The Determinants of Bitcoin returns

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Abstract

We examined nineteen potential Bitcoin returns' factors, for a period 2013-2020 (400 weekly observations), that may drive or determine its future trajectory. In a framework of two distinct periods, and using a series of different methodologies, data indicate significance in a total of nine out of nineteen variables, with only Google trends being significant for the whole sample, and Economic Policy Uncertainty emerges to be the most significant factor for the most recent years.

1. Introduction

First introduced in 2008 by a person or a group of people which have the pseudonym of Satoshi Nakamoto, Bitcoin is the most popular cryptocurrency that ever existed. Cryptocurrencies are a group of electronic-traded cash system, designed to as a mean of exchanges and electronic payments, without the intervention of financial institutions. It may be named as a (crypto)currency, but in reality, Bitcoin is considered as a commodity. The most important advantage that Bitcoin has to offer, is the anonymity that it provides, to both counterparts, during all transactions. This feature can be a disadvantage as well, while many have noted, that anonymity can be used in transactions for illegal activities. One more interesting attribute of Bitcoin, is that, while it is being produced by e-mining (using a complex mathematical algorithm), its price is not relevant with the real economy. Many claim, that its price is determined solely by the laws of supply and demand and thus it has a unique behavior for any financial asset, while all other assets have a strong correlation with financial markets, which can arise investigation of its hedging potential. During the period of 2008-2010, Bitcoin was not that popular. However, the demand of Bitcoin became greater as the years passed by. This had as a result, the great rise of its price, fact that draw the attention of the academic and investment communities. Having in mind that all traditional commodities (e.g. crude oil, gold, silver etc.) exist and traded at least before 1965, and the fact that Bitcoin became very popular around 2013, it can be considered a relatively new commodity in the market. And as a new asset that it is, a significant question arises; Once someone decides to invest on Bitcoin, the question is which are the real market determinants of the returns of Bitcoin? An investor cannot rely on some simplistic answers of this question. This contribution of this paper is to add an extra approach to the ongoing attempt to identify the determinants of Bitcoin, a such popular and ambiguous asset . This paper is going to based on some methodologies that have been used in the past to identify the determinants of Bitcoin returns. Also, we are going to use one more methodology that has not been used in this field, and add some new approaches. The rest of the paper is going to be constructed as follows: *Section 2* will be a literature review, presenting the past work that has been done on the same issue, and analyzing the papers that this article is going to be based on, *Section 3* will be a brief presentation and analysis of all methodologies that are going to be used in order to extract our results and comments, *Section 4* will be a short reference to the data that we used to extract our results, and their sources, as well as the methodology that we are going to use, *Section 5* will be the presentation of our results, *Section 6* will be our concluding remarks, and finally *Section 7* will be our references.

1.2 Is Bitcoin a type of Money?

In reality, Bitcoin is not just a currency, it is a software, a complex algorithm which uses heavy CPU load to produce the cryptocurrency. But why Bitcoin is not considered as a currency? There is a simple answer to that: Bitcoin does not share the same characteristics as all other types of money that exists and getting traded worldwide. According to the economic theory, there are three basic functions of money:

1. *Unit of account*: You can think money as a ruler, measuring the length of objects. Money has the ability to give all products and services a price, in which they can be easily traded on the market
2. *Store of value*: Money must hold its value in time. Money has the ability to be stored and preserve its value so it can be exchanged in the future. This ability solves the problem of the coincidence of simultaneous needs, that previously existed. Without these two functions, money could not be accepted as a medium of exchange, which is the third property of money.
3. *Medium of exchange*: This means that money must be a widely acceptable method of payment. This means, that, wherever the transaction is taking place all around the globe, your way of payment must be accepted by any counterpart.

Except the basic functions of money, there are some other characteristics that conventional money has, that older forms of money does not. For example, if we compare money with an older version of it (e.g., goods), we may find some interesting characteristics that modern money has. First and foremost is *durability*. Common goods spoil over time and cannot be accepted as money, and some of them may be difficult to be transferred (*portability*), and be divided (*divisibility*). Also, they may be an abundance of goods, if everyone can produce it, which eliminates the *scarcity* of the product, and thus, loses its value. So far, we compared money with older versions of it. But what about the new modern ones? What about Bitcoin? At a quick glance and thought, we can admit, that, Bitcoin meets almost all the requirements to be considered as a currency. It can be a unit of account, while many products online are priced in Bitcoin as well. Also, it can be a store of value, because of its scarce nature. It is difficult and expensive to be produced, hence, there is a limited supply of currency available in the market, and it can be easily divided and be transferred. From this point of view, we can say that Bitcoin is a decentralized type of money, while its supply is not monitored and adjusted by any kind of central bank in any country. However, the one vital function that Bitcoin cannot keep is the fact that it is not a widely acceptable medium of exchange. So far, there are not many businesses that accept Bitcoin as a method of payment for their goods or their services, and that limits the spread of the currency, and thus cannot be considered as money.

1.3 The history of Bitcoin

As Nakamoto's paper (2008) states on its title, Bitcoin is "a P2P (peer-to-peer) electronic cash system", the first cryptocurrency created based on the blockchain technology. Blockchain is a new way of record keeping of transactions. These records can be distributed but not copied, and they are not controlled by a centralized system or a single entity. Each data block is connected with another, using cryptographic principles, and thus creating a chain. This will allow the directly payment from a party to another, without going through a financial institution, providing security and anonymity of transactions. In 2009, Bitcoin released in public as an open-source software. It is worth noting, that despite the fact that Bitcoin is considered as a first-time-seen phenomenon no one ever expected, some economists pointed the future development of such currencies, long before their existence. Two major economics schools, talked about the creation of a currency with these characteristics. Back in 1909, Carl Menger, a representative of the Austrian school, described a non-government money system. In the beginning of his theory, Menger acknowledges the importance of the state in the creation of the monetary system, contradicting with his later theory, in which he depicts the monetary system as spontaneous orders in which governmental interventions should be minimized. In a more conventional statement, Milton Friedman, head of the Chicago School, being against governmental collectivism, foresaw that in the future, governmental power will be restricted, and a new form of a digital currency will be born, providing anonymity along with its drawbacks.

> *I think the Internet is going to be one of the major forces for reducing the role of government. The one thing that's missing but that will soon be developed, is a reliable e-cash, a method whereby on the Internet you can transfer funds from A to B without A knowing B or B knowing A. The way I can take a $20 bill hand it over to you and then there's no record of where it came from. You may get that without knowing who I am. That kind of thing will develop on the Internet and that will make it even easier for people using the Internet. Of course, it has its negative side. It means the gangsters, the people who are engaged in illegal transactions, will also have an easier way to carry on their business. (Milton Friedman, 1999)*

From a financial perspective, Bitcoin was not that popular for few years after its public release, with its price being very low. It is worth mentioning, that the first price boom was recorded in July 2010 were the price went up by a hundred times (from $0.0008 to $0.08). Over time, Bitcoin gained more and more fame, fact which led to a great increase of its price. Since then, its price has been very volatile with continuous booms and crashes. *Figure 01a* shows the movement of its price since its foundation. At a quick glance, it seems like a quite volatile trajectory. Magnifications of the same graph in specific volatile periods makes it easier for its eventful nature to be perceived.

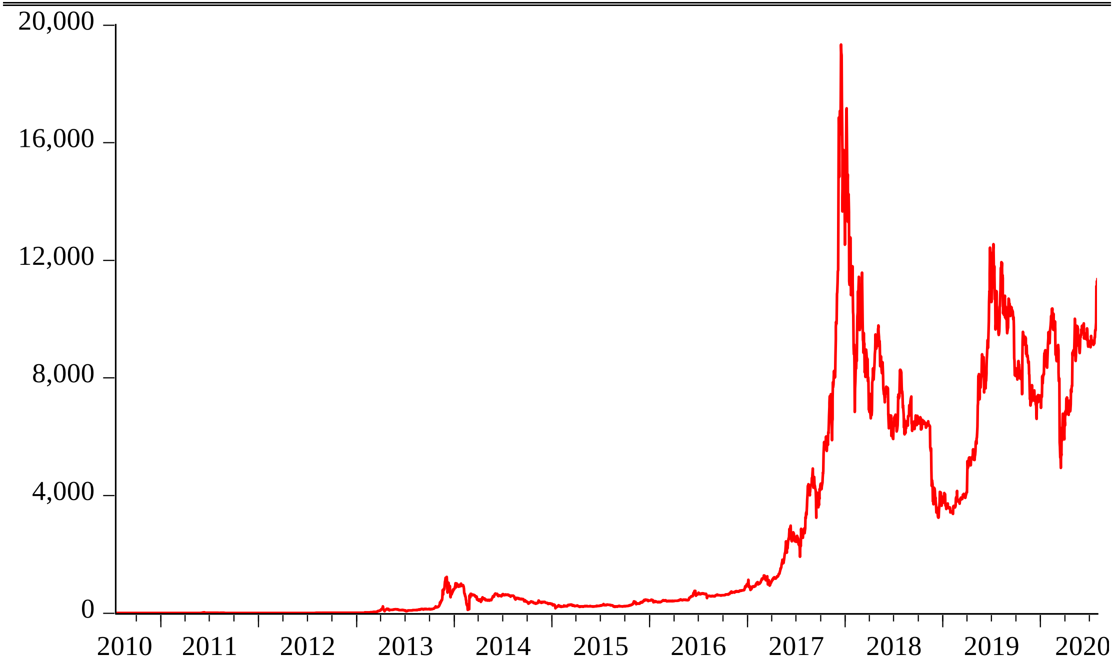
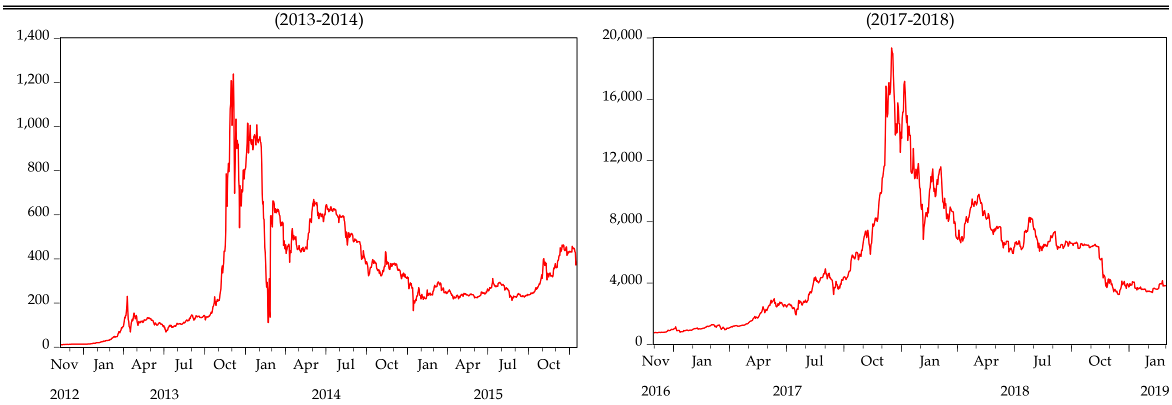


Figure 01: Bitcoin Price History

In *Figure 01b*, an accumulative graph group is created, where we can see all the small or big bubbles that have been created in Bitcoin's price since its creation. The first graph depicts an eventful period for Bitcoin (2013). We can see that in early 2013, the price was around $13 and until April 9th, it spiked to $230, and then crashed back to $80. Then, at the end of 2013, the price rallied from $123 in October up to $1,238, in December, recording a return of 906.5%. This rally was caused by new bitcoin exchanges and miners entering the marketplace. Eventually, in a period of approximately two months, when rumors were spread, indicating lack of security in Mt. Gox[1], and poor management as well, and made the market nervous. People experienced problems withdrawing their money from the website. This caused the price to drop in $541 in December 2013. In early 2014, when Mt. Gox was filed for bankruptcy in Japan, the price of Bitcoin crashed for once more, reaching a 5-months low at $112. After this period, we see a quite volatile period in mid-2014 ending up in an acute downfall for once more in early 2015. Finally, the most volatile period of all was the period of 2017-2018. The big boom of the price began in September 2017 (*Figure 01b*), where the price was in $3,243 (09/14), and until the end of October, the price climber well above $6,000. Until the end of November, the price increased again in a level of $10000 and finally peaking in the nearly double level of $20000 in the mid-December. Many experts and analysts warned about this event being a bubble. These predictions proved to be correct, with Bitcoin price taking a downward trend, with the price falling in a few weeks, and subsequently losing more than 83% of its value within a year (from $19,345 in 12/16/2017 to $3,245 in 12/15/2018). During 2018 Bitcoin experienced many attacks. Starting from January, and then followed by June and July of the same year, many websites such as Coincheck, Bithumb etc., fell victims to hacking and theft, in a total security breach cost of $760 million worth of Bitcoins. In 2019, Bitcoin price tried to recover blooming in $12,554 in 07/09, and by the end of the year, it dropped again in a level just below $7,000. During the period of the COVID-19 worldwide pandemic crisis in 2020, Bitcoin followed the same negatively-oriented path that all stock markets throughout the world created, dropping from $10,364 in 02/14 to $4,945 in 03/16 and tried to recover from there, as all stock markets, back to $11,398 in 07/31.



[1] Mt. Gox was a Tokyo-based cryptocurrency exchange that operated between 2010 and 2014. It was responsible for more than 70% of bitcoin transactions at its peak. The exchange declared bankruptcy in 2014, but it continued to be the subject of lawsuits and speculation. (Investopedia)

Figure 01b: Bitcoin price shocks in time

1.4 Why Bitcoin?

It is very rational for someone to inquire why for investors to choose bitcoin over other assets to include on their portfolios. As we have mentioned before, Bitcoin is a decentralized asset, determined only by the supply and demand, supply which is not control by ant financial institution or central bank. Although, the past literature seems to suggest to different and opposing perspectives on this matter. Many claim that while Bitcoin is an asset merely connected or totally detached from the real economy and capital markets, and thus can be used as a hedging tool in investment portfolios, while its low correlation with other assets can be beneficial for portfolios and lower their risk (standard deviation). On the other hand, many analysts have found that bitcoin can be explained by some economic and market variables through a series of approaches. That contradiction among the Bitcoin's nature in literature indicates one thing; additional research is needed to identify the true characteristics of Bitcoin, while it is one of the most recent added in the interest of the investors, but many of them are hesitant of utilizing it, due to its volatile and unpredictable nature.

2. Literature Review

Many economists have analyzed the same matter or a similar one, but in a different approach. Although, due to the fact, that Bitcoin is a relatively new asset, the literature on this matter is fairly new and limited as well. The questions that emerge here are: Once we have proved that Bitcoin has some interesting hedging abilities, taking into consideration its peculiar characteristics, can we predict the trajectory of Bitcoin's price or returns? Are there any driving factors or determinants that have explanatory power over the Bitcoin's price future fluctuation? Many analysts have done work on this issue with interesting results. Except Kristoufek (2013), which finds a bidirectional relationship between Bitcoin and both Google and Wikipedia searches, and Kristoufek (2015), which finds a diminishing in time positive relationship with hash rate on the long run, that are widely mentioned in the past literature, we are going to focus in more recent articles. We are also going to review articles, that examine the drivers or the predictors of Bitcoin price, returns and volatility. In a brief table (*Table 01*), we mention their contribution on the literature, presenting their results, as well as the method they used.

Authors:	Sample:	Determinants/Predictors:	Methodology:
Polasik et al. (2015)	07/2010-03/2014	(+) Newspaper articles (+) Google search (+) No. of transactions (+) Tone of news	Linear Regression
Dyhrberg (2016)	07/2010-05-2015	(+) FED fund rate (+) FTSE (+) USD/EUR (-) USD/GBP	GARCH E-GARCH
Bouri et al. (2017)	03/2017-10/2016	+ Global EPU	Wavelet multiscale decomposition QQ regression
Li-Wang (2017)	01/2011-12/2014 (2 periods)	(+) Value of trading volume of Bitcoin (+) Bitcoin's volatility (+) Mining difficulty (-) USD Money Supply (+) US interest rate (+) Amount of Bitcoin (-) No. of transactions	ARDL
Demir et al. (2018)	10/2010-11/2017	(+) EPU	BGSVAR OLS QQ regression
Panagiotidis et al. (2018)	2010-2017 (3 periods)	(-) Uncertainty (+) Exchange rates (+) Interest rates (+) gold and oil (+) Demand	LASSO
Adjei (2019)	07/2010-02/2018	(-) mining difficulty (-) Block size	GARCH-M
Al-Yahyaee et al. (2019)	08/2013-08/2018	VIX	Uni-Multivariate Wavelet Coherence
Panagiotidis et al. (2019)	07/2010-08/2018 (2 periods)	(+) gold and oil (+) EPU (+) US fund rate (-) EU rate	GCVAR/FAVAR Factor Analysis Principal Component Analysis
Chen et al. (2020)	08/2011-07/2018 (4 Periods)	Market indices, exchange rates, gold and oil, market cap, transactions fee and value, mining difficulty, block size, internet searches	VAR OLS Quantile Regression

Olmo (2020)	07/2010-05-2019	(+) S&P 500 (-) gold (-) FSI Google search	VECM

**(+) and (-) indicate the sign of each coefficient of the determinants*

***Table 01:** Determinants of Bitcoin's price, as shown in literature*

Except for this short review of some paper, we are going to examine some more, that testing some similar issues about Bitcoin. Georgoula et al. (2015), use time series and sentiment analysis via an algorithm, named Support Vector Machines (SVMs) to identify the determinants of Bitcoin returns in a three-month sample of daily observations (10/2014-01/2015). In the short-term, it is shown that Twitter sentiment has a positive relationship with Bitcoin prices, while a positive effect can be detected by the Wikipedia searches and mining difficulty and a negative one by USD/EUR exchange rate. Later on, a vector error-correction model is used to examine of any long-term relationships between cointegrated variables. According to their analysis, there seem to be a positive relationship between BTC and its amount of circulation (money supply), and a negative one with S&P500. In a more long-run analysis, Bouoiyour et al. (2016) utilize the Empirical Mode decomposition method and proves that despite the fact that many have characterized Bitcoin as a pure speculative asset in the past, the low frequency component seems to be the main contributor BTC's price volatility. As for the short-term price fluctuations, the media attention seem to be a main contributor.

Fang et al. (2019) examines if global policy uncertainty affects the hedging abilities of BTC over different types of assets. In a sample of a total of 8 years (09/2010-01/2018), and employing the Dynamic Conditional Correlation (DCC) and Mixed Frequency (MIDAS) GARCH models, this study proved that the volatility of BTC is significantly affected by economic policy uncertainty in the long-term, although global EPU has a weak effect on the hedging abilities of BTC over the rest of the asset classes. It is also evident that global EPU has a negative impact on the BTC-bonds correlation, and a positive one on BTC-equities and BTC-commodities correlation. All these results indicate, that investors can rely on EPU in order to predict BTC's volatility, but the effect of EPU, will not enhance its hedging performance.

In a more traditional approach, Luis et al. (2019), treats Bitcoin as a traditional form of money utilizing the classic monetary models, and changing their approach thereafter, in a sample ranging from 08/2010 to 02/2018, in order to spot the drivers of Bitcoin demand. Monetary theory results, brought the disadvantages of Bitcoin to the surface, as it failed to fulfill all the functions of money. Later, in a cointegration and GJR-GARCH approach, the results showed that in the short run, speculative trends are the main drivers of Bitcoin demand, but in the long-run this effect is diminishing. In the long term, demand is driven only by expectations.

Additionally, Zieba (2019), on a different approach, utilizing the Minimum Spanning Tree method, attempts to find any connectedness or clusters in the cryptocurrencies market, and then in a VAR model examines the transmission of a demand shock within clusters. In a three-year sample (09/2015-05/2018), they concluded that the most important cluster is the one containing the most mature cryptocurrencies (Bitcoin, Litecoin and Dogecoin). However, in the demand shock transmission analysis, it is shown that despite the significance and magnitude of Bitcoin, neither shocks of Bitcoin are transmitted in other cryptocurrencies, nor other cryptocurrencies' shocks had a significant effect on Bitcoin. In these models, the most significant variables were Litecoin and Dogecoin which seem to have an effect in the majority of the variables in a period of the whole sample. These results can pinpoint that cryptocurrencies' market is not homogenous and results cannot be extracted only by examining its prevalent asset.

Wather et al. (2019), attempts to identify what factors are driving cryptocurrencies' volatility, including Bitcoin. The mixed frequency volatility model (GARCH-MIDAS) is employed, in a set of total 17 economic and financial variables, in a sample from 05/2013 to 07/2019. It is apparent that, as in the in-sample as in the out-of-sample analysis, the best predictor that outperforms the rest of the variables is the Global Real Economic Activity, with the second best choice in predictive power being the joint combination of all other variables. This result is quite interesting due to the fact that despite the prevailing opinion that Bitcoin is a decentralized asset, they proved that its volatility can be driven by the global economic cycle, which is a fundamental factor of the real economy. It is also noted, that global FSI and China's EPU can provide additional information about BTC's volatility. In addition, in the same matter, that is examining BTC's volatility Guizani-Nafti (2019) add a different perspective. Employing the Auto Regressive Distributed Lag (ARDL), cointegration and causality methods, examines the significance of total six factors. Using a dataset of daily data over the period from 12/2011 to 02/2018, the analysis that only the demand of BTC has a significant impact, both in short and long-term. The number of users and the mining difficulty have a positive effect in the short-term, while none of the macroeconomics or financial variables have any explanatory power over BTC's volatility.

In the most recent article on this matter, Rutskiy et al. (2020), first inquiring if Bitcoin is a new form of money, then through a correlation-regression process, tries to find the economic factors of Bitcoin's price. In monthly date from 2014 to 2019, and after proving as the past literature, that Bitcoin performs only the one out of the three roles of traditional money, evidence show, that the only significant factors of BTC's price are the European Union's aggregate M1 and the Chinese Yuan/US Dollar exchange rate.

Our paper is going to be based on one more notion which has not so many applications in the field of economics. It was first introduced by Dufour and Renault (1998) in their paper named "Short Run and Long Run Causality in Time Series: Theory", where they propose a new way of conception of the Granger causality. The same method then advanced by more contemporary articles such as Breitung-Candelon (2006), Dufour-Taamuti (2010), Al-Sadoon (2019) and many others. However, their results will be discussed in the methodology section, while they are pure quantitative methods. Before getting more specific, some of the most significant work done in the field of the diversification benefits of Bitcoin will be presented below, in order to indicate why Bitcoin became a popular alternative and how it can be a beneficial investment.

Ang et.al (2012) and Bampinas-Panagiotidis (2016) used similar methods in order to determine the hedging effectiveness of individual U.S. stocks against inflation. A simple concept of inflation hedging is how strong stock prices comoves with the Consumer Price Index (CPI). They estimated the long-run inflation beta via Dynamic Ordinary Least Squares (DOLS), using the returns and the inflation data. They select stocks, that have shown significant cointegration with CPI for the entire sample. Then, they sorted the stocks by their long-run betas in descending order, to form four quartile portfolios, plus one last portfolio containing all stocks. In these portfolios, they estimate the Fama-French 3-Factor Model, with an extra addition of Carhart (1997) of the winners-minus-losers returns (MOM). An interesting observation here is that only a few of the best inflation-hedging stocks do not display high abnormal returns above the FFC factors. After the portfolio construction process, a regression was estimated of the returns of each portfolio against the inflation. However, in both papers the coefficients were not significant, except two cases in the Ang et al. article. In both articles however the explanatory power of all models was less than 0.05. Ang et al. also gives attention of the portfolio composition. As it seems, the portfolio with the highest inflation betas included more stocks from the technology sector, and the portfolio with the lowest beta included stocks from the financial sector. They also continue their analysis with out-of-sample portfolios, while it is not certain that the in-sample good inflation hedging stocks will be as good in the future. Hence, they construct dynamically rebalanced portfolios out of stocks based on the rolling cointegration statistic and inflation betas. The difference between these two papers here, is that while they both hold the portfolios for one period, then the rebalancing period is one month for Ang et al. while keeping their initial portfolios, constructed in ex-ante basis (with a success rate of around 60%). On the other hand, Bampinas-Panagiotidis, they constructed seven new portfolios at end of some of the rebalancing periods (with a success rate between 53 and 57%). The results in both papers was not any different from the in-sample analysis, while the betas of all portfolios were insignificant.

Brière et.al. (2015) examines how well diversified portfolios can benefit from the addition of bitcoin. In a sample of 3 years (2010-2013), in weekly data, Bitcoin exchange rate against the dollar (from now on BTC) benefits from low correlation with a series of different assets. In matter of fact, all indices that are used in the article indicate a non-significant correlation with BTC, such as, worldwide developed and emerging markets' stocks and bonds, hard currencies, commodities hedge funds and real estate. Only gold and inflation-linked bonds showed evidence of correlation with BTC, in a 10% level of significance. This result may be expected, because other analysts (Harper, 2013), showed the hedging abilities of BTC against the inflation. However, in their article, they pinpoint the fact that these correlations may change in the future. After proving that BTC's addition provides mean-variance trade-offs, using Markowitz's efficient frontier, in an equally weighted and an optimized portfolio, for two levels of risk tolerance (6% and 12%), without allowing short positions, proved that BTC has huge hedging capabilities. In the case of the equally weighted portfolio the Sharpe ratio increased from 0.78 to 2.36. In the diversified portfolios, the Sharpe ratio went from 1.39 up to 2.83 for the 6% volatility boundary, and from 1.05 to 2.66 for the 12%

volatility. Also, they indicate the fact that, due to the volatile nature of Bitcoin, it is hard to be included in a low-risk portfolio. According to their results, a slight increase in the investor's risk tolerance, could lead to an acute increase in the portfolio's returns.

Platanakis-Urquhart (2020), in an out-of-sample analysis, show that investors should include BTC in their portfolios. Using different allocation strategies (Markowitz mean-variance. Bayes-Stein, Black-Littermann, equally weighted etc.), with or without Gens, in different levels of risk tolerance of the investor. Using different performance metrics (Sharpe, Omega and Sortino ratios), showed that the inclusion of BTC increased along all portfolios. Then, they executed an additional robustness test, in order to confirm their results, following the same methodology, but instead of using BTC, they are using the market-weighted cryptocurrency index CRIX. Results seems to be consistent with their previous findings.

3. Methodology

Our paper is going to be based on the Vector Autoregressive methodology, with which we will try to find any relationship between Bitcoin and different type of asset classes (indices, commodities, exchange rates), as well as economic and financial indicators. However, we must bear in mind, that due to the fact that VAR methodology is based on the Ordinary Least Squares (OLS) regression, it premises stationarity among all series in the system. Thus, we are going to test our series for stationarity through a series of tests.

3.1 Stationarity Testing

In order for our results to be more accurate, we are going to test the Bitcoin price series for stationarity through the augmented Dickey-Fuller test. Then, we are dividing our sample into subsamples, according to Bai-Perron Test's proposed structural breaks.

Bai and Perron (1998, 2003b) in a further extend of the Quandt-Andrews framework, are allowing to their method to pinpoint multiple unknown structural breaks in the series. Consider a standard linear regression with T periods and m potential breaks. For each period we have the regression:

$$y_t = X'_t\beta + Z'_t d_j + u_t$$

, where j are the distinct regimes from the breaks. In this regression, the X variables are those who do not change throughout the entire sample, and that means that they through the structural breaks, and Z variables have coefficients that change in different regimes. Bai-Perron test examines the equality of d_j across multiple regimes. The Bai-Perron is performed under the null hypothesis of no structural breaks, that is $d_0 = d_1 = \cdots = d_{n+1}$, against the alternative hypothesis of n breaks, via the F-statistic. The general form of the statistic is:

$$F(\delta) = \frac{1}{T}(\frac{T-(n+1)q-p}{kq})(R\delta)'(RV(\delta)R')^{-1}R\delta$$

, where δ is the optimal n-break estimate of d, (Rδ)′ and V(δ) is the estimate of the variance covariance matrix of δ. When the number of breaks in the sample is unknown, we test the null hypothesis up to an unknown upper bound of breaks. This type of testing is called double maximum. The equal-weighted version of the test, termed UDmax, chooses the number of breakpoints that maximizes the statistic across all the choices.

An alternative approach, (WDmax) applies weights to the individual statistics so that the implied marginal probabilities (p-value) are equal prior to taking the maximum.

3.2 Vector Autoregression (VAR)

The vector autoregression (VAR) is commonly used for analyzing the dynamic impact of random disturbances on the system of variables. In other words, vector autoregression is an extension of the univariate AR model, and it is used to capture any relationship between many variables, in a time-changing environment. The reduced form VAR approach sidesteps the need for structural modeling by treating every endogenous variable in the system as a function of p-lagged values of all of the endogenous variables in the system. A VAR(p) system with i variables can be written as:

$$y_t = C_0 + \sum_{j=1}^{i} C_j y_{t-j} + B_t x_t + u_t$$

, where C_0 and C_j are two $i\ x$ 1 matrices, representing the constant and the endogenous variables' coefficients respectively, B_t representing a $k\ x$ 1 matrix of the exogenous variables' coefficient matrix, and u_t is the error term. All these coefficients are most commonly estimated with Ordinary Least Squares, Maximum Likelihood, or Bayesian methods. The constant terms can, and will in our case, be neglected throughout the estimation process.

3.3 Impulse response function (IRF)

In a VAR system, due to the fact that all variables are connected to each other, a shock to a variable not only affects the variable itself, but it is also affects all the other endogenous variables of the system, through the dynamic structure of the VAR. The impulse response function captures the effect that a shock in a given moment had to an endogenous variable in a finite time horizon. In a VAR system, u_t, or the error terms (that represent the innovations, or structural shocks) of each estimation, is more possible to be correlated, and thus this fact makes the response function more difficult to be interpreted. For this matter, it is common to use a transformation, in order for innovations to become uncorrelated, and impulse response functions be better explained. If T is transformation process, then:

$$e_t = Tu_t$$

In our case, we are going to use the Cholesky transformation. In our case, in order for a stock, index or a portfolio to be a good hedger, we expect a negative impulse response function, where positive shock in Bitcoin's returns will have a negative impact on our assets' performance.

3.4 IRF by local projections, Variance and Historical decomposition

Jordá (2005) introduced local projections in literature, in a different way of computing the impulse response function. This approach is a model-free non parametric method, while the estimators are not restricted by the invertibility assumption. The local projections estimation process can be written as:

$$y_{t+i} = \hat{A}_1^i y_t + \hat{A}_2^i y_{t-1} + \cdots + \hat{A}_p^i y_{t-p} + \varepsilon_{t+i}, \qquad \varepsilon_{t+i} \sim MA(i)$$

, where y_{t+1} and $\hat{A}_j^i$ are $nx1$ matrices including the variable and the coefficients respectively, and $\hat{A}_j^i = \hat{A}_0^{-1} C_j^i$, are the structural local projections of the impulse response function.

While impulse response function examines the effects of a shock to one endogenous variable on to the other variables in the VAR, variance decomposition divides the variation in an endogenous variable into the component shocks to the VAR, and so, variance decomposition provides information about the contribution of each innovation in affecting the variables in the VAR. An alternative method of innovation accounting is to decompose the observed series into the components corresponding to each structural shock. This method named historical decomposition and it first developed by Burbridge-Harrison (1985), who propose the transformation of the residuals to structural residuals, and then for each observation beyond some point in the estimation sample, computing the contribution of the different accumulated structural shocks to each observed variable.

3.5 Subspace Granger Causality

Standard Granger causality testing, introduced by Granger (1969) is a basic way of finding a dynamic relationship between time series. Although, it has to be differenced from correlation, while when two time series are correlated, that does not mean they necessarily Granger cause one each other. This notion (of Granger's) can be perceived as the predictive power that a vector X has from its own past, the past of another vector Y, or an auxiliary variable vector Z, at horizon 1. However, standard causality measures cannot provide evidence about any indirect causality, in a horizon over 1.

Subspace Granger causality, which was first proposed by Dufour-Renault (1998) identifies causality at different horizons and quantifies short- and long- run causality between the vectors. Subspace Granger non causality (SGNC) is based on a VAR(p) process. Let W be a variable vector $W = (X(t), Y(t), Z(t))$. The VAR(p) for the h_{th} horizon will be:

$$W(t+h) = \mu^{(h)}(t) + \sum_{j=1}^{p} \pi_j^{(h)} W(t+1-j) + \sum_{j=0}^{h-1} \psi_j a(t+h-j), \qquad t = p, \ldots, T-h$$

, where $\mu^h(t)$ is a deterministic trend, $\pi_j^{(h)}$ is the coefficient matrix of W, and ψ_j are the impulse responses. In this case, we study the predictive power of components of $W(t+h)$ with respect to current and past components of W. According to this formula, Y fails to cause X at horizon h, if at every time (t) the prediction of X does not depend on $Y(t)$ or its past.

4. Data

In an attempt to find the explanatory market determinants of Bitcoin returns, we use data which include variables from the biggest continents and markets of the world (US, Europe, Asia). In weekly data, from 01/13/2013, when Bitcoin's volume of trade began to rise, to 09/06/2020, in a framework of 400 observations. If a variable is not stationary, the first logarithmic differences will be considered through the VAR process. An accumulative table is following with all variables collected for this paper:

Variable Name:	Source:
(btc): Bitcoin closing price	investing.com
(brent): Brent Crude Oil	stooq.com
(chn_epu): China Policy Uncertainty Index	policyuncertainty.com
(cnyusd): Chinese Yuan/US Dollar	investing.com
(dji): Dow Jones Industrial	yahoofinance.com
(eu_epu) Europe Policy Uncertainty Index	policyuncertainty.com
(eurusd): Euro/US Dollar	yahoofinance.com
(fedfunds): FED Funds Rate	fred.stlouisfed.org
(gbpusd): GB Pound/US Dollar	yahoofinance.com
(gold): Gold price	yahoofinance.com
(gtrends): Google trends for the term "Bitcoin".	trends.google.com
(jpyusd): Japanese Yen/US Dollar	yahoofinance.com
(nasdaq): NASDAQ Composite Index	yahoofinance.com
(ng): Natural gas Price	stooq.com
(nikkei): NIKKEI 225 Composite Index	yahoofinance.com
(shc): Shanghai Composite Index	stooq.com
(sp_500): S&P 500 Index	yahoofinance.com
(tedrate): TED Spread Rate	fred.stlouisfed.org
(us_epu): US Policy Uncertainty Index	policyuncertainty.com
(fsi): US Financial Stress Index	fred.stlouisfed.org

Table 02: Data-Source list

5. Results

First and foremost, we test our series for stationarity in order for them to be eligible to be used in the VAR process. For this reason, we use the Augmented Dickey-Fuller test for both level and 1st difference of each variable[2]. A table presenting these results follows below:

	Level:		1st difference:	
Variables:	t-statistic:	p-value:	t-statistic:	p-value:
brent	-1.652960	0.4545	-17.66285	0.0000
btc	-1.109696	0.7132	-10.52955	0.0000
chn_epu	-1.417752	0.5741	-5.029313	0.0000
cnyusd	-1.324205	0.6194	-17.91550	0.0000
dji	-1.156642	0.6941	-21.74996	0.0000
eu_epu	-1.737801	0.4114	-8.134625	0.0000
eurusd	-1.671576	0.4450	-21.57425	0.0000
fedfunds	-1.301555	0.6300	-4.28513	0.0005
fsi	-4.020803	0.0015	-17.11046	0.0000
gbpusd	-1.465427	0.5503	-20.25152	0.0000
gold	-0.569259	0.8741	-20.69899	0.0000
gtrends	-3.044979	0.0318	-5.436179	0.0000
jpyusd	-2.996833	0.0360	-21.83588	0.0000
nasdaq	0.714182	0.9924	-19.85644	0.0000
Ng	-2.621464	0.0894	-21.20594	0.0000
Nikkei	-2.207309	0.2041	-20.59364	0.0000
Shc	-2.228151	0.1967	-17.69838	0.0000
sp_500	-0.795973	0.8188	-21.18998	0.0000
Tedrate	-5.068754	0.0000	-11.16928	0.0000
us_epu	-1.972515	0.2989	-6.133092	0.0000

Table 04: Stationarity Testing via ADF.

As it can be seen and expected, the majority of the market variables are not stationary at level, and the 1st difference will be taken into account. However, there are some variables that are stationary at level, some even at the 1% level of significance (fsi, gtrends, jpyusd, tedrate), and thus, no logarithmic differences are necessary in this occasion. An interesting preliminary approach of the determinants of Bitcoin, is to find evidence of relationship between those variables, and so, correlation should be examined. In this case, we are interested only in the correlation of Bitcoin to other variables and the rest cross-correlations. In a brief table we present the correlation coefficients along with their p-values.

[2] A detailed table of each variable's summary statistics can be found in the appendix.

Variables:						
	brent	chn_epu	cnyusd	dji	eu_epu	eurusd
Corr.:	0.059842	-0.045525	-0.052823	0.063071	0.44699	0.027730
p-value:	0.2324	0.3638	0.2919	0.2081	0.3726	0.5803
	fedfunds	gbpusd	gold	nasdaq	ng	nikkei
Corr.:	0.063203	0.009169	0.071666	0.039830	-0.02709	0.101525
p-value:	0.2072	0.8550	0.1525	0.4269	0.6797	0.0424
	shc	sp_500	us_epu	fsi	gtrends	Jpyusd
Corr.:	0.025844	0.047905	0.021840	-0.104143	0.057830	-0.095233
p-value:	0.6063	0.3393	0.6632	0.0373	0.2485	0.0570
	Tedrate					
Corr.:	-0.087925					
p-value:	0.0790					

Table 05: Correlation between Bitcoin and market factors

In this table, we can see that only a few variables have a statistically significant correlation with Bitcoin. In the 5% level of significance only NIKKEI Composite Index and the Financial Stress Index have a relationship (0.101525 and -0.104143 respectively). We observe that both are weak relationships, and one of them is negative. That means, that when FSI increases a drop in Bitcoin returns can be observed. Finally, in the 10% level of significance, the Japanese Yuan/US Dollar exchange rate and the TED Spread Rate have a negative relationship with Bitcoin. However, this only a preliminary and superficial analysis of our problem, and further investigation is needed. This table can indicate only a vague picture of what we should expect from our analysis. Before proceeding to the VAR process, we test the Bitcoin price for possible breakpoints, using the Bai-Perron test. The following table provides the results of the test, seeking five maximum breakpoints in the series.

Breaks:	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical Value	
1	1595.128	1595.128	1595.128	8.58	
2	951.1571	951.1571	1130.322	7.22	
3	664.9663	664.9663	957.2836	5.96	
4	497.7779	497.7779	855.8988	4.99	
5	397.2246	397.2246	871.6590	3.91	
UDMax statistic:		1595.128	UDMax critical value		8.88
WDMax statistic:		1595.128	WDMax critical value		9.91

Table 06: Bai-Perron Test for BTC/USD.

In this table, we can see that, according to UDmax and WDmax statistics, the optimal determined breaks is one. In this case, the selected break is at 10/1/2017, and thus we are going to divide our sample into two subsamples, one ending at 09/24/2017, and one starting at 10/01/2017. According to Akaike's information criterion, the optimal lag length for the entire sample is 2. However, for the subsamples the optimal lag length is over 8 periods in the past, without providing any additional information, and so we keep the lag length in 2 periods, to avoid overfitting. The VAR model for the first period showed that Bitcoin's returns can be explained only by four of all those variables. A significant coefficient can be observed only in Dow Jones Industrial, S&P 500, gold and Google trends. It is quite interesting to pinpoint that the significance of these variables comes from 2 periods (weeks) in the past, and not earlier. This means that Bitcoin's provides a delayed reaction to market aspects, either positive or negative. It is worth mentioning that Bitcoin has a great negative coefficient with S&P 500's returns two weeks in the past, indicating that a decrease to S&P 500 returns in the past will cause a significant increase in Bitcoin's returns. Admittedly, the explanatory power of this regression is low, while the R-squared in this case is approximately 0.255 (and the adjusted R-squared is 0.108), while the joint significance of the variables through the F-statistic cannot be rejected ($F=1.740735 > F_{0.05}(19, 224) = 1.6331$). In the second period, the VAR model can give us a better picture of the Bitcoin's returns determinants. From October 2017, Bitcoin's returns can be explained by Bitcoin itself, China's and Europe's Economic Policy Uncertainty Index, Natural Gas, Financial Stress Index, and Google trends. As it seems, in the second period, from what we saw in the first period, only Google trends remained significant, and many more economic and financial indices added to the determinants. The results of this model are quite interesting. Bitcoin has a significant negative coefficient with itself in the past. China's EPU and FSI's coefficient sign seems to be shifting, while one period in the past has negative influence on Bitcoin returns, and two periods in the past has a positive one. This can be explained; as the China's Economic policy uncertainty and the financial stress increases, Bitcoin returns will drop momentarily for one period, reacting to this change, and then it will have a positive reaction to these variables. Bitcoin also reacts negatively to Europe's EPU and Natural gas. This means that, when these variables increase, Bitcoin returns decrease and vice versa. The latter scenario is more interesting, and driven by the fact that the negative coefficients are larger than the positive ones, we can note that this model provides evidence that Bitcoin can be used in portfolios, in order to hedge the political, systemic and systematic risk that they may indulge, depending on which market are exposed to. Finally, Google trends have also a shifting sign in the model, being positive in one-step in the past, and negative thereafter. Let be noted that some of these coefficients may be significant, but they have low impact as they are close to zero. In second period, in terms of model's explanatory performance, the R-squared in this case is 0.424887 (with adjusted R-squared being at 0.22), both higher from the first period's criteria, but still low, indicating that there are more variables that can be added in the approximation. The joint significance of all variables cannot be rejected in this case either ($F= 2.0870 > F_{0.05}(19, 134) = 1.6646$). A table of all significant coefficients in Bitcoin's regression is following, as they are computed in the VAR model for both periods.

1st period (01/13/2013-09/24/2017)		2nd period (10/01/2017-09/06/2020)	
Coefficients		Coefficients	
	DJI (-2) 9.362585 [3.77260]	BTC (-1) -0.185282 [-2.06271]	
	Gold (-2) 1.415093 [-2.711758]	Chn EPU (-1) -0.866138 [-3.91260]	Chn EPU (-2) 0.539894 [2.35625]
	S&P 500 (-2) -10.23539 [-2.71758]		EU EPU (-2) -1.021951 [-2.78449]
Gtrends (-1) 0.071712 [3.87319]	Gtrends (-2) -0.071138 [-3.78222]	NG (-1) -0.352753 [-2.18352]	
		FSI (-1) -0.30218 [-1.97029]	FSI (-2) 0.031018 [2.03324]
		Gtrends (-1) 0.007460 [3.42566]	Gtrends (-2) -0.006998 [-3.24295]
R-squared=	0.255399	R-squared=	0.424887
Adj. R-squared=	0.108680	Adj. R-squared=	0.221307
F-stat =	1.740735	F-stat =	2.08076

*t-stat in brackets, critical value= 1.96

Table 07: VAR significant coefficients

Having all these evidence in mind, we should not only inquire if Bitcoin can be interpreted by these variables, but also if a shock in these determinants can affect Bitcoin. This can be examined by the impulse response function for these variables on each period. In the following graphs we are looking for significance in the impact of each variable's shock in Bitcoin. Therefore, a significant impact is the one whose its error bands does not include the zero value. Thus, for the first subsample, we observe a positive impact of Dow Jones in the third period, and we marginally can reject the positive impact of gold in the same period and S&P 500's in third and fourth period. Google trends shows a positive and significant impact for the first five periods. For the second subsample, Bitcoin in period 2 has a negative response in shocks of China's EPU, natural gas, and FSI, and a positive response in Google trends and Europe's EPU for the same period, with the latter one having a significant negative impact on fourth period as well.

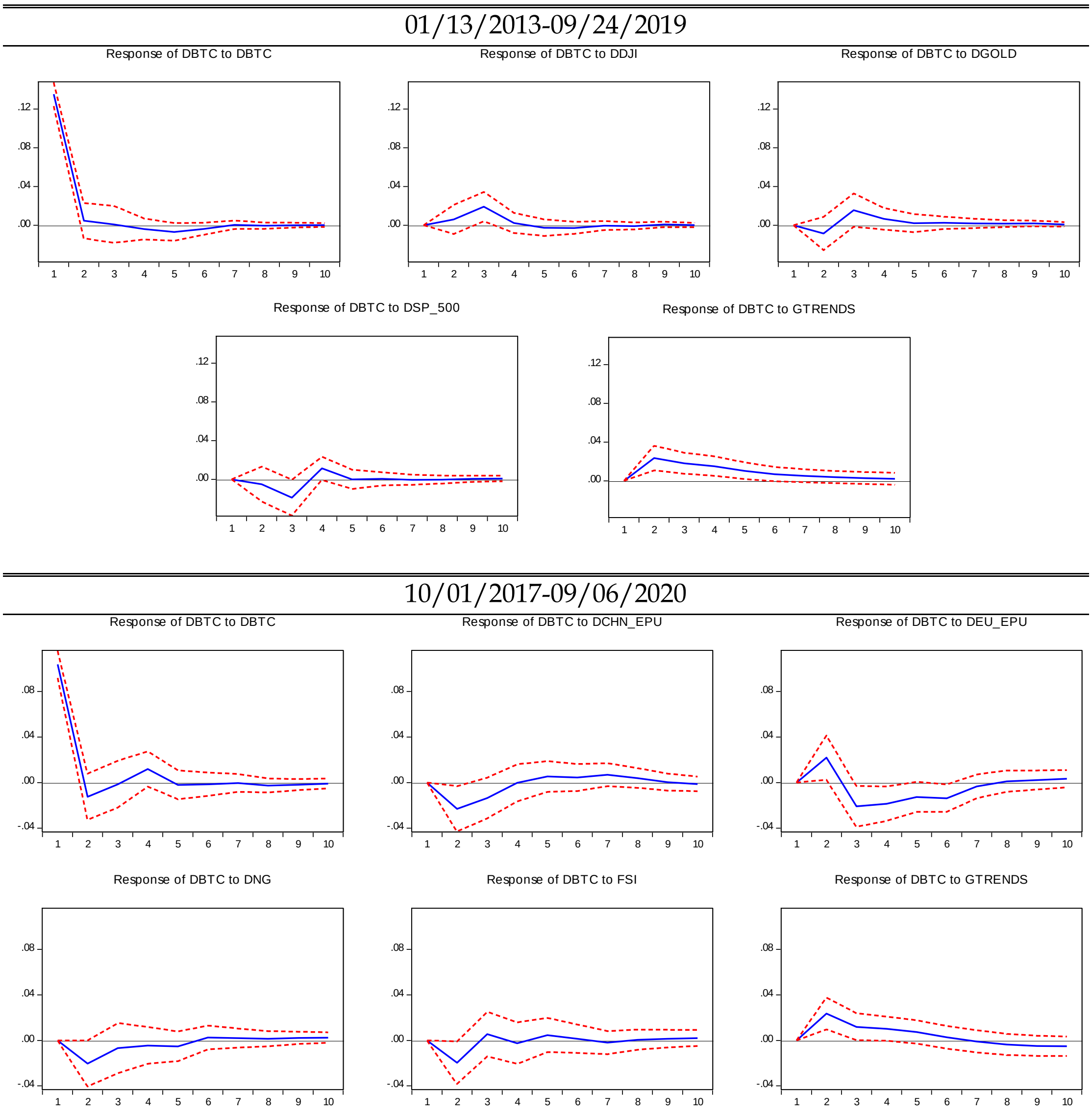


Figure 02: IRF of BTC

In a similar, but in a non-parametric way, we are going to estimate the impulse response functions by local projections for the same models, in an attempt to gather more information about Bitcoin's behavior in determinants' shocks. This method, as it can be seen by the graphs, comes to confirm our previous results. In the first subsample we still detect a positive response on a DJI shock for the first three periods, that declines over time. This result has the same impact as the results from the VAR model, but in a more dynamic approach. Google trends also have a positive impact on Bitcoin, but for a longer period of time, and seems to decline after five periods, but still being positive. This designates that a shock in Google trends does not have an impact only in the short run, but in the long run as well. In the second subsample, we see a positive impact of Bitcoin in Europe's EPU, in contrast with VAR's coefficients, and a negative in China's EPU. In addition, Google trends have a positive impact on returns for three periods. In the second model, it is quite apparent, that all these impulse responses are significant only in the short run.

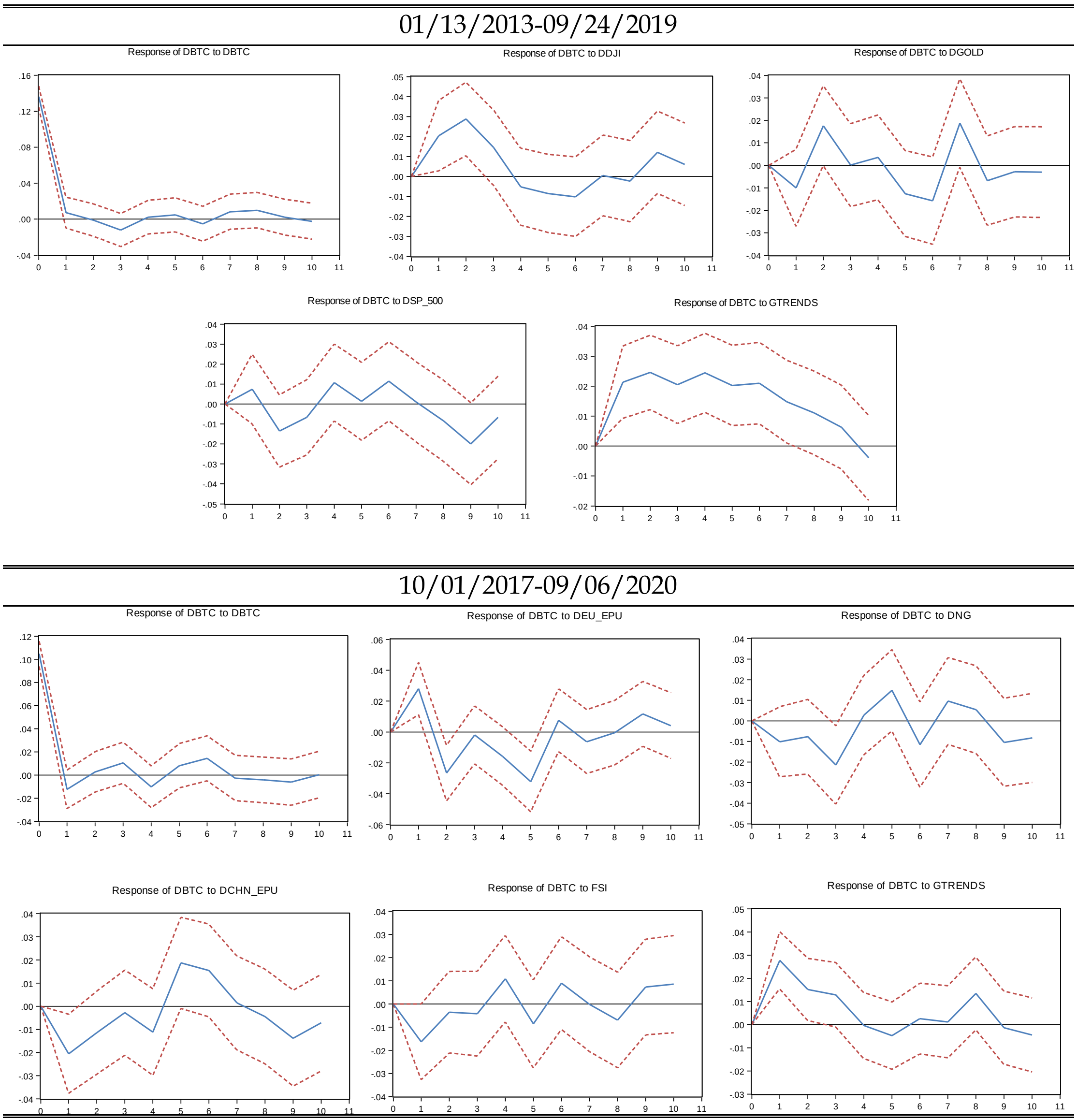


Figure 03: IRF by local projections of BTC

We are going to proceed in our analysis, by using a different approach. Variance decomposition of BTC with respect to the above-mentioned variables, will help us to pinpoint the contribution of each determinant in to Bitcoin, and what amount of information can they provide for it. It is obvious, that for both periods the amount of information that is gathered from these variables is moderately low, with Bitcoin itself covering the largest portion. In the first subsample, the contribution of all significant variables does not exceed 14% of the variance, with DJI and Google trends providing the largest proportion of information of about 4-5% each, while the latter two providing only 1-3%. In the second subsample, we can discern that a larger segment of Bitcoin's variance can be explained by its determinants of a percentage about 17-25%. Europe's EPU has the largest impact, in a percentage that grows over time, of about 12-13%. Similarly, to the first bar chart Google trends has also an increasing effect over time ranging in 5-8%. All other variables have a contribution of 2-6% each. As low as they might these percentage be, we see that they, in the majority of them, they constantly increase.

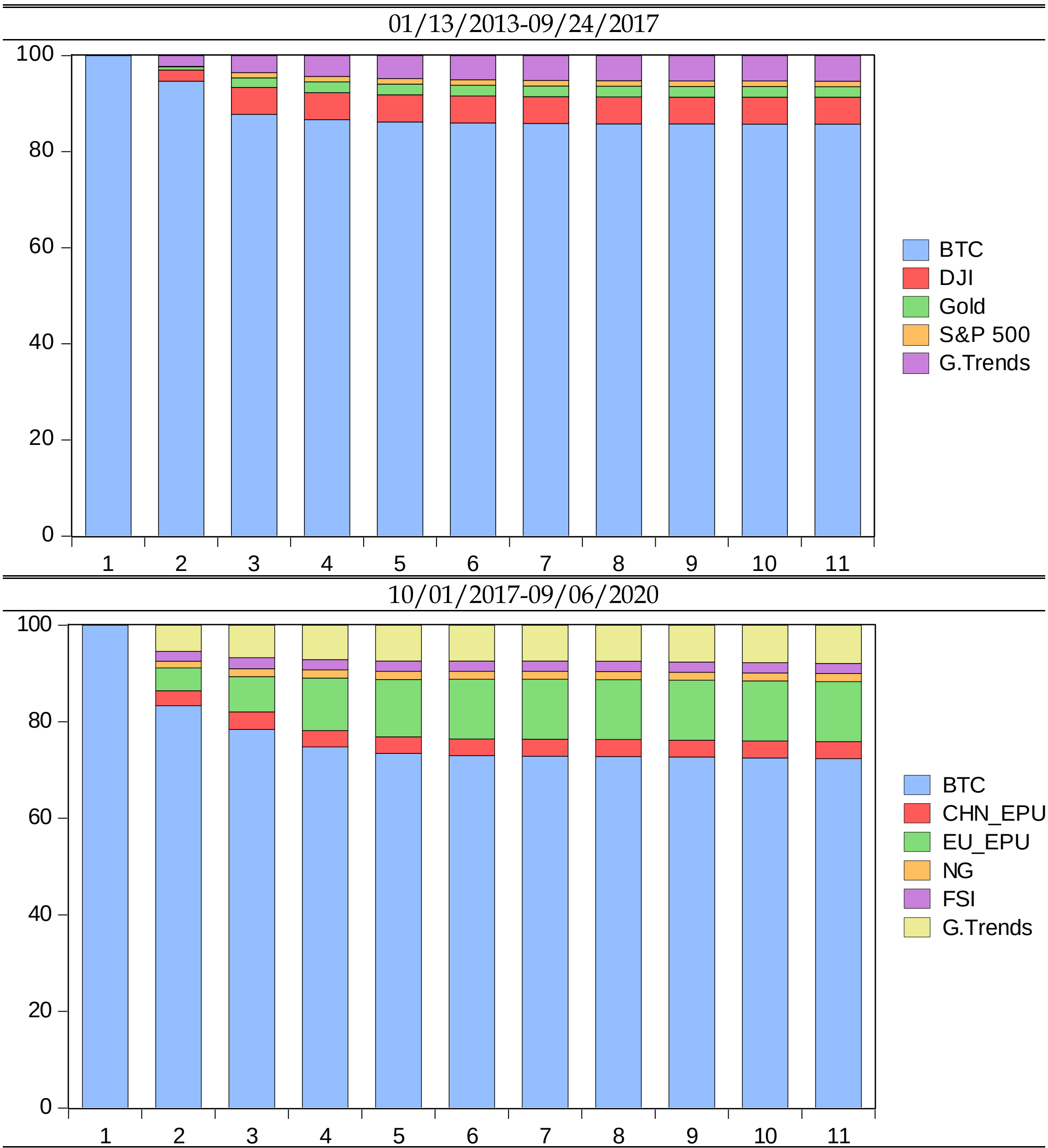


Figure 04: Variance Decomposition of BTC

In order to illustrate the importance of these shocks in time we are going to use the method of Historical decomposition. This methodology will allow us to determine and quantify the relative importance and contribution of specific shocks of each variable to Bitcoin. The first thing that we can notice from these graphs is that Bitcoin's return can be attributed to Bitcoin itself. All of the rest variables seem to have much weaker contribution, but nevertheless we cannot neglect their significance. In the first subsample Gold and S&P 500 have minor impact on returns. On the other hand, in Google trends and DJI we see a different picture. Through the years 2013-2014 Google trends seem to have higher importance in comparison with the other variables, and when that effect wanes, through the years of 2015-2016 when the returns of Bitcoin decrease as well, DJI gains some significance over the returns. Then through the last year of the sample, where the volatility rises again, Google trends have greater impact again. In the second subsample, FSI and Natural Gas are the variables of minor importance. We can see that Economic Policy Uncertainty shows a significant contribution for both indices. Europe's EPU shows a greater contribution than the other variables, and China's EPU has a weaker one, but also significant in some periods. Finally, for once more Google trends has a more noticeable impact on returns in periods of high volatility.

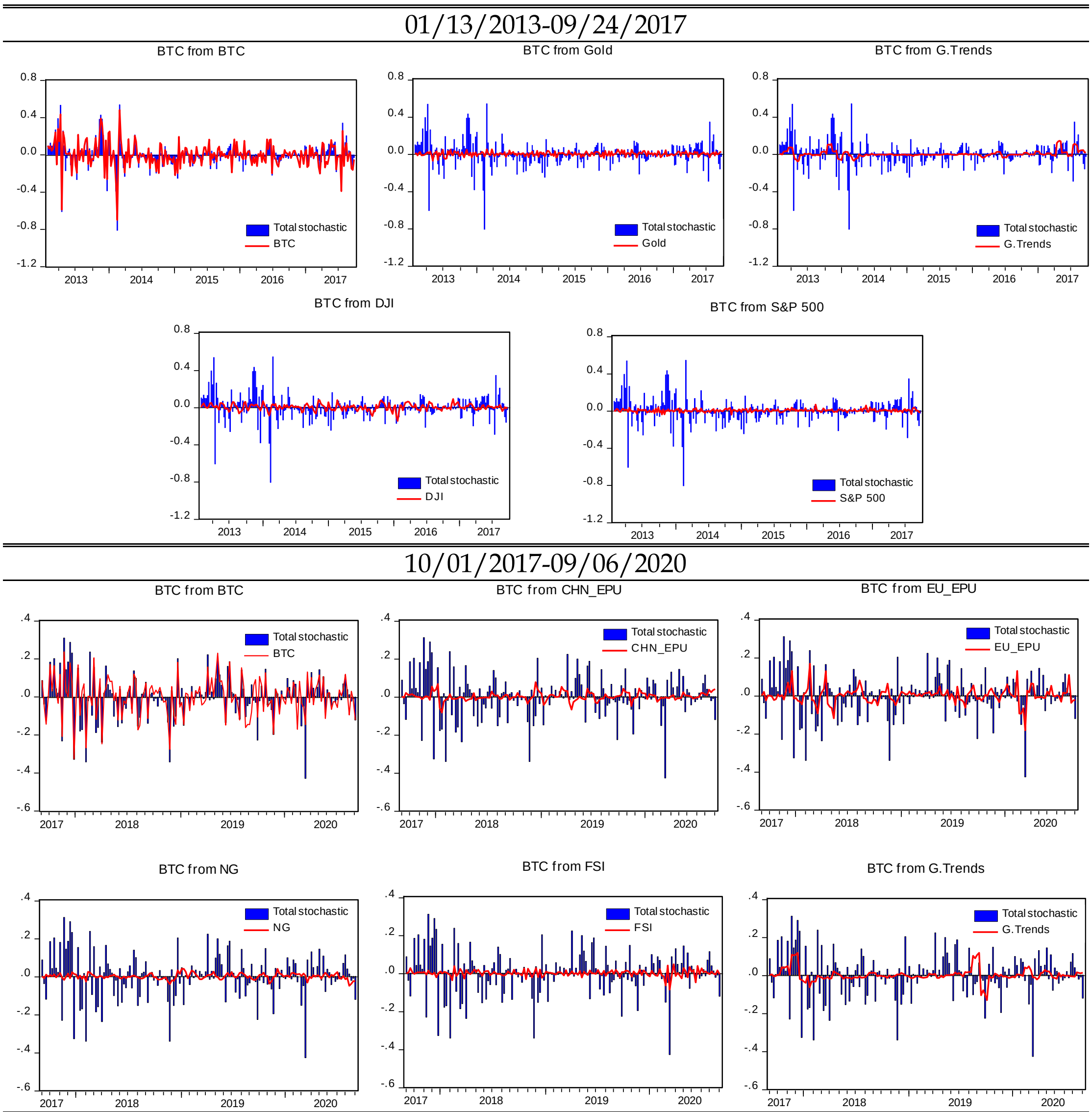


Figure 05: Historical Decomposition of BTC

So far, it is noticeable that the relationship of these variables with Bitcoin is far from constant and restricted only in one period. Thus, the standard Granger causality test will not provide us adequate information about this relationship, while this method is narrow-sighted. To alleviate this problem, we employ the Subspace Granger Causality, which has the ability to detect causality in short term as well as in long term. For these tests, we set as target of the test the Bitcoin returns, using as predictors all the above-mentioned variables. While asymptotic tests suffer from over-rejection, we utilize the bootstrap version of the test, that performs better over the hypotheses. We are going to base our analysis on the bootstrapped small-b p-values. We performed these tests in a total framework of 12 horizons, utilizing a bootstrap of N=2000, and a burn-in of 100 periods (basic parameters of the algorithm), at a α=0,05 significance tolerance (the null hypothesis here is that each given variable does not causes Bitcoin). Two tables below, presenting the test results for the two periods will help us identify in which horizons variables can predict Bitcoin returns, and help us make our total and final remarks, always in respect to our previous results (VAR coefficient significance, IRF, Variance and Historical Decomposition).

Horizons:	1	2	3	4	5	6	7	8	9	10	11	12
Bootstrapped Small-b p-value:												
dji → btc	0.228	0.060	0.358	0.769	0.324	**0.022**	0.430	0.447	0.298	0.808	0.367	0.142
gold → btc	0.074	0.179	0.301	0.244	**0.000**	**0.002**	0.183	0.911	0.295	0.164	0.596	0.680
sp_500 → btc	0.367	0.135	0.478	0.709	0.551	**0.037**	0.377	0.547	0.181	0.795	0.380	0.127
gtrends → btc	**0.009**	**0.013**	**0.029**	**0.023**	**0.010**	**0.034**	0.288	0.561	0.175	0.552	0.324	0.582
Bootstrapped Fixed-b p-value:												
dji → btc	0.766	0.343	0.530	0.706	0.617	0.526	0.644	0.631	0.676	0.809	0.484	0.067
gold → btc	0.207	0.055	0.619	0.204	**0.016**	**0.012**	0.373	0.899	0.876	0.666	0.605	0.799
sp_500 → btc	0.817	0.405	0.581	0.711	0.792	0.558	0.503	0.604	0.623	0.794	0.610	0.071
gtrends → btc	**0.001**	**0.001**	0.120	0.057	**0.018**	0.389	0.331	0.305	0.140	0.263	0.071	0.684

Table 08a: I(0) univariate SGNC test results (01/13/2013-09/24/2017)

In the first subsample, it is interesting that all variables are able to predict Bitcoin returns in horizon 6, indicating that these variables provide information about Bitcoin not in the present, but in a deeper horizon. Besides that, we cannot see any significant results for the majority of the variables, except Google trends. We can see that Google trends are able to predict returns for periods from 1 to 6. This is consistent with our previous results, confirming that Google trends and search intensity can be a significant determinant for Bitcoin, both in short and long run. DJI, that had a positive impact on Bitcoin according to IRF, does not seem to have any significant causing effect on the short run. S&P 500 who had a marginally significant IRF for one period causes Bitcoin for only period 6 and gold causes it for periods 5 and 6.

Horizons:	1	2	3	4	5	6	7	8	9	10	11	12
Bootstrapped Small-b p-value:												
chn_epu → btc	**0.003**	**0.046**	0.366	**0.009**	**0.001**	**0.010**	**0.039**	0.152	0.437	0.754	0.299	0.273
eu_epu → btc	**0.002**	0.260	0.085	0.055	**0.043**	0.223	**0.026**	0.389	0.604	0.933	0.670	0.445
ng → btc	0.664	0.325	**0.029**	**0.028**	0.057	0.080	0.133	0.172	0.553	1.000	0.971	0.758
fsi → btc	**0.029**	0.814	0.886	0.198	0.140	0.788	0.862	0.659	0.789	0.526	0.678	0.763
gtrends → btc	0.061	0.075	**0.020**	1.000	0.186	0.750	**0.009**	**0.032**	0.943	0.549	**0.000**	0.249
Bootstrapped Fixed-b p-value:												
chn_epu → btc	**0.002**	**0.017**	0.183	**0.044**	**0.006**	**0.001**	0.103	0.475	0.658	0.675	0.577	0.389
eu_epu → btc	0.186	0.247	**0.046**	0.425	**0.020**	0.138	**0.036**	0.457	0.379	0.958	0.676	0.778
ng → btc	0.791	0.309	0.439	0.341	0.144	0.170	0.082	0.075	0.532	0.996	0.968	0.610
fsi → btc	**0.028**	0.813	0.935	0.106	0.134	0.773	0.889	0.860	0.619	0.245	0.609	0.893
gtrends → btc	0.672	0.733	0.105	1.000	**0.034**	0.565	**0.001**	**0.002**	0.976	0.509	0.082	0.192

Table 08b: I(0) univariate SGNC test results (01/13/2013-09/24/2017)

In the second subsample, we get for once more a confirmation for our previous results. In this case it is interesting that Economic Policy Uncertainty can predict Bitcoin returns. China's EPU causes BTC in horizons 1,2 and 4-7, and that means that it has a causality effect for more than 1 step ahead, confirming a short/long run relationship. Europe's EPU test's small-b are significant in horizons 1, 5 and 7, which means that we cannot only trace evidence of causality in one horizon ahead, but in the future as well. Following these results, we can safely note that EPU for both regions are significant determinants of Bitcoin returns. Natural gas, without achieving any significant explanatory performance in any of the methods before, keeps without providing any additional over BTC, while we are not able to detect any causing effect, confirming its low influence over the returns. The results for FSI in this table concur with our previous results as well. Through IRF we observed that FSI's impact over Bitcoin is constricted only in the short term, fact that can be seen in this table as well, while causality is significant only in the horizon 1. Finally, in our previous analysis, it was obvious that the explanatory power of Google trends lowers in the second subsample and other variables take its place. The same conclusion can be perceived from these two tables as well, while there is no a continuous causation effect as it was present in first table. However, Google trends is certainly a Bitcoin determinant in this subsample as well, while we can trace significant causality in horizons 3, 7, 8 and 11, showing a deeper relationship with search intensity in a wide range of horizons.

6. Conclusion

Bitcoin has gained a lot of attention in the most recent years, both positive and negative. It is worth mentioning, that Bitcoin's cryptocurrencies' market share for 2020 is 66%, with a market capitalization of $495bn. For the first five years it was not that popular, although from 2013, when its price took an acute upward trajectory, it gained investors and media interest as well, becoming one of the newest assets added in the investment world. As a matter of fact, it's a quite volatile asset (not considered as a currency but as a commodity). The main argument of its supporters is that it is a decentralized asset, but this is not necessarily a virtue, while it is very unstable, with many price bubbles bursting through its course in time. Many analysts in the past literature have argued over the matter, if Bitcoin is indeed a decentralized asset and it can be used as a hedging agent in portfolios comprised from traditional assets, or if there are some determinants that can predict its course. This paper, in an attempt to give an answer to this matter, examined some possible factors that may have explanatory power over Bitcoin returns. In a dataset of a total 19 variables ranging from 01/13/2013, when the Bitcoin started gaining attention and its price met its great price increase, to 09/06/2020, we divided our sample into two subsamples according to Bai-Perron Multiple Breakpoint test. Then, we employed a series of methodologies (VAR, IRF, IRF by local projections, Variance and Historical Decomposition, Subspace Granger non-Causality test) for both periods, extracting some interesting results. For the first period, which can be named as the early stages of Bitcoin's evolution, data provide evidence for significant impact of Google trends on Bitcoin returns, and we can see a weaker relationship with Dow Jones Industrials. In the second period, we find more variables to be significant. Economic Policy Uncertainty (EPU) for two regions (Europe and China), seem to have an effect on Bitcoin, as in short as in the long run, and US Financial Stress Index has a minor effect in the short run, while Google trends' effect diminishes in this period, but it remains significant. Beyond doubt, Bitcoin is an asset, proven in the past, driven mostly by technological factors, and this fact can be seen in our data as well, with search intensity never losing its contribution over time. However, it is obvious that, even if it was disconnected from the real economy and markets in its early stages in the course of time, it gets more connected with them. This can be seen by the rise of the significance of our models through the second and most recent period. In the matter of the two contradicting theories prevailing right now, our results are nested somewhere in the middle. This means, that we proved that Bitcoin is far from being strictly connected with the markets, although we cannot neglect some of the relationships found above and thus, we cannot state that it is completely disconnected from them. We should not forget that, following the proper strategies over the portfolio management process, someone could use these relationships, in order to provide hedging abilities over some types of risks. It is safe to admit that, our data indicate the necessity of further investigation in the future, in order to identify new determinants that can be added or even replace the already existent.

Appendix: Variables Summary Statistics

	DBRENT	DBTC	DCHN_EPU	DCNYUSD	DDJI	DEU_EPU	DEURUSD
Mean	-0.0024	0.016609	0.00242	-0.00026	0.001848	0.000276	-0.00025
Median	-0.00126	0.016012	0.007292	0.000000	0.003361	0.000000	-0.00013
Maximum	0.313519	0.562858	0.381493	0.019196	0.12084	0.259118	0.040463
Minimum	-0.29071	-0.78847	-0.28849	-0.0348	-0.18998	-0.22093	-0.03901
Std. Dev.	0.052388	0.134029	0.097468	0.005217	0.023636	0.054536	0.011224
Skewness	-0.32471	-0.45156	-0.06677	-0.81204	-1.65106	0.397069	-0.18394
Kurtosis	11.01236	8.654726	3.673649	8.883236	19.48783	5.370296	4.008656
Jarque-Bera	1076.995	546.5259	7.860582	620.8347	4712.541	104.1492	19.21196
Probability	0.0000	0.0000	0.019638	0.0000	0.0000	0.0000	0.000067

	DFEDFUNDS	DGBPUSD	DGOLD	DNASDAQ	DNG	DNIKKEI	DSHC
Mean	-0.001105	-0.00048	0.000389	0.003235	-0.0006	0.002038	0.001188
Median	0.0000	-0.00072	0.001088	0.004611	0.000573	0.002605	0.002802
Maximum	0.223144	0.066987	0.090362	0.100621	0.218352	0.158171	0.090734
Minimum	-1.386294	-0.0599	-0.09772	-0.13513	-0.30039	-0.17428	-0.14291
Std. Dev.	0.087521	0.013055	0.021238	0.023805	0.061057	0.03003	0.029435
Skewness	-10.89819	-0.24844	-0.21349	-0.99013	-0.2324	-0.54595	-0.8831
Kurtosis	163.55	5.981982	5.230169	8.364509	4.942425	8.246333	6.838792
Jarque-Bera	437523.3	152.3183	85.93263	544.9894	66.48427	478.6039	297.5961
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

	DSP_500	DUS_EPU	FSI	GTRENDS	JPYUSD	TEDRATE
Mean	0.002122	0.00094	-1.87823	12.22375	109.2467	0.30905
Median	0.003784	0.0000	-2.2945	7.7500	109.400	0.2600
Maximum	0.114237	0.305905	9.8400	100.0000	125.629	1.4200
Minimum	-0.162279	-0.31964	-4.2420	1.000	90.181	0.1300
Std. Dev.	0.022079	0.0769	1.8281	14.09372	6.996362	0.150453
Skewness	-1.477376	-0.03193	2.446517	3.051818	0.044631	2.924657
Kurtosis	15.5188	4.98373	12.48383	14.55631	2.764142	17.55817
Jarque-Bera	2757.513	65.65438	1898.08	2846.712	1.059943	4102.578
Probability	0.0000	0.0000	0.0000	0.0000	0.588622	0.0000

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