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Cryptocurrencies' potential to become a wealth-preservation alternative to precious metals during capital market volatility.

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Declaration

I declare that the work undertaken for this BA Dissertation has been undertaken by myself and the final Dissertation produced by me. The work has not been submitted in part or in whole in regard to any other academic qualification.

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Abstract

Since the financial crisis of 2008, risk management has been at the forefront of financial institutions to protect themselves from another economic shock. The majority of investors are aware of the safe haven properties of gold in such cases. However, the current paper analyses the properties of 4 cryptocurrencies, in particular Bitcoin, Ripple, Litecoin and Ethereum and compares them with those of gold and silver. The approach was inspired by the work of Baur, Dimpfl, and Kuck (2018), who apply a correlation matrix and the GJR-GARCH model with (the US dollar trade-weighted index in the mean equation) and without external regressors to the log-differenced returns of the assets (financial data sourced from Yahoo Finance) to test for indications of statistical relationships. The findings reveal that gold proves its safe haven properties and silver its hedging properties. Cryptos not only have much higher average returns, coming at the price of a very high standard deviation or risk, but they also indicate to follow a completely different price path in comparison to the precious metals and macroeconomic factors such as indices (DAX and S&P500), LIBOR and major forex pairs such as EUR/USD, GBP/USD and USD/CHF. Overall, the four cryptocurrencies demonstrate their independence from the traditional markets and can serve as hedging tools in a portfolio, but investment decisions should be taken only after the risks have been carefully considered. Moreover, the results in the current work are derived from a limited time period with a limited number of assets, which calls for continuous research on the price developments of both already established and new cryptocurrencies, in order to provide an up-to-date picture of this evolving market.

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Abbreviations

BTC – Bitcoin

LTC – Litecoin

ETH – Ethereum

XRP – Ripple

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Introduction

Background

Investors and portfolio managers are constantly analysing financial instruments' characteristics for different purposes, such as providing a better return than a local/foreign market, given the same level of risk, or serving as a potential wealth protection tool in case that events such as the 2008 global financial crisis occur again. Over the years, precious metals such as gold and silver have proven to be the assets that have "store of value abilities" and a "negative correlation with the American dollar which makes [them] useful for hedging". (Capie, Mills, & Wood, 2005; A. Dyhrberg, 2016; McCown & Zimmerman, 2006)

At the end of 2008, however, the bitcoin - a "peer-to-peer electronic cash system" (Nakamoto, 2008) was introduced to the world. In its essence, the so-called cryptocurrency was invented with the purpose of becoming the digital alternative or even substitute to the traditional mediums of exchange – the fiat currencies. The invention was also the first one to resolve the issue of double-spending (Brito & Castillo, 2013; Chuen, Guo, & Wang, 2017). The event of double spending is typical of the digital world and it originates from bitcoin's characteristic as a decentralised currency, i.e. the users are the ones who store the transactions' history. In contrast, until now money transactions have been controlled by the well-established financial institutions. Therefore, should cryptocurrencies get accepted as a main currency, those institutions will become unnecessary in payments management. (Nakamoto, 2008)

For the past decade, Bitcoin laid the foundations for the creation of thousands of alternative cryptocurrencies, also known as altcoins, such as Ethereum, Ripple and Litecoin (Coinmarketcap, 2020). They try to emulate and build up on bitcoin's structure and functions by avoiding particular downsides of it (see for example the "yellow paper" by Wood (2014) for detailed description of Ethereum's structure). The evolving idea of cryptos becoming the money of the future started generating significant publicity and reached its peak in 2017, as the crypto – market's value and trading volume were growing at extreme daily rates, and bitcoin's price was leading the trend (Pollock, 2019). However, the hype was short-lived, with immense losses taking place in the following year. The high volatility caused significant concerns amongst investors about digital currencies' credibility (Xiang, 2018).

Considering the wider context, although the Basel III Agreement of 2010 (BCBS, 2010) and the Dodd-Frank Act (DFA) (Afonso, Blank, & Santos, 2018; Mohanty, Akhigbe, Basheikh, & Khan, 2018) were the main measures in response to the crisis of 2007-09 (BIS, 2019a), only partially have those resolved the issue. (Calluzzo & Dong, 2015). The current vulnerability of the financial system is expressed in the higher probability of a "systemic contagion", due to banks' increased interrelationships, which ultimately leads to a higher "systemic risk" (Acharya, 2009, p. 224). Moreover, the proposed loosening of the Volcker Rule (Cheng, 2018) (essential part of the DFA) was recently approved (Hamilton & Bain, 2019; O'Donnell, 2019). As a consequence, dozens of banks regain responsibility in investing their own money in the short-run, a practice known as proprietary trading, which causes significant concerns amongst analysts and investors. (Armstrong, 2019). Therefore, gold's (Baur & Lucey, 2010) and cryptocurrencies' (Baur et al., 2018) proven lack of correlation to the traditional stocks is a significant incentive for investors and researchers to further analyse both assets' characteristics and future importance.

Beneficiaries

This piece of research and its results intend to not only extend the available knowledge on the topic of cryptocurrencies, but also to provide an up-to-date picture of the assets' behaviour. The use of time series analysis provides a robust statistical framework that identifies a consistency in assets' behaviour examined over time. This consistency can be exploited and potentially turned into a profit or to improve the management of risk.

The current research achieves significant objectivity, due to the predominant focus on the comparison of price movements, given a number of economic factors. Moreover, the approach is aimed at quantifying the results as much as possible so that not only the emotional involvement is removed, but also the repeatability of the process is ensured.

Ultimately, this analysis could help researchers, investors, portfolio/risk managers and any other interested parties obtain a deeper understanding of this new type of assets, that will enable them to make better-informed decisions for their own projects/goals.

The next chapter sets the research aim, which outlines the purpose of the current work and the objectives that need to be executed in order to achieve the main aim. After the results are obtained, a concluding chapter provides a summary of the arguments expressed throughout the work followed by a discussion on the findings of the research. A final chapter highlights the limitations of the current work and develops recommendations for further research on the topic.

Research Aim and Objectives

This paper is aimed at analysing cryptocurrencies' characteristics as a hedge- or a safe haven tool when compared with those of precious metals under the current economic conditions. To achieve this, a set of objectives will serve as a structured guide of the research process that will lead to a valuable outcome:

Objective 1.

Critically assess prior research, such that:

- Reveals the past research done on precious metals' behaviour (gold's and silver's in particular) in order to establish a hypothesis for their performance in the current work;
- Examines relevant aspects of 4 major cryptocurrencies – Bitcoin, Litecoin, Ethereum and Ripple to determine effective analysis methods that will be applied in this piece of work
- Undertakes a comparison of both asset classes' behaviour between one another and with other instruments
- Outlines digital currencies' properties for portfolio management purposes

Objective 2.

Create a relevant data set. Data will be:

1. extracted from online financial sources such as Yahoo Finance and Investing.com;

2. adjusted in such a way that each asset is represented by an equal number of observations in order to avoid data mismatches and miscalculations.

Objective 3.

Critically analyse the returns performance of cryptocurrencies compared to other assets (similar to Baur et al. (2018)). This objective comprises:

- Constructing a correlation matrix for all the extracted and formatted time series
- Applying the statistical model GJR - GARCH (*Generalised Autoregressive Conditional Heteroskedasticity*) of Glosten, Jagannathan, and Runkle (1993), to provide an insight into the asset prices' behaviour over the sample time period.
    - Additionally, the US dollar trade-weighted index will be added to the model as an external regressor to analyse the extent of dependence of the assets' price movements on those of the dollar.
- Identifying hedging or "safe haven" properties of the four cryptocurrencies as well as of the two precious metals.

Objective 4

Discuss the findings in a separate chapter in order to draw a conclusion on cryptocurrencies' potential to become an alternative for investors in times of capital market volatility.

- And finally, develop recommendations for practice

Literature Review

This chapter provides an analysis of the already published papers that analyse the use of precious metals' and/or cryptocurrencies' characteristics as investment tools. They will not only provide an insight into the extent and depth of the available research but also will clarify where the current work positions itself relative to the existing pool of knowledge. The beginning of the chapter examines the analyses of gold and silver, which is then followed by those of cryptocurrencies.

Gold and Silver – hedging tools

Gold's value has been revered throughout a big part of human history, dating as far back as ancient Egypt. (Morrell, 1940, p. 22) For a while though, as the gold standard was abandoned in 1971, the precious metal started losing its function as a value unit.

(Irwin, 2013) It was not until 1999 when the emergence of the Central Bank Gold Agreements allowed its participants (predominantly Western Central Banks) to negotiate between each other the volumes of gold sold for the upcoming 5 years. In a press release of The Swiss National Bank, "g*old remains an important element of global monetary reserves*" and their most recent aim was to "*avoid market turmoil*" (SNB, 2014). The latter, however, according to Manly (2019), contradicts gold's nature of being a safe haven in extreme market conditions. Furthermore, the Basel III post-crisis reforms report regards the gold bullion as a risk-free asset, similar to cash reserves (BCBS, 2017).

For the past decades, gold and silver were considered to have similar market characteristics. (Adrangi, Chatrath, & Raffiee, 2003; Emmrich & McGroarty, 2013) Using the stochastic process model Vector Autoregression (VAR), Lucey and Tully (2006) provide evidence of cointegration between both metals over the greater part of the research period (1978 – 2002). The multivariate approach of Adrangi et al. (2003) also supports their results. Therefore, Lucey and Tully (2006) conclude that Ciner's (2001) work is anomalous, as he fails to find significant statistical evidence to reject the null hypothesis of no cointegration between silver and gold in the period from 1992 to 1998.

Using "a battery of stochastic copulas" however, Boako, Tiwari, Ibrahim, and Ji (2018) produce results that resemble the above-mentioned work of Ciner (2001), which is in contrast to the well-established opinions for precious metals. In essence, the reason for applying statistical methods such as copulas is that they are able to model the marginal distributions of two assets so that their dependence structure can be identified together with any co-movements. Therefore, Boako et al. (2018) find significant "co-jumps" of gold returns with 8 stock markets across the world. The authors also note that the findings might be influenced by the herding behaviour of investors as well as the non-equal weighting of commodities as in the case of gold. Nevertheless, the produced results should still be taken into consideration before undertaking investment decisions.

Levin and Wright (2006) analyse gold's hedging properties with the help of "cointegration techniques" (Levin & Wright, 2006, p. 5) that utilise various regressors such as the US dollar inflation, US Consumer Price Index as well as factors related to other major "gold-consuming countries". Their work provides support "for the belief that gold is a long-term hedge against inflation", as well as a relatively weak tendency of gold prices to diverge from their long-term direction in the event of an economic shock. In addition, the belief in gold's characteristic as an inflation hedge finds support as far back as over 40 years ago - Feldstein (1978) show gold's, together with real estate's, positive reaction to inflation movements. Moreover, it was observed that both assets' behaviours still kept increasing in value even when inflation rates remained constant.

A further evidence of the hedging properties of precious metals is provided by Conover, Jensen, Johnson, and Mercer (2009), with gold having a "better stand-alone" performance than platinum and silver. Moreover, they mention that the demand for gold is "derived from non-industrial uses" (jewellery for example, especially in India (World Gold Council, 2019)).

Hammoudeh, Yuan, McAleer, and Thompson (2010) apply two types of GARCH models – vector autoregressive moving average- (VARMA – GARCH) and the more restrictive Dynamic Conditional Correlation GARCH (VARMA-DCC-GARCH). They further and more strictly analyse the interdependency, conditional volatility and correlation dependency of "the four major precious metals (i.e., gold, silver, platinum and palladium)" (Hammoudeh et al., 2010, p. 633) in the presence of economic shocks. The results identify significant long-run volatility sensitivity to historical shocks. The use of such models, particularly ARCH and GARCH, is explained by Engle (2001). He states that the increased demand for forecasting the size of errors of statistical models has resulted in them becoming "standard tools" (Engle, 2001, p. 157)of econometricians. Prior to their emergence, the predominantly used model was ordinary least squares, which assumes homoskedasticity, that is the expected value of the error terms when squared is constant or volatility does not change over time. However, some time series data show the opposite. Moreover, they tend to remain more / less volatile for a period of time, which is known as volatility clustering. This is where ARCH/GARCH come in an attempt to model those events so that better estimations of assets' performance can be made. Furthermore, macroeconomic data can be used as regressors to explain assets' price movements / dependencies. They are ultimately used to provide implications for portfolio hedging strategies. Therefore, the usage of the GARCH model fits into the current work's aim.

Bitcoin (BTC) – where it all started

Bitcoin's purpose to be a digital alternative to tangible money has been met with significant scepticism by influential individuals and financial institutions not only because of its nature (BIS, 2019b; Chen, 2018; Harris, 2018; Meakin & Robinson, 2018; Robinson, 2018; Torres, 2017), but also because of, presumably, serving as a facilitator of illegal trade (Foley, Karlsen, & Putniņš, 2019). On the other hand, supporters of the cryptocurrency emphasize on its characteristics that aim to improve some of the issues present in the current financial system. Examples of such are smaller transaction fees, trust-based structure (Andreessen, 2014; Dwyer, 2015), and the "first decentralised peer-to-peer payment network" (We Use Coins, 2020). Moreover, bitcoin can potentially cap inflation due to its limited supply, as argued by Milton Friedman (McCallum, 2015), which contrasts with Federal reserve's recent actions of expanding their balance sheet. (Suberg, 2019)

Value of bitcoin

Whilst there are allegations that bitcoin has no intrinsic / fundamental value (Bambrough, 2019; Cheah & Fry, 2015), Dow and Gorton (1993) postulate the same for money: "…money is valuable in equilibrium, even though it has no intrinsic value" (Dow & Gorton, 1993, p. 23) . Those statements are also mentioned by Luther and White (2014) who point out that "its value derives from nothing but expectations about its future value, but the same could be said of irredeemable government-launched monies"(Luther & White, 2014, p. 1). However, as the future value of an instrument is directly related to its present value, the statement seems to have an unsound premise. Moreover, they state that as bitcoin is irredeemable, the demand for it "is in no way tied to the usefulness of some underlying commodity. Rather it depends on:

(a) The eagerness of speculators to hold bitcoin as an asset, and
(b) The willingness of transactors to hold bitcoin as a medium of exchange." (Luther & White, 2014, p. 3)

Consequently, the factors above provide an explanation to why bitcoin's price has seen such extreme ups and downs over the past years. Bouri, Gupta, and Roubaud (2019) can also serve as a confirmation since they observe herding behaviour in the cryptocurrency market. Luther and White (2014) go on further to describe the ways companies start accepting bitcoin payments. Such integration could potentially lead to an increase in both businesses and private customers switching to the "non-state money" (Luther & White, 2014, p. 6) Additionally, Ali, Barrdear, Clews, and Southgate (2014) raise the topic of trust in the payments system by stating that "digital currencies have meaning only to the extent that participants agree that they have meaning" (Ali et al., 2014, p. 278). Moreover, Brito and Castillo (2013) point out in their book that the value of Bitcoin is "not derived from gold or government fiat, but from the value that people assign to it. The dollar value of bitcoin is determined on an open market, just as is the exchange rate between different world currencies" (Brito & Castillo, 2013, p. 4). Therefore, as soon as trust in the new method of payment is established, its price is expected to become less volatile, as in the case of fiat currencies' volatility.

With the current rate of technological improvements, cryptocurrencies can become the "cheaper alternatives to existing debit and credit card systems…in regular monetary systems" (Fry & Cheah, 2016, p. 344) Additionally, in Dwyer's (2015) detailed overview of bitcoin, it is stated that by enabling smartphones to make payments "there is no technical difference between using dollars and bitcoins" (Dwyer, 2015, p. 90), which suggests the future scalability opportunity of their usage. Nevertheless, as the number of users, therefore transactions, grows, it has been reported that crypto networks find it difficult to satisfy the demand, with bitcoin's network being one of the slowest processing time (Coinsutra, 2019).

Previous statistical analyses

Despite the fact that bitcoin is considered and called (crypto) currency, past works use different approaches to test its capabilities of serving as a currency or an asset and come up with some contradictory results. Literature on the digital currency's hedging characteristics follows further in this section.

Glaser, Zimmermann, Haferkorn, Weber, and Siering (2014) use Autoregressive Conditional Heteroskedasticity (ARCH) estimation, in an attempt to identify the intentions for investing in bitcoin predominantly amongst new and weakly informed users. Their results conclude that bitcoin is perceived as an asset rather than a currency, since even if more people buy bitcoin they simply hold it "for speculation purposes" (Glaser et al., 2014, p. 13), rather than spending it on goods and / or services. A similar conclusion to the speculative character of bitcoin was also drawn by Yermack (2015) in his book, arguing that the functions of money (a medium of exchange, unit of account and store of value) were not satisfied. However, the work and results of Özdemir, Tunçsiper, and Gültekin support the idea that assets such as bitcoin were not coincidentally called cryptocurrencies, exhibiting stronger relation with the fiat money rather than the commodities. These two aspects were also discussed by Bjerg (2016) who, on the one hand provides detailed analysis of the features and potential monetary applications of bitcoin and, on the other, he proposes "its current status as a monetary curiosity and a speculative asset". (Bjerg, 2016, p. 68)

Moreover, Clark and Mihailov (2019) analyse the 10 biggest cryptocurrencies by market capitalisation in terms of their volatility and price dynamics in order to later compare them with, first, those of the traditional assets – gold and money – regarded as international reserves and, second, the digital currencies issued by the central banks. The research states that the lacking trust in private currencies, the recent attacks and attempts of fraud prevent them from becoming a valid substitute of the above-mentioned assets. Moreover, the required amount of liquidity needed in the event of a crisis cannot be provided by the cryptos. Therefore, the authors conclude that digital currencies like bitcoin "do not meet the inherent requirements for both money and international reserve assets, whereas central bank digital currencies do meet these requirements." In contrast to this statement, Demir, Gozgor, Lau, and Vigne (2018) attempt to determine how well bitcoin's daily returns can be predicted by the economic policy uncertainty (EPU) index. By applying different models such as the Bayesian Graphical Structural Vector Autoregressive model and the quantile-on-quantile regression estimations, they conclude that the association with EPU is positive as well as significant at the higher and lower quantiles of both bitcoin and EPU, with negative correlations in the middling state. The findings suggest that the cryptocurrency is a suitable hedging tool in turbulent economic conditions. However, their statement that by using this index investors “can predict the returns of Bitcoin” (Demir et al., 2018, p. 147) applies only for the time frame that they have examined (September 2010 - November 2017). The period does not include the boom-and-bust months right after, which could have had a significant influence on the end results. Therefore, such propositions should be further confirmed before being trusted.

The introduction of futures contracts of bitcoin were intended to resolve the issue of extreme price movements. However, Corbet, Lucey, Peat, and Vigne (2018) propose that this action led to an increased interest from the broader and mostly uninformed public, which also significantly influenced bitcoin’s volatility. As a consequence, those contracts were not considered “an effective hedging instrument” (Corbet, Lucey, Peat, et al., 2018, p. 23). Nevertheless, Guesmi, Saadi, Abid, and Ftiti (2019) examine cryptocurrencies’ hedging and diversification capabilities using extended specifications of the DCC – GARCH model to find the best fitting one. By implementing the GARCH (p, q) model in her work, Dyhrberg (2016a) presents bitcoin’s weak correlation with gold and the US dollar. Later on she would present bitcoin’s hedging characteristics, similarly to gold (Dyhrberg, 2016b). However, the former research is criticised by (Baur et al., 2018) who replicate the sample data analysis. They find out that the undertaken approach (the used GARCH model) is not able to provide an answer to the research question.

Bitcoin has been further compared with the traditional assets and commodities in order to assess its characteristics for portfolio management purposes. (Al-Yahyaee, Mensi, & Yoon, 2018; Bouri, Molnár, Azzi, Roubaud, & Hagfors, 2017; Wu & Pandey, 2014) Moreover, in a research paper by Burniske and White (2017) it was reported that over the period 2012 – 2016 bitcoin was predominantly used as an investment, i.e. asset, rather than an actual currency. In addition, Baek and Elbeck (2015) attempt to reveal bitcoin’s market volatility as well as the drivers of its returns – the two key questions when it comes to assessing investment opportunities. Over the period 2010 – 2014 they find out that:

- standard deviation is 26 times greater than that of S&P 500 index;
- the regression analysis done on bitcoin to find its drivers shows significant buyers' and sellers' importance, whilst no statistical significance can be noted for the fundamental economic factors that typically influence stocks.

Consequently, those results are an indication of bitcoin's speculative character prior to the period analysed in the current research. These outcomes can be partially confirmed by Ji, Bouri, Gupta, and Roubaud (2018) who analyse a longer period (2010 – 2017) and extend the research on the causal relationships between BTC and other financial assets with the help of the data–driven approach "directed acylic graph" or DAG. They suggest that "the Bitcoin market is quite isolated, and no specific asset plays a dominant role in influencing the Bitcoin market."(Ji et al., 2018, p. 203) Still, lagged relationships between some assets and BTC were found during its bear market, suggesting that the integration process varies over time.

Liew, Ziyuan Li, Budavári, and Sharma (2019) investigate daily returns from 100 cryptocurrencies and report similarities with hedge fund returns in terms of the "beta-in-the-tails" hidden risk. For further information on tail risks in credit portfolios, see Yuan (2017). Additionally, the authors deduce that day trading of digital currencies "may be very challenging". The tails risk issue is also mentioned in other studies. Osterrieder, Lorenz, and Strika (2016) examine the top 6 cryptocurrencies ranked by capitalization for November 2016. The data shows the extreme volatility of the assets, exhibiting "heavier tail behaviour than the traditional fiat currencies". (Osterrieder et al., 2016, p. 91) In addition, Feng, Wang, and Zhang (2018) report increased left tail correlations between 7 cryptocurrencies after August 2016, which implies "growing systematic extreme risks" (Feng et al., 2018, p. 4745). Moreover, the results suggest that cryptos exhibit safe – haven properties, but not as good hedging properties as gold has.

Gronwald (2019) analyses periods of explosive behaviour of Ethereum and Bitcoin, as well as their "co-explosivity". In addition, he attempts to reveal the presence of a bubble on the cryptocurrency market, i.e. whether digital currencies diverge from their fundamental value. As a further reading on the topic of bubbles, Diba and Grossman (1988) analyse the existence of such on the stock market. His findings prove that a bubble is indeed extant on the crypto market, just as Cheung, Roca, and Su (2015) did in the past, using the procedure created by Phillips, Wu, and Yu (2011). Nevertheless, Gronwald (2019) criticises previous research that examine the existence of cryptocurrencies' bubble and obtain results for their fundamental value different from zero, whilst acknowledging exactly the opposite.

Blachman and Steffen (2019) assess bitcoin's suitability as an investment by pension funds and the associated with the process risks. Although they go through the currency's benefits, their final proposition is not to risk other people's savings in expectation of a higher return, rather it should be left to the versed individuals. Similar was the aim of Dyhrberg, Foley, & Svec (2018) who analyse the transaction costs and the intraday trading patterns of bitcoin, whose results conclude that it "is investible, particularly for retail sized trades" (Dyhrberg et al., 2018, p. 143). Moreover, the work of Trimborn, Mingyang, and Härdle (2017) takes a look into 39 cryptocurrencies in order to develop "a portfolio optimization method which accounts for volatility risk and low liquidity" (Trimborn et al., 2017, p. 3). They take the well-known idea of Markowitz for portfolio formation and then add the restriction not to assign high weights on cryptocurrencies with lower liquidity. Their observations conclude that inclusion of cryptos "can improve the risk-return trade-off of portfolio formation" (Trimborn et al., 2017, p. 23). Furthermore, Bouri, Azzi, and Dyhrberg (2017) attempt to find a relationship between bitcoin's return and volatility before and after its price crash of 2013. The results reveal that bitcoin has had safe haven properties before 2013, but not after that. Still, the research provides evidence of risk reduction of a portfolio when bitcoin is included in it, due to its negative relationship with the US implied volatility index (VIX). Nevertheless, the authors advise caution in cases of undertaking investment decisions in view of the almost absent liquidity. Moreover, by applying the BEKK-GARCH model (BEKK – Baba, Engle, Kraft and Kroner (Francq & Zakoian, 2019)) to estimate conditional correlations over time, Klein, Pham Thu, and Walther (2018) find out that bitcoin does not resemble Gold and Silver in any aspects. It has rather positive correlations with downtrend markets. Therefore, they conclude that the digital currency cannot be used as a hedge or a safe haven as the precious metals in a portfolio.

Going forward in time, the study of Smales (2019) proves what was mentioned above by Bouri et al. (2017) by looking into the recent performance of bitcoin and tries to identify safe haven properties of bitcoin when compared with gold - “the traditional safe haven” (Smales, 2019, p. 385), S&P 500 stock index and stocks. His results show higher volatility and transaction costs, together with lower liquidity. The author ultimately states that despite the low return correlations with the other financial assets, which is suitable for portfolio management, as well as the indications of market maturity, it is not recommended to consider bitcoin as a safe haven yet. Nevertheless, these statements are in contrast with Guesmi et al. (2019). They show that by including bitcoin to a portfolio composed of commodities, such as gold and oil, as well as equities, the portfolio’s risk is considerably reduced.

Jiang, Nie, and Ruan (2018) analyse bitcoin market’s time-varying long-term memory and mainly due to its emerging character the results indicate its inefficiency, also proven by, Bariviera (2017) and Al-Yahyaee et al. (2018). Furthermore, Wei (2018) examines more than 450 cryptocurrencies with the help of the R/S Hurst exponent to find out diminishing predictability of their returns as the market liquidity increases. Therefore, the sign of efficiency in bitcoin returns can be justified, while others “still exhibit signs of autocorrelation and non-independence” (Wei, 2018, p. 21). As a conclusion they state that liquidity “plays a significant role in market efficiency and return predictability on new cryptocurrencies” (Wei, 2018, p. 21). However, Urquhart (2016) states that as the analysed period is broken into subsamples, bitcoin is inefficient in the initial ones, while in the latter it exhibits efficiency, therefore he concludes that bitcoin is in a transition stage to efficiency. Moreover, his conjecture has been corroborated by Brauneis and Mestel (2018). Their findings show that out of the 10 biggest cryptocurrencies bitcoin is the most efficient, with market capitalization again implying greater efficiency, i.e. weaker predictability.

In contrast, other papers propose that the observed higher returns compensate for the additional risk taken by investors (Brière, Oosterlinck, & Szafarz, 2015; Gasser, Eisl, & Weinmayer, 2015; Stensås, Nygaard, Kyaw, & Treepongkaruna, 2019) However, according to Loi (2018) who analysed five bitcoin exchanges using five liquidity measures, over the period from 2014 to 2015 bitcoin still remained less liquid than stocks.

The research does not end at the statistical significance of cryptocurrencies' returns or prices. There is also a continuous discussion by big financial institutions on the exact definition of the digital invention, with changes to it still taking place. (European.Central.Bank, 2012, 2015, 2019)

Such thorough investigations shed light upon bitcoin's imperfections and places for improvement, which provides opportunities for alternatives or the so-called altcoins to compete on the newly - emerged market. This, consequently, sparked researchers' interest in answering the question: Is there any relationship between them at all? On that note, Ciaian, Rajcaniova, and Kancs (2018) test two hypotheses of how prices of bitcoin and 16 other virtual currencies form. They show that, first, bitcoin does drive altcoins' prices and, second, it is more so in the cases where the extent of the structure similarities between altcoins and bitcoin is greater. However, this is true only for the short-term, whilst in the long-run bitcoin cannot influence their prices.

The following sections reveal the research done on the remaining 3 cryptocurrencies mentioned above.

Ripple (XRP)

The emergence and evolution of this cryptocurrency, as stated by Armknecht, Karame, Mandal, Youssef, and Zenner (2015) was independent from bitcoin's influence which can be also deduced from its structure, described in detail by Moreno-Sanchez, Modi, Songhela, Kate, and Fahmy (2018). One of the main advantages Ripple has is its much faster transaction speeds - 1500 transactions per second compared with bitcoin's 6. (Ripple, 2019) Nevertheless, its structure is not as decentralised as that of bitcoin, rather it is an incremental change to the existing financial system (Dierksmeier, 2018) which causes safety concerns. (Armknecht et al., 2015; Di Luzio, Mei, & Stefa, 2017).

Although Ripple's market capitalisation as of the time of writing (January 2020) is the third largest on the market, it drew researchers' attention as it reached the second place in the past. Fry and Cheah (2016) examine and confirm the existence of negative bubbles of bitcoin and ripple, that is, in contrast to the well - known speculative bubbles which tend to drive the prices upwards, this one does the opposite. However, an interesting fact is that a spill-over effect was observed from XRP to BTC. Moreover, concerns over Bitcoin’s dominance on the market were expressed, mainly due to its highly volatile nature.

Litecoin (LTC)

The next digital currency is inspired by bitcoin, but its advantages are lower transaction costs as well as faster transactions speeds – 2.5 minutes for a Litecoin block to be generated, while bitcoin takes 10 minutes. (Coinsutra, 2019; Meholm, 2018) In spite of this, it appears that those advantages are not the sole factors that determine the success of a currency. For example, Gibbs and Yordchim (2014) show in their qualitative survey that although both bitcoin’s and Litecoin’s characteristics are the same, Thai people regard Bitcoin as a better option just because of its higher spot price.

As Yi, Xu, and Wang (2018, p. 101) deem LTC as one of the “top – tier” cryptos next to Ripple and Bitcoin, their research aims to find the extent of volatility connectedness between 52 digital currencies. They conclude that the volatility of “mega – cap” cryptocurrencies tends to have a big impact on the smaller ones, with some exceptions such as the Maidsafe Coin.

Tu and Xue (2019) investigate the volatility spill-over from bitcoin to Litecoin between the period 2013 – 2018. They divide the data in two periods – before and after 1. August 2017 – this is the first date on which bitcoin was bifurcated. According to the results before this date, bitcoin has had significant pricing influence on the cryptocurrency market. However, during the remaining year after the event has taken place, the trend has drastically weakened.

Ethereum (ETH)

In contrast, Ethereum’s transaction speed might also be high, but is currently facing scalability problems (Wood, 2014). In addition, as Bartoletti, Carta, Cimoli, and Saia (2020) put it, the cryptocurrency world is becoming the new opportunity for Ponzi schemes, with Ethereum’s smart contracts being their main focus.

As the issue of bubbles in a market were previously discussed, Corbet, Lucey, and Yarovaya (2018) apply the same methodology of Phillips et al. (2011) in order to identify potential pricing bubbles of Bitcoin and Ethereum. Their findings conclude that over the period since Ethereum's release in mid-2015 no evidence of ETH bubbles was observed, which is in contrast to BTC which appears to be in one since its price broke above the $1000 mark. However, due to their close structure and features, the authors state that the influence of one crypto's price movements on the other can be identified for brief periods only. Moreover, they propose that those statistical results do not suggest that the prices are "correct", rather it is the absence of statistical indicators to prove it otherwise.

In a research done by Sovbetov (2018), Ethereum was compared with 4 other major cryptocurrencies in terms of the factors that influence their prices. What he discovers is that the crypto market's own factors such as the market beta, trading volume and volatility play significant roles in all assets' pricing not only in the short- but also in the long-run. However, attractiveness also turns out to be of importance in this case, in other words, the time factor is also influential. Additionally, Mensi, Al-Yahyaee, and Kang (2019) apply four generalised autoregressive conditional heteroskedasticity models in order to identify structural breaks and the levels of double long memory of Ethereum and bitcoin price returns. For further information on the long memory in time series topic, see Granger and Joyeux (1980). The authors state that the results are at odds with the random walk as well as the market efficiency hypothesis. Furthermore, their decentralized character implies a higher volatility, which must be accounted for by investors when undertaking hedging strategies.

Regarding hedging properties and volatility transmission, Beneki, Koulis, Kyriazis, and Papadamou (2019) investigate exactly those two between bitcoin and Ethereum. They apply the previously mentioned multivariate BEKK – GARCH and the VAR model to reveal "a delayed positive response of Bitcoin volatility on a positive volatility shock on Ethereum returns" (Beneki et al., 2019, p. 219). Moreover, the authors mention that the diversifying characteristics observed in the initial period have declined after the bubble burst of both assets in the beginning of 2018. The idea of a bubble presence on the crypto market and its risks has been provided by Fry (2018) who finds such both in Bitcoin and

Ethereum. However, he refrains from suggesting an upcoming bust, “as bubbles are not a necessary pre-requisite for boom – bust episodes to occur” (Fry, 2018, p. 228), and similarly does Corbet et al. (2018) by concluding that Ethereum’s price dynamics do not imply explosive bubbles.

One significant drawback of digital currencies, however, is their reliance on a digital network, making them vulnerable to power outages or hacker attacks. Theoretically, in the extreme case of a global electricity shortage, none of them could serve as a unit of account or exchange. However, it could be argued that traditional currencies have this drawback as well, since, in the case of the British pound: “of the two types of broad money, bank deposits make up the vast majority – 97% of the amount currently in circulation” (McLeay, Radia, & Thomas, 2014, p. 15)

Summary

Overall, the opinion on gold’s and silver’s hedging capabilities is mostly supported by researchers, however, there are some works that fail to prove this feature. The cryptocurrency bitcoin was intended to become the epitome of fiat money in the digital world, but without the need for a controlling institution, having lower transaction fees and potentially halting inflation due to its limited supply. A multitude of previous research analyses its properties, argued for and against its real value as well as outlined its advantages and disadvantages. The majority of them, however, deduce that not only bitcoin, but also the newer cryptos mentioned above are highly volatile and despite their higher-than-usual returns, care should be taken when investment decisions are considered, especially when liquidity is lower.

The current work aims to build up on Baur et al. (2018) and their replication study of Dyhrberg (2016a) by analysing the most recent price developments of the 4 cryptocurrencies mentioned above and comparing them with that of commodities, fiat currencies and stock indices. Thus, it can be determined to what extent the past conclusions about cryptocurrencies’ performance and suitability as an investment have altered or no actual change has taken place.

The following section provides explanations on the differences and similarities of the data collected and research methods undertaken in the current work with those of Baur et al. (2018).

Methodology

The main goal of this chapter is to present the gathered secondary data, as well as the research methods that will be applied to achieve the aim of this paper. Having reviewed the previous literature, quantitative research methods are most common, as they are attempting to identify statistical dependencies between the returns and the volatility of financial assets. Therefore, the current topic also adopts this method.

To conduct the research, as stated in the objectives chapter, the statistical model GJR-GARCH will be applied. The reason for choosing a type of GARCH model is not only due to its frequent usage in other related to the topic academic works (Guesmi et al., 2019; Hammoudeh et al., 2010; Klein et al., 2018), but also its formula gives key information about the assets' dependence on historical returns and volatility for the given sample time frame. In addition, the researcher is capable of assigning weights to multiple past periods, in order to potentially find a more complex dependence structure, which ultimately improves the validity and accuracy of the results as well as the quality of the predictions made. Furthermore, the specific type GJR (Glosten et al., 1993) is capable of accounting for "the asymmetric effect of positive and negative shocks, and volatility persistence" (Baur et al., 2018, p. 108), which matches exactly the purpose of this work, i.e. how cryptocurrencies and precious metals react to negative shocks in comparison with stock indices and forex.

To obtain reliable results and make conclusions out of them, the R language and its powerful features and packages will be utilised. Since certain preconditions have to be met before undertaking the analysis itself, this chapter will adopt a step-by-step approach, such that the initial steps will also be accompanied by their results in the chapter. Thus, the paper will:

- become easier to follow;

- enable readers to repeat the process with the same or different data according to their needs, ensuring the generalisability of the research;
- provide justifications as to how each step was undertaken, which will eventually facilitate understanding the main findings discussed in the final chapter.

Data Collection

The predominant online database used to extract the above–mentioned price movements is Yahoo Finance (2020), due to its free access in contrast to other and more costly databases such as DataStream and Bloomberg. In the remaining cases (Gold, Silver and LIBOR rates), data's sources are added in brackets.

Cryptocurrencies data

The secondary data to be collected is historical daily closing prices taken at midnight, GMT of the following cryptocurrencies:

- Bitcoin (BTC / USD);
- Ripple (XRP / USD);
- Litecoin (LTC / USD);
- Ethereum (ETH / USD)

Data details

In the current research, the time series data for Bitcoin, Litecoin and Ripple spans from 17th of September 2014 until the 27th of November 2019, amounting to 1898 days. The only exception is Ethereum as its Initial Coin Offering (ICO) took place in the middle of 2015 (Ethereum.Blog, 2015). Consequently, the data observed starts from the 7th of August 2015 and comprises 1574 days.

A brief summary of the four Cryptocurrencies over the period is given in Table 1 below:

	BTC / USD	*XRP / USD*	*LTC / USD*	*ETH / USD*
Min	178.1	0.00409	1.157	0.4348
1st Quarter	410.6	0.006955	3.646	11.221
Median	1266.3	0.03518	13.502	153.2142
Mean	3700.1	0.226722	44.039	205.5489
3rd Quarter	6621.4	0.321274	62.177	291.4663
Max	19497.4	3.37781	358.336	1396.42

Table 1 Closing prices information.

The reasons for including these 4 cryptocurrencies are their longer price history and greater liquidity levels than the majority of the newly emerged ones. Should some of the latter be included in the research, they might distort the findings of the current work, as already discovered in prior research (Wei, 2018). Moreover, once their liquidity improves, the conclusions drawn here could become obsolete shortly after. In addition, although Tether has the most liquidity according to Coinmarketcap (2020), it was not taken into consideration due to a fraud scandal followed by a lawsuit over its real value. (Kelly, 2019)

Macroeconomic factors' data

Due to the fact that Baur et al. (2018) are producing a replication study to Dyhrberg (2016a), the explanatory variables used are similar to the ones in her work. For the alternative approach, however, they have added the MSCI World Index and trade-weighted currency indices (USD and EUR). In the current work, the variables utilised are the following:

- Euro - US dollar (EUR/USD),
- British pound - US dollar (GBP/USD) and
- US dollar – Swiss franc (USD/CHF) daily exchange rates;
- The COMEX gold futures rates (XAU/USD) for a troy ounce (replacing CMX gold futures 100-ounce rates in USD in Dyhrberg's work; source: Investing.com (2020a));
- The Overnight rates of the London Interbank Offered Rate (LIBOR) (replacing the Federal Funds rate; source: Iborate.com (2020)).

- Silver futures (XAG/USD) for a troy ounce denominated in USD (source: Investing.com (2020b));
- The S&P 500 Index;
- The DAX 30 Index and
- The US dollar Trade-weighted index, used as external regressor (FRED Economic Data, 2020).

The additional foreign currency (Swiss franc) and major indices will broaden the scope of the research in a geographical way in order to establish to what extent other significant economies influence price evolution of cryptocurrencies. This has been noted by Dyhrberg whose results suggest that “regional or country specific effects are present” (Dyhrberg, 2016a, p.90). Even though her research approach was proven misleading, the current work’s outcomes could provide a hint of the validity of Dyhrberg’s statement.

Trading times across assets

There is an important aspect of comparing time series of cryptocurrencies with those of traditional stocks and commodities. Due to the fact that cryptocurrencies do not require physical exchanges, they are traded round the clock. In contrast, stocks, commodities and fiat currencies can be traded only during certain opening times on workdays.

Baur et al. (2018) use time series data that assume returns only on business days across all assets, with 0 assigned to the remaining observations. In this paper, however, to achieve a smooth transition between time gaps, the missing observation dates for the exchange-traded assets were filled using interpolation. In order to create a universal database, the process is as follows:

- Save the Internet-extracted time series as “csv” files;
- converted to “xlsx” files (Excel) whereby the “Match” function revealed the missing dates which were then fitted chronologically to the time series;
- converted back to “csv” to be used in R;

Ultimately, the interpolation function is called by:

F_GOLD <- na.approx (gold_all_xts) (an example with gold futures' price movements).

The 8 traditional assets' time series have an equal number (1898) observations as the above-mentioned cryptocurrencies, except for Ethereum, as already discussed. A summary of the traditional assets' data is presented in Table 2 below:

	GOLD	SILVER	LIBOR	SnP500	DAX	EURUSD	GBPUSD	USDCHF
Min	1071	13.67	0.0808	1829	8572	1.039	1.202	0.8544
1st Quarter	1256	15.39	0.366	2088	10560	1.103	1.285	0.9651
Median	1303	16.41	0.9282	2379	11598	1.127	1.323	0.9839
Mean	1304	16.4	1.0455	2414	11447	1.137	1.371	0.9796
3rd Quarter	1350	17.19	1.8256	2739	12363	1.165	1.469	0.9955
Max	1560	20.67	2.4028	3154	13560	1.296	1.644	1.0302

Table 2 Traditional assets' data.

And Table 3 presents the first 6 lines of the interpolated data points:

	GOLD	SILVER	LIBOR	SnP500	DAX	EURUSD	GBPUSD	USDCHF
2014-09-17	1362	18.663	0.091	2001.57	9661.5	1.295908	1.626598	0.9327
2014-09-18	1353.4	18.452	0.0907	2011.36	9798.13	1.285	1.62681	0.94229
2014-09-19	1343.1	17.781	0.0912	2010.4	9799.26	1.292006	1.643709	0.93435
2014-09-20	1343.467	17.777	0.0909	2005.03	9782.687	1.289385	1.639802	0.93629
2014-09-21	1343.833	17.773	0.0906	1999.66	9766.113	1.286763	1.635894	0.93823
2014-09-22	1344.2	17.699	0.0903	1994.29	9749.54	1.284142	1.631987	0.94017

Table 3 Regressors data after interpolation. (21^{st} of September 2014 was Sunday)

Research methodology

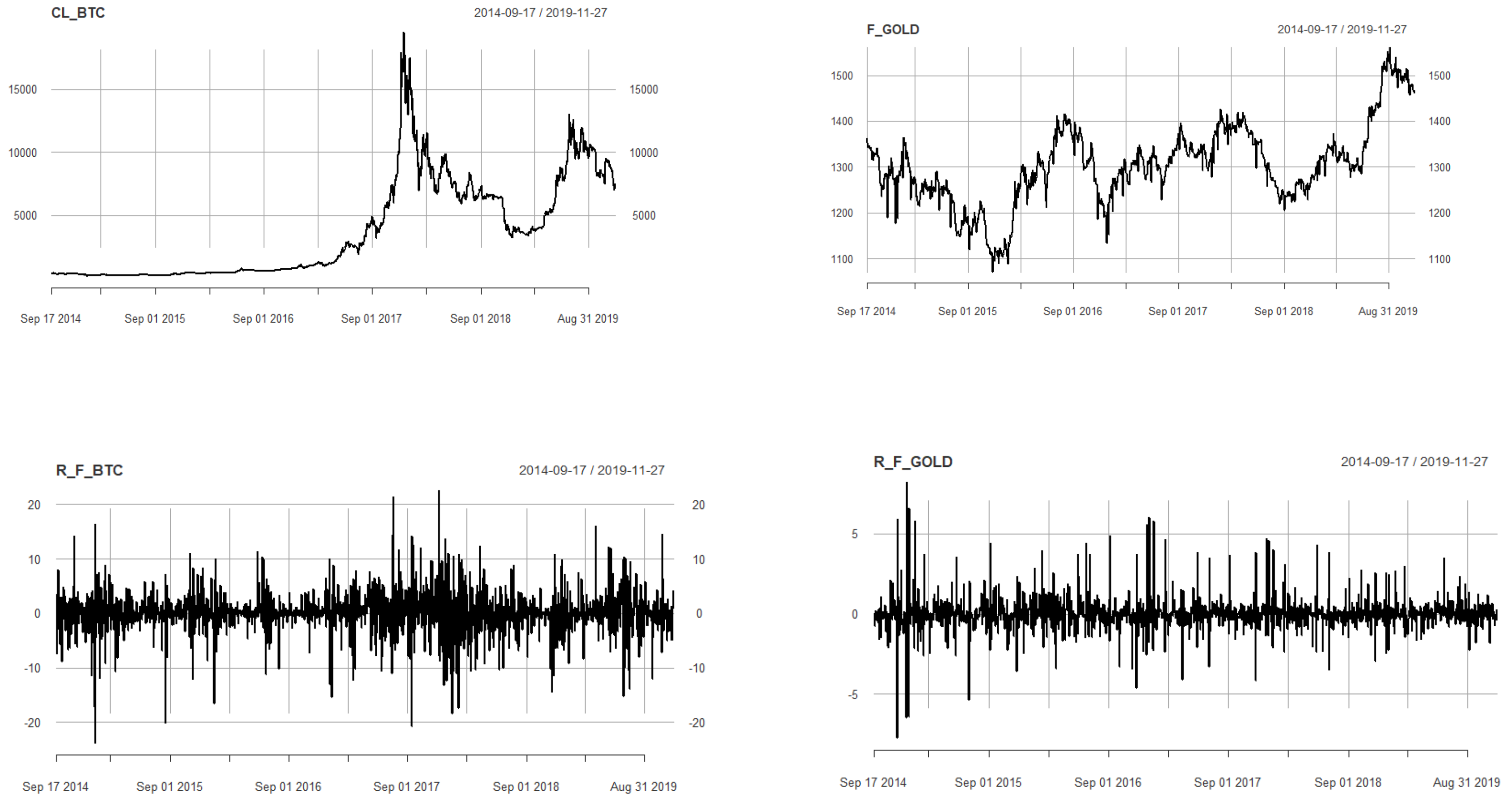
The sample period taken by Baur et al. (2018) shows clearly that bitcoin's returns are at some points 10 times higher than traditional assets'. It is important to notice here the fact that their sample ends mid-July 2017, which is still prior to the extreme breakout at the end of the same year. On Fig.1 below, Bitcoin's updated returns and closing price charts are presented next to Gold's, EURUSD's and SnP500's. For price- and returns charts of the other three cryptos, see Appendix 1.

What the graphs reveal is that, first, Bitcoin's price movement has a completely different pattern, and second, returns have remained well above all other assets, with Gold being the second most volatile, but its returns are still times smaller (on the graphs below, R_F_GOLD has a maximum value no bigger than 8%, while R_F_BTC reaches about 22%)

It can be also clearly observed, that all assets show:

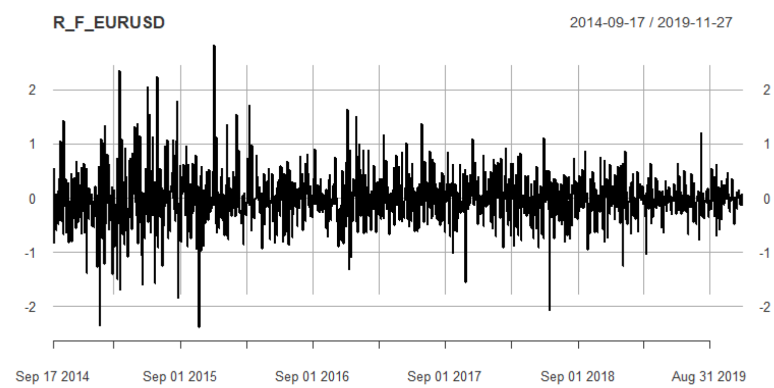
a. some sort of a time-dependent trend, which, given the definition of stationarity by Manuca and Savit (1996, p. 3), provides evidence of non-stationarity.
b. periods of high / low returns, or volatility variability (Enders, 2008) that will be further analysed in this work (e.g. bitcoin's returns during September 2016 vs end of 2017).
c. The graphs of the returns are produced by taking the logged first differences of the closing prices and then multiplying them by 100, just as per Baur et al. (2018, p. 107). Due to the fact that returns are being examined, the number of observations is reduced by 1, i.e. 1897 (1573 for Ethereum). Taking bitcoin as an example, the function used is:
d. R_F_BTC <- diff (log (CL_BTC)) * 100.

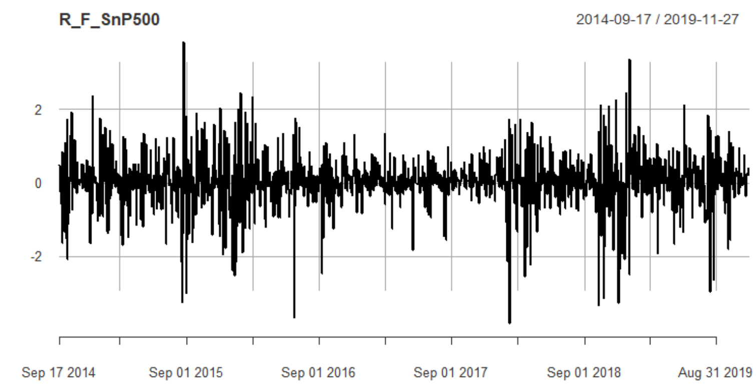
Fig. 1. *Closing prices (top) / returns (bottom) plots (all denominated in USD)*




F_EURUSD
2014-09-17 / 2019-11-27
1.25
1.20
1.15
1.10
1.05
Sep 17 2014
Sep 01 2015
Sep 01 2016
Sep 01 2017
Sep 01 2018
Aug 31 2019


F_SnP500
2014-09-17 / 2019-11-27
3000
2800
2600
2400
2200
2000
Sep 17 2014
Sep 01 2015
Sep 01 2016
Sep 01 2017
Sep 01 2018
Aug 31 2019


R_F_EURUSD
2014-09-17 / 2019-11-27
2
1
0
-1
-2
Sep 17 2014
Sep 01 2015
Sep 01 2016
Sep 01 2017
Sep 01 2018
Aug 31 2019


R_F_SnP500
2014-09-17 / 2019-11-27
2
0
-2
Sep 17 2014
Sep 01 2015
Sep 01 2016
Sep 01 2017
Sep 01 2018
Aug 31 2019

On Table 4 below, the summary statistics of all the time series is presented. As some of the returns were already graphically shown, it is no surprise that the cryptocurrencies record approximately 10-times bigger mean returns than all other assets (between 0.12% and 0.26% for the cryptos and just 0.02% for the first performer S&P 500), with the exception of LIBOR rates (0.15%). Despite the graph below, however, Gold does not stand out with a significantly larger mean return. This could potentially be explained by the reasonably favourable global economic conditions over the period, that did not invoke "flight to quality" events, or by the sale limit strategy that the banking "cartel" (Manly, 2019) employed in order to prevent the gold prices from rising. The significant mean returns are also accompanied by larger standard deviations, that are again times higher for the digital currencies. The overnight LIBOR also come first among the other assets, and the important thing in this case is that it still has a smaller standard deviation than Bitcoin, given their almost identical mean returns.

The next section will present the results from conducting three types of analysis, suggested by Baur et al. (2018):

- Correlation matrix presenting the relationships between all assets given the sample time frame;
- GJR-GARCH (1,1) statistical model applied to each asset;
- The same GJR-GARCH (1,1) model with included US dollar trade-weighted index as an external regressor in the mean equation

Detailed explanations of the approaches above and discussions of the corresponding outcomes are provided immediately after each table.

Table 4

Descriptive Statistics for all assets (legend for the AR(1) significance levels provided below)

	Mean	*SD*	*Min*	*Max*	*Skew*	*Kurtosis*	*Std. error*	*AR(1)*	*Obs.*
BTC	0.148	3.88008	-23.756	22.5119	-0.2875	5.19633	0.08909	0.0078	1897
XRP	0.197	6.67006	-61.627	102.736	2.94401	42.9698	0.15314	0.0108	1897
LTC	0.119	5.71943	-51.458	51.1417	0.70684	13.7675	0.13132	0.0156	1897
ETH	0.255	7.20331	-130.29	41.0335	-3.4188	70.6945	0.18162	0.0526*	1573
GOLD	0.004	0.97917	-7.7425	8.20928	0.76374	14.4687	0.02248	-0.0829***	1897
SILVER	0	1.37449	-7.5984	12.0505	0.19169	6.778	0.03156	-0.1294***	1897
LIBOR	0.149	2.897	-29.645	86.7422	15.9788	467.579	0.06651	0.0291	1897
SnP500	0.024	0.64937	-3.8259	3.82913	-0.504	5.7838	0.01491	0.0591**	1897
DAX	0.017	0.86332	-7.0673	4.85206	-0.3604	5.35448	0.01982	0.0464*	1897
EURUSD	-0.01	0.41012	-2.3817	2.81453	0.2585	5.4652	0.00942	0.0308	1897
GBPUSD	-0.01	0.44348	-2.8047	2.84796	-0.094	6.10802	0.01018	0.0702**	1897
USDCHF	0.004	0.56283	-17.611	2.47097	-16.206	504.63	0.01292	0.0282	1897

Significance levels for p: (…) – 0.05; (*) – 0.01; (**) – 0.001; (***) – 0

Findings and discussion

Following Baur et al.'s approach, a matrix with the unconditional correlations for all assets is produced whose results can be seen on Table 5 below. The first thing to be noticed (and rather expected) is the highly significance levels of correlation between the four cryptos' returns. To get an idea of the extent of this significance, when non-rounded, the "highest" p-value is recorded by the Ethereum - Ripple correlation pair, which has 25 zeros after the decimal point. In contrast, as Litecoin is based on the Bitcoin's structure, the pair has 196 zeros. The complete t-test and p-value tables that led to the results are available in Appendix 2.

Table 5

Unconditional correlation matrix for all assets with provided significance levels (legend below)

	BTC	*XRP*	*LTC*	*GOLD*	*SILVER*	*LIBOR*	*SnP500*	*DAX*	*EURUSD*	*GBPUSD*	*USDCHF*	*ETH*
BTC	1											
XRP	0.328***	1										
LTC	0.614***	0.353***	1									
GOLD	0.06*	-0.005	0.01	1								
SILVER	0.026	0.026	0.009	0.394***	1							
LIBOR	-0.017	0.028	-0.007	-0.035	-0.046 ...	1						
SnP500	0.011	0.05 ...	0.025	-0.081***	0.008	-0.032	1					
DAX	0.008	0.037	0.008	-0.155***	-0.04	0.039	0.524***	1				
EURUSD	-0.004	0.033	0.016	0.029	0.033	-0.043	0.007	-0.019	1			
GBPUSD	-0.025	0.021	-0.009	-0.007	0.014	-0.019	0.045 ...	0.071*	0.52***	1		
USDCHF	-0.006	-0.032	-0.039	-0.02	-0.059 ...	0.031	-0.041	0.001	-0.485***	-0.271***	1	
ETH	0.421***	0.26***	0.408***	0.043	0.014	0.001	0.023	-0.006	0.009	0.003	-0.026	1

Significance Levels	***	**	*	…
	0	0.001	0.01	0.05

It is suitable to remind here that the correlation coefficients of Ethereum (shaded in orange) with the other assets is calculated during the period for which ETH data points are available, i.e. the correlations are based on 1573 observations for each of the remaining assets as well.

The matrix above also reveals that the correlations of Bitcoin with the other assets is small and insignificant. A similar outcome was also observed by Baur et al. (2018). One different aspect in the current work is that, rather than USD, the euro and GB pound from the respective pairs are the ones under analysis. Therefore, the actual correlation of the US dollar for those pairs with bitcoin is small, but positive.

In their work, however, bitcoin has little and insignificant correlation with gold futures, both daily and weekly, whereas here, the daily observations of the pair have a correlation significant at the 1% level. This result could be indicating that currently there is an ongoing alteration of bitcoin's behaviour and sensitivity to market conditions. Nevertheless, the observed value might also be due to sampling bias, since in Baur et al. the period analysed spans from 2010 to mid-2017, whereas here it is from the end of 2014 to the end of 2019, i.e. there are less than 3 overlapping years.

It is interesting to observe a highly significant and positive correlation coefficient between gold and silver, which supports previous research that silver and gold have similar market characteristics, as already discussed in the Literature Review, for example Emmrich and McGroarty (2013). Moreover, gold shows low but negative and significant correlations with both S&P 500 and DAX indices. These outcomes support another statement that gold has safe haven properties. Silver has almost similar coefficients, but much closer to 0 and of lower significance, which suggests its hedging capabilities.

In terms of indices, the pair has quite a significant positive correlation. Interestingly, both indices present, even though small and insignificant, negative correlations with the exchange rates whose base currencies are used in their country, i.e. the pair DAX - EUR/USD has a coefficient of -0.019, and the S&P 500 – USD/CHF has -0.041. Furthermore, the DAX tends to be significantly and positively correlated with the British pound. All those factors could be attributed to the beneficial aspect of a foreign country's currency appreciation – increased profits from exports.

Finally, as all the exchange rate pairs have USD either as a base or quote currency, their correlations are also high and significant.

Table 6

GJR GARCH for all assets without external regressors. (legend below)

GJR GARCH	*BTC*	*XRP*	*LTC*	*ETH*	*GOLD*	*SILVER*	*LIBOR*	*SnP500*	*DAX*	*EURUSD*	*GBPUSD*	*USDCHF*
Mean equation												
Constant (mu)	0.0013	-0.0015	0.0001	0.0003	-0.0003	0.0001	-0.0033	0.0003 ***	0.0003	-0.0001	-0.0001	0.0001 ***
	(-1.78)	(-1.47)	(0.001)	(0.18)	(-1.68)	(0.40)	(-0.29)	(3.32)	(1.45)	(-0.91)	(-1.03)	(4.18)
AR(1)	0.0377	0.0469	0.0074	0.0196	-0.0276	-0.0955 ***	1 ***	-0.0272	0.0632 *	0.0297	0.0431	0.0497 …
	(1.39)	(1.5)	(0.27)	(0.57)	(-1.28)	(-3.91)	(50.65)	(-1.06)	(2.69)	(1.27)	(1.83)	(2.36)
Variance equation												
Constant (omega)	0.0001 ***	0.0005 ***	0.0001 ***	0.0004 ***	0.00004 ***	0 *	0 ***	0 ***	0	0	0	0 ***
	(5.60)	(8.76)	(5.71)	(5.26)	(11.62)	(2.62)	(26.93)	(11.34)	(0.89)	(0.03)	(0.7)	(20.35)
alpha1	0.1415 ***	0.5225 ***	0.0893 ***	0.206 ***	-0.029 ***	0.0402 ***	0.7934 ***	0.0069	0.0014	0.0043 …	0.0094 *	-0.0016 ***
	(6.55)	(6.41)	(6.38)	(6.67)	(-8.76)	(7.17)	(7.44)	(1.31)	(0.27)	(2.38)	(3.1)	(-150.71)
beta1	0.8216 ***	0.5483 ***	0.8909 ***	0.716 ***	0.3522 ***	0.959 ***	0	0.8673 ***	0.9577 ***	0.9881 ***	0.9755 ***	0.9949 ***
	(40.22)	(13.41)	(58.64)	(19.58)	(7.51)	(335.70)	(0)	(100.64)	(180.28)	(2298.84)	(710.28)	(7808.58)
gamma1	-0.0041	-0.2822 ***	-0.0505 ***	-0.043	0.7347 ***	-0.0278 ***	0.4113 …	0.1834 ***	0.0649 ***	0.0131 ***	0.0151 …	0.0034 ***
	(-0.18)	(-4.03)	(-3.63)	(-1.26)	(6.63)	(-3.35)	(2.02)	(8.29)	(5.74)	(3.51)	(2.14)	(255.38)
Observations	1897	1897	1897	1573	1897	1897	1897	1897	1897	1897	1897	1897

Significance Levels	***	**	*	…
	0	0.001	0.01	0.05

t-values in parentheses

To account for asymmetric returns in time series data, instead of the exponential GARCH (1,1) applied by Dyhrberg (2016a), Baur et al. (2018) propose the asymmetric GJR-GARCH (1,1) model of Glosten et al. (1993). To estimate the parameters, the equations are as follows (notations taken from Baur et al. (2018)):

$$r_t = c + \delta r_{t-1} + \varepsilon_t$$

for the mean equation (1) and

$$h_t = \omega + \alpha\varepsilon^2_{t-1} + \gamma I(\varepsilon_{t-1} > 0)\varepsilon^2_{t-1} + \beta h_{t-1}$$

$$\varepsilon_t \sim N(0, h_t)$$

for the variance equation (2), with $I(.)$ being a function that gets a value of 1 only if the previous return (ε_{t-1}) is negative, and 0 otherwise.

Table 6 above presents the results for the GJR – GARCH (1,1) model applied to the current work's assets' returns under analysis. No external regressors were included.

When compared with the past research of Baur et al. (2018), the previously observed similarities in the ARCH coefficients for bitcoin and equities do not share the same properties anymore – S&P's coefficient is negative, while bitcoin's 0.0377 represent just about half of DAX's coefficient. Interestingly enough, BTC's value is within the range of the foreign currencies' coefficients, which could imply that its behaviour is resembling that of a currency, rather than an asset, contrary to what some of the previous research (Glaser et al., 2014; Yermack, 2015) has noted.

Still, in the variance equation, the estimated parameters display a number of differences between cryptocurrencies and traditional assets. The most noticeable one is seen in the previous returns' coefficients (alpha) showing that cryptocurrencies are significantly and positively dependent on the previous returns in comparison to indices and forex. Taking the extreme case, Ripple's past return is approx. 400 times more dependent than DAX. This can serves as an explanation to the almost "exponential"-like growth of digital currencies around the end of 2017 as seen on the price charts above and in Appendix 1. In addition, Bitcoin's constant (omega) is significant and second highest (0.0001 after Ripple's 0.0005), further proving cryptocurrencies' higher volatility.

Despite the fact that the past variance coefficient for Bitcoin (in the beta row) has increased in comparison to Baur et al.'s work by about one tenth, it is still lower than those of silver, both indices and the three fiat currency pairs. Moreover, the same row shows that Gold's futures have recorded a significant decrease. This could serve as a proof that gold possesses qualities that are quite different from the rest of the assets. In fact, by comparing gold's and bitcoin's coefficients, not even close similarities between the two are to be found.

With regards to the GARCH coefficients for asymmetric effects (gamma row), a clear difference in the assets' dependence pattern is observed. Bitcoin records a negative, but non-significant dependence, which is to indicate that negative shocks do not lead to further increase in volatility, rather the opposite. Such is the case for the other 3 cryptocurrencies as well, with Ripple and Litecoin having much lower and significant coefficients. In contrast, all other assets, with the exception of Silver, show a significant and positive dependence on negative shocks. The negative dependence of Silver here could be explained by its various industrial uses, meaning that its appreciation has a direct impact on production costs for consumer companies. Therefore, futures contracts may be prone to be secured in expectation of rising silver prices.

GJR GARCH with an exogenous regressor

Table 7 below follows the augmented GJR GARCH model used by Baur et al. (2018) which adds the USD trade-weighted index to the mean equation (1) above. As the observations are daily, but incomplete during the weekends, in order to match the number of observations for all other assets, the same interpolation technique was applied. Again, as the daily returns are obtained, the number of observations is reduced by 1 to 1897.

Table 7

GJR GARCH (1,1) with Trade Weighted US dollar index (FRED Economic Data, 2020)

	BTC	*XRP*	*LTC*	*ETH*	*GOLD*	*SILVER*	*DAX*	*EURUSD*	*GBPUSD*	*USDCHF*
Mean equation										
Constant (mu)	0.0013	-0.0015	0.0001	0.0003	-0.0001	0.0001	0.0003	0	-0.0001	0.0001
	(1.8)	(-1.46)	(0.09)	(0.21)	(-0.51)	(0.51)	(1.51)	(-0.08)	(-1.22)	(1.44)
AR(1)	0.0382	0.0467	0.0074	0.0195	-0.0466	-0.1218 ***	0.0482 …	-0.1492 ***	-0.0117	-0.0492 …
	(1.41)	(1.56)	(0.28)	(0.57)	(-1.92)	(-4.95)	(2.03)	(-5.55)	(-0.45)	(-2.16)
USD Trade Weighted Index	-0.1419	-0.105	0.0461	-0.2893	-1.1381 ***	-1.6951 ***	0.4254 ***	-0.3703 ***	-0.176 ***	0.2727 ***
	(-0.68)	(-0.38)	(0.13)	(-0.57)	(-24.35)	(-20.17)	(7.62)	(-10.99)	(-5.1)	(8.78)
Variance equation										
Constant (omega)	0.0001 ***	0.0005 ***	0.0001 ***	0.0004 ***	0 ***	0 ***	0	0	0	0
	(5.61)	(8.76)	(5.71)	(5.29)	(15.55)	(8.53)	(0.69)	(0.02)	(0.48)	(1.13)
alpha1	0.1417 ***	0.5221 ***	0.0892 ***	0.2063 ***	-0.007	0.0698 ***	0.0005	0.0069 *	0.0058	0.0001
	(6.56)	(6.4)	(6.39)	(6.67)	(-0.74)	(7.09)	(0.08)	(3.18)	(1.95)	(0.22)
beta1	0.8215 ***	0.5483 ***	0.891 ***	0.7151 ***	0.32 ***	0.9207 ***	0.9499 ***	0.9846 ***	0.9803 ***	0.9943 ***
	(40.26)	(13.42)	(58.66)	(19.62)	(9.24)	(137.03)	(91.79)	(1553.35)	(1479.23)	(6616.58)
gamma1	-0.0043	-0.2823 ***	-0.0505 ***	-0.0421	1***	-0.0368 *	0.0796 ***	0.0149 *	0.0179 *	0.0014 *
	(-0.18)	(-4.03)	(-3.63)	(-1.24)	(8.48)	(-2.89)	(3.75)	(3.17)	(2.81)	(2.88)
Observations	1897	1897	1897	1573	1897	1897	1897	1897	1897	1897

Significance Levels	***	**	*	…
	0	0.001	0.01	0.05

, t-values in parentheses.

In this table, two of the time series data have been excluded – that of the Overnight LIBOR rates and the S&P 500 returns. The reason is the focus of this research – to compare the performance of cryptocurrencies with that of precious metals and stocks given the US dollar as an external variable. In the case of S&P500, it is consisted of US stocks that are directly related to its economy, whereas the DAX index has a range of other direct factors and the USD trade index could only partially influence its development. Ultimately, in this setup of the analysis, LIBOR and S&P 500 cannot provide further clarification of cryptos' price behaviour.

For the mean equation, cryptocurrencies' coefficients neither observe any change in the constant and the previous return, nor do they show any significant dependence on the USD trade index. In contrast to the results of Baur et al. (2018), bitcoin is stronger, but this time negatively related to the index. Moreover, only the precious metals confirm the strong negative relationship reported in the above-mentioned research, i.e. another confirmation of their safe haven properties, whereas for the remaining time series the sign is positive (in the case of euro and British pound pairs, the sign is negative, as the US dollar is the quote currency). In addition, the EUR/USD pair has switched to the negative territory for its AR coefficient at extremely high significance levels. Furthermore, with regards to the external regressor coefficient, the DAX obtains the highest positive and very significant relationship in comparison with the currency pairs, which implies a strong influence of the US economy on the public German enterprises. This potentially contradicts with the earlier mentioned statement made by Dyhrberg (2016a, p. 90) of the presence of "country-specific events".

Almost no changes have taken place in the variance equation. The digital currencies' coefficients change only slightly, while gold's sensitivity to negative shocks has undergone the biggest increase for all its coefficient estimates (0.7*** -> 1***). The rest do not record big differences, but some of the estimates are not as significant as they were without the Trade-weighted index.

Conclusions and Recommendations

The current work set the goal to provide an up to date insight into the safe haven properties of 4 cryptocurrencies – Bitcoin, Ripple, Litecoin and Ethereum – by comparing their price developments with those of precious metals, indices, interest rates and forex pairs. The outcomes were intended to help interested parties, such as portfolio / risk managers, investors and researchers obtain a better understanding of how the new type of assets compare with the well-known exchange-traded assets. Thus, they can make better-informed investment- or risk management decisions.

Having reviewed already published literature, the concluding opinion on cryptocurrencies is that, despite their extremely high return potential, a careful consideration of the risks should be taken, before any decisions to invest is undertaken. Eventually, the research methods of Baur et al. (2018) were chosen as the basis for the current research, as their utilisation of the GJR GARCH model was well-suited for the main aim of this work. The authors undertake a replication and an augmentation to the research of Dyhrberg (2016a) due to flagged flaws in the approach in her research. The key differences between the current research and that of Baur et al. (2018) are predominantly in the data collected:

- additional analysis of silver, three other major cryptocurrencies (Ripple, Litecoin and Ethereum), and two more fiat currency pairs (EUR/USD and USD/CHF)
- a substitution of FTSE100 and MSCI world index with DAX and S&P 500 in order to analyse a potential country-specific dependence.
- an updated sample of time series data

The findings of the research revealed that, regarding the correlation coefficients, none of the cryptocurrencies exhibited any significant correlation with the other assets, with the exception of Bitcoin with gold. When compared with the results of Baur et al. (2018), bitcoin’s correlation has increased and is highly significant at the 1% level with gold. This could be an indication of an ongoing change of bitcoin’s behaviour, however, the coefficients still remain close to 0 which confirms statements about the lack of dependence between cryptos and traditional assets, as indicated by Baur et al. (2018) and Ji et al. (2018)

The GJR-GARCH model without an external regressor revealed other changes about the Bitcoin. Such were the much smaller constants both in the mean and the variance equations than the outcomes obtained by Baur et al. (2018). However, the constants remain higher than those of the traditional assets, confirming the statement that cryptos observe very different processes. Moreover, bitcoin's lack of sensitivity to negative shocks in the variance equation is in significant contrast to the coefficient estimate for gold, casting doubts on the performance similarities between the two assets. The rest of the cryptos have even more contradictory estimates for the same coefficient.

When the US Trade weighted index is included as an external regressor in the mean equation, gold proves its strong negative relationship with the US dollar. Bitcoin, Ripple and Ethereum also showed a negative dependence, Litecoin's was positive, but still close to 0, and all were far smaller and non-significant, in contrast to DAX and the currency pairs.

As a conclusion, given the results above, the chosen cryptocurrencies have a completely different price development from gold and the remaining assets under analysis. Consequently, their inclusion in a portfolio could potentially lead to its better diversification. However, as found in the descriptive statistics of the data, even though they register the highest average returns, these returns come at the price of a much higher standard deviation i.e. risk. Therefore, investing in the above-mentioned cryptocurrencies should be preceded by careful consideration of the higher risks.

Limitations and recommendations for further research

Although the current work attempts to extend (using more and different macroeconomic factors) as well as update previous research, there are still some limitations that could be further explored. Those are the following:

- The results observed apply only for the specific sample time period, meaning that future snapshots of price developments might reveal a very different picture and provide different implications for the interested parties.
- The number of assets under analysis is also constricted – 4 cryptocurrencies, 2 indices, 2 precious metals, 1 interest rate and 3 currency pairs. Although they are

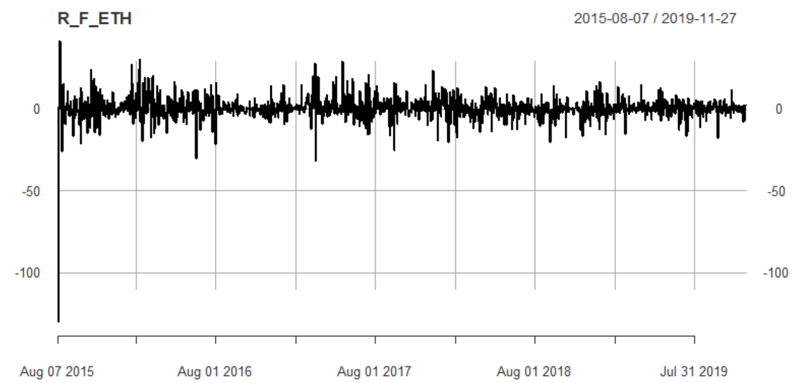
significant for the global economy, there might be other factors that can better explain cryptos' behaviour. Moreover, as the recently developed digital currencies become more liquid in the future, their analysis could also be presenting profit opportunities.

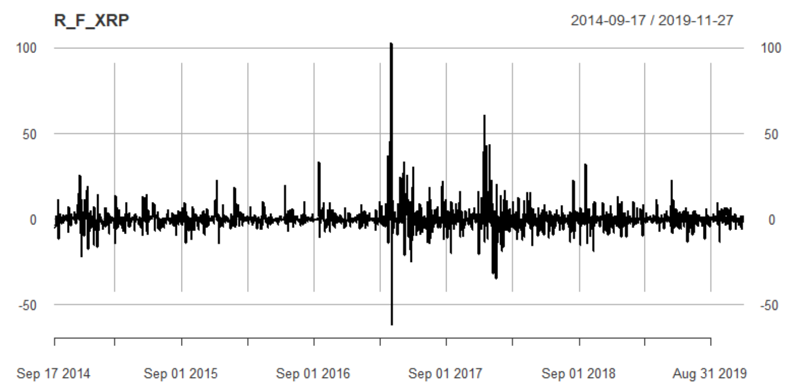
- The statistical techniques applied in this work might be providing valuable information about the new type of assets, but the hypotheses developed here could also be verified using other research methods.

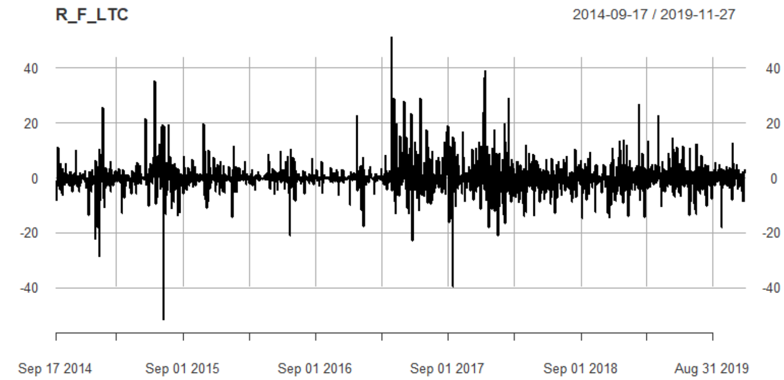
As an overall recommendation, analysis of the new generation of currencies is beneficial to all interested parties, as it can reveal early profit opportunities, that can be exploited before they get noticed by the mass media.

Appendix

App.1 Remaining price/returns charts combination for ETH, XRP and LTC







App.2 Derivation of the correlation table for all data*

t-TEST	*BTC*	*XRP*	*LTC*	*GOLD*	*SILVER*	*LIBOR*	*SnP500*	*DAX*	*EURUSD*	*GBPUSD*	*USDCHF*
BTC											
XRP	15.1377										
LTC	33.8432	16.4016									
GOLD	2.6258	-0.2221	0.4225								
SILVER	1.1535	1.1259	0.3733	18.6351							
LIBOR	-0.7239	1.199	-0.2973	-1.5256	-1.9836						
SnP500	0.49	2.1885	1.067	-3.5392	0.351	-1.3721					
DAX	0.333	1.6191	0.3393	-6.8102	-1.7584	1.6816	26.8167				
EURUSD	-0.1896	1.4494	0.6956	1.2662	1.4161	-1.8907	0.3182	-0.8189			
GBPUSD	-1.0819	0.8982	-0.3775	-0.2883	0.6015	-0.8449	1.9826	3.082	26.4764		
USDCHF	-0.2801	-1.4054	-1.6987	-0.8648	-2.5605	1.3703	-1.79	0.0243	-24.1106	-12.2614	
ETH	18.4222	10.6854	17.69	1.722	0.5456	0.0538	0.8981	-0.2493	0.37	0.1099	-1.0455

*Negative t-test results highlighted in yellow. Formula used: = r*sqrt((n-2)/(1-r^2) (r = Pearson correlation coefficient per asset)

p-values	*BTC*	*XRP*	*LTC*	*GOLD*	*SILVER*	*LIBOR*	*SnP500*	*DAX*	*EURUSD*	*GBPUSD*	*USDCHF*
BTC											
XRP	5.90511E-49										
LTC	8.6612E-197	1.23E-56									
GOLD	0.008713701	0.824258	0.672694								
SILVER	0.248864629	0.260347	0.708937	2.66348E-71							
LIBOR	0.469245259	0.230666	0.766297	0.127268957	0.047443						
SnP500	0.624192124	0.028757	0.286091	0.000411067	0.725658	0.17018					
DAX	0.73913386	0.105592	0.734415	1.30381E-11	0.078849	0.092807	1.4E-134				
EURUSD	0.849620642	0.14739	0.486791	0.205608762	0.156897	0.058821	0.750389	0.412946			
GBPUSD	0.279431433	0.369194	0.705881	0.773177453	0.547556	0.398283	0.047562	0.002086	1.066E-131		
USDCHF	0.779451216	0.160064	0.089538	0.387281982	0.010529	0.170748	0.073614	0.980594	3.0184E-112	2.58E-33	
ETH	7.58688E-70	6.41E-26	6.21E-65	0.085229218	0.585377	0.957121	0.369234	0.803145	0.711445473	0.912494	0.295916

*For the negative t-test values in the previous table, the function “t.dist.2t” used here, takes the relationship:
=T.DIST.2T(X,n-2) =T.DIST.2T(-X,n-2)"

App.3 Consent Form

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DATA PROTECTION ACT 1998

CONSENT FORM

I confirm that this dissertation is all my own work. I understand that my written permission is required for the University to post my dissertation on Moodle so that it is available to future students for reference purposes and that my name may be evident. **I hereby give my consent to my named work being made available. I confirm that my work is not confidential.**

Print name: Radoslav Stefanov Matriculation No. ……………

Signature Signed Date: 31. March 2020

FACULTY: **Business School** SCHOOL: Edinburgh Napier University

MODULE NO: **SOE10133**

DISSERTATION:

TITLE Cryptocurrencies' potential to become a wealth-preservation alternative to precious metals during capital market volatility.

LOCATION IN WHICH TO BE HELD – **Moodle**

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