generative causes of these price bubbles.

Similarly, Cheah and Fry (2015) provide proof that, like with other asset classes, bitcoin markets are prone to speculative bubbles. In fact, the existence of bubbles in bitcoin prices is not only statistically significant but also has really high value.

In general, there is a large number of studies that come to the definite conclusion that bitcoin is mainly used as a speculative asset [Huhtinen (2014), Bouoiyour and Selmi (2015), Ciaian et al. (2016b), Baur et al. (2018b)].

Bitcoin as a Diversifier

In finance, diversification is a risk management strategy that combines multiple assets and investment vehicles in an effort to limit exposure to any single asset or risk. In other words, it is the process of allocating capital in a way that reduces the overall risk of an investment portfolio. Diversification is achieved by lowering the volatility of the portfolio returns and eliminating the no systematic risk. Baur and Lucey (2010) define a diversifier as "an asset that is positively but not perfectly correlated with another asset or portfolio on average". Factors to consider include type of assets, risk levels, weight allocation, industries, and location or foreign markets. The assets selected must respond dissimilarly to specific market signals in order to neutralize losses in one asset class with gains in another asset class. This theory has been regularly applied by investors and the rationale behind it is that a portfolio constructed of a variety of assets will have less variance than the weighted average variance of the individual assets it consists of. Generally, returns of a diversified portfolio are greater than, while risks (volatility) are less than, those of a concentrated portfolio. Besides, a diversified portfolio usually provides greater returns than an undiversified portfolio given the same amount of risk. In short, diversification limits portfolio risk and offers higher returns in the long term, however, it may limit gains in the short term.

The role of bitcoin as a diversifier has widely been discussed in the literature. The efficiency of bitcoin in the diversification progress was introduced by Brière et al. (2015). Analyzing the liaison between Bitcoin and a diversified portfolio including both traditional assets and alternative investments, they prove the improvement of efficacy in a well-diversified portfolio. Having a remarkably low correlation with other assets can compensate holders of well-diversified portfolios for the high risk that bitcoin provides. The paper leads to the important conclusion that a significant improvement of the risk-return trade-off of well-diversified portfolios can be observed by including even a small proportion of Bitcoins.

Following the same notion, Eisl et al. (2015) research the effects of adding bitcoin to already well-diversified investment portfolios. Adopting a Conditional Value-at-Risk (CVaR) framework to deal with the non-normal nature of bitcoin returns, they find results similar to that of Brière et al. (2015). Specifically, the results document that both the expected return as well as the risk of the portfolios increase, with the return contribution however seemingly outweighing the additional risks faced by investors. Furthermore, they remark that an inclusion of up to 7.69% of bitcoin optimizes even the already well-diversified portfolios, concluding that bitcoin is beneficial in optimal portfolios.

Similarly, Kajtazi and Moro (2017) examine the impact of bitcoin on an optimal portfolio (naïve, long-only, unconstrained, and semi-constrained) in the Chinese market. Significant but weak correlations between bitcoin and several indices of Chinese asset classes are reported. Earlier studies do not show any correlations between bitcoin and western assets, therefore a more mature financial profile of bitcoin in China is implied. Nonetheless, the results of adding bitcoin to optimal portfolios are not consistent over time, instead, they are mixed depending on the timeframe and the optimization framework used. Bitcoin is an effective diversifier for the naïve and the long-only portfolios but only until the late 2013 price crash. In addition, semi-annual rebalancing strengthens the advantages of adding bitcoin to all portfolios but the semi-constrained one. This strategy might not be feasible though, as the significant shifts in weights revealed, are not useful in realistic scenarios.

Carpenter (2016) also shows that bitcoin can be a viable diversifier. Bitcoin appears to substantially increase the return/risk ratios of an efficient portfolio, even with the consideration of important return penalties. Once again, it appears that this performance is not permanent through the years, as using data only after February 2014 leads to underperformance of portfolios containing bitcoin compared to their non-bitcoin counterparts.

Moore and Stephen (2015), using the case of Barbados, examine whether digital currency balances could belong in a central bank's external assets. Both of the main empirical tools used in the study suggest that by including a small portion of bitcoin in its portfolio between 2009 and 2015, the Central Bank of Barbados, would not have suffered large differences in reserve balance volatility, while it would have also benefited by significant returns due to the appreciation in the value of bitcoin. Lastly, the paper recommends that weights held in bitcoin should be relatively small, in order to avoid any excess increases in the volatility of reserves.

Guesmi et al. (2019) investigate the connection between bitcoin and some financial indicators, namely stock markets (MSCI Emerging Markets Index and MSCI Global Market Index), Euro and Chinese exchange rate, gold, and oil. One of the results indicates that the risk of a portfolio consisting of gold, oil, and developing stocks reduces with the inclusion of bitcoin. Consequently, bitcoin may offer diversification benefits for investors.

Ghabri et al. (2020) examine any possible diversification benefits bitcoin can have on liquidity risk. Evidence from the study of the relationship between bitcoin and several financial assets (MSCI world stock index, gold, crude oil, and real estate) show a low time-varying correlation of liquidity innovations. This finding suggests that adding bitcoin instead of traditional assets can lead to potential gains through the diversification of the liquidity risk. Also, by giving bitcoin a small weight, investors can improve the Sharpe ratio of their portfolio.

Bouri et al. (2017c), using a dynamic conditional correlation model to investigate the relationship between bitcoin and major world stock indices, bonds, oil, gold, the general commodity index, and the US dollar index, conclude that bitcoin is an effective diversifier against movements in all the assets under study.

Selmi et al. (2018) compare the roles of bitcoin and gold against extreme oil price movements. The study shows that both bitcoin and gold have the properties of diversifier, which however are sensitive to their respective market conditions and different degrees of oil price movements, and therefore cannot hold at all times. Nevertheless, they underline the usefulness of bitcoin and gold in expanded oil portfolios, as diversifiers.

Bouri et al. (2017b) examine the daily relationship between bitcoin and commodities, energy commodities in particular. After 2013 and the price bubble, bitcoin diversifies both the indices selected (general commodity index and energy commodity index). Moreover, bitcoin becomes a diversifier for the whole period examined in the case that energy commodities are not included in the general commodity index.

According to Hussain et al. (2020), investors in G7 stock markets (Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States) can have considerable diversification benefits using bitcoin or gold. However, it seems that gold provides stronger and more stable diversification benefits than bitcoin.

Stensås et al. (2019) examine a sample of several developed and developing countries, regional indices, and commodity series. Bitcoin is revealed to act as an effective diversifier for investors in the developed markets, regional indices, and for all the 10 commodities studied.

Kliber et al. (2019) employ daily data between main stock indices of Japan, Venezuela, China, Estonia, and Sweden and bitcoin price in local currencies as well as between main stock indices and the bitcoin price in the US dollar, to determine the role of bitcoin in those stock markets. When using local investments, bitcoin behaved as a diversifier only in Japan and China.

Su et al. (2020) investigate the association between the bitcoin currency and the GPR index, which is used as a measure of the risks associated with global geopolitical events, and circumstances. By analyzing the data, they conclude that bitcoin can be considered by potential investors as an asset able to diversify their portfolio.

Urquhart and Zhang (2019) use hourly data of bitcoin and six developed currencies in order to determine their intraday relationship. A negative correlation between bitcoin and some currencies is revealed, a result that indicates that bitcoin has a diversifier's features against the AUD, CAD, and JPY.

Lastly, Wu et al. (2019) inspect the properties of gold and bitcoin against the US EPU index, an index used to measure the economic policy uncertainty (EPU). The study shows that both gold and bitcoin can be utilized as portfolio diversifiers during the average condition of the market, that is when the market is not subject to extreme conditions.

Bitcoin as a Hedge and Safe Haven

Diversification is only one of two main techniques used for reducing investment risk. The second is hedging. Hedging is a risk management procedure through which a position in one market is employed to offset and balance against the risk and potential losses of a different initial investment or opposing market. A hedge is an investment that protects an individual's finances from exposure to risks that may lead to loss of value, by mitigating the losses of the investment by gains in another investment. According to Baur and Lucey (2010) "A hedge is an asset that is uncorrelated or negatively correlated with another asset or portfolio on average". Hedging carries a risk-reward trade-off, as the decline in risk it creates, is also typically accompanied by a reduction in potential gains. There exist various instruments used by investors in order to appropriately hedge different types of financial risk. Derivatives, such as options and futures contracts, are the most commonly used type of hedging tool, with other financial instruments, such as stocks, exchange-traded funds, and insurance also being involved in the hedging process. Sometimes even diversification of a portfolio can be considered a hedge. Following Baur and Lucey (2010) notion, "a strict hedge is (strictly) negatively correlated with another asset or a portfolio on average", while "a perfect hedge can be considered one that eliminates all risk in a position or portfolio". Alternatively, a perfect hedge is a hedge that is completely inversely correlated to the vulnerable asset. However, this is very uncommon and more than ideal in the real world. In practice, hedging is imperfect, and hedges do not always move in the direction expected. Investors refer to this discrepancy as basis risk.

We already mentioned that investors seek hedges that mitigate the risk of their investments. However, they are also interested in acquiring some sort of insurance against extreme market turbulence. While such market events cannot be avoided, some investors seek to limit their losses in the event of economic and stock market unrest. The type of insurance investors look to buy is called safe haven. We could say that safe haven assets are a kind of hedge against stock or market volatility. A safe haven, unlike most assets, is an asset that is expected to either hold or increase its value during times of market downturns.

"A safe haven is uncorrelated or negatively correlated with another asset or portfolio in times of market stress or turmoil" [Baur and Lucey (2010)]. Several different types of assets have been proved to be safe-haven investments. The most commonly accepted safe haven is gold. More assets, like precious metals, stable currencies such as the Swiss franc, and stocks from particular sectors, have proven effective safe havens in the past. However, safe haven properties of each asset may vary depending on the particular down market and/or period of market volatility. That means that there is no consistent safe haven and that investors must perform ample due diligence when naming an asset safe haven.

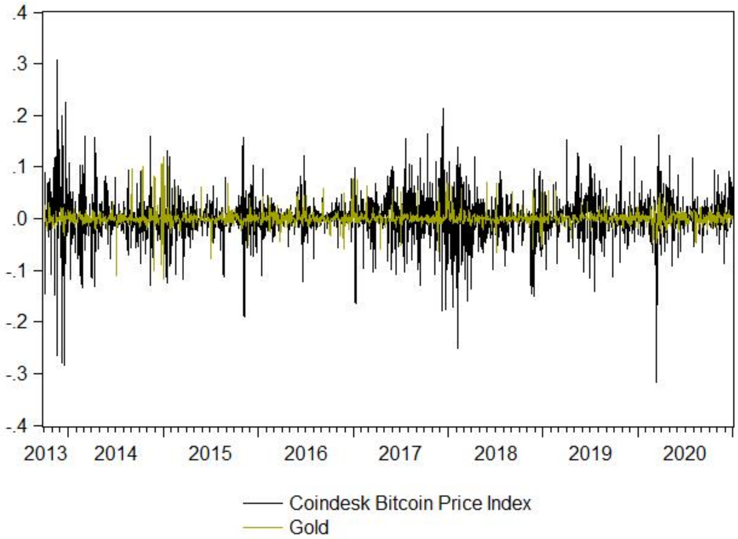

Figure 2.4: Bitcoin and gold returns

Further, some crucial common characteristics between bitcoin and gold have led to a comparison between the two assets. The characteristics that bitcoin -sometimes even proclaimed as digital gold- and gold share, include the limited supply and supply growth through mining as well as the non-centrality and independent nature of the assets. It is logical for investors to assume that bitcoin might also be a safe haven against financial turmoil. Arguments to substantiate this point of view are that bitcoin is not confined by a single country's politics and thus may be uncorrelated with the global economic instability. Indeed, bitcoin has shown resilience during periods of turmoil, signifying its potential as a strong hedger and a safe haven against global financial uncertainty.

Ennis (2013) uses a GARCH analysis for the US and EU to discover low correlations and therefore statistical independence of bitcoin returns in relation to equity and bond markets. An additional finding of the research is that bitcoin could serve as a (weak) hedge and safe haven for sovereign debt markets in the US and Europe, as well as for the euro, but not the dollar.

Dyhrberg (2016b) uses daily observations of the USD/EUR and USD/GBP exchange rates as well as the FTSE Index to compare the hedging capabilities of bitcoin and gold. He concludes that bitcoin presents strong hedging features against stocks in the FTSE, as well as hedging abilities against the US dollar in the short term. Overall, both bitcoin and gold can be employed to reduce specific market risks, and therefore can be considered as effective hedging tools.

Bouri et al. (2017c), using daily and weekly data of bitcoin and of various major financial assets which include stocks, bonds, currencies, and commodities, discover that frequency matters to investors as the hedging and safe haven properties of bitcoin differ between horizons. Daily data indicate a strong hedge role of bitcoin against movements in Japanese and Asia Pacific stocks, as well as against movements of the commodity index. Weekly data indicate that bitcoin can be regarded as a strong hedge only against movements in Chinese stocks, but also a strong safe haven against extreme movements in Chinese and Asia Pacific stocks.

Bouoiyour and Selmi (2017) analyze the connection of the bitcoin price to the U.S. stock price index during the post-U.S. election period of 2016. The results document the time-varying hedge and safe-haven features of bitcoin. Specifically, bitcoin primarily acts as a weak safe haven in the short-term, and as a hedge in the medium- and the long-term. Furthermore, even though gold and silver seem to lose their hedge and safe haven properties over time they can still be characterized as safer assets in comparison with bitcoin.

Baur et al. (2018b) cannot find strong evidence of bitcoin's hedge or safe haven characteristics against S&P500, however, for negative or extreme negative S&P500 returns bitcoin tends to be a weak safe haven, as bitcoin returns are uncorrelated with the ones of S&P500.

Chan et al. (2019) examine the role of bitcoin on the Euro STOXX, Nikkei, Shanghai A-Share, S&P 500, and the TSX Index. Counter to the findings of Baur et al. (2018b), they find that under daily and weekly data bitcoin is a weak hedge while over the monthly horizon it is an effective strong hedge. In addition, bitcoin hedging abilities change depending on the frequency dependence models used. Over low data frequency bitcoin is a strong hedge against Shanghai A-Share, over medium data frequency bitcoin is a strong hedge against S&P 500 and Euro indices, while over high data frequency bitcoin is only a weak hedge against the market indices. Generally, the results suggest that bitcoin could prove as a useful hedger for investors. Moreover, findings indicate that the long-term returns bear more robust hedging properties than the short-term returns.

Okorie (2020) expands further the relationship between bitcoin and S&P 500 stock market. Using the bitcoin returns and volume during the Initial Coin Offering (ICO) ban period in China, he examines whether a government risk affects the bitcoin market. Concerning hedging, an inextricably intertwined liaison is revealed as it is implied that bitcoin can hedge S&P500 stocks' risks and vice versa. This is an important finding, as investors could theoretically form robust portfolios using these two assets while having safely hedged returns.

Hussain et al. (2020) compare the safe haven and hedging capabilities of gold and bitcoin for the G7 stock markets (Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States). Both bitcoin and gold appear to offer hedging benefits for investors in G7 stock markets, however, it seems that the hedging performance of gold is stronger than that of bitcoin. The results show that bitcoin is a weak safe haven for the stock markets of Canada and France, a strong hedge for Canada and Japan, and a weak hedge for France and Italy.

Kliber et al. (2019) employ daily data between main stock indices of Japan, Venezuela, China, Estonia, and Sweden and bitcoin price in local currencies as well as between main stock indices and the bitcoin price in the US dollar, to determine the role of bitcoin in those stock markets. When using local investments, bitcoin behaved as a safe haven in Venezuela and as a weak hedge in Sweden and Estonia. With the use of the bitcoin price in the US dollar, the results change and suggest that bitcoin is a weak hedge in all the out of sample markets.

Akhtaruzzaman et al. (2020) search the effects of the inclusion of bitcoin in global industry portfolios and bond index (PIMCO investment grade bond index). Results demonstrate that allowing investment in bitcoin provides an efficient hedging mechanism against the risk of industry portfolios and bonds.

Urquhart and Zhang (2019) use hourly data of bitcoin and six developed currencies in order to determine their intraday relationship. It is shown that bitcoin operates as a hedge for the CHF, EUR, and GBP, and as a safe haven during times of market unrest for the CAD, CHF, and GBP.

Bouri et al. (2017b) examine the daily relationship between bitcoin and commodities, energy commodities in particular. Bitcoin is an efficient hedge and a safe haven for both the indices selected (general commodity index and energy commodity index). Bitcoin keeps these properties for both the entire period and the pre-crash period but loses them when only the after-crash period is examined. This is proof of the disorder caused in the relationship between bitcoin and energy commodities by the 2013 bitcoin crash.

Selmi et al. (2018) analyze the differences of bitcoin and gold against extreme oil price movements. The study shows that both bitcoin and gold have strong hedging and safe haven properties, which however are sensitive to their respective market conditions and different degrees of oil price movements, and therefore cannot hold at all times. Moreover, there are indications that bitcoin is a more dynamic hedge and safe haven than gold against downside oil price movements. Therefore, bitcoin is more suitable for reducing the downside risk of oil.

Hoang et al. (2020) study the connection between bitcoin and commodity volatilities, namely oil, wheat, and corn. The results present a scarce association between bitcoin and the three commodity volatilities, an indication of bitcoin's possible hedging abilities against commodity uncertainty. Besides, the hedging capacity of bitcoin becomes more beneficial in the long term.

Stensås et al. (2019) examine a mix of developed and developing countries, regional indices, and commodity series. It is revealed that bitcoin is a strong hedge tool for investors in most developing markets (Brazil, Russia, India, and South Korea) and a strong safe haven for a few national equity indices, regional indices, and commodities. Moreover, the paper investigates the movements of bitcoin in periods of extreme market uncertainty. Examining the periods of the United States presidential election of 2016, the Brexit of the same year, as well as the Chinese stock market turbulence of 2015, they find that bitcoin is either a strong or a weak safe haven for most of the out of sample countries. They conclude that bitcoin can be an effective safe haven asset during times of high market instabilities.

Kristoufek (2014) investigates the connectedness of bitcoin prices with the Financial Stress Index (FSI), a general index that represents financial uncertainty, and the gold price in Swiss francs. Even though the results of the research do not signify general safe haven capabilities of bitcoin, an interconnection between the FSI and the bitcoin price reveals that the latter acted as a significant safe haven during the period of the Cypriot crisis.

Bouri et al. (2017a) use the Volatility Index (VIX) of 14 developed and developing equity markets in order to search if bitcoin can hedge against global uncertainty. Bitcoin is indeed shown to act as a hedge against uncertainty, especially at short investment horizons. Investors can use bitcoin to hedge the risks of the global equity market, both in bear and bull market regimes and also at lower and upper ends of uncertainty.

Li et al. (2019) investigate the origins of the bitcoin bubbles. They underline the importance of exogenous foreign or domestic economic shocks in the creation of bubbles, as this kind of crises may lead investors' trust in centralized currencies to fall, therefore, increasing the bitcoin price. There are also implications that bitcoin can act as a hedge, and even sometimes as a safe haven, against market-specific risk.

Wu et al. (2019) inspect the properties of gold and bitcoin against the US EPU index, an index used to measure the economic policy uncertainty (EPU). The study shows that both gold and bitcoin have hedge and safe-haven properties against EPU when the market is subject to extreme conditions, but these properties are only weak.

Lastly, Su et al. (2020) investigate the association between the bitcoin currency and the GPR index, which is used as a measure of the risks associated with global geopolitical events, and circumstances. By analyzing the data, they conclude that the bitcoin can be considered to potentially hedge geopolitical risk, but only during specific time periods of extreme geopolitical events.

In this section of the thesis, we described thoroughly the multiple uses of bitcoin. After analyzing the characteristics of the cryptocurrency as a currency and as an investment asset, for us, it does not make sense to include bitcoin in one of these categories. The use of bitcoin both as a medium of exchange and as a speculative, diversification, hedge, and safe haven tool has been proved by several pieces of research. We, therefore, believe it is logical to consider bitcoin as a unique asset with special characteristics.

2.3 Literature Review

The ever-increasing interest in bitcoin, as well as its ability to affect various fields, has led to the existence of expanding literature. Researchers typically study bitcoin in the context of four main areas [Polasik et al. (2015)]. The first area relates to technological issues, but also includes security problems such as cryptographic problems, and vulnerability to attack. The second path of literature examines public and legal issues, while the third one discusses the political, sociological, and ethical implications of bitcoin. This thesis contributes to the fourth and final area that studies bitcoin from an economic and investment perspective. The rise of bitcoin has resulted in substantial literature that examines bitcoin in general and bitcoin price formation in particular. Several factors driving bitcoin prices and explaining its volatility have been identified over time. These factors, examined in the existing literature, can be divided into 4 categories, namely technology-related or technical factors, market forces of bitcoin's supply and demand, investors' attractiveness to bitcoin, and global macroeconomic and financial indicators.

Technical Factors

The most limited literature, compared to the other categories of factors that affect bitcoin returns, concerns the bitcoin technological drivers. Kristoufek (2014) using wavelet coherence for hash rate and difficulty, finds a positive, long-run relationship between the two indicators and bitcoin price. The hash rate refers to the computational power needed for the mining process, while difficulty refers to the increasing difficulty of solving the mining problem. Both of the indicators are measures of the system productivity and the mining difficulty. The results reveal that the increasing price of bitcoin attracts new miners. However, the positive correlation vanishes over time and even becomes negative in the short term. This effect can be explained by the specialized equipment needed and the increased difficulty and cost of mining.

Bouoiyour and Selmi (2015) adopt an ARDL Bounds testing approach to investigate the association between bitcoin price and the hash rate, which is used as the technical drive of this study. The main results obtained indicate a positive and statistically significant impact of hash rate on bitcoin price. Nevertheless, the hash rate seems to only have a weak effect on the cryptocurrency.

Supply and Demand

One of the first areas, that was studied by researchers, has to do with the market forces of bitcoin's supply and demand. To our knowledge, Buchholz et al. (2012) first study the effect that interactions between supply and demand have on bitcoin price. As supply (total number of bitcoins mined) is inelastic and exogenous all observed price fluctuations should be explained by changes in demand. The demand for bitcoin mainly relies on consumption and transaction demand as a medium of exchange. The paper results in that the relation between bitcoin's supply and demand is an important determinant of its price.

Similarly, Gronwald (2015) argues that the total number, the number in circulation, and the growth rate of Bitcoins, therefore the supply of bitcoins, are known without any uncertainties. The observations of the paper imply that the fluctuations in bitcoin price can only be caused by factors in demand.

Following the same notion, de la Horra et al. (2019), base their research on the belief that all price movements are the result of changes in demand. Using the number of bitcoin transactions as a proxy for the size of the bitcoin economy, they find that transactions have a positive significant affair with bitcoin prices, both in long-term and short-term horizons.

Huhtinen (2014) states that, in the short run, the actual supply of bitcoins deviates from its theoretical value. By studying the supply of bitcoin, he finds a statistically significant negative correlation between bitcoin supply and the bitcoin returns. The inflationary effect of the increasing supply revealed, means that an increase in the supply causes a decrease in the price of bitcoin.

Li and Wang (2017) hypothesize that the bitcoin exchange rate reacts to the total number of bitcoins in use (supply) and transaction volume (demand). Indeed, their theoretical prediction is verified as they find a significant relationship between the exchange rate and the number of bitcoin-supported transactions but only in the long term.

Kristoufek (2014) finds that the bitcoin appreciates in the long run, verifying the standard economic theory. In the short run, the increasing price results in a rise in the demand for the currency at the exchanges, creating potential bubbles. As for the supply, only a weak insignificant relationship with the bitcoin price is noted, without even resulting in a clear leader.

Polasik et al. (2015) attempt to assess whether demand and supply factors can have a significant effect on the performance of bitcoin. They find evidence that transaction volume is an important pricing consideration as the number of transactions leads to price increases. This phenomenon is consistent with the network externality theory, according to which, the value of a network should increase as its size increases. Furthermore, in order to capture the influence of supply, they use the total number of Bitcoins in circulation, resulting, however, in statistically insignificant effects.

Bartos (2015) confirms that supply and, particularly, demand factors have a crucial effect on bitcoin price. Therefore, bitcoin can be seen as an economic good that follows a standard model of currency price formation.

Likewise, Ciaian et al. (2016b) confirm that market forces of bitcoin supply and demand significantly influence bitcoin price. Especially, the demand-side variables appear to have a stronger effect on bitcoin price than the supply-side drivers. Besides, the magnitude of both the traditional determinants of currency price seems to increase over time, when the number of Bitcoins in circulation is larger.

Ciaian et al. (2016a) also prove that the market forces of supply and demand have a strong effect on bitcoin price, with demand having, once again, a more pronounced impact than supply. In detail, results, which are in line with the quantity theory, report that an increase in the number of bitcoins decreases bitcoin price, while an increase in the size of the bitcoin economy increases bitcoin price. The quantity theory implies that an increase in the velocity and the stock of bitcoins should lead to a decrease in the price of bitcoin, whereas an increase in the size of the bitcoin economy should result in an increase in the price of bitcoin.

Balcilar et al. (2017) examine the causality relationship between trading volume and bitcoin returns. He reveals a nonlinear relationship between the two variables, but only in a normal market regime. In other words, trading volume can predict returns in every state of the market except when the market is bearish or bullish.

From all the variables examined by Aalborg et al. (2019), only the number of unique addresses is found to be positively related to bitcoin returns. A positive but weak relationship stands for both weekly and daily time horizons, indicating that an increase in relative changes in the number of users will result in an increase in bitcoin returns. Besides, results indicate that bitcoin's transaction volume has a small, significant predictability capacity on daily returns.

Kjærland et al. (2018) reveal a significant, negative relationship between bitcoin's volume and price. Increased volume, however significant, barely affects bitcoin's price, not providing sufficient evidence that bitcoin follows the traditional supply and demand theory.

Investment Attractiveness

A big piece of the literature focuses on investors' sentiment as a price driver, on the basis that the digital currency price is driven mainly by the investors' faith in perpetual growth. Kristoufek (2013) uses search queries on Google Trends and Wikipedia as a proxy of investors' sentiment. According to the research, there is a strong, positive, bidirectional, relationship between prices of the bitcoin currency and related searched terms on Google Trends and Wikipedia. Moreover, an asymmetry between the effects of search queries on bitcoin prices and a short-term trend is revealed. Specifically, if the prices grow, the increasing interest will result in even higher prices, while if the prices decline, the growing interest will produce even lower prices.

Bouoiyour and Selmi (2015) find similar results. Examining Google trends, they reveal a positive, significant effect on bitcoin prices, especially in the short run. They conclude that investors' attractiveness emerges as the major driver of bitcoin price, dominating other variables, and explaining better the bitcoin price formation.

Kristoufek (2014) confirms the co-movement of both search engines used with the bitcoin price. Using a wavelet coherence analysis, he adds that the directionality of the relationship changes through time. Initially, price leads popularity, but along the way, the relationship produces mixed signals for a leader. The asymmetric effect is once again evident, especially during the bubble period. Interestingly, the increased interest has a stronger effect during the bubble bursting than during the bubble build-up.

Ciaian et al. (2016b) find that bitcoin attractiveness has an important effect on bitcoin price but with variation over time. Alongside Wikipedia searches, the number of new members, as well as new posts on online bitcoin forums are also used as a measure of investment attractiveness. In the short run, and specifically in the first years after the introduction of bitcoin, all variables have a significant positive relationship with bitcoin price. In the following years, as well as in the long run in general, only the variable new posts holds its properties as a driver. The insignificant effect of Wikipedia searches in recent years can be justified by the fact that the general type of information Wikipedia provides has probably become common knowledge for most users, so far.

Ciaian et al. (2016a) prove that bitcoin popularity variables have the most prominent impact on bitcoin price, in comparison to all the other variables examined. Applying time-series analytical mechanisms, they find that the attractiveness indicators' relations with bitcoin price strengthen in the long run. To be more precise, the new members variable has a negative impact, the variable new posts has a positive impact, and the Wikipedia views variable has a positive statistically significant impact on bitcoin price.

Li and Wang (2017) examine the dynamic between Google trends and Twitter with bitcoin price. Google trends have a positive impact on the long-term bitcoin value, and a significant positive impact, with a 3- day lag, on the short-term. Twitter mentions have a significant negative impact, with a 5-day lag, in the short-term, while they are insignificant on the long-term pricing process. In addition, it is implied that the long-term impacts of these variables are stronger in the early market. The results hint that Google search is a better indicator of the bitcoin market.

Panagiotidis et al. (2018) examine the importance of several factors, including internet trends, on bitcoin returns. Using a LASSO regression, they conclude that search intensity, measured by Google trend for the term 'bitcoin', is one of the most important drivers of bitcoin returns. Wikipedia trend for the article on bitcoin does not lead to similar results. One would expect the effect of information demand on bitcoin returns, as positive information leads to increases in price while negative information results in declines in price.

Panagiotidis et al. (2019) apply four models (a standard VAR with Granger causality, a FAVAR, factor analysis, and principal components analysis) to determine the impact of nineteen (19) variables on bitcoin returns. Irrelevant from the model used, popularity proxies, mostly resulted in a weak or insignificant effect on bitcoin price. Generally, the Google trend tends to be a better driver than the Wikipedia trend. These results provide proof that the impact of popularity on bitcoin price is getting weaker.

Kjærland et al. (2018) examine nine potential explanatory factors of bitcoin's price fluctuations. The research reveals a positive, significant relationship between bitcoin price and online searches, proxied by Google's search volume.

Phillips and Gorse (2018) examine the link between several online factors (Various social media factors derived from Reddit, Google search volume, and Wikipedia views) and the price of Cryptocurrencies. In their majority, variables impact the price negatively and weakly, in the short run. Further, price is the main leader of the relationship, indicating that online factors may not be the best driver in the shorter term. In the medium term, periods of strong positive relationships interchange with periods of no relationships at all, while there is no clear leader of the relationship. As for the long term, a positive relationship between price and online activity is suggested. The variables with the strongest predictive power are the Reddit-derived ones. Additionally, a wavelet coherence analysis reveals that long-term and, predominately, medium-term relationships benefit from periods of bubble-like regimes. This strengthening action, however, appears to have a noticeable less pronounced impact on bitcoin in comparison with other Cryptocurrencies.

Bukovina and Marticek (2016) try to uncover the effect that sentiment has on bitcoin volatility. As a measure of sentiment, they employ data from the website reddit.com. Overall, sentiment is found to have significant and influential, but minimal, explanatory properties for excessive volatility. During periods of excessive volatility, the explanatory power of sentiment seems to strengthen. Lastly, it is implied that the positive sentiment is more dominant than the negative one.

The work of Vockathaler (2015) revises the previous literature and assesses its findings ex-post. Interestingly, the findings of this study contradict the ones of previous research.

Specifically, the Google trend is found to be an insignificant contributor to bitcoin price movement. The lack of a significant relationship between public interest and the price movement is awarded in the stability of the prices of the examined period.

Similarly, Bartos (2015) finds that Wikipedia search queries do not significantly impact the price of bitcoin. No relationship is found, neither in long-term nor in short-term horizons.

At last, Shen et al. (2019) investigate the relationship between the number of previous day tweets from Twitter, involving the term 'bitcoin' and 'bitcoin returns', finding that the volume of tweets is a significant driver of bitcoin's realized volatility and volume, but not returns.

Global Macroeconomics and Financial Developments

Perhaps the factors most extendedly examined by researchers are related to global macroeconomics and financial developments. Wijk (2013) tries to determine the daily influence of a number of financial data, including stock exchange indices, exchange rates, and oil price indices, on the value of bitcoin. The findings reveal that several financial indicators significantly impact the bitcoin price in the long run, such as the Dow Jones Index, which has a significant positive effect, and the euro-dollar exchange rate, and the WTI oil prices, which are negatively related to the price. Furthermore, the value of the Dow Jones Index is a strong, positive, driver of bitcoin in the short run.

Li and Wang (2017) examine the dynamic between economic indicators and the bitcoin price. According to the analysis, in the short term, USD money supply changes and federal fund interest rates, affect bitcoin, positive and negative accordingly. In the long term, bitcoin responds to economic fundamentals only in the late market.

Bouoiyour and Selmi (2015) examine the relationship of bitcoin with the Shanghai market index, as the Shanghai market is considered to be one of the most important determinants of the bitcoin economy. He uncovers a positive, significant impact of the index on bitcoin, in the short run.

As already mentioned, Bouoiyour and Selmi (2017) analyze the relationship between the bitcoin price and the U.S. stock price index during the post-U.S. election period of 2016. The results document that the hedge and safe haven features of bitcoin are time-varying.

Specifically, bitcoin primarily acts as a weak safe haven in the short term, and as a hedge in the medium and the long term.

Dyhrberg (2016a) considers the impact of several financial variables on bitcoin. The findings imply that a positive relationship between bitcoin returns and the federal funds rate, the FTSE Index and the USD/EUR exchange rate exists. On the contrary, the relationship between bitcoin returns and the USD/GBP exchange rate is negative.

Interestingly, Dyhrberg (2016b) concludes that the USD/EUR, as well as, the USD/GBP exchange rates are positive but weak drivers of bitcoin. Also, the Financial Times Stock Exchange Index (FTSE) tends to be uncorrelated with the cryptocurrency.

Wang et al. (2016) investigate the relation between bitcoin price and some variables including the Dow Jones industrial average index and the WTI crude oil price of the New York Mercantile Exchange. The analysis results in a short-term positive weak impact of stock price index on bitcoin, as well as a short-term positive larger impact of oil price on bitcoin price. In the long run, bitcoin price is negatively related to both the Dow Jones industrial average index and the WTI crude oil price.

MacDonell (2014) examines several exogenous variables but finds only the Chicago Board of Exchange Market Volatility Index (CBOE VIX) to have a significant effect.

Apart from the CBOE VIX, Akyildirim et al. (2020) also examine the DAX VSTOXX relationship with cryptocurrencies. The indices measure the implied volatility of the United States and European financial markets, respectively. Calculations considering the entire period of investigation present no significant relationship between bitcoin and the VIX and VSTOXX. However, taking into account only higher deciles, both of the financial market stress indices display positive interrelationships with bitcoin.

Bouri et al. (2017a) analyze the relationship between global uncertainty and bitcoin returns at various frequencies, using implied volatility indices (VIXs) of 14 developed and developing equity markets. Results show that, at lower quantiles, uncertainty has a negative and significant effect on bitcoin returns, while, at higher quantiles, the impact is positive and significant.

Erzurumlu et al. (2020) investigate the relationships between six cryptocurrencies and 18 external factors. A relationship between uncertainty (VIX), the leading factor, and bitcoin, the lagging factor, is confirmed. Furthermore, bitcoin tends to generally lag the coins it co-moves. In more detail, after 2017, at low frequencies, bitcoin presents an inverse coherence with Ethereum, which is the leader of the relationship. Besides, a significant liaison between bitcoin and other altcoins (Litecoin, Monero, and Dash) is revealed in higher frequencies. However, bitcoin lags the altcoins only for low frequencies and for after 2017.

Demir et al. (2018) wonder whether the economic policy uncertainty (EPU) index has predictive power on the daily bitcoin returns. Findings of the analysis provide evidence that, altogether, the EPU leads a negative association with bitcoin returns, yet, at lower and higher quantiles the EPU has a positive and significant impact on bitcoin returns.

Panagiotidis et al. (2019) employ four alternative VAR models to determine the impact of nineteen (19) variables on bitcoin returns. Results vary depending on the specific model used as well as on the period examined. Some general results include the significant positive effect gold shocks have on bitcoin and the robust association between bitcoin with some traditional financial markets (especially Dow Jones and Nasdaq). Bitcoin also reacts to uncertainty shocks in the traditional markets (CBOE VXD), whereas proof of a positive response to oil is provided. On the contrary currency markets seem to have only a weak effect on bitcoin (only Yen provides proof of correlation). Bitcoin's response to a federal funds rate rise might be positive, excluding an ECB deposit facility rate rise where the response is negative. Lastly, bitcoin reacts positively to shocks of the US and European policy uncertainty.

Conrad et al. (2018) analyze the most frequently claimed drivers of long-term bitcoin volatility. Findings of the research hint that global macroeconomic and financial activity plays a major role in bitcoin volatility. Specifically, the S&P 500 realized volatility has a negative, significant impact on bitcoin volatility, while the Variance Risk Premium (VRP) is significantly but positively related to the long-term bitcoin volatility. Likewise, both the VIX and RV-S&P Global Luxury Index (Glux) have a negative effect on long-term bitcoin volatility. Last but not least, long-term bitcoin volatility is confirmed to have a robust positive link with the Baltic dry index.

From all the economic and financial variables Walther et al. (2019) examine, the Global Real Economic Activity (GREA) best predicts cryptocurrencies' volatility. Moreover, the

Global Economic Policy Uncertainty index (GEPU) has the greatest predictive power for 1-day and 30-day ahead bitcoin forecasts, while the Chinese Economic Policy Uncertainty index (CEPU) has the greatest predictive power for 1-week ahead bitcoin forecasts. Other significant drivers are the Global Financial Stress Index (GFSI) and the realized volatility of the S&P 500.

Kjærland et al. (2018) use dummies to investigate the impact of positive and negative political incidents and statements on bitcoin prices. The strength of the shocks' effects depends on the model used. In general, both positive and negative shocks have the expected effect on bitcoin returns, with negative shocks being more significant than positive ones.

Lastly, Polasik et al. (2015) find only a weak and statistically insignificant association between bitcoin return and three important macroeconomic variables (growth in industrial production, unemployment, and inflation). Results lead to the conclusion that bitcoin is not much connected with macroeconomic factors.

To summarize, the empirical literature has constantly been investigating factors that could potentially explain the movements of bitcoin prices. By studying previous pieces of research, we can conclude that even the most extensively proven determinants of bitcoin returns cannot be unequivocally accepted. The information content of exogenous factors is time-varying and dependent on the model adopted. Therefore, results can vary due to differences in periods and horizons examined, as well as variations of models used.

3 Data

3.1 Data Description

In the technical part of this paper, an empirical analysis will be performed in order to determine which day-to-day technical, economic, and financial data influence the value of bitcoin. Our research focuses mainly on financial data as this is the part of bitcoin we are more interested in exploring.

The dataset used in the analysis consists of the dependent variable -Coindesk Bitcoin Price Index- and 36 explanatory variables. Coindesk Bitcoin Price Index represents the average value of bitcoin in USD using prices from leading bitcoin exchanges. The data employed include 7-day week, daily observations, as bitcoin exchanges are constantly operative. We feel that it is of utmost importance to show some specifics of the variables investigated. Below, we provide a brief description of all analyzed series, presented according to the category to which they belong: technical factors, supply and demand, investment attractiveness, and global macroeconomics and financial developments. In the Appendix, Table A.1 summarises the data and the sources, and Figure A.1 plots the levels for all the variables.

Technical Factors

We include two technical variables in the analysis, namely the hash rate [HASH] and the network difficulty [DIF]. The value of hash rate is a key security metric, it is used as a measure of the system productivity, and it represents the estimated number of terahashes per second the bitcoin network is performing in the last 24 hours. We use 7-day average data, instead of raw values, because it is a better representation of the underlying power. Network difficulty refers to the increasing difficulty of mining a new block for the blockchain. For the purpose of keeping the average time between each block at 10 minutes, the data is adjusted almost every 2 weeks.

Supply and Demand

Regarding the factors related to the supply and demand sides of bitcoin, three variables are included in the model. The total number of bitcoins in circulation [TBC] works as an indicator of bitcoin's supply. Oppositely, the number of daily confirmed transactions, or else transaction volume [VLM], as well as the daily number of unique addresses used on the blockchain [ADRS], describe the demand of bitcoin.

Investment Attractiveness

Four are the variables used to proxy the investors' sentiment. The first two, Google Search Volume of the term "bitcoin" [GOOGLE] and Wikipedia daily views on bitcoin page [WIKI] have been extensively used in previous studies. The following two, daily posts involving the term bitcoin on Twitter [TWITTER] and daily posts on the largest subreddit -discussion group- about bitcoin (/r/bitcoin) of Reddit [REDDIT], are traditionally less studied as indicators but we feel they might be equally important. It is important to mention that the Google trend data describe the search interest relative to the highest point of the given time period. The value 100 corresponds to the highest popularity for the term, while a score of 0 implies a lack of data for this term.

Global Macroeconomics and Financial Developments

Lastly, the greatest portion of the analysis concerns time series related to global macroeconomics or financial developments. Six market indices have been selected, specifically three major U.S. -the Dow Jones NYSE index [DJI], the Nasdaq index [NASDAQ], the S&P 500 index [SP500]- one of the biggest European -the FTSE 100 index [FTSE]- and two major Asian -the Nikkei 225 index [NIKKEI] and the Shanghai Composite Index [SSEI]. Moreover, in order to measure market risk, we use two volatility indices. The Chicago Board of Exchange Market Volatility Index [VIX] is based on real-time price inputs of the S&P 500 index call and put options and reflects the U.S. market's 30-day expected volatility. Similarly, the EURO STOXX 50 Volatility EUR Price Index [VSTOXX] is derived from EURO STOXX 50 real-time options prices and represents Europe's market expectations. In addition, four of the variables are Economic Policy Uncertainty (EPU) indices. Each EPU index reveals the volume of own-country newspaper articles that contain terms relevant to the Economy, Policy, and Uncertainty. The EPU selected are the Global Economic Policy Uncertainty index [GEPU], the Europe Economic Policy Uncertainty index [EEPU], the U.S. Economic Policy Uncertainty index [USEPU], and the China Economic Policy Uncertainty index [CEPU]. The Daily Infectious Disease Equity Market Volatility Tracker [IDEMV] tracks newspaper articles of approximately

3,000 US Newspapers that mention at least one term pertaining to each of concepts of Economy, Stock Market, Volatility, and Epidemic. The analysis also includes four pairs of currencies trading in the Forex market. These pairs are the EUR/USD exchange rate [EUR/USD], the GBP/USD exchange rate [GBP/USD], the CNY/USD exchange rate [CNY/USD], and the JPY/USD exchange rate [JPY/USD]. Besides, we add the Gold price in USD [GOLD], the Brent oil price in USD [BRENT], and the West Texas Intermediate oil price [WTI]. Lastly, the Fed Funds effective rate [EFFR] as well as the ECB deposit facility rate [ECBDFR] are also included in the model.

Due to data availability, the time frame of the analysis spans from October 1st 2013 to December 31st 2020, an interval that covers 2639 observations. This thesis does not only examine the full sample but also three sub-periods separately. In order to determine these sub-periods, we take into consideration the different phases of the bitcoin price as well as some major macroeconomic events.[1] The first period spans from October 1st, 2013 to March 26th, 2017. This period is generally characterized by stability in bitcoin prices and portrays the gradual recovery of the 2013 crash. The second period commences on March 26th, 2017, and ends on March 15th, 2020. It includes the 2017 bubble, the crash, and the recovery, therefore making it the most volatile era of our dataset. The third and last sub-period examined spans from March 15th, 2020 until December 31st, 2020. It is the period in which the COVID-19 global pandemic halted most activities of the world economy while bitcoin prices soared to all-time highs.

3.2 Data Transformation

The majority of the time series used in the analysis are in a 5-day week or even a more sparse frequency. Similarly, in several variables, some dates are omitted due to the fact that exchanges would close due to holidays. To cover the gaps of these variables we use interpolation. Of all the interpolation methods available in the econometrics software EViews we use the Catmull-Rom Spline interpolation method as the generated series cumulative distribution function is closer to the initial sample one, compared to the other alternatives like linear, log-linear, Cardinal Spline, and Cubic Spline methods. This allows

[1] We tested an ADF Breakpoint unit root on the returns of bitcoin, breaking for both the trends and the intercept, however, the suggested break date [19/11/2013] is too close to the starting date of the data [01/10/2013] so we choose to ignore it. In the Appendix, Figure A.3 presents the ADF breakpoint unit root test coefficients and Figure A.4 the sub-periods selected.

us to keep the 7-day series as close as possible to the 5-day one in terms of financial properties and distribution characteristics. [2]

As far as bitcoin is concerned, it is clear from Figure 2.1 that its value shows a trend over time. To examine the statistical properties of the dependent time series, we plot the histogram of the first differences of the bitcoin price. At first differences, bitcoin presents a slight positive Skewness paired with a high Kurtosis (first graph of Figure 3.1). Therefore, the distribution is leptokurtic an indication that it produces more outliers than the normal distribution. Subsequently, to resolve these problems we calculate the growth rate (first logarithmic differences) of bitcoin value. When examining the new histogram (second graph of Figure 3.1) we observe that even though the Skewness grows in absolute value and becomes negative, the Kurtosis declines significantly. Thus, while the distribution remains only approximately symmetric it improves the shape of the probability.

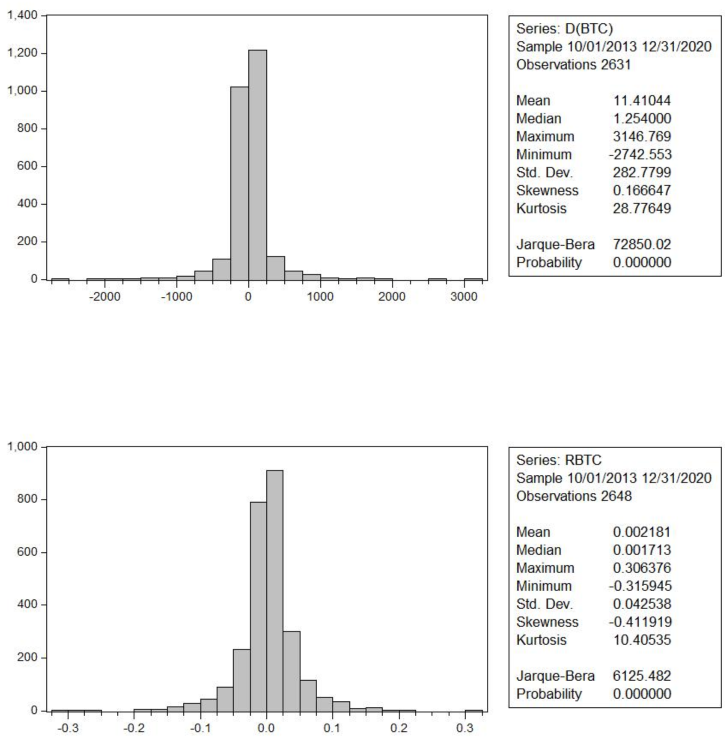

Figure 3.1: Histogram and descriptive statistics of bitcoin's first differences and returns

[2]We could use a Two-sample Kolmogorov–Smirnov test to compare the alternatives in pairs, but the result was visible in the first place when plotting the CDFs and their differences with that of the original sample. Figure A.2 in the Appendix shows an example of the CDFs comparison for the EUR/USD variable.

A stationarity test is necessary before we use the variables in the regression, in order to avoid spurious regression results. We test the stationarity using the Augmented Dickey-Fuller (ADF) Unit Root Test. The model used for the test is the following:

$$\Delta Y_t = \gamma Y_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta Y_{t-i} + u_t \tag{3.1}$$

where Y_t = the value of the time series at time 't', α = the autocorrelation coefficient, and u_t = the error term. The test's null hypothesis, $H_0 : \gamma = 0$, implies the existence of a unit root and therefore the non-stationarity of the variable examined. Contrariwise, the alternative hypothesis, $H_1 : \gamma < 0$, implies the stationarity of the time series. Consequently, for a time series to be stationary we have to reject the null hypothesis. Moreover, the above equation can be modified to include an intercept and a trend term,

$$\Delta Y_t = \mu + \gamma Y_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta Y_{t-i} + u_t \tag{3.2}$$

$$\Delta Y_t = \mu + \lambda_t + \gamma Y_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta Y_{t-i} + u_t \tag{3.3}$$

where μ = the intercept, and λ = the trend.

All variables are tested using the ADF Unit Root Test, including trend and intercept. The test results in most of the variables being non-stationary in levels but stationary when calculating their returns. Returns are obtained by calculating the logarithmic first difference of the series' prices, as shown in equation 3.4.

$$R_t = log(P_t) - log(P_{t-1}) \tag{3.4}$$

Even though some of the time series proved to be stationary in levels we decided, for the sake of convenience in comparisons and interpretation, to include their growth rates in the regression. The only variables used in levels are the ECB deposit facility rate [ECBDFR] and the Fed Funds effective rate [EFFR], while the total number of bitcoins in circulation [TBC] is used in logarithms.[3] In the Appendix, Figure A.5 presents the growth

[3] From now on, we proceed the analysis using these modified series. To symbolize the logarithmic first differences in the tables and figures following we use the letter R before the name of each variable, while for [TBC] we use the letter L to symbolize logarithms. For convenience, references to the variables in the text are made in their full name.

rates of the variables -excluding [EFFR], [ECBDFR], and [TBC]- Figure A.6 includes the histograms of the variables, Table A.2 summarizes the results of the unit root test while Table A.3 displays the descriptive statistics of the returns.

At last, following the notion of previous studies [Kristoufek (2013), Kristoufek (2014), Panagiotidis et al. (2018), Panagiotidis et al. (2019)] we use a short-term trend to account for differences between effects of internet trends related to positive and negative events of bitcoin. In other words, we compare the price of bitcoin with its 7-day simple moving average. If the value of the price is higher than the one of the 7-day trend then the search query is associated with a positive event. Similarly, if the value of the rate is lower than that of the trend, it is associated with a negative event. To determine this association we introduce a dummy variable that takes the value 1 if the price is higher than the 7-day trend level and the value 0 if it is lower than the 7-day trend level. Subsequently, we use the dummy variable to investigate the effects of all variables used as measures of investment attractiveness ([GOOGLE], [WIKI], [TWITTER], [REDDIT]).[4] We simply multiply the internet trend variable with the dummy variable for above the trend information and with (1 - the dummy variable) for below the trend information. Let D denote the dummy variable and if we use the variable GOOGLE as an example:

$$GOOGLE+ = GOOGLE \cdot D$$

$$GOOGLE- = GOOGLE \cdot (1 - D)$$

[4]The effects of internet trends related to positive events of bitcoin are symbolized using the name of the internet trend variable followed by the symbol "+". For negative related events, we use the symbol "-".

4 Methodology

4.1 LASSO Regression

For empirical purposes, this study investigates the relationship between the potential drivers on bitcoin returns using the Least Absolute Shrinkage and Selection Operator (LASSO) technique. The LASSO, introduced by Tibshirani (1996), is a regression analysis method for estimation in linear models. The application of standard regression estimates, such as the Ordinary Least Squares (OLS), is sometimes not the best way to generate predictive models due to the nature of the estimates. An issue that may arise while using standard regression is that of prediction accuracy. OLS regression tends to overfit the data resulting in low bias but high variance. Another problem that may concern the analyst is the one of interpretation. Including a large number of explanatory variables and therefore making the model complex could result in less efficient predictions.

Even though there is not a fixed solution, there are some ways of improving the overall prediction accuracy of a model suffering from the problems aforementioned. To address the first issue, we can introduce a small amount of bias to significantly reduce the variance of the predictors. To achieve these results, some coefficients will have to shrink or even be set to 0. Concerning the second issue, two criteria, Akaike's information criterion (AIC) and Bayesian information criterion (BIC), also known as Schwarz information criterion (SIC), are often used to determine the appropriate subset of predictors that would result in more accurate predictions.

Various regression techniques have been developed in order to improve the predictive strength of OLS. LASSO was created in an effort to combine the positive characteristics of Subset selection and Ridge regression, without featuring their drawbacks. To be more specific, Subset selection is a procedure that removes seemingly redundant variables, therefore, dealing with the problem of interpretation, while Ridge is a penalized regression technique that shrinks coefficients improving the prediction accuracy of the model. Nonetheless, Subset selection can reduce the predictive strength of the model, and Ridge regression cannot provide interpretable models. LASSO, similarly to OLS, minimizes the sum of the squared residuals. Besides, it resembles Ridge regression as it includes a penalty term. The uniqueness of LASSO comes in the fact that it can actually shrink the bias term, which is the absolute value of the slope of the regression (the coefficients), exactly to 0, unlike Ridge regression that can only shrink it asymptotically close to 0, thus giving interpretable models. The LASSO estimator function is:

$$(\hat{\alpha}, \hat{\beta}) = argmin + \sum_{i=1}^{N} \left(y_i - \alpha - \sum_j \beta_j x_{ij} \right)^2 \text{subject to} \sum_j |\beta_j| \leq t \tag{4.1}$$

where y_i symbolizes the dependent variable, $x_{i,j}$ the explanatory variables, α a constant, and β_j the coefficients. $\sum_j |\beta_j| \leq t$ is the constraint of the regression, where $\sum_j |\beta_j|$ is the $L1$ norm, and t is a pre-specified tuning parameter, that determines the degree of shrinkage applied.

Written in its Lagrangian form LASSO becomes:

$$(\hat{\alpha}, \hat{\beta}) = argmin + \sum_{i=1}^{N} \left(y_i - \alpha - \sum_j \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \tag{4.2}$$

where $0 \leq \lambda \leq \infty$ and λ is determined using cross validation. As λ increases the slope of the regression line becomes more horizontal and the regression itself becomes more robust to changes of the independent variable. In simple words, one could say that the following is true:

Least Squares Regression:

$$\text{min(sum of the squared residuals)}$$

LASSO Regression:

$$\text{min(sum of the squared residuals) } + \lambda |slope|$$

Examining the following graph, that illustrates a hypothetical scenario of an OLS and a LASSO regression, we can observe that LASSO flattens the regression line, the greater λ is. In the case that $\lambda = 0$ the two regression lines would overlap.

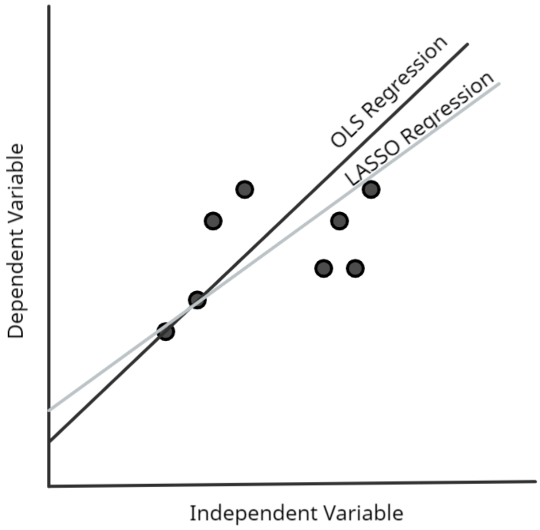

Figure 4.1: OLS and LASSO depiction

At last, it is important to underline the particularity concerning the standard errors of LASSO regression. Specifically, penalized regression models may not provide valid standard errors. As already mentioned, penalized regressions introduce substantial bias in order to reduce the variance of estimators. Thus, the bias introduced contributes significantly to the mean squared error, alongside variance. In models which include penalized estimates, however, the estimates of the bias obtained are neither precise nor reliable. Standard errors can be calculated, usually, through the use of bootstrap methods, methods that average estimates from multiple data samples to estimate quantities about a population. Even these methods nonetheless, can only give an assessment of the variance. Some solutions to the reliability problem of the LASSO regression standard errors have been examined. Casella et al. (2010) propose the use of some LASSO variations and especially the Bayesian LASSO, while Lockhart et al. (2014) try to introduce a significance test for the LASSO. To our knowledge nevertheless, reliable methods for acquiring valid standard errors are not available. For this reason, we ignore the question of statistical significance and only consider the size and rank of the estimates.

4.2 GARCH model

As we already mentioned, bitcoin is characterized by leptokurtic distribution (Figure 3.1). That means that bitcoin returns do not follow the normal distribution, and present positive excess kurtosis. Moreover, by observing Graph 4.2 we can see that the volatility of bitcoin changes over time, and periods of large changes, either positive or negative, are followed by periods of large changes, while periods of small changes are followed by periods of small changes. The phenomenon where volatility is manifested in groups is known as volatility clustering and is pretty common amongst financial time series. It is important to remind ourselves that in order to use a standard OLS regression[5] the model used must satisfy a number of assumptions. Both leptokurtosis and volatility clustering can create numerous problems if we try to calculate the correlation coefficients or the standard errors via simple OLS as it would fail some of the Classical Linear Regression Model assumptions. In order to resolve these problems in our data, we use the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model.

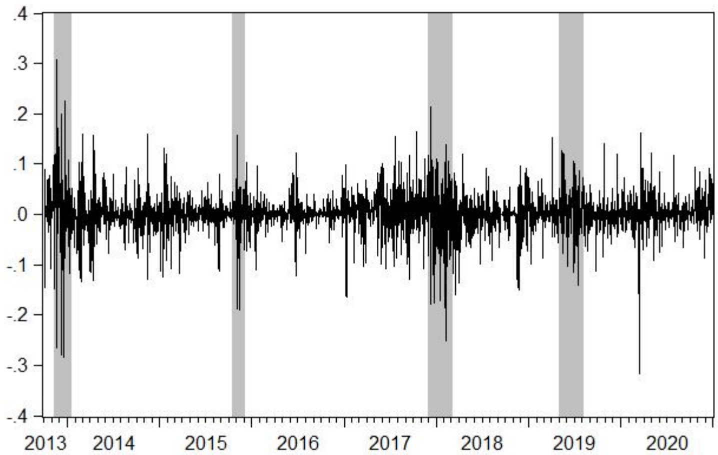

Figure 4.2: Volatility Clustering of Bitcoin returns

4.2.1 ARMA model

Before we describe the GARCH model functions, it is important to introduce some notions that will help us understand better how the GARCH model works. Initially, we ought to explain what an Autoregressive (AR) model is. The autoregressive model is a linear regression that uses information of past behavior of the output variable to predict the future behavior of the output variable. It is a stochastic process that assumes that the

[5]In our model we use the LASSO regression instead of the OLS, however, we consider LASSO regression a special case of the General Linear Model. Therefore, the assumptions that apply to OLS should also apply to LASSO.

output variable depends on its own past data and on a random term. The simplest form of an AR model is AR(1) which includes information only from the previous term in the process with equation,

$$Y_t = c + \varphi_1 Y_{t-1} + \varepsilon_t \tag{4.3}$$

while for the more general form AR(p), where a number of p previous terms contribute to the output, the model is defined as:

$$Y_t = c + \sum_{i=1}^{p} \varphi_i Y_{t-i} + \varepsilon_t \tag{4.4}$$

where φ_i are the coefficients of the model, c a constant, and ε_t is white noise.

Similar to the AR model is the Moving-Average (MA) model. The MA is a process that implies that current and past values of the random term affect the output variable. The simplest form of a MA model is MA(1) which includes information only from the previous stochastic term in the process,

$$Y_t = \mu + \vartheta_1 \varepsilon_{t-1} + \varepsilon_t \tag{4.5}$$

while for the more general form MA(q), where order q is the number of previous stochastic terms that contribute to the output, the model is defined as:

$$Y_t = \mu + \sum_{i=1}^{q} \vartheta_i Y_{t-i} + \varepsilon_t \tag{4.6}$$

where ϑ_i are the parameters of the model, μ is the mean of the series, and ε_t is white noise.

Both of the aforementioned models, that is AR and MA, are components of a more generalized model known as the Autoregressive–Moving-Average (ARMA) model. This model is used when the time series data has slow-declining autocorrelation and partial autocorrelation functions. The simplest form of an ARMA model is ARMA(1,1) which includes information only from the previous term of the output variable and the stochastic term in the process,

$$Y_t = c + \varphi_1 Y_{t-1} + \vartheta_1 \varepsilon_{t-1} + \varepsilon_t \tag{4.7}$$

while for the more general form ARMA(p, q), where p refers to the autoregressive terms and q to the moving-average terms, the model is defined as:

$$Y_t = c + \sum_{i=1}^{p} \varphi_i Y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \tag{4.8}$$

4.2.2 ARCH model

It is important to note that, due to the concentration of volatility in periods it is more useful to study the conditional than the unconditional variance. Conditional variance is the variance of a random variable given some extra information. In contrast, unconditional is the variance that is constant over time. If we assume that the error term of the regression is ε_t then under the Gauss Markov assumptions $\mathrm{Var}(\varepsilon_t) = \sigma^2$ should apply and the error term would be homoscedastic. However, in our case, as for several other financial variables, the model appears to be conditional heteroscedastic, as the assumption of constant variance is violated. Engle (1982) was the first to suggest that this volatility of the residuals variance could be explained via an autoregressive model. This kind of model is named the Autoregressive Conditional Heteroscedasticity (ARCH) model. In the ARCH model, the error term of the series ε_t is divided into an independent stochastic term u_t, with mean equal to 0 and variance equal to 1, and a standard deviation σ_t.

Therefore, an ARCH model considers:

$$\varepsilon_t = u_t \sigma_t,$$

$$u_t \approx i.i.d.\,(0, 1)$$

The main concept of the ARCH model is that the non-linear dependence that the error term demonstrates can be interpreted with the use of previous values of the squared error ε_t^2. For the simplest form of ARCH(1) the equation is,

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 \tag{4.9}$$

while for the more extensive form, an ARCH(q) model will be written as,

$$\sigma_t^2 = a_0 + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 \tag{4.10}$$

where σ_t^2 is the conditional variance of the error term, and a_0 is a constant.

4.2.3 GARCH model

Even though ARCH models are really useful, in some cases they seem to present some drawbacks. Previous research seems to agree that the most appropriate model for capturing the volatility clustering of financial time series is the Generalized Autoregressive Conditional Heteroscedastic (GARCH) model. The GARCH model was introduced by Bollerslev (1986) and expands the ARCH model making it possible for the conditional variance σ_t^2 to depend not only upon the previous values of the squared error ε_t^2 but also upon the previous values of the conditional variance itself. The simplest form of GARCH(1,1) is formed as,

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{4.11}$$

while the GARCH(p, q) equation is

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \tag{4.12}$$

In order to ensure the non-negativity of σ_t^2, a_0, a_i and β_i must also be non-negative. These are the GARCH parameter restrictions. Moreover, the stationary condition that must apply is $a_i + \beta_i < 1$. The sum of a_i and β_i is the statistic that interests us more as it is a measure of persistence that reveals the duration of the volatility after a shock. A sum close to 1 indicates that the volatility of the conditional variance is persistent.

ARCH and GARCH models consist of a conditional mean equation and a conditional variance equation. In financial time series, usually, the conditional mean equation that is specified is an AR, ARMA, or an MA process. It has been noted that the ARCH model shares more similarities with a MA process while the GARCH model has an ARMA form. Besides, it has been proposed that GARCH(1,1) is notably suitable for capturing volatility clustering. For that reason, we decided to apply a GARCH(1,1) model in the analysis following. Specifically, we use a GARCH filter in order to incorporate the impact of the conditional variance on bitcoin returns.

5 Analysis

5.1 GARCH model results

As a first approach, and in order to form an overview of the analysis that follows, we examine the correlation between bitcoin and the explanatory variables. Table 5.1 summarizes the correlation coefficients as well as their p-values. This is a preliminary way to indicate the existence of a relationship between bitcoin with the rest time series. The results, presented in Table 5.1, indicate that several variables have a statistically significant correlation with bitcoin. To be specific, 11 variables are found to be significantly correlated to bitcoin in the 5% level. Another 3 variables are added if we take into account the 10% level of significance. None of the relationships revealed, however, seem to be strong, as the highest correlation coefficient is only 0.11 (0.101307).

Table 5.1: Correlation between Bitcoin and explanatory variables

	RADRS	LTBC	RVLM	RDIF	RHASH	RGOOGLE-	RGOOGLE+
Correlation	0.101307	-0.004038	0.062664	0.040703	0.033535	-0.069389	0.095521
Probability	0.0000	0.8371	0.0014	0.0382	0.0877	0.0004	0.0000
	RREDDIT-	RREDDIT+	RTWITTER-	RTWITTER+	RWIKI-	RWIKI+	RDJI
Correlation	-0.031958	0.068082	-0.002691	0.063490	0.006252	-0.014993	-0.028875
Probability	0.1037	0.0005	0.8910	0.0012	0.7503	0.4453	0.1415
	RFTSE	RNASDAQ	RNIKKEI	RSSEI	RSP500	RCNY/USD	REUR/USD
Correlation	-0.000720	-0.020261	0.038045	0.022588	-0.025932	0.002063	0.040300
Probability	0.9708	0.3023	0.0527	0.2501	0.1867	0.9164	0.0401
	RGBP/USD	RJPY/USD	RBRENT	RWTI	RGOLD	ECBDFR	EFFR
Correlation	0.030753	-0.010250	0.026176	0.011278	0.026553	0.004081	-0.019162
Probability	0.1174	0.6018	0.1826	0.5659	0.1764	0.8354	0.3293
	RVIX	RVSTOXX	RCEPU	REEPU	RGEPU	RUSEPU	RIDEMV
Correlation	-0.000375	-0.036498	-0.003631	-0.063408	-0.068399	-0.068710	0.013434
Probability	0.9848	0.0631	0.8534	0.0012	0.0005	0.0005	0.4940

The next step of the analysis is to test the returns of bitcoin for the possible presence of ARCH effects. By running an AR(1) model we conduct a Heteroscedasticity, ARCH test including 1 lag on the residuals. The results, presented in Table 5.2, show that the probability value for Observations*R-squared statistics is 0, and therefore statistically significant at the 1% level. Moreover, the lagged value of the residuals is statistically significant at the 1% level, with a coefficient value of 0.26. Hence, the null hypothesis of no ARCH effects is rejected and we accept the alternative that there is presence of ARCH effects.

Table 5.2: Results of the ARCH test

F-statistic	200.5111	Prob. F(1,2644)	0.0000
Obs*R-squared	186.5179	Prob. Chi-Square(1)	0.0000

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001323	0.000109	12.10961	0.0000
RESID(-1)^2	0.264880	0.018706	14.16019	0.0000

We proceed to estimate the GARCH model and its specifications. The dependent variable of the mean equation is the BTC and for simplicity, we consider a mean equation assuming no ARMA coefficients. That means that the mean equation includes only a constant. For the variance equation, we include one lag for each term, resulting in a GARCH(1,1) model. The results are shown in Table 5.3.

Table 5.3: Results of the GARCH(1,1) model

Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
Mean Equation				
C	0.001283	0.000624	2.056694	0.0397
Variance Equation				
GARCH = C(2) + C(3)RESID(-1)^2 + C(4)GARCH(-1)				
C	7.51E-05	5.31E-06	14.13279	0.0000
RESID(-1)^2	0.183420	0.012463	14.71686	0.0000
GARCH(-1)	0.787793	0.012029	65.48892	0.0000

The constant parameter of the mean equation is positive and statistically significant at the 5% level. The constant represents the average bitcoin return which in our case is 0.001283. All coefficients of the conditional variance equation are positive and statistically significant at the 1% level. Moreover, the ARCH (RESID(-1)^2) and GARCH parameter's sum is lower than 1. Therefore, all coefficients meet the stability conditions of the conditional variance specification. The fact that both ARCH and GARCH coefficients are statistically significant implies that the conditional variance of the squared errors of the bitcoin returns includes a constant (7.51E-05), a component which depends on past squared errors (ARCH effect = 0.183420), and its past value (GARCH effect = 0.787793). Hence, the current period's volatility of bitcoin is influenced by the previous period's information of bitcoin return as well as by the previous period's volatility of bitcoin.

We already mentioned the significance of the sum of the ARCH and GARCH coefficients in GARCH analysis. As one can understand by the results of Table 5.3, the sum of these two components is large and approximately 1 (0.971213). This fact indicates a large persistence of volatility shocks, while it denotes that the effect of today's shock remains in the forecast of variance for a long time in the future. Moreover, GARCH has a larger coefficient than ARCH (0.787793 > 0.183420) revealing a superior effect of past volatility relative to one of past shock.

5.2 LASSO Regression results

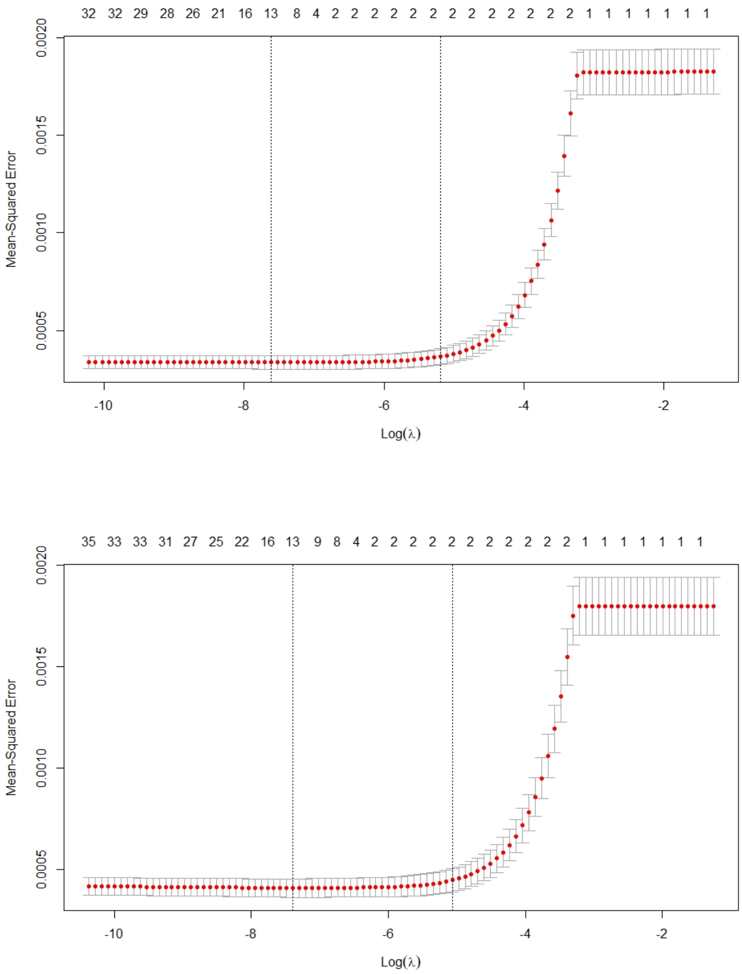

Figure 5.1: Plot of cross-validation curve (Full sample and 1st Period)

Figure 5.1 shows the cross-validation curve, alongside the upper and lower standard deviation curves, as well as the lambda values used. The two lambda's highlighted (vertical dotted lines) are the optimal (λ), that is the lambda that minimizes the mean cross-validated error of the model, and the lambda that gives the most regularized model such that the error is within one standard error of the minimum. The top axis reveals the number of non-zero coefficients for each value of lambda. For example, the 1st plot of Figure 5.1, that represents the cross-validation curve of the full sample, indicates that for optimal lambda 13 explanatory variables are non-zero, a result that is verified by Table 5.4.

Table 5.4: Results of the LASSO regression for the total sample and the 3 sub-periods

Rank	Variable	Full Sample	1st Period	2nd Period	3rd Period[6]
	lambda min.	0.00049	0.00061	0.00061	0.00061
1	RUSEPU	-0.04231	-0.09896	-	-
2	RGBP/USD	-0.03493	-	-0.06057	-0.01429
3	RDIF	0.01782	0.01865	-	-
4	RDJI	-0.01639	-	-0.03144	-
5	REEPU	-0.01196	-	-0.03381	-
6	RWTI	-0.01006	-0.00719	-	-0.01630
7	RJPY/USD	-0.00921	-	-	-0.63103
8	RTWITTER+	0.00464	0.00846	-	-
9	ECBDFR	0.00210	0.00500	-	-
10	RGOOGLE-	-0.00089	-	-0.00995	0.00942
11	RVIX	0.00077	0.00807	-	-
12	LTBC	0.00014	0.00018	0.00009	0.00010
13	RADRS	-	0.00288	-	-0.00081
14	RVLM	-	-	0.00326	-
15	RHASH	-	-	-	-
16	RGOOGLE+	-	-	-	-
17	RREDDIT-	-	-	-	-
18	RREDDIT+	-	-	-	-
19	RTWITTER-	-	0.00161	-	-
20	RWIKI-	-	-	-	-
21	RWIKI+	-	-	-	-
22	RFTSE	-	-	-	-
23	RNASDAQ	-	-	-	-
24	RNIKKEI	-	-	0.06285	-
25	RSSEI	-	-	-	-
26	RSP500	-	-	-	-0.03864
27	RCNY/USD	-	-	-0.10763	-
28	REUR/USD	-	-	-	-
29	RBRENT	-	-	-	-
30	RGOLD	-	0.03408	-0.01060	-
31	EFFR	-	-	-	-
32	RVSTOXX	-	-	-	0.00299
33	RCEPU	-	-	-	-
34	RGEPU	-	-0.00713	-	-
35	RIDEMV	-	-0.00011	-	0.00000
36	GARCH	0.03795	0.03870	0.03830	0.03099

[6]ECBDFR is constant during the entire 3rd period so we decided to not included it in the model.

Table 5.4 presents the results of the LASSO regression for the total sample and the 3 sub-periods independently. We obtain the results using the 'glmnet' package of the statistical software environment R. Through cross-validation the program selects the optimal lambda and then for this specific optimal lambda it provides the coefficients of the independent variables. The optimal lambda can be seen in the first row of Table 5.4. For the full sample $\lambda = 0.00049$ and for the first period $\lambda = 0.00061$. For the last two sub-periods, and for the sake of comparison through time, we use the same optimal lambda that minimizes the cross-validated error in the first period.

The coefficients' rank is determined by the magnitude of the absolute value of the coefficients of the total sample. GARCH variable represents the GARCH filter of the model and is placed at the bottom of the table. It measures the importance of conditional variance on bitcoin returns. The US Policy Uncertainty index (USEPU) and GBP/USD seem to have the largest negative effects for the full sample. Contrariwise, GARCH and network difficulty (DIF) appear to have the largest positive effects. In total 7 variables are found to have negative effects, 6 variables have positive effects, and 23 variables have a coefficient equal to zero.

Observing each sub-period on its own can help us extract some useful information about how the relationship of explanatory variables with bitcoin returns changes through time. The 1st period is the largest in duration and we expect to affect the full sample to a great extent. For the 1st period US Policy Uncertainty index (USEPU) remains the variable with the largest negative impact even though its coefficient equals zero in the next two sub-periods. Apart from GARCH and network difficulty which have positive and large effects on 1st period, gold appears to also impact positively bitcoin returns. In the 2nd period CNY/USD and GBP/USD have the largest negative effects while the Nikkei 225 index and GARCH have the largest positive effects. Interestingly enough, gold in the 2nd period is associated with negative effects on bitcoin returns. The last period consists of a small amount of the data and was included in an effort to capture the behaviour of bitcoin during the COVID-19 pandemic. JPY/USD is by a great margin the variable that presents the largest negative effects while GARCH presents once again large positive effects.

The results can also be supported by Figures 5.2, 5.3, 5.4, and 5.5. These plots graphically represent the coefficient paths against log lambda and L1 norm for different values of lambda. Axis Y presents the magnitude of the coefficients, while axis X presents either the values of lambda or the values of the L1 norm. The axis above shows the degrees of freedom for the LASSO, that is the number of variables with non-zero coefficients at each lambda value. At the vertical dotted lines we showcase the optimal lambda value that minimizes the mean cross-validated error term of the model. The coefficients at this point are shown at Table 5.4. Lastly, at the right of the plots, the names of the variables with the 15 highest final coefficient values are displayed. Generally, the two plots of each figure reveal the same information but in a different scale.

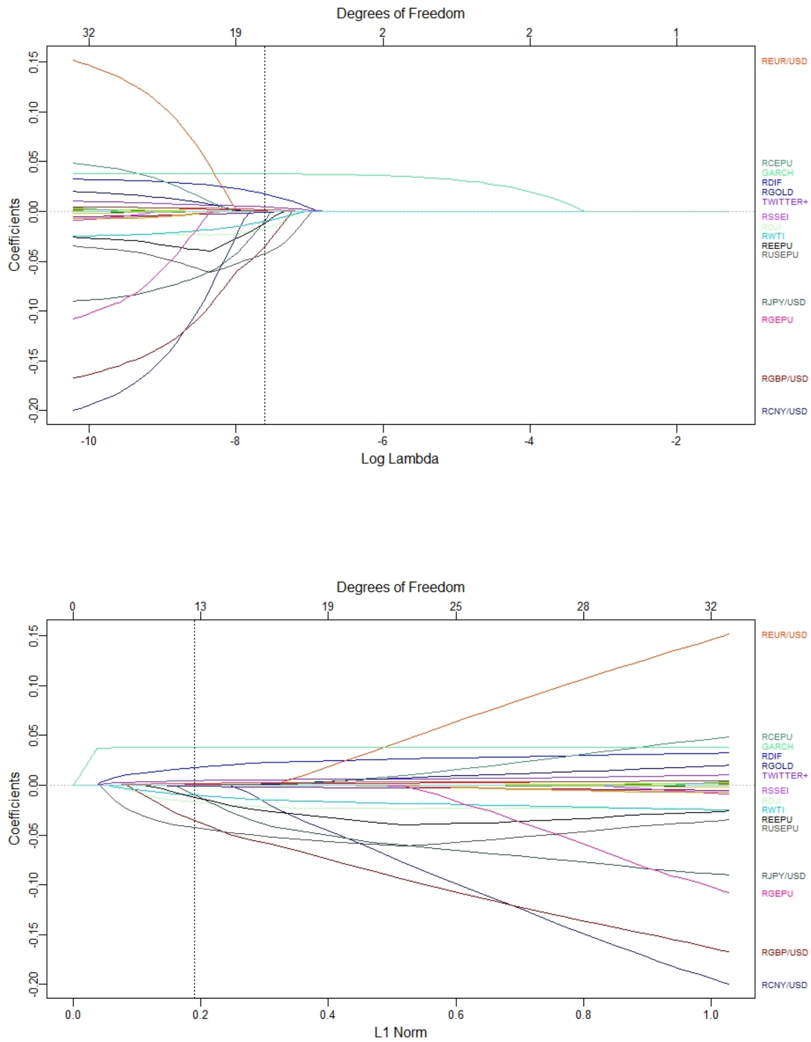

Figure 5.2: Trace plot of coefficients against lambda and L1 norm (Full sample)

Figure 5.2 presents the coefficients of LASSO regression for the full sample. The covariate that first enters the model is GARCH, followed by network difficulty (DIF) and the US Policy Uncertainty index (USEPU). These variables enter early in the model, hence they are important for small models. However, after other variables enter the model they are not so important anymore as they seem to have relatively constant and low coefficients. In some cases the trend of the coefficients even reverses (see USEPU). On the contrary, some covariates enter late the model but have immediately high effects. Interestingly enough, in our model these covariates are almost exclusively associated with the exchange rates with the exception of the Global Economic Policy Uncertainty index (GEPU). Concerning the model at optimal lambda, GARCH and DIF have the most significant positive coefficients while USEPU and GBP/USD the most significant negative coefficients.

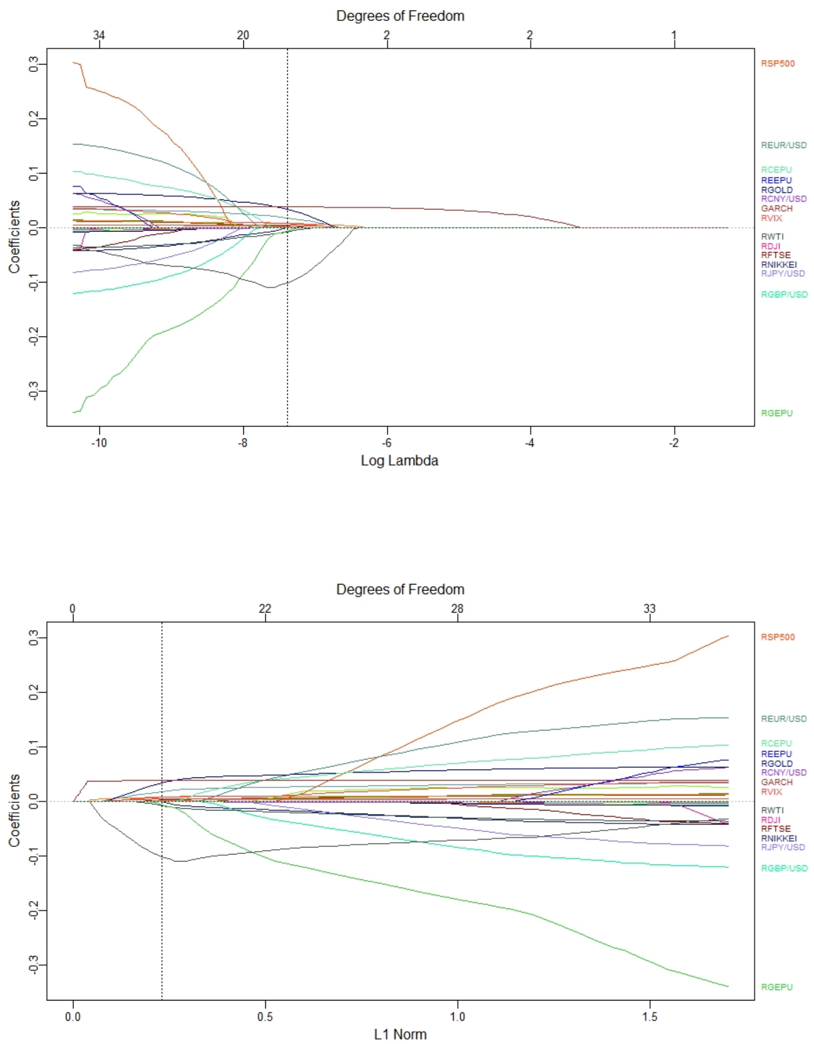

Figure 5.3: Trace plot of coefficients against lambda and L1 norm (1st Period)

Figure 5.3 plots the coefficients of LASSO regression for the 1st sub-period of the sample. The first variable that diverges from 0 is GARCH, followed by USEPU. These variables are suitable for small models as they enter early in the model. Once again, the trend of the coefficients of USEPU reverses when more variables enter the model. S&P500, GEPU, EUR/USD and GBP/USD enter late the model but have important effects for large models. At optimal lambda, GARCH and GOLD have the most significant positive effects while USEPU has the largest negative coefficient.

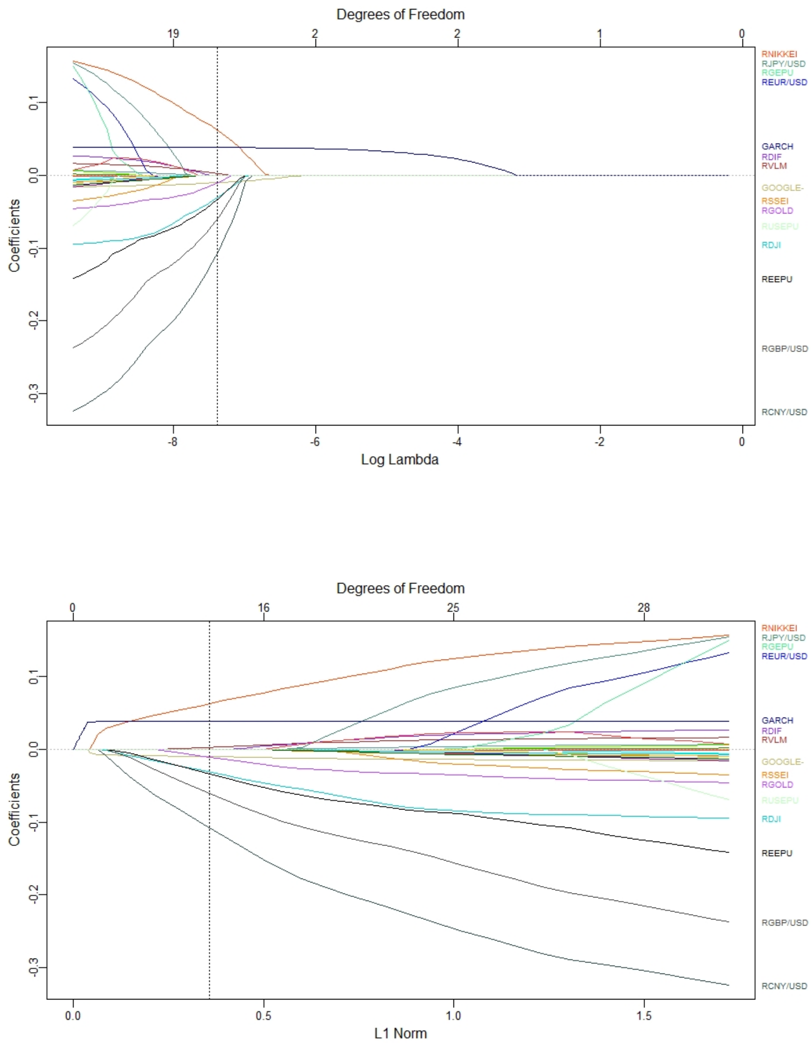

Figure 5.4: Trace plot of coefficients against lambda and L1 norm (2nd Period)

For the 2nd period, the coefficients of LASSO regression are depicted in Figure 5.4. Again the first covariate to enter the model is GARCH, this time followed by GOOGLE- and NIKKEI. The last variable, unlike the two first, has a steady ascent to its final value. All of the exchange rate variables, alongside GEPU and EEPU, are late to diverge from 0 but once they do they proceed to reach high coefficient values. CNY/USD, GBP/USD, and EEPU have significant negative effects at the lambda that minimizes the mean cross-validated error. Similarly, NIKKEI and GARCH present the most significant positive coefficients.

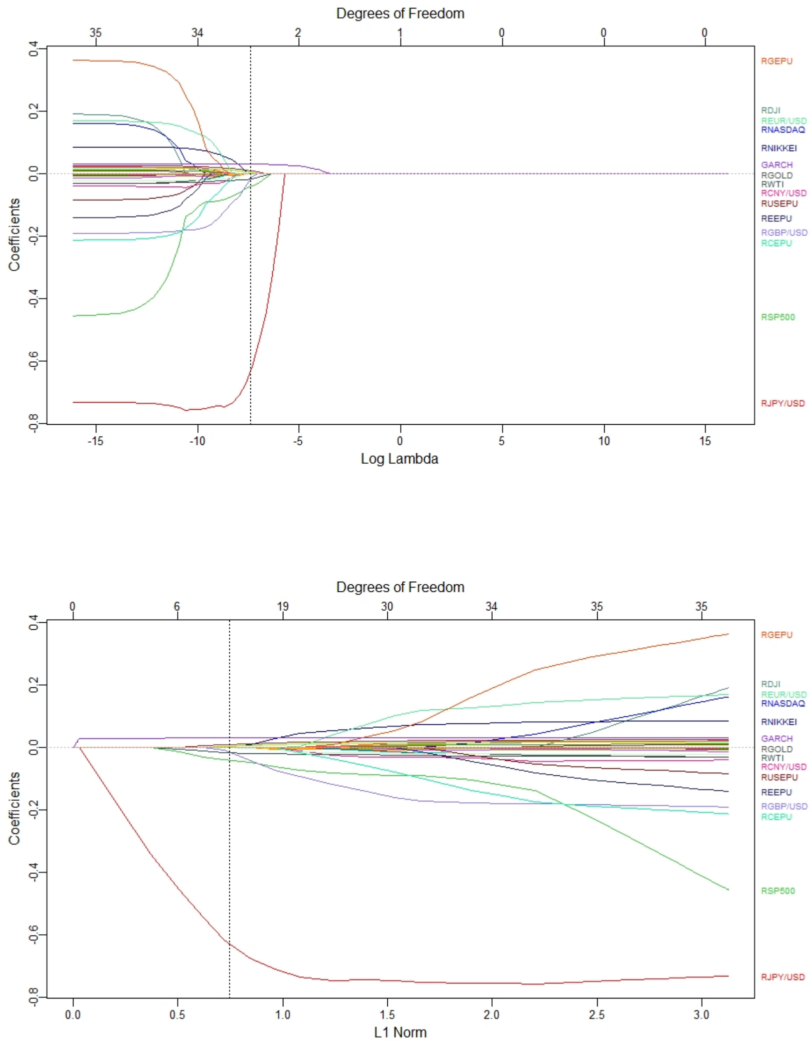

Figure 5.5: Trace plot of coefficients against lambda and L1 norm (3rd Period)

Figure 5.5 presents the LASSO results for the last period. The three covariates that first enter the model are GARCH, JPY/USD, and S&P500 in that order. GEPU and S&P500 seem to enter late the model but end up with high coefficients when the number of variables included increases. At optimal lambda, JPY/USD has by far the most significant negative effect on bitcoin returns. GARCH is the only variable with a significantly positive coefficient.

6 Discussion

In this part of the thesis, we interpret the results of the model and discuss the similarities and differences that exist with the evidence already provided by the existing literature. We proceed to a most detailed comparison of our results with the results of the Panagiotidis et al. (2018) paper, as it is the one our research resembles the most, technical-wise. Even in this case, nevertheless, the conclusions that are drawn from the comparison should be treated with caution.

In our models, the most consistent and important variables are found to be policy uncertainty (especially USEPU), exchange rates (especially GBP/USD), and GARCH. All exchange rates have negative effects on bitcoin returns as do all uncertainty indices. Adversely, volatility indices and interest rates (that of the European Central Bank) seem to have positive effects. Concerning the technical factors, network difficulty is found to have positive effects mainly on the 1st period, while coefficient of hash rate is zero. The variable that works as a measure of supply (TBC) indicates a positive relationship between supply and bitcoin returns that holds in time. Conclusions about demand indicators cannot be drawn as the results are mixed and unclear. Similar is the picture of stock markets. The Dow Jones NYSE index and S&P500 index provide evidence of negative effects, and the Nikkei 225 index positively affects bitcoin returns. Unclear are also the results of the variables that capture the search intensity. Even though the signs are the expected for the variables that were not set to zero for the full sample, some deviations of the expected exist in some sub-periods. To be more specific, GOOGLE- has a positive sign in the 3rd period as does TWITTER- in the 1st period. Oil effects are found to be positive while gold provides mixed signs. Lastly, the variable that operates as the GARCH filter is constantly positive, independently of the period and the sample.

To a large extent, the results of the full sample regression agree with the findings of past research. Existing literature has provided proof of negative relationships between several exchange rates [Wijk (2013), Dyhrberg (2016a)], as well as between Economic Policy Uncertainty indices [Demir et al. (2018)], with bitcoin returns. Moreover, a number of papers [MacDonell (2014), Erzurumlu et al. (2020), Panagiotidis et al. (2019)] come to similar conclusions regarding the significance of the CBOE Market Volatility Index. Alike

Kristoufek (2014) results, network difficulty is found to have positive long-run effects that vanish over time. As far as market indices are concerned, an expected effect has not been yet established, as several papers, as well as ours, produce mixed signs depending on the period and the specific stock index selected. As for the investment attractiveness, the results of this thesis confirm what a crowd of researchers has already proven, that it is an important indicator of bitcoin returns. The last variable that agrees with the established literature is the oil which provides evidence of negative effects on bitcoin returns [Wijk (2013), Wang et al. (2016)]. Unlike the previous cases, part of the model's results does not agree with any existing literature. For example, the positive effects of the total number of bitcoins in circulation to bitcoin returns oppose what one would expect based on the economic quantity theory [Ciaian et al. (2016b)].

Of all the papers with the objective of finding out the determinants of bitcoin returns, Panagiotidis et al. (2018) is the one that resembles this thesis the most. We believe that it would be interesting to explore the differences in the results of the two papers, in an effort to grasp the behavior of bitcoin returns through time. Panagiotidis et al. (2018) in their analysis use a LASSO framework. Two different R packages estimate their models, 'glmnet' and 'lars', however, we will only compare the results of the 'glmnet' package as it is the one we also use in the analysis. It is necessary to underline that the models used are not identical and, therefore, interpretations of the results should be taken with caution. Panagiotidis et al. (2018) study the effects of 21 independent variables using daily data for the period June 17th, 2010 to June 23rd, 2017. Our analysis adds 15 more variables and spans from October 1st, 2013 to December 31st, 2020. Moreover, differences in the sources selected to obtain the data and different methods adopted during the transformation of the data may have led to small discrepancies between the data of the common variables used in the two papers. Nevertheless, we believe that a comparison between the results is achievable.

Table 6.1 presents the coefficients of each independent variable used in the two papers. We rank the results by the size of the absolute value of the coefficients found in the Panagiotidis et al. model. The 21 first variables of the table are the ones included in the model of Panagiotidis et al.. Our thesis uses all the variables except the ones in italics (S&P350 and USD/EUR). The coefficients that were found to be non-zero in both papers and were not dropped by any of the LASSO models are marked with an asterisk (*).

Table 6.1: Panagiotidis et al. and Kirmizis results

Rank	Variable	Panagiotidis et al.	Kirmizis
1	RGOOGLE+	0.127	-
2	RGOLD	0.072	-
3	RGOOGLE-*	-0.069	-0.00089
4	RCEPU	-0.060	-
5	ECBDFR*	0.033	0.00210
6	RDJI*	0.030	-0.01639
7	RVIX*	-0.025	0.00077
8	REEPU*	-0.024	-0.01196
9	RWIKI-	-0.023	-
10	EFFR	0.019	-
11	RJPY/USD*	0.019	-0.00921
12	RUSEPU*	-0.017	-0.04231
13	RCNY/USD	0.017	-
14	RBRENT	0.015	-
15	RSSEI	0.013	-
16	*RSP350*	-0.011	-
17	*RUSD/EUR*	0.009	-
18	RNIKKEI	-0.006	-
19	RWIKI+	0.002	-
20	RGBP/USD	-	-0.03493
21	RNASDAQ	-	-
22	RDIF	-	0.01782
23	RWTI	-	-0.01006
24	RTWITTER+	-	0.00464
25	LTBC	-	0.00014
26	RADRS	-	-
27	RVLM	-	-
28	RHASH	-	-
29	RREDDIT-	-	-
30	RREDDIT+	-	-
31	RTWITTER-	-	-
32	RFTSE	-	-
33	RSP500	-	-
34	REUR/USD	-	-
35	RVSTOXX	-	-
36	RGEPU	-	-
37	RIDEMV	-	-
38	GARCH	-	0.03795
	Period	2010-2017	2013-2020

Comparing the results, we observe that in the Panagiotidis et al. model 19 of the 21 independent variables have non-zero coefficients, while in our model the non-zero coefficients are only 13 out of 36. Of all the common variables, only 7 have non-zero coefficients for both models: GOOGLE−, ECBDFR, DJI, VIX, EEPU, JPY/USD and USEPU. GOOGLE− drops form -0.069 to -0.00089, meaning that Google search volume associated with negative events of bitcoin impacts bitcoin returns less on the period 2013-

2020 than it did on the period 2010-2017. Europe and US Economic Policy Uncertainty indices remain negative in both models. EEPU affects bitcoin returns less in our model, while the USEPU effect is higher than it is in Panagiotidis et al. model. The persistent negative coefficients of this kind of indices reveal the importance of policy-related economic uncertainty to bitcoin prices. Contrariwise, the ECB deposit facility rate has a positive relation to the bitcoin returns in both periods. The rest of the non-zero coefficients seem to have opposite effects on bitcoin returns. To be specific, DJI and JPY/USD have positive coefficients while VIX has a negative coefficient on Panagiotidis et al. LASSO model. This thesis reveals negative coefficients for DJI and JPY/USD and a positive coefficient for VIX. All told, bitcoin returns seem to be affected by fewer variables in the most recent period. Moreover, most of the variables that are found to indeed impact bitcoin returns have a smaller effect in the period 2013-2020 than they had in the period 2010-2017. Out of all variables, GOOGLE$-$, ECBDFR and Economic Policy Uncertainty indices are proven to be the most persistent drivers of bitcoin returns.

7 Conclusion

This thesis examines the relationship between bitcoin returns and 36 potential explanatory variables for the period 2013-2020 (2639 observations). After briefly presenting some essential information about bitcoin and its uses, we extensively review the literature. We are primarily interested in how technical factors, market forces of bitcoin's supply and demand, investors' attractiveness to bitcoin, and global macroeconomic and financial indicators affect bitcoin returns. In the empirical application part, we use a GARCH filter to incorporate the effects of volatility clustering in our models. Then we employ a LASSO framework that allows our models to apply both variable selection and regularization. We decided to consider not only the full sample but also 3 sub-periods of it separately.

By studying the existing empirical literature we try to discover which are the factors that have been proven to potentially explain the movements of bitcoin price. Generally speaking, some factors tend to have greater effects on bitcoin returns than some other factors, even though most relationships provide mixed results. Technical factors seem to have a positive relationship with bitcoin returns. Further, variables that proxy bitcoin's demand regularly have positive effects on bitcoin, unlike variables that measure bitcoin's supply which have negative effects. Besides, investors' sentiment factors tend to influence bitcoin price with the expected sign. That means that positive news about the bitcoin tends to increase bitcoin returns, while negative news usually leads to bitcoin returns reductions. As for the financial indicators, the results are mixed. However, even the most extensively proven determinants of bitcoin returns cannot be unequivocally accepted. We can conclude that results can vary due to differences in periods and horizons examined, as well as variations of models used.

In the analysis, a GARCH(1,1) model is considered to determine the existence and the magnitude of volatility clustering. Indeed, evidence is provided indicating a large persistence of volatility shocks, meaning that the effect of today's shock remains in the forecast of variance for a long in the future. Moreover, a superior effect of past volatility relative to one of past shock is revealed. After these results, a GARCH filter is used in the regression in order to correct the standard errors.

The most consistent and important variables in the analysis are found to be policy uncertainty, exchange rates, and GARCH. All exchange rates have negative effects on bitcoin returns as do all uncertainty indices. Adversely, volatility indices and interest rates seem to have positive effects. Concerning the technical factors, network difficulty is found to have positive effects mainly on the 1st sub-period. Bitcoin's supply indicator has a positive effect on bitcoin returns that holds in time, opposite to what one would expect based on the economic quantity theory. The results of stock markets are mixed. The Dow Jones NYSE and S&P500 indices provide evidence of negative effects, and the Nikkei 225 index positively affects bitcoin returns. Unclear are also the results of the variables that capture the search intensity. Even though the signs are the expected for most of the variables, some deviations of the expected exist in some sub-periods. To be more specific, GOOGLE- positively affects bitcoin in the 3rd period as does TWITTER- in the 1st period. Oil effects are found to be positive while gold provides mixed signs. Lastly, the variable that operates as the GARCH filter is constantly positive, independently of the period and the sample.

On average the results of the analysis are compatible with findings of past research. The empirical results confirm that bitcoin's price formation is difficult to forecast and determinants differ based on the period and the conditions examined. It is important to underline the necessity of future investigation on the topic so as to enrich the literature and to fill in any inconsistencies.

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Appendix

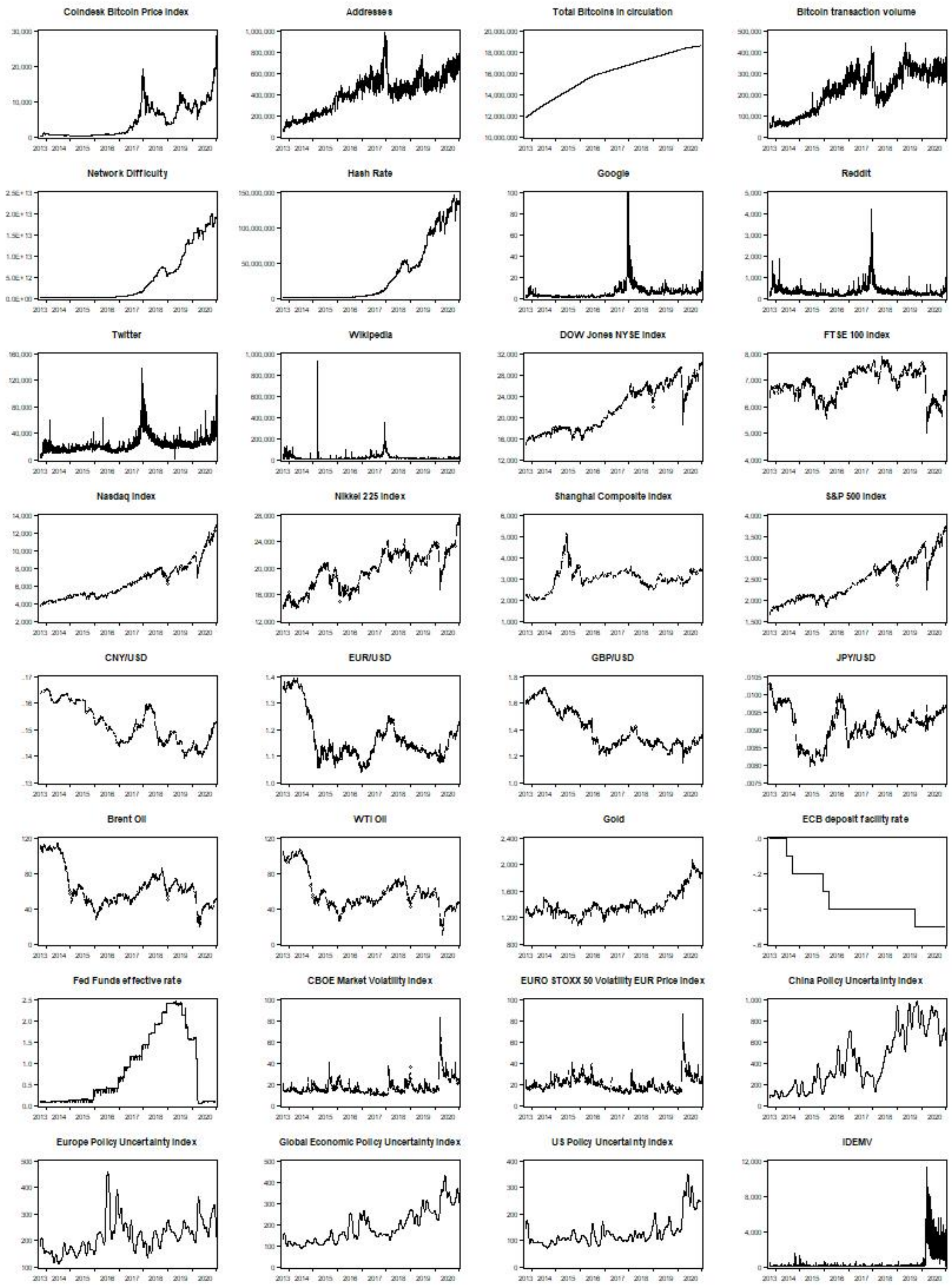

Figure A.1: Plot of all the series used

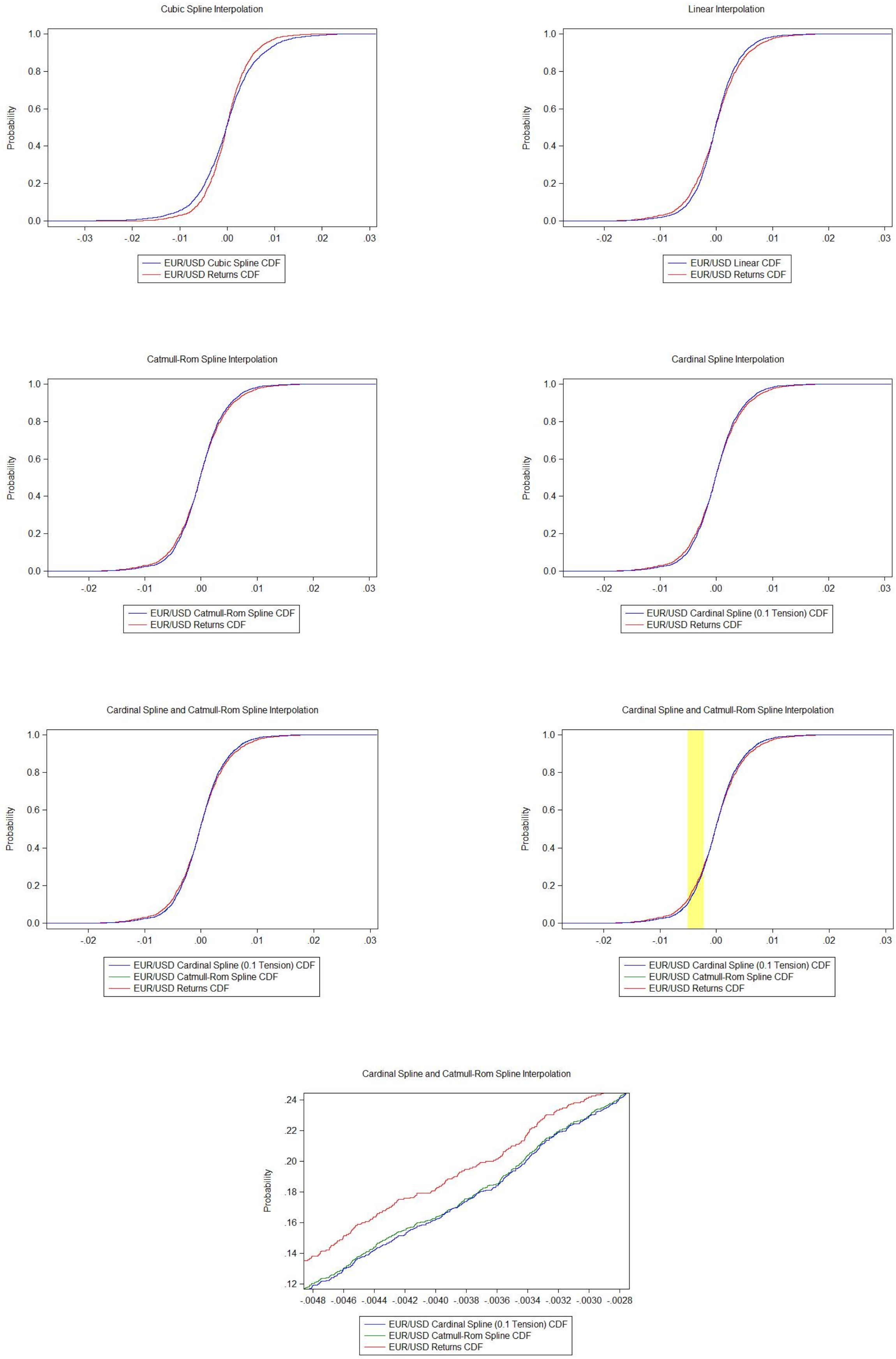

Figure A.2: EUR/USD Empirical CDFs Comparison

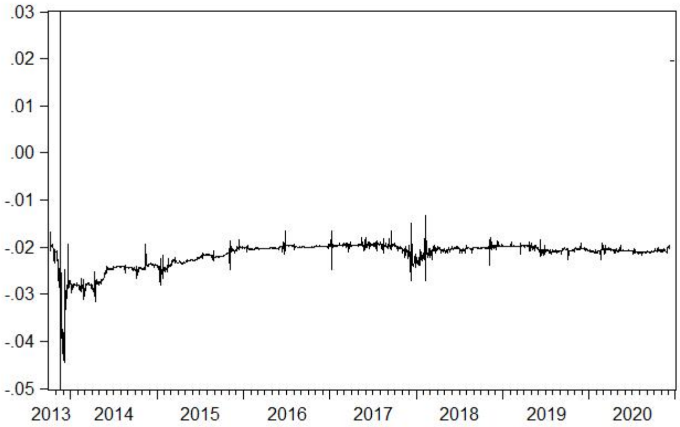

Figure A.3: ADF breakpoint unit root test coefficients

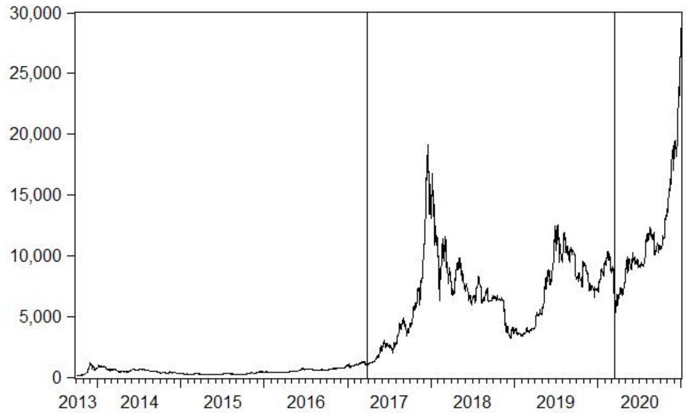

Figure A.4: Coindesk bitcoin price index sub-periods

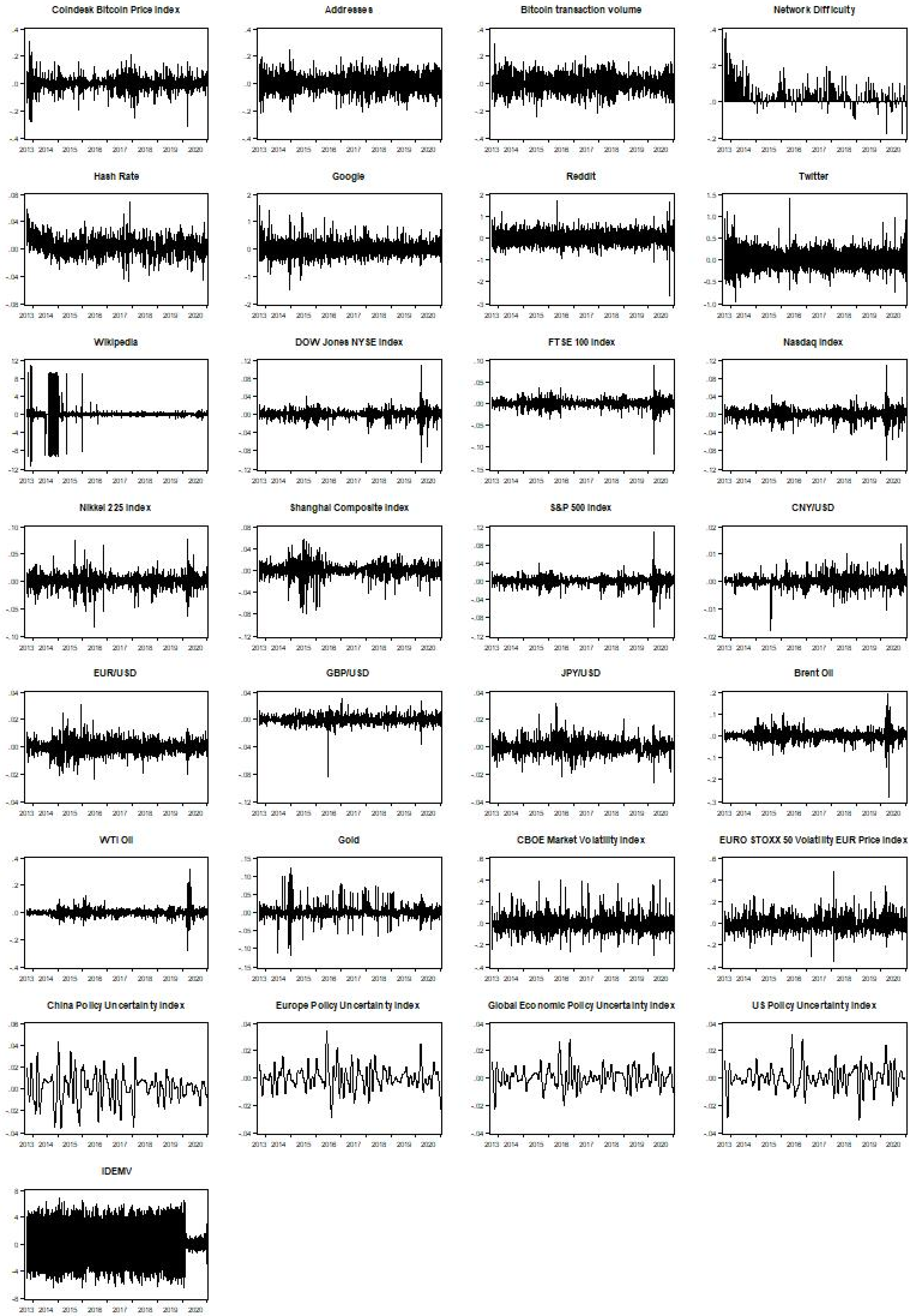

Figure A.5: Plot of the series growth rates

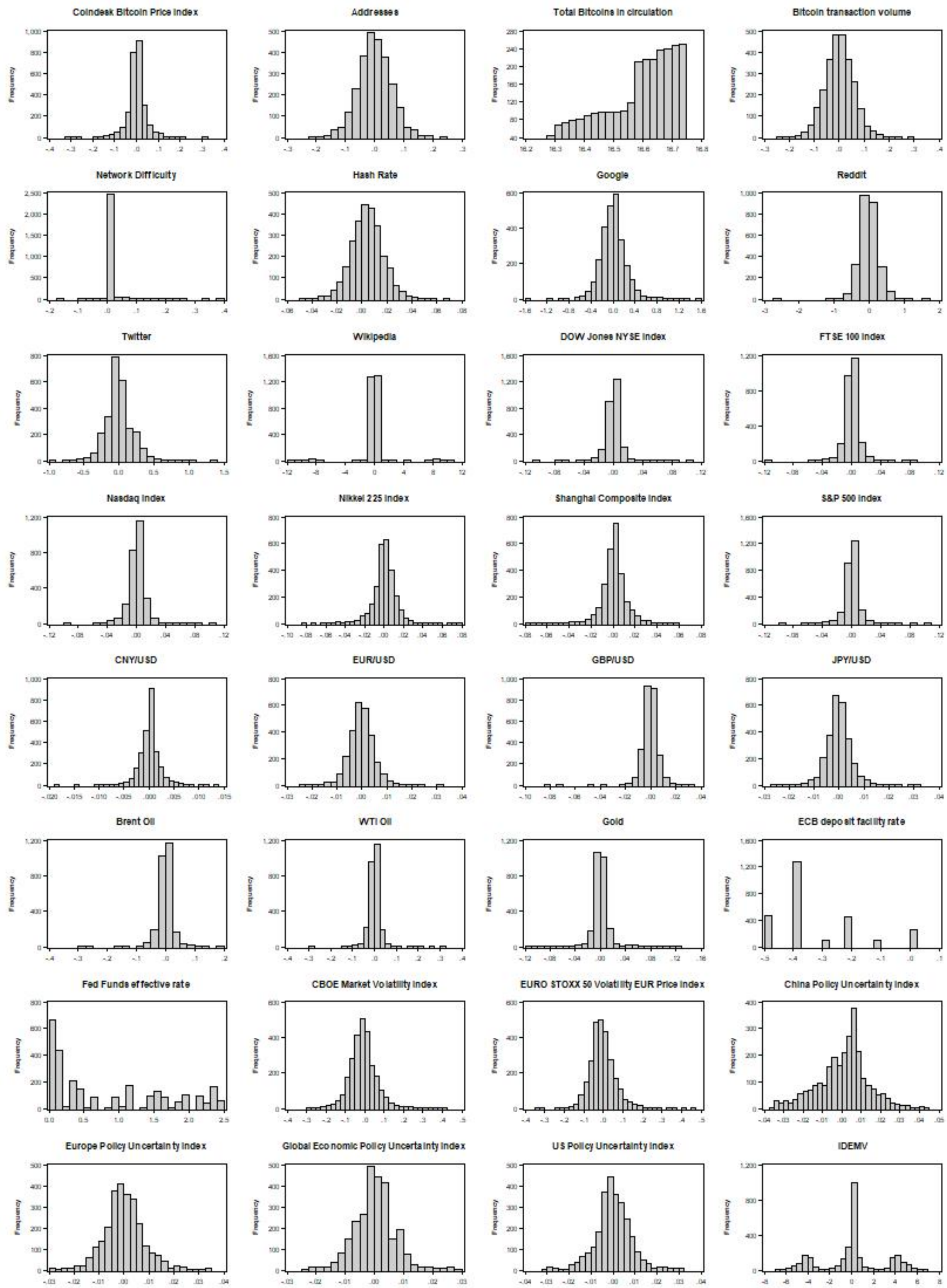

Figure A.6: Plot of the series histograms

Table A.1: Variables employed in dataset: October 1st 2013-December 31st 2020

Variable name	Source
Coindesk Bitcoin Price Index [BTC]	coindesk.com
Hash Rate [HASH]	blockchain.com
Network Difficulty [DIF]	blockchain.com
Total number of bitcoins in circulation [TBC]	blockchain.com
Confirmed transactions per day [VLM]	blockchain.com
Unique adressess used [ADRS]	blockchain.com
Google Search Volume [GOOGLE+ and GOOGLE-]	trends.google.com
Wikipedia daily views [WIKI+ and WIKI-]	R package 'wikipediatrend'
Daily posts on /r/bitcoin [REDDIT+ and REDDIT-]	github.com
Daily posts on Twitter [TWITTER+ and TWITTER-]	Python package 'snscrape'
Global Economic Policy Uncertainty index [GEPU]	policyuncertainty.com
US Policy Uncertainty index [USEPU]	policyuncertainty.com
China Policy Uncertainty index [CEPU]	policyuncertainty.com
Europe Policy Uncertainty index [EEPU]	policyuncertainty.com
Infectious Disease Volatility Tracker [IDEMV]	policyuncertainty.com
Nikkei225 index [NIKKEI]	Investing.com
S&P500 index [SP500]	Thomson Reuters Eikon
DOW Jones Industrial average index [DJI]	Thomson Reuters Eikon
Nasdaq Composite index [NASDAQ]	Thomson Reuters Eikon
FTSE100 index [FTSE]	Thomson Reuters Eikon
Shanghai SE Composite Index [SSEI]	Thomson Reuters Eikon
CBOE Market Volatility Index [VIX]	Thomson Reuters Eikon
EURO STOXX 50 Volatility EUR Price Index [VSTOXX]	Thomson Reuters Eikon
Euro/US Dollar FX Spot Rate [EUR/USD]	Thomson Reuters Eikon
UK Pound Sterling/US Dollar FX Spot Rate [GBP/USD]	Thomson Reuters Eikon
Chinese Yuan/US Dollar FX Spot Rate [CNY/USD]	Thomson Reuters Eikon
Japanese Yen/US Dollar FX Spot Rate [JPY/USD]	Thomson Reuters Eikon
Brent oil price in USD (1 barrel) [BRENT]	Thomson Reuters Eikon
West Texas Intermediate oil price (1 barrel) [WTI]	Thomson Reuters Eikon
Gold price in USD (1 Troy Ounce) [GOLD]	Investing.com
Fed Funds effective rate [EFFR]	newyorkfed.org
ECB deposit facility rate [ECBDFR]	ecb.europa.eu

Table A.2: ADF Unit Root Test results summary

Null Hypothesis: Variable has a unit root

		Test critical values	
Variable	t-Statistic	5% level	1% level
RBTC	-52.25052	-3.411505	-3.961510
RADRS	-10.77872	-3.411523	-3.961547
LTBC	-3.124928	-2.862444	-3.432654
RVLM	-10.05144	-3.411524	-3.961549
RDIF	-9.849304	-3.411512	-3.961525
RHASH	-9.144365	-3.411520	-3.961541
RGOOGLE	-29.66229	-3.411508	-3.961517
RREDDIT	-12.01606	-3.411523	-3.961546
RTWITTER	-12.02614	-3.411523	-3.961546
RWIKI	-13.50088	-3.411523	-3.961546
RDJI	-14.29106	-3.411513	-3.961527
RFTSE	-26.67802	-3.411506	-3.961513
RNASDAQ	-15.99424	-3.411512	-3.961525
RNIKKEI	-28.82465	-3.411506	-3.961512
RSSEI	-24.70124	-3.411506	-3.961513
RSP500	-14.47233	-3.411513	-3.961527
RCNY/USD	-31.79016	-3.411505	-3.961510
REUR/USD	-31.12595	-3.411505	-3.961510
RGBP/USD	-24.25223	-3.411506	-3.961513
RJPY/USD	-16.01040	-3.411510	-3.961519
RBRENT	-30.01084	-3.411505	-3.961510
RWTI	-29.68465	-3.411505	-3.961510
RGOLD	-35.38115	-3.411505	-3.961510
RVIX	-26.54091	-3.411506	-3.961513
RVSTOXX	-30.53321	-3.411506	-3.961512
RCEPU	-8.749575	-3.411514	-3.961529
REEPU	-7.153369	-3.411514	-3.961529
RGEPU	-7.764182	-3.411514	-3.961529
RUSEPU	-8.619619	-3.411514	-3.961529
RIDEMV	-25.22065	-3.411511	-3.961523

Table A.3: Descriptive Statistics of returns

	RBTC	RADRS	LTBC	RVLM	RDIF	RHASH	RGOOGLE	RREDDIT
Mean	0.002181	0.000930	16.57779	0.000641	0.004432	0.004367	0.001447	0.000576
Median	0.001713	0.000293	16.60894	0.000713	0.000000	0.004228	-0.010207	-0.005980
Maximum	0.306376	0.243369	16.73792	0.286133	0.378542	0.068640	1.562185	1.716444
Minimum	-0.315945	-0.216828	16.28227	-0.242427	-0.174948	-0.047889	-1.514128	-2.629488
Std. Dev.	0.042538	0.056611	0.126348	0.056579	0.026527	0.012969	0.227233	0.260346
Skewness	-0.411919	0.021973	-0.663333	0.009559	6.141516	0.103030	0.547439	0.008819
Kurtosis	10.40535	3.633694	2.314534	3.640634	59.66401	4.118215	7.481696	8.830416
Jarque-Bera	6125.482	44.45223	245.9400	45.28817	370905.7	142.5384	2348.374	3750.678
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	5.773969	2.458306	43881.41	1.697255	11.73592	11.55556	3.831980	1.524243
Sum Sq. Dev.	4.789796	8.470309	42.24023	8.467071	1.862681	0.444845	136.6768	179.4141
Observations	2648	2644	2647	2646	2648	2646	2648	2648

	RTWITTER	RWIKI	RDJI	RFTSE	RNASDAQ	RNIKKEI	RSSEI	RSP500
Mean	0.001080	0.000359	0.000566	0.000424	0.000759	0.000331	0.000589	0.000641
Median	-0.011859	0.000000	0.000957	0.000664	0.001204	0.000666	0.001116	0.000950
Maximum	1.399606	10.74845	0.107643	0.086668	0.107935	0.077314	0.056036	0.107150
Minimum	-0.968317	-11.46165	-0.105232	-0.115124	-0.099099	-0.082529	-0.079375	-0.099945
Std. Dev.	0.184814	1.474349	0.010516	0.009448	0.011494	0.011935	0.012187	0.010229
Skewness	0.570590	-0.022033	0.785078	-0.396074	0.431602	-0.361869	-1.136166	0.861646
Kurtosis	6.618973	35.80483	25.43636	17.60578	15.64329	8.765514	10.25609	23.94407
Jarque-Bera	1588.718	118736.2	55812.75	23606.51	17719.31	3723.993	6378.844	48725.80
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	2.861089	0.950918	1.498252	1.123935	2.010711	0.877477	1.560734	1.698519
Sum Sq. Dev.	90.41153	5753.795	0.292717	0.236298	0.349673	0.376913	0.393119	0.276945
Observations	2648	2648	2648	2648	2648	2647	2648	2648

	RCNY/USD	REUR/USD	RGBP/USD	RJPY/USD	RBRENT	RWTI	RGOLD	ECBDFR
Mean	6.24E-05	-0.000189	-0.000211	-0.000117	4.64E-05	0.001115	0.000771	-0.331219
Median	0.000000	-0.000222	-0.000252	-0.000237	0.000800	0.001321	0.000000	-0.400000
Maximum	0.013486	0.030352	0.030261	0.031397	0.190774	0.319634	0.120709	0.000000
Minimum	-0.018177	-0.024001	-0.084095	-0.026686	-0.279761	-0.279920	-0.117970	-0.500000
Std. Dev.	0.002040	0.004814	0.006050	0.004801	0.023386	0.027569	0.014812	0.150563
Skewness	-0.190810	-0.019688	-1.757344	0.232411	-0.776137	1.415182	1.098605	0.959209
Kurtosis	10.15494	5.332986	27.27511	6.105024	21.34064	25.68836	20.63986	2.830998
Jarque-Bera	5664.380	600.6961	66380.30	1087.582	37379.67	57679.27	34864.48	409.3687
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	0.165208	-0.500782	-0.557673	-0.310622	0.122740	2.952973	2.041644	-877.4000
Sum Sq. Dev.	0.011020	0.061343	0.096899	0.061018	1.447620	2.011924	0.580763	60.02816
Observations	2648	2648	2648	2648	2648	2648	2648	2649

	EFFR	RVIX	RVSTOXX	RCEPU	REEPU	RGEPU	RUSEPU	RIDEMV
Mean	0.827902	-0.007617	-0.004551	0.000817	5.70E-05	0.000304	0.000202	0.000635
Median	0.400000	-0.010497	-0.009501	0.002675	-0.000324	0.000248	-2.14E-05	0.000000
Maximum	2.450000	0.401011	0.473629	0.042715	0.034425	0.027858	0.031395	6.766192
Minimum	0.040000	-0.295739	-0.345301	-0.035667	-0.028766	-0.022609	-0.031172	-6.514713
Std. Dev.	0.826333	0.070937	0.065149	0.012879	0.008075	0.006943	0.008225	2.712032
Skewness	0.699305	0.787057	0.882203	-0.249180	0.311895	0.320327	-0.020085	0.015312
Kurtosis	1.964173	6.961657	7.690587	3.523840	4.878749	4.761168	5.070749	2.785388
Jarque-Bera	334.3309	2005.039	2769.946	57.67898	432.3755	387.5071	473.2876	5.185213
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.074825
Sum	2193.113	-20.17089	-12.04586	2.163003	0.150812	0.804976	0.533605	1.680511
Sum Sq. Dev.	1808.123	13.32000	11.23072	0.439077	0.172619	0.127582	0.179087	19469.00
Observations	2649	2648	2647	2648	2648	2648	2648	2648